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Bankruptcy Prediction

The Credit Relevance of Reclassfied Financial Statement Ratios

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Master thesis, MSc, Business Analysis and Performance Management

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Contents

Abstract

In this thesis, we present research within the field of financial statement analysis. We seek to investigate the credit relevance of financial statements reclassified for analytical purposes, and in particular the marginal and absolute credit relevance of accounting ratios derived from the reclassified financial statement. To the best of our knowledge, this is one of the first studies addressing this particular topic.

We have conducted several tests, using a conditional logistic model, to assess the credit relevance of the reclassified accounting ratios. The tests were conducted on a sample consisting of 28,081 group financials registered in the Brønnøysund Register Center in the period from 1999 - 2014.

We find a reclassification of the traditional financial statement to increase the credit relevance of some liquidity ratios. Our test output indicates that Current interest bearing liabilities/Current financial assets, Working capital/Invested capital and Non-current operating assets/Invested capital have both marginal and absolute credit relevance when tested individually. We also get indications that the combination of these reclassified ratios improves the predictive abilities of traditional bankruptcy prediction models.

Keywords: Bankruptcy prediction, reclassification, accounting ratios, credit analysis, logistic model

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We hope our thesis will contribute to the interesting field of credit analysis and that it sheds light on the implications of using a reclassified financial statement for credit analysis purposes.

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Finally, we want to give special thanks our beloved families for their wholehearted support and encouragement.

1. Introduction

In the following section we will present the motivation for our thesis, followed by a presentation of our research question and hypotheses. We will also give a brief presentation of our main results and how our thesis may contribute to current literature on credit analysis. The section ends with a short overview of the structure of this thesis.

Surviving in competitive markets is a challenge for many companies. Recent economic cycles have shown that periods of economic recession tends to increase the number of companies failing to meet their obligations and experiencing financial distress. The consequences of financial distress are many, and most of the repercussions affect both internal and external stakeholders. Depending on the situation, financial distress might lead to costly restructuring or in worst case, bankruptcy.

In the Norwegian bankruptcy legislation, "Konkursloven, 1984, §§60-61", a company is considered bankrupt when the debtor is considered insolvent and a bankruptcy petition is submitted, either by the debtor or any of the debtor's creditors. *The debtor is considered insolvent if he is unable to fulfil his economic obligations as they mature. However, he is not to be considered as insolvent if his property and income are sufficient to cover the obligations given time to be liquidated.*

As a consequence of bankruptcy, owners may lose their investments, employees their jobs and customers and suppliers might lose an important part of their business. Another stakeholder greatly affected by a bankruptcy are the creditors, as they risk significant losses on outstanding debt.

To assess and potentially avoid the costs associated with a bankruptcy, several parties has interest in predicting a company's probability of default. Creditors normally want to optimize profits by maximizing loans to companies that are able to pay interest and instalments and minimize loans to companies that are unable to fulfil its obligations. Credit analysis can help the capital-providing stakeholders in this matter by assessing the creditworthiness of a company. In case of wrongly classifying companies as bankrupt or non-bankrupt, the stakeholders risk incurring severe losses.

Another purpose of bankruptcy prediction is for central banks to monitor the financial stability in the business sector. As an example, Norges Bank (the central bank of Norway) has developed the SEBRA-model (Sjøvoll, 1999; Bernhardsen, 2001). The model is developed for predicting the probability of corporate default and to estimate a bank's expected loss on loans within different industries.

As we can see, there several parties interested in knowing whether a company goes bankrupt or not, as bankruptcies has serious consequences for a variety of stakeholders. Considering the fact that large bankruptcies also have the potential to affect both national and global economies, we notice that the focus on credit analysis and bankruptcy prediction has increased following recent financial crises. The ability to correctly predict corporate default at an early stage is something that would be an enormous advantage for any stakeholder, which is why we see so many institutions trying to develop the best prediction model possible.

During the last couple of decades there has been a change in "traditional" business environments, where we now observe a new technology driven breed of companies with quite different financials than the traditional industrial firms. As a result of these changes, Beaver, McNichols and Rhie (2005) raises the question whether the traditional financial statement classifications are as credit relevant as they used to be. They find indications that the predictive abilities of traditional financial ratios have decreased over time.

An alternative approach to classification is proposed by investors with the practice of reclassifying financial statements into operational and financial items, as it simplifies an evaluation of the different compositions of assets and liabilities (Petersen, Plenborg & Kinserdal, 2017, p. 107-120). A reclassification into an investor-oriented financial statement is also claimed to increase the relevance of accounting ratios used for credit analysis purposes (Petersen et al., 2017, p. 107-120, 221-235). Nevertheless, we experience that none of the traditional studies on bankruptcy prediction have incorporated a reclassification of the financial statement.

This forms the basis of our research question; are reclassified financial statement ratios relevant for credit analysis purposes?

To answer this question we have formed the following hypotheses, and conducted several tests on a sample of Norwegian group financials[1].

$H0_m$: Ratios derived from the reclassified financial statement does not have marginal credit relevance

$H0_a$: Ratios derived from the reclassified financial statement does not have absolute credit relevance

We find three reclassified liquidity ratios and one profitability ratio to have marginal credit relevance when added to our baseline model. The performance of the three liquidity ratios also indicate a disproval of the second hypothesis, as they are able to improve already well-recognized bankruptcy prediction models, such as the one developed by Ohlson (1980) and Norges Bank's SEBRA-model (Bernhardsen, 2001). Interestingly, liquidity ratios are found less important for predicting corporate default in previous literature. However, our research suggests that a reclassification of the financial statement improve the credit relevance of some of the ratios.

The main aim of our research has been to go beyond the best-fitting-model problem, which has been the main focus in previous literature. We hope to contribute to the field of credit analysis by addressing the implications of using a reclassified financial statement and accounting ratios derived therefrom. In our opinion, the bankruptcy prediction literature has evolved without exploring the possibility of developing any new ratios that are able to increase the predictive abilities of static models. The findings from our research do not only suggest that a reclassification of liquidity ratios might be relevant for bankruptcy prediction, but also addresses a field of study that potentially can lead to a disruption of current bankruptcy prediction practices.

In the next section of our thesis, we will present and review some of the important mainstream literature on bankruptcy prediction, as well as literature suggesting that a reclassification of financial statement ratios are relevant for credit analysis and valuation. This leads to the development of our research question and main hypotheses. In section 3, we will present the applied methodology and our approach for testing the hypotheses. In section 4, we will present the data and sample selection procedure, as well as descriptive statistics and a correlation matrix for the main variables in our study. Our main results are

[1] The final sample consists of 271 bankrupt and 27,810 non-bankrupt observations.

presented in section 5, followed by some additional tests to further assess the robustness of our results in section 6. The thesis ends with an overall conclusion in section 7.

2. Literature and Hypothesis Development

In this section we will present some of the general characteristics of the creditor- and investor-oriented financial statements and how the current classifications addresses different needs of the capital investors. We will also do a presentation of previous literature on why the traditional classification of financial statements are better for credit analysis purposes, followed by some critics of the traditional classification and mainstream accounting ratios. The section ends with a statement of our research question and the development of our initial hypotheses.

2.1 Creditor- vs. Investor-oriented Financial Statements

As the main purpose of our study is to assess the credit relevance of reclassified financial statements, i.e. financial statements reformulated for analytical purposes, and ratios derived therefrom, it is important to understand the basic traits of the ordinary and reclassified financial statement. When talking about the creditor- and investor-oriented financial statement, we are referring to the structure and standards that are considered to best meet the preferences of the different stakeholders (Alexander, Britton & Jorissen, 2007, p. 25-31). On the one hand we have the equity-oriented stakeholders interested in knowing the intrinsic value of a firm in order to assess whether an investment has the potential to generate a return on capital above the required rate (Koller, Goedhart & Wessels, 2015, p. 17-23). In other words, the equity-oriented stakeholders are interested in knowing the potential “upside” of a company, as any value exceeding what is needed to cover debt obligations accrues to the investors (Berk & DeMarzo, 2014, p. 727-728).

On the other hand we have the debt-capital-oriented stakeholders. Their primary focus is on the potential loss of their investments, as their “upside” is limited to the interest earned on the loan given (Berk & DeMarzo, 2014, p. 170-186). Whereas, in the case of a bankruptcy, the debt-capital-oriented stakeholders risk losing all their outstanding obligations as bankruptcy is a highly uncertain and costly event (Petersen et al. 2017, p. 371-373). Thus, creditors are more concerned by the potential “downside” of an investment, as they only partake in it should a company experience a decline in financial position. The interests and focus of the stakeholders mentioned above are quite different, and as a result of these differences, stakeholders find different characteristics of the financial statement useful.

The creditor-oriented financial statement are considered to be somewhat conservative in the way assets and liabilities are recognized and in the valuation of different accounting items. As an example, accounting principles involving the value of underlying assets, such as prudency, historical cost and impairment, are some of the reasons why the traditional financial statement regulation has been considered to be somewhat creditor-oriented (Alexander & Britton, 2004, p. 159 – 170). The classification of items into current and non-current also supports the creditor's point of view, as the classification meet the preferences of the creditor's to a greater extent than the investors (Penman, 2012, p. 682).

The information given by the "conservative" accounting principles and classifications are not particularly interesting for the investors, as they prefer knowing the true performance and value of the assets when evaluating a company (Kaldestad & Møller, 2016, p.19-21). The investor-oriented financial statement can thus be thought of as fair value- and performance-oriented, as an investors main interest is to find the fair value of the different composition of assets based on their cash-generating abilities. By finding the actual invested capital, an investor can extract the true return on invested capital without the effect of any post-recognition value adjustments. This is used to evaluate the true return on operating assets and to assess the value of the company's equity. As a result, the fair value- and performance-orientation is considered to be the most prominent characteristic of the investor-oriented financial statement (Alexander & Britton, 2004; Schipper, 2005; Ball, Askon & Sadka, 2008).

As previously mentioned, the investor-oriented financial statement has also been said to increase the relevance of the credit analysis, as one of the main fields of interest when analyzing a company's creditworthiness is the profitability of core operations (Altman, 1968). However, we experience that the investor-oriented financial statement is mainly used for equity analysis purposes, whereas the traditional financial statement has been the go-to structure for credit analysis and bankruptcy prediction.

2.2 Financial Statements – Creditor-oriented

If we look at the objective of current financial reporting, stated in IASB's Conceptual Framework, it is clear that the general purpose of financial reporting is to provide stakeholders with relevant and faithful information about a firm's financial position (Picker et al., 2016, p.10-18). Hence, the current classifications and standards are considered to provide both investors and lenders with reliable and relevant information for assessing a company's value and creditworthiness. However, as we know, the different stakeholders have different preferences when it comes to the classification of financial statements.

Because of the fundamental principle of conservatism historically used in accounting regulations (Watts, 2003), the traditional financial statement classification was considered to be somewhat creditor-oriented. An example of this is the Norwegian Generally Accepted Accounting Principles (NGAAP), where prudency is one of the main accounting principles (Regnskapsloven 1998). The prudency-principle is to prevent opportunistic behavior by management, as companies have to recognize unrealized losses in the financial statement (Stenheim & Madsen, 2014). By making the profit and value estimates rather conservative the prudency principle works as a safeguard for creditors. However, with today's IFRS regulations where relevance and faithful representation is implemented as main qualitative characteristics, the use of prudency as an accounting principle has been somewhat negated.

With the new IFRS regulations, where there are more elements of fair value measurement, there is a tradeoff between the interests of the two stakeholders. Even though the fair value measurements might seem relevant for both creditors and investors, the high degree of subjective judgment in the estimation process can potentially lead to less reliable and verifiable accounting numbers (Petersen et al., 2017, p. 23-24). Despite of increasing fair value measurement in today's accounting standards, the current financial regulations are still thought of as creditor-oriented, as some IFRS requirements are meant to increase the relevance of the information available for creditors (Florou, Kosi & Pope, 2016). For instance, the recognition of previously unrecognized pension deficits under IAS 19 provides the creditor with more information on the effective debt obligations of the company, and the impairment accounting under IAS 36 are meant to give a more timely loss recognition (Ball et al., 2008). Florou et al. (2016) also find increased credit relevance in seventeen countries after the introduction of IFRS.

The credit relevance of the traditional financial statement classification is also stressed by Penman (2012, p. 682-683), as he claims the traditional classification is more credit relevant than a reclassified financial statement, as all debt, no matter if its operational or financial, has to be paid when it is due.

2.3 Previous Literature on Bankruptcy Prediction

There have been several accounting ratios that has, based on the traditional creditor-oriented financial statement, proven to be important in previous bankruptcy prediction studies.

One of the first major studies was the one of Beaver (1966). He applied a univariate approach where he sorted accounting ratios into 6 different categories[2] (to reduce the amount of common elements when applied in a multi-ratio analysis) and chose the variable within each category that had the lowest percentage prediction error in a classification test[3] over a 5-year period (see table 1). Beaver found that ratios for the bankrupt firms had a clear deterioration as they approached failure, and the difference in mean values was evident for the last 5 years prior to default.

Out of the 6 ratios tested, three proved to have good predictive abilities. The ratio with the highest predictive abilities was CFTL, measuring the proportion of total debt covered by a company's annual cash flow, followed by the NITA and TLTA ratio. The NITA ratio measured a company's relative profitability, whereas TLTA captured the firm's financial structure. All the liquidity ratios, measuring a company's ability to repay short-term liabilities, performed least well out of the ratios tested. Beaver concludes that it seems to be the flow of liquidity that supplies the ”reservoir”, rather than the size of the ”reservoir” itself, that is most important when predicting corporate default.

Altman (1968) also used a framework where ratios were categorized into different groups: Liquidity, profitability, leverage, solvency and active ratios. The main difference from Beaver (1966) was that he took the correlation between variables into account when choosing the group of variables with the highest predictive ability (See table 1).

Compared to the accounting ratios identified by Beaver (1966) there are several alterations. The first is the RETA ratio as a solvency measure, where the ratio measures both the cumulative profitability of a firm and the effect of age on the probability of default[4]. Altman also used the market value of equity over total liabilities (mEQTL) as a measure of solidity. By including market variables, his model captures information not necessarily reflected in the accounting numbers.

2 Cash flow ratios, net income ratios, debt-to-total asset ratios, liquid asset-to-total asset ratios, liquid asset-to-current debt ratios and turnover ratios.
3 The test was conducted by identifying the cut-off value that minimized the frequency of incorrect predictions for each ratio. The firms are then categorized as failed or non-failed based on their ratio-score.
4 Altman (1968) states that young firms have a higher probability of bankruptcy than older firms.

Table 1: Ratios from Traditional Literature

Definition	Abbreviation	Beaver	Altman	Ohlson
Net income / Total assets	NITA	X		X
Earning before interest and taxes / Total assets	EBITTA		X	
Total liabilities / Total assets*	TLTA			X
Retained earnings / Total assets	RETA		X	
Market value of equity / Total liabilities	mEQTL		X	
Cash flow / Total liabilities	CFTL	X		
Cash flow from operations / Total liabilities	CFOTL			X
Working capital / Total assets	WCTA	X	X	X
Current liabilities / Current assets**	CLCA	X		X
Defensive assets - current liabilities / Fund expenditures for operations	"No-credit interval"	X		
Sales over total assets	SALESTA		X	
Logarithm of total assets***	logTA			
Dummy = 1 if: Total liabilities > Total assets	OENEG			X
Dummy = 1 if: Net income < 0 (in any of last two years)	INTWO			X
Change in net income from the previous year	CHIN			X

Notes: The table shows the ratios included in the models by Beaver (1966), Altman (1968) and Ohlson (1980). Definition is the description of the ratio as in the original paper. Abbreviation is the notation that will be used for the respective ratio throughout the thesis. The X under the column of Beaver, Altman and Ohlson indicates in which of the models each ratio is included.

As a profitability measure, Altman (1968) uses the EBITTA ratio, which measures the profitability of the firm´s assets without leverage or tax effects. Altman argues that this is a particularly relevant ratio for bankruptcy prediction because a firm's survival ultimately depends on the core profitability of its operations. He also included SALESTA as a turnover ratio as it shows the assets ability to generate income. Interestingly, the ratio had the lowest predictive power out of the ratios in the model on an univariate basis, and turned out to be statistically insignificant. However, when included in the model it is rated the second best contributor to overall discriminant ability because of an unique relation to the other variables in the model.

Ohlson (1980) states that in his study no attempt was made to find any "new or exotic variables", and that the predictors included in his model are based on the variables most frequently mentioned in the previous literature. In his model, three factors are of particular importance when predicting corporate default: Measures of financial structure, performance measures and measures of current liquidity. His model includes some variables previously discussed by Beaver (1966) and Altman (1968), such as TLTA[5], WCTA, CLCA[6] and NITA.

However, he also introduced other variables (see table 1), such as CFOTL, which only includes cash flow from operations in the numerator. Ohlson also includes a size variable LOGTA[7], as size is considered to be an important predictor when it comes to corporate default. Another alteration in Ohlson's model is the OENEG variable, which works as a correction factor for TLTA in the special case of negative book value of equity. Survival will in those cases depend upon a variety of complex factors, which are to be captured by the OENEG variable[8]. Ohlson also included a dummy variable which equals 1 if net income was negative the last two years [INTWO], and a variable measuring the change in net income one year to another [CHIN]. He found that all of the variables except WCTA, CLCA and INTWO were significant. Ohlson also found that the "financial structure variables" were uncorrelated with the "performance variables", and that both sets of variables independently contributed to the explanatory power of the model.

Even though most of the mainstream studies on bankruptcy prediction have been conducted on US data, we do have some studies addressing probability of default among Norwegian companies. One of the most prominent is the working paper developed by Bernhardsen (2001) in cooperation with the Central Bank of Norway. The SEBRA-model introduces several alternative variables to the ones previously discussed.

As a measure of profitability they include net income (before special items) + depreciation and amortization, after tax, over total assets. By excluding special items, the ratio is somewhat robust to "one-off" items that are of less value for predictive purposes (Petersen et al., 2017, p.623-625). As liquidity measures they include (Cash – Short term debt) /Sales, Trade payables/Total assets[9] and Public tax payables/Total assets. Eklund, Larsen and Bernhardsen (2001) argues that an increasing TAXTA ratio is a clear indication of weak liquidity, as most firms are very concerned about paying taxes and tax-authorities in many cases file a petition for bankruptcy if taxes are not paid when due. As measures of solidity

[5] Beaver included TDTA, where the only difference between the two is that "debt" does not include provisions.
[6] Beaver included "the inverse" CA/CL
[7] Beaver also discussed size in terms of total assets. He found the variable to be significantly different for the bankrupt and non-bankrupt companies.
[8] Ohlson experienced a negative sign of the coefficient, which means that a situation with an extremely high TLTA-ratio is bad indeed, but not "that" bad due to the negative OENEG.
[9] PAYTA was included as it had marginal contribution in excess of the other liquidity ratios.

they include total equity over total assets, which is equivalent to the solvency measures TDTA and TLTA used by Beaver (1966) and Ohlson (1980). The SEBRA-model also includes a dummy variable for dividends paid in the last fiscal year, and[10] a dummy that is equal to 1 if current equity is less than paid-in equity. The last dummy variable is meant to capture the cumulative profitability factor, as with the RETA ratio from Altman (1968). The variable is accompanied with a "years since establishment" dummy to capture the "age-effect" of the ratio. Another alteration, compared to prior models, is the inclusion of industry averages for TETA and PAYTA and industry standard deviation for NBNITA. These variables are meant to capture information about the risk associated with operating within certain industries[11].

Table 2: Ratios in the SEBRA-model

Definition	Abbreviation
Net Income (before special items) + depreciation and amortization - taxes / Total assets	NBNITA
(Cash – short term debt) / Sales	LIKSALES
Trade payables / Total assets	PAYTA
Public tax payables/ Total assets	TAXTA
Total equity / Total assets	TETA
Dummy for dividend last year	DIV
Dummy for reduction in paid-in equity	LOEQ
Industry average for TETA	meanTETA
Industry average for PAYTA	meanPAYTA
Industry standard deviation for NBNITA	stdNBNITA
Years since establishment	AGE

Notes: The table shows the ratios included in the SEBRA-model. Definition is the description of the ratio as in the original paper. Abbreviation is the notation that will be used for the respective ratio throughout the thesis.

As seen by this literature review, bankruptcy prediction studies has evolved without any clear consensus on which accounting ratios to use or how many accounting ratios to include to best assess the probability of financial distress. These decisions have more or less been

[10] The dividend dummy is included as there is reason to believe that a reasonable management would cut dividends in times of financial trouble (Eklund et al., 2001).
[11] Eklund et al. (2001) states that there is observed more bankruptcies in industries with high debt levels (i.e. low level of equity) and high trade payables. There is also reason to believe that the risk of bankruptcy is higher in industries with high variation in earnings.

based on the intuition of the researcher or what previous researchers have found to be important when assessing corporate default. In some way, traditional studies have looked like academics trying to develop “the better mousetrap” without agreeing on ”optimal” model design or which specific variables that best predicts corporate default.

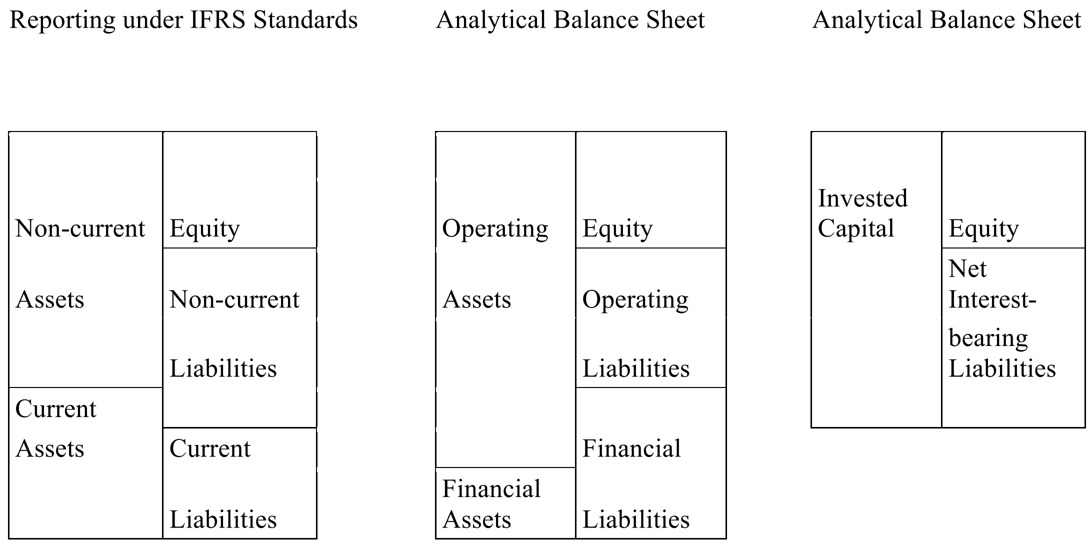
However, some trends appear from previous studies. Ratios describing a firm’s profitability, leverage and cash-generating abilities seem to be of great importance when predicting corporate default. Many researchers have also incorporated liquidity measures in their models, but some studies find these to have less predictive ability than ratios from the categories mentioned above. Variables that describe a firm's size, age, activity and variation in earnings has been tested and found to be significant in prior studies.

Even though there are no clear consensus on which or how many variables to include, all of the abovementioned studies have reported impressing ability to correctly classify firms as bankrupt or non-bankrupt. Altman´s (1968) MDA model was able to correctly classify 96% of the estimation sample one year in advance. Ohlson (1980) also reports a correct classification ability of 96% using a logistic model with only accounting ratios. High predictive abilities have also been reported in studies on Norwegian companies (Olsen, 1991; Bernhardsen, 2001) where regular financial statement classification has been used. Despite that no best single model has been found, all the studies based on traditional creditor-oriented financial statements has yielded good results when predicting corporate default. This raises the question whether it is the models and ratios used that generate these impressive results, or if it is the traditional financial statements where the information is obtained.

2.4 Reclassified Financial Statements – Investor-oriented

As previously mentioned, the main interest for equity holders is the core profitability of a company's operational assets (Penman, 2012, p. 682). Thus, there is a common practice of reclassifying the financial statement into operational and financial items as this enables a thorough analysis of the return on invested capital [IC]. IC can be seen as the net operating assets, which equals the sum of equity and net interest bearing liabilities. In other words, it is the net amount a firm has invested in its operating activities and which require a return.

Table 3: The Different Balance Sheets



Notes: The table shows how the financial statements are organized (Petersen et al., 2017, p.114). To the left is the traditional classification structured after today's IFRS standards. The second model shows how an analytical balance sheet is structured after a reclassification. The third shows how the analytical balance sheet "summarizes" operational and financial items into invested capital and net interest bearing liabilities.

The reclassified financial statement provides several "new" ratios that make a thorough analysis of a company's operations possible. One can argue that most of the previous literature on credit analysis and bankruptcy prediction has evolved without much effort in finding "new" ratios that can increase the predictive ability of traditional bankruptcy prediction models. However, modern literature suggests that a reclassification of the financial statements into financial- and operating items could provide the creditors with more relevant information about a firm's creditworthiness (Petersen et al., 2017, p.107-120, 221-235).

For instance, Petersen et al. (2017, p. 231-233) discusses the relevance of the CACL ratio as a liquidity measure. They suggest that the traditional ratio ignores the fact that some parts of the current operating liabilities[12] are constantly re-financed as a result of a firm's ongoing operations. Another problem with the ratio is that the book value of operating current assets poorly reflects the short-term cash potential of these assets[13]. As a consequence, the classification of items into current and non-current will not necessarily be a good measure of a firm's short-term liquidity.

[12] For example, account payables in the current ratio. The same applies to the asset side, e.g. accounts receivables.
[13] Inventory is valued based on an assumption of "going concern". This means that in case of a "fire sale", the true value of these assets may be way below book value.

This problem is also addressed by Penman (2012, p. 683) who suggests reclassifying long-term marketable securities as short-term assets when assessing a company's short term-liquidity reserve, as these assets could be sold without affecting core operations if a short-term liquidity problem arises.

Petersen et al. (2017, p. 233) suggests an alternative to the classic current ratio that separates operational debt from financial debt. By measuring a firm's liquidity as Cash flow from operations (CFO) / Current net interest bearing liabilities (CNIBL), the ratio will avoid the convertibility-to-cash problem that occurs when using current assets[14]. Another advantage with the ratio is that it only considers the part of current debt that is not refinanced through ongoing operations.

Another potential flaw with the original classifications is that firms with large amounts of financial assets are discriminated in several ratios used in previous bankruptcy prediction studies. For instance, ratios addressing a company’s operating profit before interest and taxes in relation to its total assets (EBITTA) have traditionally been used as a measure of core operating profitability (Altman, 1968). However, a firm with large amounts of cash or cash equivalents will be “punished” in this ratio if total assets is computed based on the traditional classification. A firm with a large amount of financial assets will have a larger denominator (total assets), but will not “benefit” from these assets as interest/financial income is not reflected in the nominator (EBIT). A possible solution is to calculate total assets using net interest bearing liabilities[15]. “Large cash firms” will then no longer be “punished” for its large denominator as the financial assets are netted against the company’s financial liabilities.

As depicted above, there is literature suggesting that a reclassification of the financial statements is relevant for a credit analysis. In our thesis we will look at the implications a reformulation has on the financial statement and how the reclassification affects traditional ratios used for bankruptcy prediction. Further, we will look at various key accounting figures presented by Petersen et al. (2017, p. 222-234) that addresses potential flaws related to ratios derived from the traditional financial statements (we will refer to these figures as “reclassified ratios”). We will test these reclassified ratios and see how they perform in a credit analysis model compared to mainstream ratios used in previous research.

[14] CFO might reflect the short-term cash potential of operational assets better.
[15] Calculated as sum of equity + net interest bearing liabilities or calculated as total assets - financial assets

2.5 Research Question and Hypothesis Development

The predictive abilities from the models presented in previous literature suggest that the ordinary financial statements and the ratios extracted therefrom are the most relevant for bankruptcy prediction. If this was not the case, why haven't these academics taken reclassifications into account in their studies? This argument support the practice of using the traditional financial statement and ratios for credit analysis, and leave the practice of reclassifying accounting items into operational and financial for equity analysis and valuation.

The use of reclassified financial statements are, to the best of our knowledge, not particularly widespread in the current credit analysis literature, and after doing research on previous studies we have not been able to come up with any studies that have tested the predictive abilities of ratios calculated from reclassified financial statements. The empirical results from previous studies on bankruptcy prediction and literature on the creditor-oriented development of the ordinary financial statement regulations form the basis of our research question; are reclassified financial statement ratios relevant for credit analysis purposes?

To investigate the relevance of reclassified ratios and hopefully be able to answer our research question, we have decomposed the research question into addressing the marginal and absolute credit relevance of reclassified ratios. The marginal credit relevance addresses the significance of reclassified ratios when added as an additional variable to the benchmark model, whereas the absolute credit relevance addresses the significance of the ratios when replacing its traditional “counterpart” in the benchmark model.

$H0_m$: Ratios derived from the reclassified financial statement does not have marginal credit relevance

$H0_a$: Ratios derived from the reclassified financial statement does not have absolute credit relevance

3. Methodology

We have used a conditional logistic model to test our initial hypotheses. In this section we will present some literature on models used in prior studies and the reason why the logistic model has proven solid in predicting corporate default. We will then explain the main characteristics and properties of the logistic regression model and how we have applied the logistic model to test our hypotheses. In our presentation of the logit model we will not focus on the mathematics behind the model as this is outside the scope of our study. For a more thorough review of the logistic model we refer to *Applied Logistic Regression* by Hosmer & Lemeshow (2000).

3.1 Past Approaches: Univariate, MDA, Logit and Others

In the wake of the univariate approach introduced by Beaver (1966) there have been several different model designs developed for bankruptcy prediction. Altman (1968) criticized the univariate approach and applied a multiple discriminant analysis [MDA] as it combines several measures into one model to increase the predictive ability. The main advantage of the inclusion of several variables is that it takes the interaction between variables into account. However, Beaver (1966) reported that in many instances the predictive power of a multivariate model, compared to the best single ratio, did not appear to be overwhelming. The main explanation for this was, according to Beaver, the increased multicollinearity among the variables as the number of variables increased.

Ohlson (1980) introduces an alternative model to the multiple discriminant analysis used by Altman, the conditional logistic model (logit). He addressed several advantages of using the logit model compared to the MDA approach. The first was that the MDA approach had to strict assumptions regarding the explanatory variables included in the model. MDA requires that the variance-covariance matrix is the same for bankrupt and non-bankrupt firms, and that the predictors have to be normally distributed[16]. Another advantage of the logit model is that it gives an "intuitive" output regarding the probability of default. The MDA only gives output that can be used for ranking firms in different categories, which means that to "translate" MDA scores into probability of default, one would have to set prior probabilities to the categories of firms and then derive the posterior likelihood of default based on the firm's score (Ohlson, 1980).

[16] Eisenbeis (1977) finds that financial ratios often are non-normally distributed.

Later studies have suggested that there are other model designs that have reported higher predictive ability than the logistic model, such as the neural networks[17] method and hazard models[18] (Gissel, Giacomino & Akers, 2007). Despite these findings, the logistic model has proven to be robust in predicting corporate default[19] and is the preferred choice by institutions such as the central bank of Norway. However, as our main focus is to test the credit relevance of reclassified financial statement ratios (not to develop the best model possible), the logit model is favorable as it's relatively easy and intuitive compared to other modeling techniques and imposes fewer restrictions on the explanatory variables compared to MDA.

3.2 The Logit Model

For any regression model there is an assumption that for a given set of independent variables (predictors), X_{ij}, there is a mean value for the dependent variable, Y (Hosmer & Lemeshow, 2000, p. 1-10).

$$E(Y_i|X_{ij}) = \beta_0 + \beta_1 X_{ij} \tag{1}$$

Where β is the unknown vector of parameters for the set of the independent variables, X_{ij}.The footnote *i* represents which firm, and *j* which explanatory variable. There are a total of *n* firms, and *k* explanatory variables.

$$X = (X_{ij}), i = 1, \dots, n; \ j = 1, \dots, k. \tag{2}$$

For logistic regression models the function of E (Y_i| X_{ij}) is given by the cumulative logistic distribution function:

$$E(Y_i|X_{ij}) = \pi(X) = \frac{e^{(\beta_0 + \beta_1 X_{ij})}}{1 + e^{(\beta_0 + \beta_1 X_{ij})}} \tag{3}$$

$$\lim_{X \to \infty} Y = 1 \ and \ \lim_{X \to -\infty} Y = 0$$

[17] Neural network is a method that analyzes inputs and finds patterns in samples. It is used for developing a model capable of emulating a decision-making process, which is tested on a hold-out sample

[18] The hazard model is a multi-period logistic regression model developed by Shumway (2001).

[19] Galil & Sher (2015) finds that static logistic models perform as well as hazard models.

However, we apply the logit transformation, were the dependent variable E $(Y_i|X_{ij})$ is given by the logarithm of odds (Tufte, 2000):

$$E(Y_i|X_{ij}) = ln\left[\frac{\pi(X)}{1-\pi(X)}\right] = \beta_0 + \beta_1 X_{ij} \tag{4}$$

The logit transformation means that the dependent variable will have the desirable properties of the linear regression model, where $E\ (Y_i|X_{ij})$ is continuous, have an infinite outcome $(0 < E(Y_i|X_{ij}) < \infty)$ and is linear in its parameters (Hosmer & Lemeshow, 2000, p. 1-10).

The vector of parameters (β) in the model is obtained from maximum likelihood estimation [MLE]. The MLE approach yields estimates for the unknown parameters, that maximizes the likelihood of obtaining the observed set of data, by maximizing the log likelihood function in 5). The log likelihood function is the logarithm of the function that expresses the probability of obtaining the observed set of data (Hosmer & Lemeshow, 2000, p. 1-10).

$$L(\beta) = ln[L(\beta) = \sum_{i=1}^{n}\{Y_i \ln[\pi(X_i)] + (1-Y_i)\ln[1-\pi(X_i)]\} \tag{5}$$

Where Y is coded as a dichotomous dependent variable, 1 or 0 (bankrupt or non-bankrupt), which makes π (x) the conditional probability of Y=1 given X (P (Y=1|X).

As the log-likelihood function is non-linear in its unknown parameters (β), the value of β is found using the iterative approach applied in the software Stata.

When using a regression model there is a risk of heteroscedasticity occurring, which causes standard errors to be invalid for constructing interval estimates and testing hypotheses (Hill, Griffiths & Lim, 2012, p. 299-302). However, in our model we have overcome the problem by using robust standard errors[20].

3.3 Hypothesis and Model Evaluation

To evaluate our initial hypotheses we have used well-known evaluation methods from previous studies. As we have decomposed our research question into addressing the marginal and absolute credit relevance of reclassified ratios, we have also established corresponding test procedures.

[20] This is done using the vce (robust) option in Stata.

Evaluation of the H0m Hypothesis - Marginal Credit Relevance

The test procedure for our H0m hypothesis entail an inclusion of the reclassified variable in the full baseline model to assess whether the variable has any marginal contribution to the overall explanatory power.

The test procedure can be viewed as:

$$E(Y|X) = \beta_0 + \beta_1 X_{baseline-model} + \beta_2 X_{reclassified-variable} \tag{6}$$

Where the test hypotheses are:

H0: $\beta_2 = 0$

H1: $\beta_2 \neq 0$

We have used the z-test to assess whether the variables have significant contribution to the predictive ability of our baseline model[21]. As the coefficients in logistic regression models are asymptotically normally distributed, the z-test is considered to be a robust test statistic to assess the significance of the variables (Tufte, 2000). We have also applied the likelihood ratio test, as this is considered a more reliable measure of significance when working with logistic regression (Tufte, 2000; Hill et al., 2012, p. 598-599). The likelihood ratio test is used to assess whether there is a significant change in the likelihood ratio of the model when including additional variables (Tufte, 2000). In other words, the test is comparing the goodness of fit of the unconstrained models against the constrained baseline model (Tufte, 2000; Hill et al., 2012, p. 598-599).

Evaluation of the H0a Hypothesis: Absolute Credit Relevance

To evaluate the absolute credit relevance of the reclassified ratios we have conducted two swap-tests. First, we swapped the reclassified variable with its traditional counterpart based on correlation. Next, we looked at the combined predictive ability of including several reclassified ratios into one model. The different evaluation methods are meant to capture both the absolute credit-relevance of the single reclassified ratio, as well as the absolute relevance of a group of reclassified ratios[22].

[21]The z-test is the default test procedure when running logistic regressions in Stata.
[22] The groups of reclassified ratios are formed combining the ratios found to have marginal credit-relevance in one group and the ratios found to have absolute credit relevance in the single swap-test in another.

Single Variable Swap-test

The first test used to evaluate the absolute credit relevance of reclassified ratios is the single variable swap-test. In this test, the main interest is whether a swapping of a traditional ratio with its reclassified counterpart increases the predictive ability of our baseline model.

The point of departure is the test statistics of the benchmark model, as this serve as reference value to the revised model. The theoretical benchmark model is shown below.

$$E(Y|X) \ = \ \beta_0 \ + \ \beta_1 X_{baseline-model} \tag{7}$$

To test the absolute relevance of the reclassified ratios we include them one-by-one into the baseline model by swapping them with their traditional peer. This gives us the following model, where we have some common variables with the benchmark model and the swapped reclassified ratio.

$$E(Y|X) \ = \ \beta_0 \ + \ \beta_1 X_{Common\ varibales} + \ \beta_2 X_{Reclassfied-variable} \tag{8}$$

Based on this, we get the following test hypotheses, where R denotes the respective models predictive ability, measured as pseudo R^2 and AUROC[23].

$$H0: R_{traditional} \geq R_{reclassified}$$
$$H1: R_{traditional} < R_{reclassified}$$

Multiple Variable Swap-test

The multiple variable swap-test is designed to take into account any correlation between the reclassified ratios that might affect the discriminating abilities of the model.

In this test we include multiple variables proven relevant for bankruptcy prediction, either by having marginal credit relevance or by improving the predictive ability in the individual swap-analysis. The main purpose of this test is to see whether a combination of the significant reclassified ratios makes a noteworthy improvement of the baseline model, and thereby gives us a better premise for answering our research question.

The first test is to assess the combined contribution of the variables found significant in the marginal contribution test.

[23] Area under the receiver operating characteristics curve [AUROC]

$$E(Y|X) = \beta_0 + \beta_1 X_{Common\ varibales} + \beta_2 X_{Marginal\ credit\ relevance\ j1} + \beta_3 X_{Marginal\ credit\ relevance\ j2} \quad (9)$$

As in the single ratio swap-test, we have a model with some common variables with the benchmark model. However, in the multiple swap-analysis we include a set of reclassified ratios instead of only one single ratio.

The second test assesses the combined contribution of the variables found to have absolute credit relevance in the individual swap-test.

$$E(Y|X) = \beta_0 + \beta_1 X_{Common\ varibales} + \beta_2 X_{Absolute\ credit\ relevance\ j1} + \beta_3 X_{Absolute\ credit\ relevance\ j2} \quad (10)$$

The variables found to increase the predictive ability in the singe ratio swap-test are swapped with its traditional counterparts, giving us a model consisting of some common variables and the variables with indications of absolute credit relevance.

This gives us the following hypotheses:

$$H0: R_{traditional} \geq R_{reclassified}$$
$$H1: R_{traditional} < R_{reclassified}$$

As previously noted, the results from the swap-tests are evaluated using the pseudo R^2 measure and a comparison of the AUROC of the different models.

The pseudo R^2 ratio (also known as the McFadden's likelihood ratio index) measures the explanatory power (log likelihood) of the fitted model relative to the "null-model" consisting of only an intercept (Tufte, 2000). The measure is best used to compare different specifications of the same model (nested models), which also is the intended use of pseudo R^2 in our thesis.

The AUROC measure is based on the models ability to correctly classify observations as bankrupt (sensitivity) and non-bankrupt (specificity), as well as the frequency of incorrect classifications of bankrupt firms (type 1 errors) and non-bankrupt firms (type 2 errors)[24].

Table 4: Classification Matrix for Bankruptcy Prediction

Classified	Observed	
	Bankrupt	Non-bankrupt
Bankrupt	Correctly predicted	Type II error
Non-bankrupt	Type I error	Correctly predicted

Notes: The table shows the four possible classification outcomes when predicting bankruptcy.

To classify observation into the bankrupt or non-bankrupt group we need a threshold point that, based on the probability of default, separates the different observations. AUROC measures the classification accuracy of the model for the total range of possible threshold points[25], measured as the likelihood that a bankrupt firm has a higher probability of default than those that do not go bankrupt (Hosmer & Lemeshow, 2000, p. 160-164). The AUROC measure can range from 0.5 to 1, where results at 0.5 means the model is equally predictive as flipping a coin.

In both tests, we reject the H0 if the evaluation measures from the revised model prove to be better than the one of the benchmark model.

To the best of our knowledge, there is no easily available method for testing the significance of the change in pseudo R^2 and AUROC. As a consequence, we have used the test outputs as indications of absolute credit relevance instead of a measure of certain absolute relevance. However, one way to test the significance of the results is by bootstrapping the pseudo R^2 and AUROC to identify the standard error of the output. This would show whether the revised pseudo R^2 and AUROC are within the standard error of the initial results, and therefore subject to coincidences. This type of estimation process is outside the scope of our thesis due to time-limitations.

[24] The costs associated with type 1 errors are that the creditor loses interest, instalments and possibly outstanding obligations at the time of bankruptcy. The cost associated with type 2 errors is loss of potential business for the lender (Penman, 2012, p. 691-692).
[25] Not just at the point that maximizes sensitivity and specificity (minimizes errors).

4. Data, Variables, Descriptive Statistics and Correlation

In this section, we will present the sample selection procedure and a review of the quality of our data, followed by a discussion of the bankruptcy definition and the main variables used in our thesis. We will then present some descriptive statistics and a correlation matrix to highlight the most prominent characteristics of our main variables.

4.1 Sample Selection

Our data is obtained from SNF`s and NHH`s database with financial and company information on Norwegian firms. The complete dataset consists of the full population of companies from 1992 to 2014, with some minor exceptions for entities with completely missing data, making it 4,102,551 observations in total. For a closer description of the data we refer to *Regnskapsboken* by Berner, Mjøs and Olving (2015).

To get a consistent and reliable sample we based our sample selection on restrictions found reasonable in prior studies, as well as a supplementary analysis to see whether these restrictions make sense in our data. The restrictions included, and number of observations deleted, can be seen in table 5.

To have a dataset with consistent classifications of financial information, we have excluded data prior to 1999 as there were issued a new law for financial reporting *Regnskapsloven av 1998* in 1998. The new regulations included new rules for classifications and allowed recognition of some assets to market value (Melle & Tømta, 1998). These changes made the NGAAP more in line with international regulations (IFRS). As our data includes groups reporting under both NGAAP and IFRS, our sample is more consistent when excluding observations prior to 1999.

Further, we have decided to remove observations with missing values as they caused noise in our model. We started by removing companies with missing values for revenue and total assets before removing companies without a year of establishment and industry code. The removal of missing values also entailed a removal of companies with missing values in the main accounting ratios used in our study (5 deleted). These restrictions give us a more complete sample of companies and observations with more comprehensive financial information. A potential problem by excluding firms with missing data is the "sample selection bias" presented by Zmijewski (1984). The bias relates to the risk that bankrupt firms (or firms that are in risk of bankruptcy) tend to have more missing data than "healthy" companies. However, we considered the benefits of having a "clean" sample as more important than the risk of a "sample selection bias".

Table 5: Overview of Sample Restrictions

Restriction	Number of Observations Deleted
Total Sample	**4,102,551**
Missing values: Revenue, total assets, year of establishment, industry code	3,993,411
Total asset <20.000.000 or sales < 5.000.000 (CPI adjusted)	64,684
Current assets, long-term debt, fixed assets or short term debt < 0	57
Invested capital < 0	1,902
Other than limited liabilities company	4
Sectors: Finance -, utility -, government owned-, R&D- and public health- and culture- companies	14,412
Final Sample	**28,081**

Notes: The "Restriction" column gives a short description of the restrictions. The top row named "Total Sample" shows the total number of observations in the data set provided by SNF. The right column shows the number of observations deleted for each restriction, whereas "Final Sample" shows the final number of observations in our estimation sample.

One of the most important criteria for inclusion was that the observations had to be registered as limited liability companies. This eliminates the problem with sole proprietorship where the finances of the owner and the company are collectively exhaustive. However, in our data we had very few instances of groups not being limited liability companies, hence not many observations was affected by this restriction.

As we wanted to look at the predictive ability of the model on a sample with relatively homogenous companies, we decided to remove companies in breach of the audit obligation requirements on total assets and revenue. This criterion removes many of the small groups from our sample, which may seem counter intuitive given our size variable and the fact that some critics find these types of restrictions to cause biased results. However, as we use all limited liability groups in Norway, and not only public companies[26], the size criterion helps us increase the reliability and relevance of the accounting data as companies with an auditor are believed to have financial statements of a higher quality.

We have also removed observations with "extreme" values in terms of negative current assets, fixed assets, long-term debt and short-term debt. By including these restrictions we excluded 57 observations that appeared to be somewhat ambiguous.

We also removed observations with negative invested capital (1,902 deleted). Observations with negative IC do not only make little empirical sense, but also creates ratios without any meaningful interpretation.

To deal with extreme values in our variables we applied the Winsor2 command in Stata. This replaces values below (above) the 1 percentile (99 percentile) with the value of the 1 percentile (99 percentile) for all accounting ratios used. The winsorizing of these "extreme values" could lead to biased coefficients if the model is applied out of sample, but as previously mentioned, developing the best out-of-sample prediction model is not within the scope of our thesis.

The last criteria for inclusion are that groups must not be registered as a finance company, utility company, government owned, R&D or public health and culture company. The reason for the removal of these industries and type of companies is that their financials cannot be treated on equal terms as other "traditional" industries. Finance, utility and R&D companies has very different balance sheets and income statements compared to the other sectors included. We also excluded companies with government ownership as they oftentimes get support from the government in times of financial trouble, something that may not be reflected in the companies accounting ratios. Even though we made some restrictions regarding industry and company type in our sample, we still have a sample with sufficient variation to conduct a thorough test of the predictive abilities of traditional and reclassified financial statement ratios[27].

The final sample of our study consists of 28,081 group observations were 271 observations are bankruptcy observations in the period from 1999 - 2014. Compared to previous studies,

[26] Beaver (1966), Altman (1968) and Ohlson(1980) used data sets consisting of publicly owned companies, excluding many of the smaller firms from the samples. Beaver (1966) and Altman (1968) reports observations with total assets and earnings in the range of approximately 0.6m – 0.7m and 45m – 25.9m measured in 1966 dollars.

[27] Most of the literature on bankruptcy prediction previously presented has been conducted on U.S industrial (Beaver, 1966, Ohlson, 1980) or manufacturing companies (Altman, 1968).

such as Beaver (1966) and Altman (1968), we have a more "natural" sample in terms of bankruptcy frequency relative to the true frequency of the population[28]. By using a more "natural" sample we reduce the risk of "choice-based sample bias", which relates to having a higher bankruptcy frequency than the population when developing bankruptcy prediction models (Zmijewski, 1984).

An overview of the bankruptcy observations in the period from 1999 to 2014 is depicted in the table 6.

Table 6: Sample Overview - Years

Year	Total	Non-bankrupt	Bankrupt	% Bankrupt
1999	1,727	1,704	23	1.33
2000	1,738	1,713	25	1.44
2001	1,801	1,772	29	1.61
2002	1,799	1,775	24	1.33
2003	1,564	1,550	14	0.90
2004	1,530	1,509	21	1.37
2005	1,591	1,575	16	1.01
2006	1,507	1,489	18	1.19
2007	1,664	1,645	19	1.14
2008	1,611	1,598	13	0.81
2009	1,760	1,745	15	0.85
2010	1,712	1,695	17	0.99
2011	1,725	1,713	12	0.70
2012	1,795	1,782	13	0.72
2013	2,230	2,224	6	0.27
2014	2,327	2,321	6	0.26
Total	28,081	27,810	271	0.97

Notes: The table gives an overview of the sample, where all the bankrupt and non-bankrupt observations are distributed across years.

As we can see from table 6, the number of bankruptcies is highest around the time of the "dot-com" crisis where most of the western countries experienced economic recession. The

[28] Both Beaver and Altman used balanced data sets in their studies.

reason why we see a majority of bankruptcies in early 2000 is probably a result of the exclusion of financial companies from our sample. By excluding financial companies we reduce the number of bankruptcies around 2008, something that dampens the effect of the global financial crisis (2007-2008). All over, the bankruptcy observations are relatively evenly distributed across years, but with a trend of decreasing frequency as we approach 2014.

Another interesting aspect of our data is how the bankruptcy observations are distributed across industries. In table 7, we can see how our data is divided into different sectors and how the default frequencies are within each sector.

Table 7: Sample Overview - Sectors

Sector	Total	Freq. (%)	Non-bankrupt	Bankrupt	% Bankrupt
Agriculture	1,233	4.39	1,223	10	0.81
Offshore/Shipping	2,264	8.06	2,249	15	0.66
Transport	946	3.37	934	12	1.27
Manufacturing	4,576	16.30	4,518	58	1.27
Telecom/IT/Tech	1,400	4.99	1,387	13	0.93
Construction	9,428	33.57	9,361	67	0.71
Wholesale/Retail	6,511	23.19	6,433	78	1.20
Other services	1,723	6.14	1,705	18	1.04
Total	28,081	100	27,810	271	0.97

Notes: The first two columns show the frequency of companies in different sectors. The next column shows the percentage of total sample within each sector. The "Default" column shows the frequency of non-bankrupt (0) and bankrupt (1) firms in each sector. The last column shows the default frequency within each sector.

Construction and Wholesale/Retail are the two largest industries in our sample, making up more than 50 percent of our total observations. The bankruptcy frequency is highest in the transport and manufacturing sector with a 1.27% of the companies going bankrupt. Wholesale/Retail and other services follow with respectively 1.20% and 1.04% of the sector observations going bankrupt. As we know, previous studies has mostly used industry and manufacturing companies in their samples, but we are of the opinion that a more "natural" sample gives us more applicable results.

In order to achieve sufficient data quality we have reviewed the collected data and compared it to accounting figures provided by Proff (https://www.proff.no) to make sure the values in our sample are consistent with the numbers actually reported. We also did an analysis of the company's organizational number to ensure that no company was listed twice.

The original data-set has been revised multiple times and there have been discovered some inconsistencies regarding minor posts, especially on residual variables such as “other” non-current items. Even though there have been discovered flaws on some of the minor accounting items, there has not been detected any major mistakes on the “sum” variables (Berner et al., 2015). We have tried to base our definitions of the different sets of variables on the “sum” variables, as they to a smaller degree are subject to mistakes.

However, we discovered that some companies had “double counted” minority interests[29], meaning that the sum of equity, minority interests and total liabilities exceeded the sum of total assets by the exact value of the minority interests. For these companies, we generated a new variable for minority interest correcting for this error. For the purpose of our analysis there is no need to distinguish between equity and minority interests, which makes the re-calculation of minority interests less problematic.

Comparing our data with the numbers from Proff (https://www.proff.no), we also experienced some minor deviations in total assets unrelated to the problems with minority interests, but as the differences was only minor and related to a small proportion of the observations, we decided to keep the numbers provided by SNF.

Based on the review of our data, we are confident in our data’s quality and the ability to generate unbiased test estimates.

4.2 Variables

Definition of Bankruptcy

In this thesis we have defined the bankruptcy variable, DEF, as when a company is removed from the Brønnøysund Register Center, and the reason for the removal is either bankruptcy or liquidation (Konkursloven, 1984, §§60-61). Although the preferred variable for bankruptcy is when the company actually goes bankrupt, we have used the year the

[29] Minority interests double counted as both regular equity and minority interest.

bankruptcy petition is filed and bankruptcy proceedings are opened[30], as companies normally stops releasing annual reports when bankruptcy proceedings are begun (Berner et al., 2015). For most of the observations, the year of the bankruptcy opening equals the first year after the last annual report. In cases where there are several years between the last annual report and the year of the bankruptcy opening, we have defined the year after the last annual report as the year of bankruptcy.

Explanatory Variables

The traditional variables used in this thesis are based on ratios found relevant in previous studies. In our study we have focused on the variables Ohlson (1980) found relevant for predicting bankruptcy (see table 1).

Ohlson (1980) used financial ratios found credit relevant in previous studies and ratios easily extracted from the financial statements. Hence, his model summarizes and incorporates many of the variables traditionally found significant for bankruptcy prediction.

By using Ohlson's logistic model as our baseline model, we have a model that has been acknowledged by academics all over the world for the last couple of decades and that has proven robust for predicting corporate default. Because of the performance reported by Ohlson, we believe his model makes a solid fundament for testing our hypotheses. Although we are using a well-recognized model, it is important to stress that static models based on only accounting figures has their flaws when it comes to explaining corporate default, but for the purpose of our study we believe this model will suffice.

When replicating Ohlson's logistic model we tried to the best of our ability to make the variables as similar to their initial definition as possible. After a detailed analysis of our accounting data, we are convinced that our variable definitions are in line with the ones of Ohlson.

[30] We have used the variable "Konkaar" provided by (Berner et al., 2015).

Reclassified Financial Statements and Ratios Derived Therefrom

To be able to correctly reclassify the financial statements into operating and non-operating items, one often need to thoroughly search through the notes to find in which group the items belong (Koller et al., 2015, p. 169). This type of reclassification oftentimes requires subjective judgment to get the level of detail desired. As an example, Stern Stewart & Co Consulting has identified over 160 reclassifications and adjustments to reported earnings only (Viebig, Podding & Varmaz, 2008, p. 30-31). However, based on theory on reclassification of financial statement data (Petersen et al., 2017; Kaldestad & Møller, 2016; Koller et al., 2015) we will discuss some of the important provisos when "mechanically" reclassifying a financial statement.

Some items are relatively easily categorized as operational or financial, such as "Property, Plant and Equipment"[31]and "Long-term financial assets"[32], but there are accounting items in need of a more thorough analysis to uncover the true nature of the respective activity. Some of the accounting items in need of a careful consideration are cash and cash equivalents, minority interest, deferred tax liabilities and pension liabilities. In our thesis we have treated "cash and cash equivalents" as financial. Some distinguishes between operational and financial cash, but as the rules of thumb used to estimate operational cash often has only modest effects on the accounting ratios, we have chosen to treat all cash as financial.

We have also treated pension obligations as financial, even though the items emerge from the company's operations. As pension liabilities are interest bearing and assets devoted to the employees, it makes more sense to classify them as a part of net interest bearing liabilities than part of operations.

Another accounting item frequently discussed in the reclassification literature is minority interests. These "non-controlling" interests represent investments in subsidiaries not fully owned by the parent firm. The question regarding minority interest is whether they should be included as equity or interest bearing liabilities. As the required rate of return on minority interest often is closer to the one of other investors than the one of creditors (Petersen et al., 2017, p. 120), we have treated minority interest as equity capital alongside the parent.

[31] As previously noted, there is a risk that PPE could include non-operational property that not necessarily contributes to operating income (Kaldestad & Møller, 2016, p.195).
[32] Investments in subsidiaries are classified under non-current financial assets. However, these investments could be considered an extension of the company's operations and a part of operating assets (Petersen et al., 2017, p. 118). As we are unable to subjectively assess whether this is the case, we have decided to treat all non-current financial assets as a part of net interest bearing liabilities.

We have treated deferred tax liabilities (and assets) as operational. Deferred tax arises from temporary difference between the book value and tax value of accounting items. The deferred tax items do not carry any interest, thus they do not share the same characteristics as net interest bearing liabilities (Petersen et al., 2017, p. 117-118).

The last accounting items in need of careful evaluation were the "other" items on both the credit and debit side of the balance sheet. After an analysis of the different "other" items, using the information provided by *Regnskapsboken* (2015), we decided to classify all "other current items" as operational and all "other non-current items" as financial.

Based on these assumptions, the reclassified balance sheet[33] is defined in table 8.

Based on these reclassifications, we are left with some reclassified substitutes to the original variables included in our baseline model, as well as some other reclassified ratios presented by Petersen et al. (2017, p. 222-234). A complete list of the reclassified variables tested in this thesis is shown in table 9.

When forming our reclassified profitability measures (ROIC) we have used EBIT, EBITDA and a mechanically normalized EBITDA[34] as measures of operational income. Petersen et al. (2017, p. 505-515) highlights the subjective assessments related to amortization, depreciation and impairments. By using EBITDA instead of EBIT we eliminate some of the issues related to these subjective estimations. Petersen et al. (2017, p. 623-625) also suggests that profitability measures should be normalized and adjusted for "non-recurring items", as this improve the predictive ability. However, they highlight that adjusting numbers is a disputed practice as there is a risk of erroneous adjustments. Nevertheless, we have tried to do some minor adjustments to reported earnings to get a reasonable estimate of adjusted EBITDA. We have decided to measure the operational profitability before tax, as the practice of finding an effective tax rate is quite complex (Petersen et al., 2017, p. 111-114).

[33] The initial classification is provided by the Norwegian accounting legislation (Regnskapsloven, 1998), which is in line with international regulations (IFRS) (Berner et al., 2015).
[34] We have adjusted for "Other operating income" as well as "Loss on claims"

Table 8: Reclassification of the Balance Sheet

Category	Asset Type	Name in Data	Reclassification
Assets			
Non-current	Intangible assets	immeiend	Operational
	Property, plant and equipment	vardrmdl	Operational
	Financial assets	finanml	Financial
Current	Inventory	varer	Operational
	Receivables	fordr	Operational
	Other current	andfor + aoml	Operational
	Financial	invest	Financial
	Cash	cash	Financial
Equity			
	Equity	ek	
	Minority-interests	minintbal	Equity (Alongside the equity of the parent)
Liabilities			
Non-current	Pensions	pforpl	Financial
	Deferred tax	utssk	Operational
	Provisions	avsforpl (-pforpl - utssk)	Operational
	Interest bearing	rlgjeld	Financial
	Other non-current	usplgj	Financial
Current	Interest bearing	rkgjeld_max	Financial
	Payables	levgj	Operational
	Taxes	betsk + offavg	Operational
	Other current liabilities	skyldutb + skyldkid + akgjeld	Operational

Notes: The "Category" column shows the structure of the data under the traditional financial statement classification. The "Asset Type" column shows the line items in the financial statement. We also included a column showing the name of the items used in the dataset provided by SNF. The "Reclassification" column shows where the items are classified in a reclassified financial statement.

Out of the reclassified solidity ratios discussed by Petersen et al. (2017, p. 222-223) we have decided to test the "Long-term financial coverage ratio" that measures the proportion of non-current operational assets and "fixed" working capital financed by long-term financing. The ratio does not just evaluate the overall leverage ratio of invested capital, such as NIBLIC, but sees the financing in relation to which part of operating assets it is meant to finance[35]. What level of net working capital that is fixed is a highly subjective assessment. To define the fixed part of net working capital with a mechanical approach, we measured net WC in percentage of sales for each company and defined fixed part of net WC as the lowest observed proportion of net WC in percentage of sales.

When assessing a company's liquidity and to what degree funds from operations are able to cover liabilities, the literature on reclassified financial ratios imply using net interest bearing liabilities in relation to a measure of cash flow from operations. However, a simple CFO ratio does not reflect the fact that a company must constantly reinvest to keep current operations going. As a result, we tried to use CFO - net investments in the numerator as a proxy for cash flow from operations after reinvestments. Kaldestad & Møller (2016, p. 61-64) and Petersen et al. (2017, p. 90-98) address the possibility of using accrual based accounting numbers as a substitute for cash flow numbers, as they tend to have a higher explanatory power on a firms earnings capacity. As a result, we included ratios applying EBITDA as a proxy for CFO in the relevant liquidity ratios[36].

As discussed in section 2, Petersen et al. (2017, p. 231-233) criticizes the traditional current ratio (CLCA), as it poorly reflects the true liquidity position of a firm. We have tested several alternatives to the current ratio, one of which is the CFOCNBIL ratio mentioned in section 2, as well as CIBLCIBA and LIQRESCIBL. The only difference between the CIBLCIBA and LIQRESCIBL ratio is that LIQRESCIBL also includes non-current financial assets. We tried testing both, as non-current financial assets might be an extension of the firm's operations, thus not as "liquid" as other financial assets and of less relevance when analyzing short-term liquidity.

Another liquidity ratio introduced is the LANGLANG ratio, which sees what part of IC that finances non-current operating assets. The ratio can be seen as the inverse of WCIC, except that LANGLANG does not include non-current operating liabilities implicitly included in WCIC.

[35] Petersen et al. (2017, p. 222-223) argue that the ratio should not deviate too much from 1, as long-term financing should finance non-current assets and fixed part of net working capital.
[36] We have also applied EBIT / NIBL, which implies using depreciation as a proxy for reinvestments.

Table 9: Reclassified Ratios

Ratio	Variable name	Definition
Other	N_SIZE	CPI adjusted invested capital (log)
	N_OENEG	A dummy = 1 if net interest liabilities are larger than invested capital
Solidity	NIBLIC	Net interest bearing liabilities / Invested capital
	LONGFINCOV	NIBL / Non-current operational assets + minimum level of WC - Equity
Liquidity	WCIC	Working capital / Invested capital
	LANGLANG	Non-current operational assets / Invested Capital
	CIBLCIBA	Current interest bearing liabilities / Current financial assets
	LIQRESCIBL	Financial assets / Current interest bearing liabilities
	CFOCNIBL	CFO / CNIBL
	EBITDACNIBL	EBITDA / CNIBL
	SHORTLIQ1	CFO + financial assets / CIBL
	SHORTLIQ2	EBITDA + financial assets / CIBL
	CFONIBL	CFO / NIBL
	adjEBITDANIBL	Adjusted EBITDA / NIBL
	EBITDANIBL	EBITDA / NIBL
	EBITDANETINVNIBL	EBITDA - net investments / NIBL
	CFONETINVNIBL	CFO - net investments / NIBL
	EBITNIBL	EBIT / NIBL
Profitability	NIIC	Net income / Invested capital
	EBITDAIC	EBITDA / Invested capital
	AdjEBITDAIC	Adjusted EBITDA / Invested capital
	EBITIC	EBIT / Invested capital

Notes: The first column gives an overview of whether the reclassified ratios are classified as a measure of profitability, liquidity, solidity or “other”. We have given each variable a short name that is presented in the next column, followed by the definition of the ratio.

4.3 Descriptive Statistics

To give a more thorough description of the most noteworthy variables in our study, we have made a table showing the main characteristics of the different ratios.

As seen from table 10, all ratios from the baseline model, and some of the most significant reclassified variables, are depicted with mean, standard deviation and quartiles. The descriptive table makes an identification of extreme values easier as it provides information about the distribution of each variable. Based on the descriptive table we see that some of the reclassified variables have somewhat "extreme" values compared to their mean and quartiles. However, as we already winsorized all of the variables, the variation left is considered to be rather reasonable in practical terms. We experience that about ⅓ of our sample has zero current interest bearing liabilities, making ⅓ of our CIBLCIBA ratios equal to zero. However, as it is possible to have zero short-term interest bearing liabilities, we have chosen to keep the variable as it is.

Table 10: Descriptive Statistic – Main Ratios

Variables	Obs	Mean	Std.Dev	Min	25%	75%	Max
logTA	28,081	12,273	1,437	10,075	11,199	13,081	16,723
TLTA	28,081	0,683	0,210	0,147	0,551	0,827	1,265
CLCA	28,081	0,773	0,496	0,105	0,488	0,907	2,507
WCTA	28,081	0,163	0,196	-0,386	0,033	0,284	0,691
OENEG	28,081	0,040	0,196	0,000	-	-	1,000
NITA	28,081	0,030	0,096	-0,426	-0,002	0,075	0,331
CFOTL	28,081	0,445	2,903	-10,502	-0,224	0,503	19,098
INTWO	28,081	0,065	0,247	0,000	-	-	1,000
CHIN	28,081	-0,012	2,431	-11,525	-0,921	0,913	11,418
CIBLCIBA	28,000	3,391	9,371	0,000	0,000	2,202	66,337
WCIC	28,081	1,754	3,441	-4,517	-0,038	0,479	0,993
LANGLANG	28,081	0,944	0,783	0,034	0,554	1,087	6,048
EBITDAIC	28,081	0,340	0,694	-0,916	0,090	0,360	4,996

Notes: The table includes descriptive statistics for variables included in benchmark model and reclassified found to have marginal credit relevance. The second column shows the number of observations, followed by mean, standard deviation, minimum value, 25-percentile, 75-percentile and maximum value. The definition of the variables can be seen in table 1 and 9.

We have also looked at the correlation between the variables, as this is the basis of our swap-analysis. The correlation between the variables is more or less in line with expectations (See table 11). Nevertheless, we see that WCIC has incorrect correlation with DEF considering general economic theory.

Table 11: Correlation Matrix

	DEF	logTA	TLTA	CLCA	WCTA	OENEG	NITA	CFOTL	INTWO	CHIN	CIBLCIBA	WCIC	LANGLANG	ebitdaIC
DEF	1.00													
logTA	-0.05	1.00												
TLTA	0.09	-0.10	1.00											
CLCA	0.08	0.02	0.44	1.00										
WCTA	-0.07	-0.13	-0.55	-0.76	1.00									
OENEG	0.09	-0.09	0.43	0.23	-0.22	1.00								
NITA	-0.12	-0.01	-0.29	-0.23	0.29	-0.29	1.00							
CFOTL	-0.01	-0.10	-0.06	0.00	0.01	-0.01	0.09	1.00						
INTWO	0.06	-0.01	0.10	0.08	-0.10	0.11	-0.29	-0.03	1.00					
CHIN	-0.00	0.18	-0.06	-0.01	0.00	0.01	0.01	-0.09	0.00	1.00				
CIBLCIBA	0.08	-0.03	0.22	0.23	-0.20	0.11	-0.14	-0.01	0.07	-0.02	1.00			
WCIC	0.00	-0.03	-0.05	-0.26	0.35	-0.07	0.01	-0.02	0.00	-0.02	0.16	1.00		
LANGLANG	-0.00	0.05	0.05	0.24	-0.32	0.06	0.02	0.01	-0.00	0.03	-0.15	-0.98	1.00	
ebitdaIC	-0.05	1.00	-0.09	-0.05	0.10	-0.08	0.48	0.06	-0.13	0.01	-0.12	-0.51	0.53	1.00

Notes: Correlation matrix for variables included in benchmark model and reclassified ratios with marginal contribution to benchmark model. The definition of the variables can be seen in table 1 and 9.

5. Main Results

In this section we will elaborate and discuss the empirical findings from our research. We will start by presenting our baseline model and the included variables, followed by a presentation and discussion of our results. The section ends with a conclusion.

5.1 The Baseline Model and the Included Variables

The results from our estimation of the baseline model are somewhat in accordance with the results in Ohlson's original study. The estimated coefficients of our model can be seen in the first column of table 12.

As shown in the regression output, five of the variables are found highly significant. Previous research has found leverage and profitability ratios to be important for bankruptcy prediction, something our results also substantiates with TLTA and NITA as the most significant ratios.

The OENEG variable is also one of the ratios proven significant in our model, where the negative coefficient of the variable works as a correction factor for the TLTA ratio.

Another interesting result from our baseline model is the fact that CFOTL is found insignificant. This is a rather peculiar result as this is a ratio proven solid for predicting corporate default in previous studies. One reason why this ratio is insignificant might be because of sample selection differences between the studies. Beside the variable discussed above, the model also wrongly estimates the sign of the CHIN variable. Ohlson (1980) states that this could be explained by a scenario proposed by Deakin (1972). Firms with a positive change in net income could be particularly tempted to raise external capital through borrowings, implying that they will become high-risk companies at some subsequent point. However, this is just one of many possible explanations.

When running a stepwise logistic regression test[37] including all variables from Appendix A, many variables in Ohlson's (1980) model is found significant. TLTA, WCTA, logTA,

[37] The test assesses the significance of the variables through the likelihood ratio chi-square test (Hosmer and Lemeshow, 2000 p.116).

INTWO are significant at a 5% level, whereas CLCA is found significant at a 20% level[38]. This indicates that many of the most important bankruptcy predictors on our data are included in our baseline model. However, the fact that NITA, CFOTL and OENEG is excluded when running the stepwise function, suggests that there may be other traditional ratios which could have increased the predictive ability of our baseline model. This is further assessed in the additional testing section.

The baseline model scores a pseudo R^2, also called likelihood ratio index [LRI], of 0.1448. Compared to the initial study of Ohlson (1980), who reports a LRI of 0.831, the results indicate that his data was a much better fit for the model. However, there are several reasons why comparing results like these are problematic. First, there are differences in the lead-time from fiscal year end to the time of bankruptcy (1.7 years vs 3.7 years) that may affect the classification results. Second, the studies are based on different accounting data, from different countries, and periods of time. If we also consider the fact that Ohlson limited his study to US industrial firms traded over a counter, we see that the terms of the sample selection are quite divergent. These factors make the comparison of the LRI results difficult, as we do not compare "apples with apples". When considering the overall classification ability, our baseline model scores an AUROC of 0.826, which is considered excellent (Hosmer & Lemeshow, 2000, p. 160-164). We arrive at the conclusion that the overall performance of our baseline model is sufficient given the main purpose of our study.

5.2 The Marginal Credit Relevance of Reclassified Ratios

Out of the profitability ratios, only EBITDAIC turns out to significantly improve the model, increasing the pseudo R^2 to 0.1483. The fact that the other reclassified profitability ratios, such as AdjEBITDAIC, are found insignificant may indicate that some of our mechanical adjustments create noise rather than increasing the predictive ability. To further address the robustness of the contribution of EBITDAIC we performed a test where we included the "traditional" equivalent to EBITDAIC, the EBITDATA ratio, to our benchmark model[39]. The likelihood ratio test still shows that EBITDAIC has significant marginal contribution to the model at a high significance level.

[38] Lee and Koval (1997) find that a 5% significance level is too stringent when working with stepwise logistic regression as it often leads to exclusion of important variables. Choosing a significance level from 15% to 20% is therefore highly recommended (Hosmer and Lemeshow, 2000, p.118).
[39] EBITDATA is found insignificant in the benchmark model

Table 12: Maximum Likelihood Estimates for Model 1-5

Variables	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
logTA	-0.335***	-0.342***	-0.347***	-0.344***	-0.341***
	(0.0611)	(0.0617)	(0.0639)	(0.0628)	(0.0625)
TLTA	3.143***	3.150***	2.928***	2.830***	2.895***
	(0.524)	(0.523)	(0.523)	(0.526)	(0.526)
WCTA	-0.501	-0.498	-0.341	-1.228**	-1.074*
	(0.551)	(0.546)	(0.549)	(0.610)	(0.608)
CLCA	0.234	0.249*	0.182	0.300**	0.286**
	(0.143)	(0.141)	(0.147)	(0.141)	(0.141)
OENEG	-0.770***	-0.735***	-0.771***	-0.700***	-0.709***
	(0.273)	(0.271)	(0.272)	(0.270)	(0.269)
NITA	-4.837***	-3.758***	-4.912***	-5.036***	-4.992***
	(0.483)	(0.701)	(0.492)	(0.496)	(0.492)
CFOTL	-0.0439	-0.0412	-0.0368	-0.0366	-0.0378
	(0.0269)	(0.0272)	(0.0262)	(0.0261)	(0.0262)
INTWO	0.496***	0.474***	0.465***	0.465***	0.471***
	(0.169)	(0.169)	(0.169)	(0.170)	(0.170)
CHIN	0.00385	0.00473	0.00456	0.00433	0.00446
	(0.0245)	(0.0243)	(0.0243)	(0.0236)	(0.0237)
ebitdaIC		-0.450*			
		(0.232)			
CIBLCIBA			0.0239***		
			(0.00332)		
WCIC				0.535***	
				(0.151)	
LANGLANG					-0.406***
					(0.143)
Constant	-3.293***	-3.131***	-3.107***	-3.022***	-2.666***
	(0.848)	(0.854)	(0.874)	(0.872)	(0.880)
Observations	28,081	28,081	28,000	28,081	28,081
LR significance		0.0071	0.0000	0.0000	0.0000
Pseudo R^2	0.1459	0.1483	0.1575	0.1541	0.1520
AUROC	0.8263	0.8286	0.8301	0.8337	0.8324

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Model 1 is the benchmark model. Model 2-5 is the benchmark with an additional reclassified ratio. There are fewer observations in the model where CIBLCIBA is included, as there are 81 companies with missing value for CIBLCIBA.

Out of the reclassified liquidity ratios tested, four of the measures are found significant in the likelihood ratio test. CIBLCIBA turned out to be highly significant, both in the z-score and lr-test, giving strong indications of actual credit relevance. When added to the baseline model, the pseudo R^2 increased from 0.1459 to 0.1575.

WCIC and LANGLANG also turn out as highly significant in both the z-score and lr-test. The fact that LANGLANG proves statistically significant is not particularly surprising given that WCIC is found significant, and the only difference between the two ratios are the non-current operating liabilities (provisions)[40]. However, the fact that any of the ratios proves significant are quite surprising given that both CLCA and WCTA was insignificant in the benchmark model. These results indicate that a reclassification of the financial statement might increase the predictive ability of liquidity ratios.

5.3 The Absolute Credit Relevance of Reclassified Ratios

The Absolute Credit Relevance of The Single Reclassified Ratio

From table 13, we can see that three ratios increase AUROC and pseudo R^2 when included in the benchmark model. These ratios are the liquidity measures found significant in the marginal contribution test. CIBLCIBA improves the model when substituted with CLCA, whereas LANGLANG and WCIC yield good results when substituted with WCTA. These results indicate that an inclusion of these ratios actually improve the predictive abilities of the overall model. All of the variables is found highly significant.

Table 13: Results from the Single Variable Swap-tests

Model	SWAP	Corr	Coefficient	P> |z|	AUROC	Pseudo R^2
WCIC	WCTA	0.3448	0.4568256	0.000	0.8329	0.1524
LANGLANG	WCTA	−0.3214	-0.3510687	0.003	0.8319	0.1507
CIBLCIBA	CLCA	0.2272	0.0244977	0.000	0.8289	0.1564
Benchmark					**0.8263**	**0.1459**
EBITDAIC	NITA	0.4800	-1.302396	0.000	0.8181	0.1339

Notes: The table presents four ratios from the single variable swap-test. "SWAP" indicates which ratio in the benchmark model that the respective ratio is swapped with. The next column shows the correlation between the ratios. "Coefficient" indicates the coefficient of the reclassified ratio when included in the model. "P>|z|" is the p-value of the ratio from the default z-test. Followed by overall model evaluation measures, AUROC and Pseudo R2.

EBITDAIC was one of the reclassified ratios found significant in the marginal contribution test, but when substituted with NITA the overall model fit decreases to 0.1339. So does the classification ability, as AUROC decreases from 0.8263 to 0.8181.

[40] The correlation between WCIC and LANGLANG is -0,9818.

One possible reason for this is the fact that impairments are left out of the ratio. Based on general economic theory, impairments should be an important indicator of tougher market conditions and decreasing asset values, which should lead to increased probability of bankruptcy. Based on this reasoning, a model consisting of EBITDA ratios as a measure of profitability should also include some measure of impairments. We conducted a retest of the model consisting of EBITDAIC, where we also included the ratios Impairments/IC and Impairments/EK. However, the AUROC did not improve compared to the initial results.

The Combined Credit Relevance of Reclassified Ratios

The result from the multiple swap-tests can be seen in table 14. For ratios with somewhat similar correlation to a traditional variable, such as LANGLANG and WCIC, we only included the ratio with the highest individual explanatory power.

From table 14, we see that model 2 has a lower explanatory power than the benchmark model. By swapping the traditional ratios with the ratios found to have marginal credit relevance, the pseudo R^2 goes from 0.1459 in our baseline model to 0.1448 in the revised model. The ability to correctly classify observations as bankrupt or non-bankrupt also decreases, as AUROC drops from 0.8263 to 0.8181. We also see that OENEG has lower significance when NITA is left out of the model, and that WCIC is found insignificant.

However, CIBLCIBA is still significant at a 1% significance level, indicating a relatively high robustness of the ratio. As our test criteria is that the revised model should outperform the benchmark model on both evaluation measures, we cannot disregard the null hypothesis unless both proves better than the ones of the benchmark.

From model 3, we can see that the pseudo R^2 increase quite substantially from 0.1459 to 0.1564, indicating that this model is a better fit for our data. The only difference between the two revised models is the inclusion of NITA and EBITDAIC, where model 3 includes the traditional NITA ratio. Model 3 has an AUROC of 0.8300, compared to 0.8263 of the benchmark model.

Table 14: Maximum Likelihood Estimates - Absolute Credit Relevance

Variables	(1) Model 1	(2) Model 2	(3) Model 3
logTA	-0.335***	-0.365***	-0.337***
	(0.0611)	(0.0666)	(0.0648)
TLTA	3.143***	3.583***	3.322***
	(0.524)	(0.511)	(0.487)
WCTA	-0.501		
	(0.551)		
CLCA	0.234		
	(0.143)		
OENEG	-0.770***	-0.427*	-0.767***
	(0.273)	(0.257)	(0.268)
NITA	-4.837***		-5.331***
	(0.483)		(0.483)
CFOTL	-0.0439	-0.0315	-0.0293
	(0.0269)	(0.0265)	(0.0253)
INTWO	0.496***	0.560***	0.448***
	(0.169)	(0.169)	(0.169)
CHIN	0.00385	0.0200	0.00691
	(0.0245)	(0.0250)	(0.0241)
WCIC		0.0588	0.151*
		(0.0940)	(0.0843)
CIBLCIBA		0.0238***	0.0241***
		(0.00334)	(0.00340)
ebitdaIC		-1.460***	
		(0.303)	
Constant	-3.293***	-3.030***	-3.437***
	(0.848)	(0.867)	(0.841)
Observations	28,081	28,000	28,000
Pseudo R^2	0.1459	0.1448	0.1564
AUROC	0.8263	0.8187	0.8300

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Model 1 is the benchmark model. Model 2 includes ratios with marginal credit relevance. Model 3 includes ratios with absolute relevance from the single variable swap-test. There are fewer observations in the models where CIBLCIBA is included, as there are 81 companies with missing value for CIBLCIBA.

5.4 Conclusion - Main Results

The tests done on the reclassified ratios gives us somewhat mixed results. Most of the ratios do not increase the predictive ability of our baseline model, neither individually nor together. However, we found some ratios to be statistically significant and also increase the overall performance of our baseline model when "swapped" with its traditional counterpart.

From our test outputs, there are results indicating that a reclassification might be of some relevance for bankruptcy prediction. The reclassified liquidity ratios CIBLCIBA, WCIC and LANGLANG shows significant marginal contribution when added to the baseline model, even though their traditional equivalents does not. The ratios also improve the overall classification ability when substituted with their traditional counterparts both on an individual basis and when all of them are swapped at once.

When evaluating the reclassified long-term liquidity and solvency ratios, none of the reclassified ratios showed any sign of significant contribution to the model. Out of all the profitability ratios tested, only EBITDAIC showed a marginal contribution when added to our baseline model. However, it was not able to improve the model when substituted with NITA.

The results show us that there may be of some relevance to reclassifying financial statements for credit analysis purposes, especially considering the liquidity ratios. However, most of the reclassified ratios does not have any contribution in excess of the traditional ratios, and does not improve the predictive abilities of our benchmark model.

6. Additional Testing

To further assess the robustness of our results we have conducted seven additional tests. When deciding which additional test to include in our thesis, we looked at different test methods used in prior studies and at methods easily applicable to our data. The tests chosen are:

- Test for misspecifications and omitted variables
- Test of discriminating ability using the classification matrix
- Test of the effect of using only one fiscal year per company
- Testing the robustness of our main results by using a different baseline model
- Testing the effect of changing our data-restrictions
- Testing if we obtain divergent results when using only company data
- Other tests on robustness

We are of the opinion that these additional tests are important supplements to our main section, as they address potential weaknesses in our initial results.

6.1 Test for Misspecification in the Benchmark Model

We have conducted a test to check whether omitted variables or misspecified functional forms could have affected our results. We tested for model misspecification by applying the link-test provided by Stata. The test entails an estimation of the predicted values for y, where $\hat{y}$ and $\hat{y}^2$ are included as explanatory variables in the original model.

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 \tag{11}$$

The test is performed by estimating:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \delta_1 (\hat{y})^2 + \delta_2 (\hat{y})^2 + \epsilon \tag{12}$$

And testing:

$$H_0 : \delta_1 = \delta_2 = 0$$

The test shows that our baseline model might have a problem with misspecification or omitted variables, as we find the squared predicted value significant in the test statistics.

However, as we wanted to use an acknowledged and well-established model as our baseline model, it makes no sense to do any modifications as this would affect the basis for comparison.

When testing our revised model with variables proven to have marginal credit relevance we obtain solid test-results, indicating that the model is well specified.

In the case of the model consisting of variables with indications of absolute credit relevance, we experienced that both the linear and the squared predicted value are significant. This means that there might be some omitted variables or misspecified functional form in the model.

The Linktest command in Stata is considered to be an efficient way to test the properties of different regression models. However, oftentimes a review of the model and its included variables, based on economic theory, might be the best way to identify any misspecifications or omitted variables. Even though we experience that some of our models performs relatively poorly in the Linktest, this is quite expected, as we know there are other relevant variables we could have included. However, as we wanted to replicate a well-known model consisting of only nine accounting ratios, we were aware that omitted variables could occur.

6.2 Test of Discriminating Ability using the Classification Matrix

We have used the classification matrix to further evaluate the robustness of our model's discriminating abilities. The baseline model has 99.04% correctly classified observations using the default setting with a 0.5 cutoff. This might seem solid at first, but the classification matrix is heavily dependent on the distribution of the dependent variable (Tufte, 2000). If we predict all observations based on the mode value (non-bankrupt) we would correctly classify 99.03% of the observations, indicating a poor ability to identify bankrupt companies. By using the cutoff point that maximizes sensitivity and specificity (minimizes the type 1 and type 2 errors), we experience that the overall correctly classification decreases due to a lower percentage correctly predicted in the non-bankrupt group. However, the models ability to correctly identify bankrupt companies increase from 0.7% to 71.22% correctly classified one year prior to bankruptcy.

With an overall correctly classification of 78.23% (given optimal cutoff), the baseline model has proven solid in discriminating between the companies that goes bankrupt and those that do not. However, compared to the classification results from Ohlson's initial study we see that his model outperform ours in terms of correctly discriminating between bankrupt and non-bankrupt firms. By using the cutoff point that minimizes the sum of errors, Ohlson gets an overall correctly classification of 85.1%

If we look at the classification abilities of our revised models, we find that none of the single swap models perform any better than the baseline model in terms of discriminating ability. The model that comes closest, with an overall classification ability of 74.69%, is the one including CIBLCIBA. However, when testing the discriminating abilities of the complete revised model with variables proven to have absolute credit relevance (model 3 in table 14), we get an overall discriminating ability of 79.91%. Even though it is below Ohlson's original score, it is above the classification abilities of our benchmark model.

It is important to stress that the classification matrix is considered a less reliable evaluation method than AUROC when it comes to assessing the discriminating ability of a logistic regression (Hosmer & Lemeshow, 2000, p. 156-164).

6.3 Test of the Effect of using One Fiscal Year per Company

We have conducted a re-estimation of our main tests using only one fiscal year per company. Some previous studies have used one fiscal year per company when assessing the model's one-year predictive ability, whereas our initial sample consists of multiple observations for both bankrupt and non-bankrupt firms. The potential problem with this is that a bankrupt firm will have several fiscal year observations where the company is classified as non-bankrupt, before the classification changes the year the bankruptcy petition is filed. The reason why we chose this sample structure in our initial sample was to get as much variation as possible, and to have a bankruptcy frequency more similar to the one of the population.

By including only one fiscal year per company we exclude 22,587 observations, ending up with a total of 271 bankruptcy observations and 5,494 non-bankruptcy observations.

As we can see from table 15, the percentage of bankruptcy observations increases quite drastically from 0.97% in the original sample to 4.93% after the exclusions. If we compare this to the bankruptcy frequency of Ohlson's original study (5.10%), we see that our revised sample is more in line with what originally reported by Ohlson. It is also worth mentioning that other studies, such as Altman (1968), also reported bankruptcy frequencies around 5% of total sample.

Table 15: Revised Sample

DEF	Frequence	Percent
0	5,223	95.07
1	271	4.93
Total	5,494	100.00

Notes: DEF indicates whether observations are bankrupt (1) or non-bankrupt (0).

The results from the re-estimation of our baseline model shows that the revised sample has only modest effect on the explanatory power of the model. The pseudo R^2 of the model increases to 0.1482 (0.1459), whereas the AUROC decreases to 0.8059 (0.8263).

To evaluate the reclassified ratios, we replicated the tests conducted in our main study. From the test of marginal credit relevance, we find the same accounting ratios as in our initial study to be credit relevant. The variables found significant was; CIBLCIBA, WCIC, LANGLANG and EBITDAIC.

From the test of the absolute credit relevance of individual ratios we also find the exact same variables to be significant and to improve the model when swapped with its traditional counterpart (see table 13). The same goes for the multiple swap-test, where only the model consisting of variables with indications of absolute credit relevance outperform our baseline model. The model with the variables found significant in the single ratio swap-test yielded a pseudo R^2 of 0.1581 and an AUROC of 0.8116.

6.4 Retesting with SEBRA as Benchmark

We have also conducted a retest of both hypotheses using the SEBRA-model as our benchmark model. In the first column of table 16, we see the coefficients of the replication of the SEBRA-model[41]. We find all of the significant coefficients to have the expected signs. NBNITA, LIKSALES, PAYTA, DIV and sdNBNITA are highly significant, whereas

[41] We excluded all of the age-dummies (a1-a8) from our output. All of them were found insignificant except from a7, which turned out significant at a 10% level.

meanPAYTA and meanTETA are significant at a 5% and 10% level. TAXTA and LOEQ are found insignificant. Our replication of the SEBRA-model has a pseudo R^2 0.1639[42] and an AUROC of 0.8343[43].

Table 16: Maximum Likelihood Estimates – SEBRA-model

Variables	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7
NBNITA	-5.606***	-5.120***	-5.584***	-5.726***	-5.697***		-5.873***
	(0.699)	(0.878)	(0.716)	(0.712)	(0.707)		(0.712)
LIKSALES	-0.475***	-0.478***	-0.352**	-0.497***	-0.492***		
	(0.128)	(0.129)	(0.139)	(0.132)	(0.132)		
TAXTA	-0.388	-0.367	0.604	0.107	-0.0179		
	(1.919)	(1.932)	(1.921)	(1.959)	(1.960)		
PAYTA	2.491***	2.513***	2.456***	2.607***	2.586***	2.615***	2.419***
	(0.484)	(0.487)	(0.495)	(0.492)	(0.493)	(0.498)	(0.487)
TETA	-2.102***	-2.110***	-1.876***	-2.143***	-2.136***	-2.421***	-2.042***
	(0.386)	(0.387)	(0.392)	(0.391)	(0.391)	(0.422)	(0.390)
LOEQ	0.269	0.270	0.257	0.290	0.283	0.466***	0.275
	(0.182)	(0.182)	(0.181)	(0.182)	(0.182)	(0.175)	(0.182)
DIV	-1.029***	-1.013***	-0.988***	-1.007***	-1.010***	-1.043***	-0.982***
	(0.208)	(0.207)	(0.209)	(0.209)	(0.209)	(0.203)	(0.209)
meanTETA	-7.810*	-7.724*	-8.750**	-8.423**	-8.303**	-9.195**	-8.889**
	(4.049)	(4.050)	(4.162)	(4.140)	(4.123)	(4.197)	(4.209)
meanPAYTA	4.865**	4.865**	4.590**	4.096**	4.251**	3.649*	3.671*
	(1.949)	(1.952)	(1.977)	(2.005)	(2.019)	(1.958)	(1.966)
sdNBNITA	23.10***	22.94***	25.83***	25.40***	24.85***	23.06**	26.31***
	(8.858)	(8.863)	(9.052)	(9.103)	(9.062)	(9.320)	(9.243)
a1 – a8	-	-	-	-	-	-	-
EBITDAIC		-0.167				-1.205***	
		(0.178)				(0.292)	
CIBLCIBA			0.0194***			0.0223***	0.0210***
			(0.00367)			(0.00345)	(0.00356)
WCIC				0.207**		0.0952	0.111
				(0.0915)		(0.0981)	(0.0821)
LANGLANG					-0.152*		
					(0.0875)		
Constant	-1.374	-1.414	-1.097	-1.116	-0.995	-0.331	-0.791
	(2.145)	(2.146)	(2.207)	(2.190)	(2.194)	(2.219)	(2.228)
Observations	28,081	28,081	28,000	28,081	28,081	28,000	28,000
LR Significance		0.3099	0.000	0.0167	0.0511		
Pseudo R^2	0.1639	0.1642	0.1706	0.1558	0.15651	0.1565	0.1687
AUROC	0.8343	0.8352	0.8371	0.8355	0.8354	0.8329	0.8367

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Model 1 is the benchmark SEBRA-model. Model 2-5 includes reclassified ratios for marginal contribution testing. Model 6 includes ratios with marginal credit relevance. Model 7 include ratios with indications of absolute credit relevance from the single variable swap-test. There are fewer observations in the models where CIBLCIBA is included, as there are 81 companies with missing value for CIBLCIBA.

[42] Initial benchmark had 0.1459
[43] Initial benchmark scored 0.8263

It can be argued that the SEBRA-model should have been used as our benchmark model because of its predictive abilities and overall model fit. However, the reason why we chose Ohlson's conditional logit model as our benchmark was that we wanted to use a well-renowned model proven solid in an international context.

Column 2-5 in table 16 summarizes the re-estimated results from the test of marginal credit relevance. When comparing the results to the ones of our initial study, we see that we obtain somewhat similar outputs. The CIBLCIBA ratio (see column 3) is still highly significant in the likelihood ratio test, whereas WCIC (column 4) and LANGLANG (column 5) are significant at a 5% and 10% significant level. Even though the results are weaker than our initial, we can conclude that these liquidity measures also have marginal credit relevance when added to the SEBRA- model. However, EBITDAIC (column 1) does no longer have significant marginal contribution to the baseline model.

When evaluating the absolute credit relevance, the same trends as with the test of marginal credit relevance appear. All of the abovementioned liquidity ratios are significant within a 10% significance level (see table 17) and increase both pseudo R^2 and AUROC when swapped into the baseline model. From the marginal credit relevance test, we can see that EBITDAIC reduces both AUROC and pseudo R^2 despite that the variable is highly significant.

Table 17: Single Swap-test - SEBRA-model

Model	SWAP	Corr	Coefficient	P> |z|	AUROC	Pseudo R^2
CIBLCIBA	LIKSALES	−0.2500	0.21912	0.000	0.8363	0.1681
WCIC	TAXTA	−0.1055	0.20674	0.023	0.8355	0.1658
LANGLANG	TAXTA	0.0895	-0.15242	0.079	0.8354	0.1651
Benchmark					**0.8343**	0.1639
EBITDAIC	NBNITA	0.5030	-1.0710	0.000	0.8307	0.1525

Notes: The table presents four ratios from the single variable swap-test. "SWAP" indicates which ratio in the benchmark model that the respective ratio is swapped with. The next column shows the correlation between the ratios. "Coefficient" indicates the coefficient of the reclassified ratio when included in the model. "P>|z|" is the p-value of the ratio from the default z-test, followed by the overall model evaluation measures, AUROC and pseudo R2.

When conducting the multiple variable swap-test we obtain results in line with the ones in our main tests. Column 6 in table 16 show the output from the model consisting of variables with marginal credit relevance. From the regression output, we can see that the baseline model outperforms the revised model on both pseudo R^2 and AUROC. However, when estimating a model consisting of variables with indications absolute credit relevance (column 7 in table 16) both pseudo R^2 and AUROC are improved compared to our benchmark model.

6.5 Retesting Applying Different Restrictions

To further address the "out-of-sample" robustness of our results, we have conducted retests of our initial hypotheses on less restrictive samples. We have used three alternative samples, where we in two of the samples have used the original restrictions except that we; 1. Did not exclude any sectors and 2. Did not remove companies with negative invested capital. In the third sample we only excluded data with missing values on sales, total assets and the included variables.

In sample 1, we experience that all of the ratios found significant in our main results still show strong marginal contribution to the benchmark model and are highly significant (1%) in the likelihood ratio test.

In sample 2, the liquidity ratios still show significant marginal contribution. However, WCIC and LANGLANG are only significant at a 5% and 10% significant level, whereas CIBLCIBA still is highly significant (1%). The EBITDAIC ratio turns out to be insignificant in sample 2. This indicates that the significance of EBITDAIC is affected by the removal of companies with negative IC[44]. In sample 3, we experience that all of the variables found significant in the main results section still are highly significant (1% level).

When testing the marginal credit relevance using different sub-samples, we discovered that several new reclassified ratios proved to have marginal credit relevance (see Appendix B). However, the most important finding is that the liquidity ratios; CIBLCIBA, WCIC and LANGLANG, are found significant in all of the marginal credit relevance tests based on revised samples. This supports the initial findings and strengthens the robustness of our results.

The results from our retest of absolute credit relevance can be viewed in table 18. In line with our initial results, CIBLCIBA, WCIC and LANGLANG improve both pseudo R^2 and AUROC when using sample 1 and 2. However, in sample 3 only CIBLCIBA are able to improve the benchmark model. As in our initial test, EBITDAIC results in a lower pseudo R^2

[44] 1.902 observations have negative IC.

and AUROC[45] in all of the samples. The results from the multiple variable swap-tests are similar to the results found in our main section, where the model consisting of variables with absolute credit relevance outperformed the baseline model in terms of both pseudo R^2 and AUROC.

Table 18: Single Variable Swap-test

	Sample 1		Sample 2		Sample 3	
	R^2	AUROC	R^2	AUROC	R^2	AUROC
Benchmark	0.1378	0.8203	0.1549	0.8317	0.1336	0.8176
CIBLCIBA	0.1469	0.8240	0.1656	0.8346	0.1434	0.8211
WCIC	0.1411	0.8245	0.1558	0.8333	0.1330	0.8178
LANGLANG	0.1402	0.8244	0.1555	0.8331	0.1330	0.8178
EBITDAIC	0.1318	0.8108	0.1303	0.8040	0.1107	0.7789
Multiple Marginal	0.1318	0.8082	0.1348	0.8063	0.1170	0.7814
Multiple Absolute	0.1424	0.8216	0.1643	0.8348	0.1435	0.8215
Observations	40,770		29,983		50,411	

Notes: The pseudo R^2 and AUROC performance of the different estimation samples. First row shows the benchmark model. CIBLCIBA, WCIC, LANGLANG and EBITDAIC show the results from the single variables swap test. Multiple marginal and multiple absolute shows the results from the multiple swap analysis.

6.6 Retesting with Company Data

According to the Norwegian bankruptcy legislation, it is the independent entity and not the group as a whole that goes bankrupt. To investigate any effect this might have on our initial results, we have replicated our initial tests using a sample consisting of only independent companies. We have excluded all companies with a registered “mother” due to the risk of internal transactions not being reflected in the accounting ratios. The final sample consisted of 48,135 observations.

[45] EBITDANETINVNIBL also improved the model with pseudo R^2 of 0.1395 and AUROC of 0.8209

Table 19: Maximum Likelihood Estimates using Company Data.

Variables	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7
logTA	-0.637***	-0.640***	-0.624***	-0.645***	-0.642***	-0.625***	-0.610***
	(0.0659)	(0.0660)	(0.0659)	(0.0662)	(0.0662)	(0.0658)	(0.0658)
TLTA	2.397***	2.395***	2.346***	2.278***	2.295***	3.090***	2.620***
	(0.297)	(0.297)	(0.299)	(0.301)	(0.301)	(0.301)	(0.280)
WCTA	-0.613***	-0.622***	-0.602***	-0.962***	-0.900***		
	(0.207)	(0.207)	(0.212)	(0.228)	(0.230)		
CLCA	0.00578	0.00565	-0.00783	0.0111	0.00922		
	(0.0218)	(0.0217)	(0.0238)	(0.0217)	(0.0217)		
OENEG	-0.0814	-0.0738	-0.101	-0.0535	-0.0583	0.249*	-0.108
	(0.160)	(0.160)	(0.164)	(0.160)	(0.159)	(0.150)	(0.163)
NITA	-4.261***	-4.034***	-4.321***	-4.246***	-4.250***		-4.510***
	(0.364)	(0.419)	(0.368)	(0.370)	(0.368)		(0.372)
CFOTL	-0.0409	-0.0399	-0.0393	-0.0299	-0.0320	-0.0388	-0.0232
	(0.0249)	(0.0248)	(0.0251)	(0.0241)	(0.0242)	(0.0260)	(0.0232)
INTWO	0.253**	0.251**	0.238*	0.244**	0.243**	0.434***	0.236*
	(0.120)	(0.120)	(0.122)	(0.120)	(0.120)	(0.123)	(0.122)
CHIN	-0.00409	-0.00359	-0.00242	-0.00245	-0.00271	0.00650	-0.00233
	(0.0139)	(0.0138)	(0.0140)	(0.0138)	(0.0138)	(0.0145)	(0.0140)
ebitdaIC		-0.0724				-0.565***	
		(0.0675)				(0.187)	
CIBLCIBA			0.000810***			0.000902***	0.000850***
			(0.000290)			(0.000264)	(0.000280)
WCIC				0.273***		0.0326	0.123*
				(0.0850)		(0.0684)	(0.0630)
LANGLANG					-0.212***		
					(0.0802)		
Constant	0.822	0.872	0.724	0.966	1.153	0.129	0.242
	(0.714)	(0.716)	(0.716)	(0.721)	(0.728)	(0.715)	(0.703)
Observations	48,135	48,135	47,283	48,135	48,135	47,283	47,283
LR – Significance		0.1746	0.1112	0.000	0.0001		
Pseudo R^2	0.1268	0.1271	0.1262	0.1298	0.1290	0.1093	0.1254
AUROC	0.8073	0.8071	0.8085	0.8118	0.8111	0.7890	0.8106

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Model 1 is our original benchmark model. Model 2-5 shows the output from our marginal credit relevance tests. Model 6 includes multiple ratios with marginal relevance. Model 7 includes multiple ratios with absolute relevance from the single variable swap-test.

From the test of marginal credit relevance, we find the same three liquidity ratios as in our main results to have marginal contribution to our baseline model. The regression output from the tests can bee seen in table 19. WCIC and LANGLANG are highly significant (1% level) in the likelihood ratio test, whereas CIBLCIBA are significant at a 5% level. The main differences from the initial analysis are that EBITDAIC no longer is significant, and that EBITNIBL is found significant at a 10% level.

From the single variable swap-test, we find none of the ratios to outperform the benchmark model in both AUROC and pseudo R^2. CIBLCIBA, WCIC and LANGLANG perform better in terms of AUROC, but have a lower pseudo R^2 than the benchmark model.

Table 20: Single Variable Swap-test – Company Data

Model	SWAP	Corr	Coefficient	P> |z|	AUROC	Pseudo R^2
Benchmark					**0.8073**	**0.1268**
CIBLCIBA	CLCA	0.1508	0.0007952	0.006	0.8093	0.1261
WCIC	WCTA	0.3793	0.2067409	0.016	0.8097	0.1264
LANGLANG	WCTA	-0.3557	-0.1229074	0.052	0.8093	0.1260
EBITDAIC	NITA	0.4309	-0.52467	0.002	0.7891	0.1119

Notes: The table presents four ratios from the single variable swap-test. "SWAP" indicates which ratio in the benchmark model that the respective ratio is swapped with. The next column shows the correlation between the ratios. "Coefficient" indicates the coefficient of the reclassified ratio when included in the model. "P>|z|" is the p-value of the ratio from the default z-test, followed by the overall model evaluation measures, AUROC and pseudo R^2.

This trend also appears in the multiple variable swap-test shown in Table 19, column 6 and 7. Model 6 performs worse both in terms of pseudo R^2 and AUROC, whereas model 7 has a higher AUROC, but a lower pseudo R^2 than our benchmark.

When retesting with only company data, we get somewhat ambiguous results. From the test of marginal credit relevance, the liquidity ratios CIBLCIBA, WCIC and LANGLANG prove significant, as they did in the main results section. However, when considering absolute credit relevance, none of the ratios are able to improve our benchmark model. This contradicts the results in our initial study, where the abovementioned liquidity ratios were found credit relevant.

6.7 Other Additional Tests

Clustered Standard Errors

As an alternative to applying robust standard errors, we have also conducted the initial tests using clustered standard errors at company level (organizational number), as the error terms of each individual (organizational number) are likely to be correlated over time (Hill et al, 2012, p.541).

Applying clustered standard errors did not lead to any change of results, compared to our main results section. The liquidity ratios still prove highly significant (1% level), whereas EBITDAIC is slightly significant (10% level) when assessing the marginal contribution using the default z-test.

Industry and Year Dummies

We have also done a retest of our models where we added industry- and year – dummies to capture any fixed effects related to industry and fiscal year. We included sector- and year – dummies as control variables in addition to the original variables in the benchmark model. All the sectors depicted in table 6 were included, where the "other services" sector was set as reference category. For the year-dummies, 2014 was set as reference year. By including the dummy variables, pseudo R^2 and AUROC increases to 0.1643 and 0.8433.

All of the variables found significant in our main results still have marginal contribution at a high significant level (1% level) in the likelihood ratio test. When considering the absolute credit relevance from the single ratio swap-test, all of the liquidity ratios still increase both pseudo R^2 and AUROC[46]. As in our initial results, EBITDAIC yields a lower pseudo R^2 and AUROC. In the multiple variable swap-test we obtain results in line with the results from our initial test.[47]

[46] CIBLCIBA: Pseudo R^2: 0.1739, AUROC: 0.8459; WCIC: Pseudo R^2: 0.1692, AUROC: 0.8477 LANGLANG: Pseudo R^2: 0.1677, AUROC: 0.8469; EBITDAIC: Pseudo R^2: 0.1573, AUROC: 0.8343

[47] Absolute relevance model: Pseudo R^2: 0.1729 AUROC: 0.8451, marginal model: Pseudo R^2: 0.1617, AUROC: 0.8324

Probit Model

To assess the initial results sensitivity to model design, we have conducted the same tests as presented in our main results section using a probit model. For an explanation of the probit model, we refer to *Principles of Econometrics* by Hill et al. (2012). In the revised estimation we used the same variables as in our initial benchmark model. The benchmark probit model scores a pseudo R^2 of 0.1496 and an AUROC of 0.8276.

The three liquidity ratios found to have marginal credit relevance in our initial test are also highly significant (1% level) when using the alternative model design, whereas the EBITDAIC ratio prove significant at a 5% level.

When testing the absolute credit relevance of revised accounting ratios, all of the liquidity ratios improve the model when swapped on a single ratio basis[48].

As in the main results section, the model consisting of ratios found significant in the single ratio swap-test increase both pseudo R^2 (0.1585) and AUROC (0.8313) in the multiple variable swap-test, whereas the model consisting of ratios with marginal relevance gives a lower pseudo R^2 and AUROC than the benchmark model.

[48] CIBLCIBA: Pseudo R^2: 0.1592, AUROC: 0.8306, EBITDAIC: Pseudo R^2: 0.1386, AUROC: 0.8179, WCIC: Pseudo R^2: 0.1562, AUROC: 0.8339, LANGLANG: Pseudo R^2: 0.1546, AUROC: 0.8330

Conclusion

We have looked at the marginal and absolute credit relevance of ratios derived from the reclassified financial statement and how these ratios affect the predictive abilities of our traditional baseline model. In our main tests, we have used a sample consisting of Norwegian group financials, giving us a sample of 271 bankruptcy and 27,810 non-bankruptcy observations.

First, we find the reclassified ratios; Current interest bearing liabilities/Current financial assets (CIBLCIBA), Working capital/Invested capital (WCIC), Non-current operational assets/Invested capital (LANGLANG) and EBITDA/Invested capital (EBITDAIC) to have marginal credit relevance when added to our baseline model. Interestingly, three out of four ratios are liquidity ratios, which in prior studies were found to be of less importance when predicting corporate default.

When testing the absolute credit relevance of the reclassified ratios, we again find the three liquidity ratios to perform well in terms of pseudo R^2 and AUROC. Out of the ratios found significant, the CIBLCIBA ratio has the highest contribution to the baseline model when swapped with its traditional counterpart. The fact that we find these liquidity ratios to be significant might substantiate the critique of the traditional ratios portrayed by Petersen et al. (2017, p. 231-233), where they question the traditional liquidity ratios ability to show the true short-term liquidity risk of a company. By reclassifying the ratios, we are able to eliminate the effect of current operational assets and liabilities not easily valuated, and “refinanced” through ongoing operations. It may seem like a reclassification of the financials give a more reasonable picture of the company’s liquidity and improve the predictive ability of the ratios.

To validate our results we have added a comprehensive section with additional tests. In this subsection we have conducted multiple tests addressing the robustness of our initial results. A majority of the tests turn out to substantiate our initial findings, which are that the reclassified liquidity ratios perform well in a statistic credit analysis.

The main question is; do we find reclassified financial statement ratios relevant for credit analysis purposes? The answer to this is not as straightforward as we hoped, as most of the reclassified ratios turn out to be insignificant in terms of both marginal and absolute credit relevance. However, we have strong indications that the reclassified liquidity ratios, CIBLCIBA and WCIC, are credit relevant and might give better insight into a company's liquidity position than traditional ratios.

Even though we have strong indications that some liquidity ratios may improve the predictive ability of static bankruptcy prediction models, there is always a question whether the cost of reclassification outweighs the benefits of improved predictive ability. A thorough reclassification of the financial statement can be a time consuming and costly task, implying that there must be a significant gain from using reclassified ratios to make the reclassification "profitable" for the stakeholders. At this point, we are of the opinion that a reclassification may improve the predictive abilities of some ratios, but that the cost/benefits associated with a reclassification could make it "unprofitable". Further research on the cost and benefits of a reclassification would provide valuable insight into the profitability of using a reclassified financial statement for credit analysis purposes.

In our thesis, we have limited the research to entail only annual accounting information on Norwegian companies registered in the period from 1999 to 2014. As mentioned earlier, the use of annual accounting data gives a lead-time between the last annual report and the bankruptcy opening that might affect the predictive ability of the ratios. Thus, employing quarterly or monthly accounting data may improve the predictive ability of some accounting ratios. This could be an interesting prospective for future research. Second, it would have been interesting to conduct the test using modern estimation procedures, such as neural network methods. Further research may reveal that modern estimation procedures yield other results than what found using a traditional logistic model.

It would also be interesting to check whether a more detailed reclassification could affect the credit relevance of reclassified ratios. Altman, Haldeman and Narayanan (1977) included off-balance sheet items in the financial statement, entailing an inclusion of items such as non-cancellable operational and financial leases and imputed interest costs related to these liabilities. Franzen, Rodgers and Simin (2007) also used a reclassified financial statement where expensed R&D costs were recognized and depreciated over a 5 year period. More comprehensive and detailed reclassifications like these could be an interesting field of study for future research, as it may give new insight into the information value of reclassified financial ratios.

Finally, as we did not perform a test of statistical significance of the change in pseudo R^2 and AUROC outputs, this would be an interesting subject for future research on the credit relevance of reclassified financial statement ratios.

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Appendix

Appendix A: Traditional Financial Statement Ratios

Category	Variable Name	Variable Definition
Leverage	RETA	Retained earnings / Total assets
	TETA	Total equity / Total assets
	TETL	Total equity / Total liabilities
	TETD	Total equity / Total debt
	TLTA	Total liabilities / Total assets
	TLTE	Total liabilities / Total equity
	MEANTETA	(Industry average) Total equity / Total assets
Liquidity	CACL	Current assets / Current liabilities
	CLCA	Current liabilities / Current assets
	CLTA	Current liabilities / Total assets
	CLTE	Current liabilities / Total equity
	TAXTA	Public tax liabilities / Total assets
	PAYTA	Trade payables / Total assets
	MEANPAY	(Industry average) Trade payables / Total assets
	CFTL	Cash flow / Total liabilities
	CFOTL	Cash flow from operations / Total liabilities
	CFOIE	Cash flow from operations / Interest expenses
	CFOCL	Cash flow from operations / Current liabilities
	CFOFE	Cash flow from operations / Financial expenditures
	EBITTL	Earnings before interest & taxes / Total liabilities
	EBITIE	Earnings before interest & taxes / Interest expenses
	EBITCL	Earnings before interest & taxes / Current liabilities
	NICL	Net income / Current liabilities
	NITL	Net income / Total liabilities
	FESALES	Financial expenses / Sales
	CASHTA	Cash / Total assets
	CASHSALES	Cash / Sales

	CASHCL	Cash / Current liabilities
	NCI (No Credit Interval)	Defensive assets - current liabilities / Fund expenditures for operations
Activity	TESALES	Total equity / Sales
	TASALES	Total assets / Sales
	QASALES	Quick assets / Sales
	SALESCA	Sales / Current assets
	SALESTA	Sales / Total assets
	SALESFA	Sales / Fixed assets
	WCTA	Working capital / Total assets
	WCTE	Working capital / Total equity
	CATA	Current assets / Total assets
	QATA	Quick assets / Total assets
	CASALES	Current assets / Sales
	WCSALES	Working capital / Sales
	INVSALES	Inventory / Sales
	QAINV	Quick assets / Inventory
	QASALES	Quick assets / Sales
Profitability	EBITTA	Earnings before interest & taxes / Total assets
	EBITFA	Earnings before interest & taxes / Fixed assets
	EBITTE	Earnings before interest & taxes / Total equity
	EBITSALES	Earnings before interest & taxes / Sales
	CFOTA	Cash flow from operations / Total assets
	CFOFA	Cash flow from operations / Fixed assets
	CFOTE	Cash flow from operations / Total equity
	NITA	Net income / Total assets
	NIFA	Net income / Fixed assets
	NITE	Net income / Total equity
	NISALES	Net income / Sales
	SDNITA	Industry standard deviation for NBNITA
Other Variables	TA	Total assets
	LOGTA	Log of total assets / GNP
	OENEG	Dummy variable equal 1 if: Total liabilities > Total assets

	INTWO	Dummy variable equal 1 if: Net income was negative the last two years
	CHIN	(NI t – NI t-1) (NIt + NI t-1)
Dummy	Age	Number of years since start-up
	Div	Dummy for dividend the last year
	LOEQ	Dummy for lost

Notes: Most of the ratios are gathered from Chen & Shimerda (1981), Charitou, Neophytou & Charalambous (2004). Working Capital (WC) = Current Assets – Current Liabilities; Cashflow from Operations (CFO) = NI + Depreciation +- Change in WC (except financial items); Defensive Assets = Financial Assets; Financial Expenditures (FE) = Interest expences + short term debt; Quick Assets (QA) = (Current assets – inventories)/Current Liabilities; NorgesBank Net Income (NBNI) = Net Income (Before Extraordinary items) + depreciation + impairments - tax

Appendix B: Other Ratios with Indications of Absolute Credit Relevance

Likelihood ratio – Significance	1) All sectors	2) No IC restriction	3) Only missing excluded
1%	LONGFINCOV CFONETINVNIBL	-	-
5%	NIBLIC adjEBITDAIC EBITIC	-	LONGFINCOV SHORTLIQ2
10%	EBITDACNIBL EBITDANETINVNIBL	CFONETINVNIBL EBITDANETINVNIBL	NIBLIC N_Size FINKNIBL CFONIBL EBITIC EBITDANETINVNIBL
Observations	40.770	29.983	50.411

Notes: The table shows other ratios proved to have marginal credit relevance under different sample selection (See additional testing). The left column shows at what significance level the ratios show to have contribution from the likelihood ratio test. The three columns to the right indicate which sample was applied for the respective test. At the bottom row the number of observations for each sample is presented.