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Prediction of Financial Distress among Swedish Listed Companies

- A study of Ohlson's O-score and an alteration of the model using Swedish data

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ABSTRACT

The prediction of bankruptcy and financial distress related to companies has interested many researchers and two of the more notable published contributions are attributable to Altman (1968) and Ohlson (1980). As the studies within this field of research are many, few can be been related to Swedish listed companies. This thesis mimics the research done by Ohlson in the pursuit of trying to find a model suitable for the Swedish stock market, with a starting point in the studies of the same. By comparing the results of three different models derived through logistic regression analysis, Ohlson’s model still seems to provide some usable input. However, the results indicate that a revised model, incorporating information related to the audit report and the opinion expressed by the auditor, improves the prediction of financial distress among Swedish listed companies. We found this model, Model B, to be the most suitable one amongst the three.

Key words: Bankruptcy, Financial distress, Prediction model, Audit report, O-score, Swedish listed companies

TABLE OF CONTENTS

1 INTRODUCTION

Without exaggerating, money is by many means a fundamental cornerstone of our society. Many have at some point come across the expression “money makes the world go around”, once sung in the musical, *Cabaret*. This expression can easily be applied to and observed within the reality of corporations. Without funds, the world of the company will simply stop spinning, since without funds one will have trouble paying suppliers’ bills and in most cases this results in the suppliers discontinuing supplying their goods and services to the company. A recent case involves the subcontractors of the Swedish car manufacturer Saab Automobile, who amongst others, was negatively affected by the financial distress presented by this big industrial actor.[1] One of the more alarming indications of a forthcoming bankruptcy of Saab Automobile, was its inability to pay its subcontractors which consequently lead to material shortages.[2] Without the input provided by suppliers a business will not sustain for long and operations will be forced to cease, as in the case of Saab Automobile. Such an undesirable situation could, as observed, ultimately lead to the company being liquidated or forced into bankruptcy.

From 2007 to 2009 the numbers of corporate bankruptcies in Sweden increased by almost 32 percents from 5 791 to 7 638. Since then the numbers have somewhat decreased reaching a level of 6 958 bankruptcies treated by the district courts in 2011.[3] Apart from the suppliers and subcontractors, a bankruptcy might have serious implications also for other stakeholders. For one, the employees and managers might lose their jobs and thus their income if their employer has to close operations and can no longer provide work nor pay out salaries. Customers whose operations are dependent on the financially distressed company and the goods or services that it purchases will naturally also be affected. Further down the line of economic instability, the company might also have to cancel its pending payments towards creditors, thus not fulfilling its debt obligations.

With this in mind, it could very well be considered an advantage if one with great ease and certainty was able to determine the likelihood of a firm, in a not too distant future, reaching a

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[1] TT, ”Saab går i konkurs”, *Dagens Nyheter*, 2011-12-19, http://www.dn.se/ekonomi/saab-begars-i-konkurs, (Downloaded 2012-04-17)

[2] Rabe, M., ”Saab har problem – betalar inte underleverantörer”, *Teknikens värld*, 2011-03-29, http://www.teknikensvarld.se/2011/03/29/12375/saab-har-problem--betalar-inte-underleverantorer/, (Downloaded 2012-05-10)

[3] Tillväxtanalys, Konkurser och offentliga ackord 2011: Statistikrapport 2012:01, 2012-02-13, http://www.tillvaxtanalys.se/tua/export/sv/filer/statistik/konkurser/Statistik_2012_01.pdf, (Downloaded 2012-04-17)

state of financial distress. Because, as described above, in such a state the future of the company is by many means at risk and there is often a significant possibility that this will lead to a situation where the company has to discontinue its operations. This could have serious implications for all these stakeholders of the company. However, the stakeholder often assuming the riskiest position is the shareholder investing equity capital in exchange for shares.

From the perspective of an equity investor, it might be sufficient if the company simply performs poorly and gets itself into a financially troublesome situation, in order for the investment to become worth close to nothing as the share price could be very vulnerable to such implications. With the possibility of losing a lot or even everything, it would thus probably serve them best if a tool could be used to predict when and if a company could get itself into a state related to financial distress. By taking such information into account one could perhaps easier evade such events.

Such tools do in fact exist and the research considering them is in fact rather extensive. When describing the research conducted regarding this area there are however a couple of seminal studies that needs to be mentioned. In 1966 Beaver sought to analyze single financial key ratios to find whether these could predict bankruptcy on their own, using univariate analysis.[4] Later on, Altman conducted a study where he instead of using only single key ratios, developed a model consisting of five different ratios.[5] Afterwards, Ohlson wrote a paper where he developed another model, promoting other statistical methods[6] and seeking to better predict corporate bankruptcy.[7]

This leads us to the this thesis, which presents some empirical results of a study evaluating and focusing on Ohlson's O-score and its performance and uses when depicting the probability of financial distress. The study centres around Swedish listed firms and the probability that such will, within one year, reach a state of financial distress. We present results describing how well Ohlson's original model, based upon American data originating from the 70's,[8] functions when studying Swedish firms of today. We also develop an updated

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[4] Beaver, W. 1966. "Financial Ratios as Predictors of Failure", *Journal of Accounting Research*, Vol. 4, No. 3, p. 100

[5] Altman, E. "Financial Ratios, Discriminant Analysis and Prediction of Corporate Bankruptcy", *Journal of Finance*, Vol. 23, No. 4, 1968, pp. 594ff.

[6] Ohlson, J. "Financial Ratios and the Probabilistic Prediction of Bankruptcy", *Journal of Accounting Research*, Vol. 18, No. 1, 1980, pp. 111ff.

[7] Ibid., p. 109

[8] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", p. 109

model and analyze the differences between it and the original model. This updated model is fabricated using the same statistical methods and variables as used by Ohlson when constructing his O-score. However, our sampling method is somewhat different from Ohlson's.[9] Finally, we incorporate variables describing the quality of the financial reports as described by the auditor in the audit report. The effects are consequently sought out and analyzed.

1.1 PURPOSE

The purpose of this study is to examine the possible uses of Ohlson's O-score in relation to Swedish data and to observe how it applies to modern Swedish firms of today. That includes analyzing the differences between the original model, published in a paper in 1980 and an altered model based upon the same statistical methods and variables, but on Swedish listed firms being active during recent years. Basically, we aim to examine how Ohlson's studies can be employed today in order to determine the probability of a Swedish listed firm becoming bankrupt or reaching another condition related to financial distress. Furthermore, since the models are almost entirely relying on accounting-based information derived from the annual reports, we would like to examine whether there is a gain to be attained in also considering the quality of these reports, with regard to the model. That is, can we increase the predictability of corporate failure by inducing an audit element and incorporating data regarding the audit reports into the model?

Above all this, the underlying purpose is, with Ohlson's O-score as a starting point, to find a model that can easily be understood and applied by investors investing in Swedish stocks on as many levels as possible. This also includes that the data should be easily acquirable and used as input in the model.

1.2 QUESTION FORMULATIONS

The questions that are connected to the purpose of the study are formulated as follow:

- How can Ohlson's O-score be applied when examining the probability of Swedish listed firms reaching a state of financial distress?
    - How would a similar model, based on the same statistical methods and variables look like and would it differ from the original model?

[9] Ibid., p. 114

- What are the implications of adding information regarding the quality of the annual reports to the model?

2 LITERATURE REVIEW

2.1 EARLY SEMINAL RESEARCH: *BEAVER AND ALTMAN*

During the 1960s the foundation of the research related to ratio analysis and how the use of it could help determine the probability of firm-related bankruptcy was laid. In 1966 Beaver published a study where he analyzed a set of thirty financial ratios in order to distinguish their uses when evaluating the probability of companies going bankrupt. He found that there were a lot of financial ratios that could be used as predictors of this matter.[10] Soon after Beaver's study, Altman published a paper based on a study analyzing 66 different companies of which 33 were defined as healthy companies that had not gone bankrupt. The other 33 were instead defined as bankrupt companies. Based on this sample and the method of multiple discriminant analysis (MDA) he developed the Z-score model. Unlike Beaver he analyzed a set of financial ratios at the same time and after having run numerous different ratio profiles through the computer, the final appearance of his model was the following:[11]

$$Z = .012X_1 + .014X_2 + .033X_3 + .006X_4 + .999X_5$$

$$X_1 = Working\ capital/Total\ assets$$

$$X_2 = Retained\ Earnings/Total\ assets$$

$$X_3 = Earnings\ before\ interest\ and\ taxes/Total\ assets$$

$$X_4 = Market\ value\ equity/Book\ value\ of\ total\ debt$$

$$X_5 = Sales/Total\ assets$$ [12]

The final summarized product, the so called Z-score, was then compared to an accompanying discriminant value which determined whether the firm would go bankrupt or not.[13] All of these variables were based upon accounting data, except for the fourth variable which considers the market value of equity. The traditional Z-score has later on been followed by the ZETA model[14], as well as a number of other similar models.[15]

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[10] Beaver (1966), "Financial Ratios as Predictors of Failure", pp. 106ff
[11] Altman (1968), "Financial Ratios, Discriminant Analysis and Prediction of Corporate Bankruptcy", pp. 593ff.
[12] Ibid., p. 594
[13] Ibid., p. 592
[14] Altman, E., Haldeman, R. and Narayanan, P. "ZETA™ ANALYSIS, A New Model to Identify Bankruptcy Risk of Corporations", *Journal of Banking and Finance*, Vol. 1, No. 1, 1977, pp. 29-54
[15] Altman, E. "Predicting Financial Distress of Companies: Revisiting the Z-Score and ZETA® Models", Stern School of Business, New York University, July 2000, pp. 25ff., http://pages.stern.nyu.edu/~ealtman/Zscores.pdf, (Downloaded 2012-05-05)

2.2 LOGIT MODELS: *OHLSON*

Apart from Beaver and Altman, an extensive array of studies have been conducted within this research area and there are now a wide variety of models that have been developed and which attempts to predict the bankruptcy of firms. The most important one regarding this study is the one conducted by Ohlson, who presents a binary model. It is similar to Altman's original Z-score in the sense that it is meant to predict corporate failure as evidenced by the event of bankruptcy. Another similarity is the almost exclusionary use of key ratios and accounting-based information. However, this binary model uses a different statistical approach enabling a more unhampered sample and sampling method. The statistical approach enabling this is the logistic approach (or the logit approach) and Ohlson has, unlike Altman, not used a small sample were failing companies and non-failing companies have been paired together. Instead he has used a sample consisting of 105 failing companies and 2,058 non-failing companies, all of which had been or was listed companies.[16]

Instead of five variables, like Altman's Z-score model,[17] Ohlson's so called O-score is constituted out of nine variables, including both financial ratios and specific dummies attempting to enhance predictability of his model.[18] Each variable is described below by the words of Ohlson himself:

1. ***SIZE*** = log(total assets/GNP price-level index). The index assumes a base value of 100 for 1968. Total assets are as reported in dollars. The index year is as of the year prior to the year of the balance sheet date. The procedure assures a real-time implementation of the model. The log transform has an important implication. Suppose two firms, A and B, have a balance sheet date in the same year, then the sign of P_A - P_B is independent of the price-level index. (This will not follow unless the log transform is applied.) The latter is, of course, a desirable property.
2. ***TLTA*** = Total liabilities divided by total assets.
3. ***WCTA*** = Working capital divided by total assets.
4. ***CLCA*** = Current liabilities divided by current assets.
5. ***OENEG*** = One if total liabilities exceeds total assets, zero otherwise.
6. ***NITA*** = Net income divided by total assets.
7. ***FUTL*** = Funds provided by operations divided by total liabilities.

[16] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", pp. 109f
[17] Altman (1968), "Financial Ratios, Discriminant Analysis and Prediction of Corporate Bankruptcy", p. 594
[18] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", pp. 118f

8. ***INTWO*** = One if net income was negative for the last two years, zero otherwise.
9. ***CHIN*** = $(NI_t - NI_{t-1})/(|NI_t| + |NI_{t-1}|)$, where NI is net income for the most recent period. The denominator acts as a level indicator. The variable is thus intended to measure change in net income.[19]

In his study he presented results for three different models, which sought to predict the probability of bankruptcy one year in advance, two years in advance given that the firm did not go bankrupt during the first year and either one or two years in advance.[20] However, it is only the first model which is of interest in this study as it is devoted to analyzing the probabilities of financial distress one year in advance. Ohlson's first model was presented with the following appearance, describing the O-score:

$$O = -1.32 - 0.407SIZE + 6.03TLTA - 1.43WCTA + 0.0757CLCA - 1.72OENEG - 2.37NITA - 1.83FUTL + 0.285INTWO - 0.521CHIN$$ [21]

Regarding the signs preceding these coefficients they could very well be logically explained with regard to the essence of what these variables are trying to capture. This is however not explained by Ohlson in his study. *SIZE, WCTA, NITA, FUTL* and *CHIN* are although ratios that decreases the probability of failure, consequently presented as negative coefficients. As the value they assume increase they are considered as being healthier, which is reflected in a decreased probability of bankruptcy. *OENEG* is a variable trying to compensate for companies whom present negative equity, or alternatively has total liabilities which are exceeding total assets. This variable is by Ohlson described as neither truly negative nor truly positive and its interpretation is thus not as clear-cut as for the others. *TLTA, CLCA* and *INTWO* do understandably are positive coefficients, since a higher share of liabilities over assets and a negative net income do not typically have a positive effect on a company's well-being. This means that they have an increasing effect on the probability of bankruptcy.[22]

2.3 Swedish Bankruptcy Prediction Models: *Skogsvik*

Skogsvik has developed two models based upon a statistical method related to the logit analysis – the probit analysis. His sample, aside from being Swedish, consists of industrial companies with a data period ranging from 1966 to 1980. The observations were however obliged to have had assets amounting to at least 200 million SEK or, as a minimum, 200

[19] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", pp. 118f
[20] Ibid., p. 120
[21] Ibid., p. 121
[22] Ibid., p. 119

employees any year between 1966 and 1971. Comparable as to our study he defined the failing firms, or the firms that had reached a state of financial distress, as either having gone bankrupt, reached a composition agreement, voluntarily shut down the primary production activity or received a receipt of a substantial subsidy provided by the state. His sample did eventually contain 51 failing companies and 328 non-failing companies.[23] One of the models was based upon current cost accounting (CCA), whilst the second one on the more commonly used historical cost accounting (HCA) approach. This second one was intended to be used as a reference model. The two models were developed independently and had slightly differing sets of variables.[24] What he found was however that their performances were very alike, at least as to their Type-I and Type-II error rates.[25] HCA ratios thus seemed to still prove to be good predictors of business failure, in the sense that they have been employed earlier in the studies of Beaver, Altman and Ohlson amongst others.[26]

2.4 Research Considering Audit Reports and Bankruptcy

Auditing can be defined as "*a systematic process of objectively obtaining and evaluating evidence regarding assertions about economic actions and events to ascertain the degree of correspondence between those assertions and established criteria and communicating the results to interested users*".[27] The results communicated to interested users are the audit reports as well as the opinions derived from the financial statements of the company. The most common opinion is an unmodified opinion, proclaiming that the statements are presented fairly according to the auditor. If this is not the case, but rather that a modified opinion is presented, there is probably something wrong with regards to the financial statements and the accounting procedures of the company. It could be that the auditor has found a material misstatement, but the company has refused to change it. It could also be that the auditor has not been able to perform a satisfying evaluation. There can be several other underlying reasons resulting in a modified opinion[28] and it is the relationship between these reasons and bankruptcy which the following studies seek to undertake.

[23] Skogsvik, K. "Current Cost Accounting Ratios as Predictors of Business Failure: The Swedish Case", *Journal of Business Finance & Accounting*, Vol. 17, No. 1, 1990, pp. 141f
[24] Ibid., pp. 137f
[25] Ibid., p. 152
[26] Ibid., p. 138
[27] Eilifsen, A., Messier, W., Glover, S. and Prawitt, D. *Auditing & Assurance Services*, 2nd revised ed., Berkshire: McGraw-Hill Education, (2010), p. 10
[28] Ibid., pp. 18-20

2.4.1 Hopwood, McKeown & Mutchler

Regarding earlier research examining the relationship between audit reports and bankruptcies there are many of whom that have proven its existence. The statements made by the auditor could thus, to some extent, be used to foresee a bankruptcy. Hopwood et al. studied the relationship between the audit reports and the financial failure of American companies. They used one univariate test and two multivariate tests to examine this relationship. The univariate test examined the dependence of the different kinds of opinions presented by the auditor. The opinions were divided into three groups depending on whether they were related to consistency, going-concern or other "subject-to" qualifications. All groups were proven to be somewhat associated to bankruptcy.[29]

Regarding these groups and the different opinions; a consistency exception is attributable to a change in accounting principles, a going-concern opinion refers to whenever an auditor have doubts about the continued existence of an entity and a subject-to opinion is stated whenever an auditor expresses uncertainties regarding something specific in the financial statements which cannot be reasonably estimated and that is believed to have a material impact on the appearance of the statements. The first multivariate test used the audit report variables in conjunction with each other. It indicated a relationship between bankruptcy and both the going-concern and other subject-to qualifications. In the second multivariate test the audit report variables were jointly tested in a model together with a set of ratios that were solely based upon accounting-based information. They then found that the consistency exception and the going-concern opinions had incremental explanatory power. In relation to the ratios and other subject-to opinions they did prove to have unique explanatory effects beyond these other variables.[30] They concluded the paper by stating that the study in fact does provide credence to the use of auditors' qualified opinions as an early warning signaling possible entity failure.[31]

2.4.2 Gaeremynck & Willekens

Gaeremynck & Willekens have also examined the relationship between audit reports and company failure. Their definition of company failure included bankruptcies and voluntary liquidations and the results which they presented in their study did point towards a strong

[29] Hopwood, W., McKeown, J. and Mutchler, J. "A Test of the Incremental Explanatory Power of Opinions Qualified for Consistency and Uncertainty", *The Accounting Review*, Vol. 64, No. 1, 1989, p. 28
[30] Ibid., pp. 29ff.
[31] Hopwood et al. (1989), "A Test of the Incremental Explanatory Power of Opinions Qualified for Consistency and Uncertainty", p. 47

relationship between the two.[32] The study they conducted was based upon 114 private Belgian companies which had either become bankrupt or voluntarily liquidated in 1995 or 1996, as well as a matched set of 114 healthy companies whose operations had not ceased during this same time period. Both the financial statements and audit reports were subsequently analyzed. Regarding the type of audit reports, out of this sample of 228 companies, they found that 155 had received a clean audit opinion, whilst the remaining 73 had received a non-clean audit opinion. Out of these 73 non-clean audit reports, 62 belonged to the failing companies and most of them (41 to be precise) pertained to the bankrupt companies.[33] The relationship was also tested by the authors when performing a logistic regression analysis. The analysis confirmed that there also was a statistical significance between the audit report opinion and bankruptcy or voluntary liquidation.[34]

Other studies similar to these ones, also confirming there is a relationship between the information provided by the audit report and company failure, have been carried out by Altman & McGough and Sundgren.[35] [36]

2.5 Relevant Recent Bachelor and Master Theses

Similar studies, that have recently been performed and which we found interesting when conducting this study first of all involve Andersson & Johansson. Their study is also heavily influenced by the research done by Ohlson. However, they used another one of his models, i.e. not the O-score. Nevertheless, they performed a logistic regression analysis evaluating the performance of the model in predicting bankruptcies of Swedish non-listed companies.[37] As part of their analysis they evaluated the error rate of Type-I and Type-II errors against a thesis presented by Nyberg & Pesula who also employed a logistic regression analysis on bankruptcies.[38] However, their study primarily focused on the work made by auditors. Their regression analysis emphasized what remarks had been made by the auditors, but they also performed a test where financial key ratios were used collectively with the audit remarks.

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[32] Gaeremynck, A. and Willekens, M. "The Endogenous Relationship Between Audit-Report Type and Business Termination: Evidence on Private Firms in a Non-Litigious Environment", *Accounting and Business Research*, Vol. 33, No. 1, 2003, p. 65
[33] Ibid., pp. 72f.
[34] Ibid., pp. 74ff.
[35] Altman, E. and McGough T. "Evaluation of a Company as a Going Concern", *The Journal of Accountancy*, Vol. 138, No. 6, 1974, pp. 50-57
[36] Sundgren, S. "Auditor choices and auditor reporting practices: evidence from Finnish small firms", *The European Accounting Review*, Vol. 7, No. 3, 1998, pp. 441-465
[37] Andersson, A. and Johansson, H. "Prognostisering av Konkurs – En Logistisk Regressionsanalys av Svenska Företag", Företagsekonomiska Institutionen, Uppsala Universitet, 2009, pp. 15ff.
[38] Ibid., p. 37

What their study pointed toward was a strong relationship between their factors (both key ratios and audit-based variables) and the bankruptcies of these Swedish medium-sized companies, studied in the thesis.[39] Kullerback & Löf has also made a study regarding bankruptcy models and their uses related to Swedish firms. They used Altman's Z-score to evaluate its performance on a small sample of Swedish listed firms. However, their analysis focused on the variables of the Z-score and the differences between them and the failing and non-failing firms, as well as the outcome of the prediction results of the model.[40]

What all these theses do have in common is that they monitor Swedish firms, using the insights of earlier studies made by some of the most notable researchers within this area.[41] [42] [43] The same goes for our study. However, ours still distinguishes itself by concentrating on Ohlson's O-score and Swedish listed firms, and at the same time employing an element of auditing information. Our study could thus be considered to be partly influenced by these studies, but by simultaneously displaying some other important and distinguishing features.

[39] Nyberg, E. and Pesula, J. "Revisionsberättelsen – är en användbar i en konkursförutsägelse?", Institutionen för företagsekonomi, Handelshögskolan i Umeå, Umeå Universitet, 2008, pp. 66f.
[40] Kullerback, K. and Löf, M. "Konkursanalys av bolag noterade på stockholmsbörsen - ett test av Edward I Altmans Z-scoremodell", Företagsekonomiska institutionen, Uppsala Universitet, 2008, pp. 15ff.
[41] Andersson & Johansson (2009), "Prognostisering av Konkurs – En Logistisk Regressionsanalys av Svenska Företag", pp. 6ff.
[42] Nyberg & Pesula (2008), "Revisionsberättelsen – är en användbar i en konkursförutsägelse?", pp. 9ff.
[43] Kullerback & Löf (2008), "Konkursanalys av bolag noterade på stockholmsbörsen - ett test av Edward I Altmans Z-scoremodell", p. 2

3 METHOD

As outlined above, this study focuses on analyzing data in order to draw scientific conclusions and find empirical evidence concerning the prediction of financial distress, with a starting point in Ohlson's O-score. The perspective of the analysis is based upon the external stakeholders, since the internal stakeholders often have access to more information about the company, i.e. insider information. The information obtainable by the external stakeholders is also often the same information that we have easily been able to acquire. This involves financial reports, audit reports and data describing the national economic development.

When conducting the study a deductive approach has been used. The purpose and aim of the study is to test and evaluate the statistical relationships between accounting-based information and financial distress. The main focus is to test Ohlson's O-score and its appliance to Swedish listed firms. We further test how the incorporation of audit information affects the overall performance of the model and its predictability related to financial distress. This could however be argued to be a somewhat inductive approach as we merge the theories of Ohlson and his O-score and the theories regarding the relationship between bankruptcy, financial distress and the opinion of the audit report. It might just as well be argued to be strictly deductive as the analysis originates from already existing theories which we try to apply jointly, rather than to generate new theories based upon our empirics and analysis.

While the approach of the study is, at least mainly deductive, the methods of it are truly quantitative. A considerable part of the time committed when performing the research, has been devoted to managing the sample in such a way that it corresponds to the methods used by Ohlson in his paper about the O-score.[44] The sample is then used and tested via certain statistical models to subsequently have its outcome analyzed. First follows the collection of the data and managing of the sample and the focus group, i.e. the financially distressed companies. Afterward follows more about the methods used to test the relationship between the variables and financial distress.

3.1 THE SAMPLE

The data is originating from three different sources. Most of it has been gathered from the Affärsdata database, which contains accounting information of Swedish companies based on

[44] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", pp. 109ff.

the financial statements. Information has also been extracted from Bureau van Dijk's database Orbis, including industry belongingness. From the Swedish Central Bureau of Statistics, Statistiska Centralbyrån or SCB, we have collected information depicting the development of the Swedish gross domestic product (GDP).

When formulating and creating the sample, we decided to use a couple of requirements or restrictions for reasons more thoroughly described and discussed below. At the same time we carefully describe the whole process of gathering the data and compiling the sample. The requirements are compiled in a list below.

I. The firm should be listed on or have been delisted from the Aktietorget, Nordic Growth Market (NGM) or Nasdaq OMX Stockholm stock exchanges.
II. The firm should be Swedish, possessing a Swedish organization identity number.
III. The firm should not be dissolved through a merger.
IV. The firm should not be dissolved by unidentified reasons.
V. The firm should not be operating within the financial sector.
VI. The firm should be able to present reports for at least three consecutive accounting periods.
VII. The thirdly collected reporting period of each firm should end in the end of year 2000 or later.
VIII. The firm should display complete reports, making sure that the calculation of each variable in the model is enabled.

As an initial step, we turned to Orbis to assemble a list containing the name, organization identity number (*organisationsnummer*) and *status* of each and every firm listed on the Aktietorget, Nordic Growth Market (NGM) and Nasdaq OMX Stockholm stock exchanges. In order to achieve this we used stock exchanges as the search criteria and selected the exchanges just mentioned. As we only wish to investigate Swedish firms, foreign firms listed on these stock exchanges were not included. This way a list of 649 Swedish firms being listed on or delisted from one of these exchanges was consequently compiled.

At this stage, the sample contains firms that have met the criterions of (I) being listed on or delisted from one of the three stock exchanges and (II) having a Swedish organization number. Since the objective is to examine firms in financial distress we have (III) not included mergers. Seventeen observations were since dropped due to having merged, whilst another six due to committing to an upcoming merger. The rationale is that the financial state of these companies would have otherwise been complicated to determine, as the reasons and circumstances behind the merger could be of a different nature than simply being related to the financial shape of the acquired company. The acquirer could have other strategic reasons for committing to the purchase. The required information related to this issue was sought out by running the 649 identification numbers towards Affärsdata and its search tool identifying certain "district court codes" (*tingsrättskoder*). The search items corresponding to a completed merger and a merger in progress are 41 and 49, respectively. Another three companies were excluded (IV) since they have been dissolved because of reasons not defined. These were identified by the *status* search tool in Orbis, since there was no corresponding district court code that could be utilized in Affärsdata. At this stage the sample consisted of 617 observations.

Furthermore, companies that are operating in the industries related to the financial sector often distinguish themselves from others as to their structure, bankruptcy environment and commonly used accounting regulations, rules and principles. This was also a criterion stated by Ohlson. However, he also excluded utilities and transportation companies.[45] An attempt to exclude these kinds of businesses has not been made in this study as we do not wish to neglect such companies. It is rather only (V) the financial sector which we have chosen to exclude since it is the industry considered to possess the most distinguishing features compared to other industries. This was done by using our list of identification numbers and the Orbis database to allocate and exclude all firms with a *NACE rev. 2* index code in the range of 6400-6600. A total of 57 firms were excluded in this phase, leaving 560 observations. There was however a number of firms that did not have any specific industry codes registered. Hence, we examined the Articles of Association and excluded all firms whose main area of operations was related to the financial markets or who primarily worked with supplying financial services. This resulted in the exclusion of one observation. There were however another eighteen observations that did not display any industry codes. These companies were not interpreted as mainly operating in the financial sector as we examined the Articles of Association and were thus kept in the sample.

The remaining number of observations, i.e. 559 companies, was then supplied with accounting data from Affärsdata. We used the modified list of identification numbers to seek out the information needed to calculate the variables that constitute the O-score.

[45] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", p. 114

Consequently, we established a sample containing information on total assets, total equity, current assets, current liabilities, net income and funds from operating activities for each company. As this study also aims to take some concern towards the quality of the annual accounts with regard to the auditor's report, remarks from the auditor concerning the financial reports were also extracted. This variable is defined via a coding system supplied by Affärsdata with: "1" indicating that there was no remarks made by the auditor, "2" indicating that there was remarks made by the auditor, "3" indicating no existing audit report and "4" indicating that there was no remarks but rather a comment made by the auditor. The third code was not observed for any company, consequently all firms had an audit report accompanying their annual report. Together with this information and a Swedish real GDP index denoting the year of 1968 as index 100, just like Ohlson,[46] all variables were made possible to calculate.

The Affärsdata database does only supply data for the four most recent accounting periods. That is however sufficient for this study as our main priority is to determine the probability of the firm reaching a state of financial distress approximately one year in advance. We did however set up a requirement (VI) obligating each observation to have been active and reported annual accounts for at least three consecutive accounting periods. If the firm was considered reaching a state of financial distress, the same requirement was applied, however prior to the period it reached this state. Hence, an additional nine observations were excluded. It could also be mentioned that Ohlson did set up a similar requirement. He did also study listed firms, but excluded those that had not been traded during a three-year period prior to the date of bankruptcy.[47]

As a penultimate requirement, (VII) we controlled that each firm's third reporting period ended no earlier than in the very end of 2000. By doing so we separated all observations whose data did not entirely relate to the year of 2000 or later, however disregarding whether the accounting period did follow the calendar year or not. This was merely a capricious cut-off point. No observations were however dropped due to this requirement. As a final step (VII) we also decided to exclude each firm that, after calculating the variables of the model, could not display values for each and every variable. These observations did, in other words, not have sufficient data for us to completely calculate the O-score. At this stage one observation was excluded due to insufficient data regarding the computation of the CLCA

[46] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", p. 118
[47] Ibid., p. 114

variable and another sixteen for not displaying any values denoting the cash flow from operations and thus preventing the assessment of the FUTL variable.

3.1.1 THE FOCUS GROUP

The concluding step in the data gathering and sample setup was to determine what firms would be defined as being in, or had already reached a state of financial distress. For this study we used a somewhat multifaceted, yet clear and unwavering definition when isolating these firms. From Affärsdata we were able to identify a number of financially distressed firms by running our modified list of identification numbers towards the database and pinning down different district court codes indicating certain conditions related to financial instability.

From Orbis we were also able to determine what firms had recently defaulted on payments by searching for their present *status*. We also used two of the Affärsdata codes related to bankruptcy; 20 and 21 indicating a commenced bankruptcy process and bankruptcy, respectively. A second pair of codes was related to a liquidation of the company; 31 and 32 indicating a finished liquidation process as well as one about to commence. A fifth code was corresponding to a business reorganizations about to commence; 80. The distribution among each reason of financial distress is denoted below in Table 1.

TABLE 1

Distribution of Financially Distressed Firms

Type of Financial Distress	Code	N
Default on payments		9
Bankruptcy process has commenced	20	23
Bankruptcy process is finished	21	2
Liquidation is finished	31	1
Liquidation shall commence	32	7
Business reorganization shall commence	80	6
Firms in financial distress		48

When deciding upon which states or district court codes that were to be included in the definition of financial distress, the main purpose was to include such states that did imply a situation where the future existence of the company would be at peril. As the future existence of a company is at peril, investors are often exposed to a significant risk of losing their whole investment as they are not prioritized in the liquidating process of the bankrupt company. The second code, indicating bankruptcy, is however representing an absolute state where the company by many means has ceased to exist. This is also indicated by the third and sixth code. The other codes do instead indicate a state of financial distress connected to instability as a significant possibility of bankruptcy, liquidation or business reorganization has emerged. A company defaulting on payments does also indicate a financially distressed company, as it has failed to meet its debt obligations.

Furthermore, other district court codes do exist which would also have fitted our definition and interpretation of financial distress. Of course, these were all reviewed and considered for inclusion. However, including them would have added little to the study, since they were not represented within the sample.

Below, in Table 2, the descriptive statistics of the whole sample is compiled with respect to the different accounts used and derived from the financial statements. The data is mainly derived from the latest accounting period, but net income from the second latest accounting period is also collected in order to assess the last two variables of Ohlson's model. The statistics are further divided into two groups – the financially distressed firms, i.e. the focus group and the other surviving firms. The data from the focus group is thus compiled of accounting information related to the latest available accounting period before reaching a state of financial distress.

T A B L E 2

Data Summary for Sample

	Account	N	Median	Mean	Standard Deviation	Min	Max	10th percentile	90th percentile
All Firms in Sample	**Net Income Y1**	533	-914	225 237	1 568 247	-1 994 000	25 422 000	-54 910	189 800
	Net Income Y2	533	-1 196	219 015	1 839 946	-2 239 000	33 774 000	-53 555	148 000
	Total Assets Y1	533	136 591	3 666 263	17 082 687	91	239 336 000	8 865	4 323 000
	Total Liabilities Y1	533	32 935	1 987 214	9 976 313	2	144 763 008	1 600	2 036 100
	Total Equity Y1	533	84 202	1 679 050	7 450 952	-114 466	94 573 000	3 629	2 077 000
	Current Assets Y1	533	37 318	951 280	5 556 434	55	93 198 000	1 651	837 200
	Current Liabilities Y1	533	20 191	936 161	5 320 189	2	76 948 000	1 125	774 100
	Working Capital Y1	533	4 474	15 120	4 271 853	-70 829 000	45 064 000	-126 251	334 900
	Cash Flow from Operations Y1	533	-1 911	128 589	1 107 702	-6 650 000	13 686 000	-119 789	152 100
Surviving Firms	**Net Income Y1**	485	-383	250 264	1 641 865	-1 994 000	25 422 000	-45 627	201 400
	Net Income Y2	485	-773	242 248	1 927 301	-2 239 000	33 774 000	-53 678	156 679
	Total Assets Y1	485	155 894	4 017 740	17 871 234	994	239 336 000	10 538	5 596 000
	Total Liabilities Y1	485	36 137	2 178 032	10 439 874	2	144 763 008	1 639	2 382 000
	Total Equity Y1	485	95 758	1 839 708	7 793 216	-114 466	94 573 000	4 667	2 847 000
	Current Assets Y1	485	45 000	1 042 522	5 817 469	55	93 198 000	1 856	963 000
	Current Liabilities Y1	485	21 404	1 025 187	5 569 818	2	76 948 000	1 125	823 051
	Working Capital Y1	485	6 107	17 335	4 478 651	-70 829 000	45 064 000	-134 235	369 400
	Cash Flow from Operations Y1	485	-1 204	143 517	1 159 979	-6 650 000	13 686 000	-134 447	192 900
Focus Group (Financially Distressed)	**Net Income Y1**	48	-8 726	-27 640	79 598	-425 400	213 404	-86 905	2 034
	Net Income Y2	48	-4 982	-15 737	81 542	-313 815	393 000	-53 555	2 276
	Total Assets Y1	48	30 382	114 889	182 295	91	647 100	3 309	539 900
	Total Liabilities Y1	48	19 645	59 156	107 743	518	452 877	1 304	179 290
	Total Equity Y1	48	10 018	55 733	104 198	-41 723	489 435	-4 314	228 474
	Current Assets Y1	48	8 393	29 362	51 953	59	246 000	210	99 948
	Current Liabilities Y1	48	9 635	36 621	64 666	518	299 100	1 110	114 534
	Working Capital Y1	48	-893	-7 259	39 121	-114 475	100 074	-53 160	23 130
	Cash Flow from Operations Y1	48	-7 964	-22 244	82 297	-477 700	169 580	-56 374	10 387

3.2 Statistical Methods

Three distinctive features can be outlined as part of the analysis inherent in this study. First, we analyzed how well Ohlson's original model, the O-score, behaves in the context of our sample. For this, no certain statistical tests were needed, except the percent correctly predicted measure. Second, we established a revised model (Model A), based upon the same variables inherent in Ohlson O-score.[48] For this we needed to perform a logistic regression analysis. This was conducted in Stata using the command for logistic regression and the *coef* option (the *logit* command would have provided us with the same output), resulting in the coefficients of the regression analysis being displayed. If not using this option the odds ratios will instead be displayed. Third, we incorporate two dummy variables related to the audit report as well as test this new model (Model B). The first variable (code 2 in Affärsdata considering audit remarks) is denoting whether or not the auditor had assured (by reasonable

[48] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", pp. 118f.

assurance) that there are no material misstatements related to the financial statements, whilst the second one (code 4 in Affärsdata considering audit remarks) is denoting whether the auditor did just leave a comment related to the accounting or financial reports. The second variable is thus a lighter version, considering the flaws were deemed to be non-material. A logistic regression analysis is once again performed to test this new model. All three models – the O-score (Model 1), Model A and Model B – are then analyzed upon their predictive power in relation to the established sample. We do also put some emphasis on the statistical properties generated through the logistic regression analysis, used to generate Model A and Model B. These include the Wald chi-square test, the pseudo R-squared and the z-statistics of each independent variable. A likelihood ratio test is also used to examine the difference between Model A and Model B. Another measure, mentioned earlier, is the percent correctly predicted (PCP) measure, which tries to capture and establish a sense of the performance of the model. The construction of this measure is rather intuitive, as it is estimated by calculating how many of the estimated failures and non-failures that are correctly predicted out of the whole sample.[49]

3.2.1 THE LOGISTIC REGRESSION

As this study attempts to analyze the O-score, it is simply natural to employ the logistic regression, or the logit model. Ohlson mentioned several advantages of this econometric methodology in comparison to the Multivariate Discriminant Analysis (MDA), which at the time had been a very popular technique for predicting corporate bankruptcy. For one, he said that the logit model does not require that the predictors are normally distributed. This property enables the use of dummy independent variables. Furthermore, the output of this model is fairly intuitive as it more clearly manifests the impact of each factor by providing either a negative or positive sign preceding each coefficient. Another advantage is that the specific matching procedures of MDA, which often are rather arbitrary, become unnecessary.[50] Grice & Ingram further discuss the MDA approach and the early studies of Altman by performing tests related to his original Z-score model.[51] Hillegeist et al. discourage the use of both the Z-score and the O-score in favor of other market-based models – more specifically the Black-

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[49] Wooldridge, J. *Introductory Econometrics*, 4th ed., Mason, Ohio: South-Western Cengage Learning, 2008, p. 581
[50] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", pp. 111f
[51] Grice, J. and Ingram, R. "Test of the Generalizability of Altman's Bankruptcy Prediction Model", *Journal of Business Research*, Vol. 54, No. 1, 2001, p. 60

Scholes-Merton Probability of Bankruptcy (BSM-Prob).[52] However, this study is devoted to the accounting-based model of Ohlson because of the simplicity of the model and its recently mentioned advantages.

Regarding the model and the logit approach, Ohlson describes it as a logistic test where X_i denotes a vector of predictors for each observation. We also let β be a vector of unknown parameters and $P(X_t, \beta)$ denote the probability of bankruptcy for any given X and β. *P* is then some probability function, $0 \leq P \leq 1$. The logarithm of the likelihood of any specific outcome is then given by:

$$l(\beta) = \sum_{i \in S_1} logP(X_t, \beta) + \sum_{i \in S_2} logP\,[1 - P(X_t, \beta)]$$ [53]

In this setup, S_1 is the (index) set of bankrupt firms and S_2 is the set of non-bankrupt firms. For any specified function P, the maximum likelihood estimates of β_1, β_2 …, are obtained by solving:

$$\max l(\beta)$$ [54]

From this Ohlson stated the probability of bankruptcy as:

$$P = (1 + exp\{-y_i\}^{-1}), \qquad where\ y_i = \sum_j \beta_j X_{ij} = \beta' X_t$$ [55]

This further implies that *P* is increasing in y; and y is equal to log[P/(l — P)].[56] As all β's are multiplied by their respective coefficient for each firm and the product of these are summarized, a higher score will then indicate a higher probability of bankruptcy. A most certain case of bankruptcy should thus assess a score corresponding to a probability equal to 1 (or 100%), whilst the other extreme will be a score resulting in a probability equal to 0 (or 0%).

3.2.2 THE WALD CHI-SQUARE TEST

The Wald test is used to test multiple exclusion restrictions for logit models. It has an asymptotic chi-square distribution which the Wald statistic is compared against. A higher

[52] Hillegeist, S., Keating, E., Cram, D. and Lundstedt, K. "Assessing the Probability of Bankruptcy", *Review of Accounting Studies*, Vol. 9, No. 1, 2004, p. 5
[53] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", p. 117
[54] Ibid., pp. 117-118
[55] Ibid., p. 118
[56] Ibid.

Wald statistic will indicate a lower probability of the results of the model being due to chance.[57]

3.2.3 The Likelihood Ratio Test

The likelihood ratio (LR) test is, in similarity with the Wald test, a way of testing exclusion restrictions for logit models. The LR-test uses a similar concept as the F-test does in a linear model. More specifically, the F-test measures the increase in the sum of squared residuals when variables are dropped from the model. Hence, we can use the LR-test to evaluate whether the two additional audit variables jointly improve the O-score. The test is based upon a chi-square distribution and the difference in the log-likelihood functions of the unrestricted model (Model B) and the restricted model (Model A). The notion is such that, because the maximum likelihood estimation (MLE) maximizes the log-likelihood function, we usually arrive at a smaller log-likelihood by dropping variables. At least the log-likelihood should not increase. The same notion goes for the R-squared which also never can increase after one has excluded one or some variables. However, in order to establish whether these two variables are important we need to examine whether the decrease in log-likelihood is large enough. To determine if the decrease is large enough we need to compare it towards a critical value. Hence, we compare the likelihood ratio statistic, which is twice the difference between the log-likelihoods,

$$LR = 2(\mathcal{L}_{ur} - \mathcal{L}_{r})$$

towards the chi-square distribution.[58] However, when using Stata we can instead calculate the p-value corresponding to the statistic. A low p-value indicates that by jointly adding the variables inherent in the unrestricted model results in a statistically significant improvement in the fit of the model.[59]

3.2.4 The Pseudo R-squared – McFadden's R-squared

The typical R-squared is used as a goodness-to-fit measure, which provides an approximation on how well future outcomes are to be estimated by the model. If we analyze the R-squared of an OLS regression the interpretation is relatively straightforward as it measures how much of the total variability that is accounted for by the model. If, for instance, a specific model attains

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[57] Wooldridge, *Introductory Econometrics* pp. 579f.
[58] Ibid., p. 580
[59] UCLA: Academic Technology Services. Stata FAQ – How can I perform the likelihood ratio, Wald, and Lagrange multiplier (score) test in Stata?. http://www.ats.ucla.edu/stat/stata/faq/nested_tests.htm (Visited 2012-04-26)

a R-squared of 0.5, the variables of the model predict 50% of the variability of the dependent variable.[60]

The problem which accompanies the use of logistic models is that this typical R-squared measure cannot be employed. A wide variety of similar measures has consequently been developed and do essentially try to capture the same thing, i.e. the explanatory power of the variables. One of these, so called, pseudo R-squared measures is the McFadden's R-squared. This is also the one which accompanies the output provided by Stata when running a logistic regression. Even though this measure, alongside with other pseudo R-squareds, has its limitations it can still be used to interpret the results. Its usages in this study, mostly circulates around the simple notion that a higher pseudo R-squared is more desirable. Furthermore, as one can observe when examining this R-squared, there are some similarities between it and the likelihood ratio test.

$$McFadden's\ R - squared = 1 - \mathscr{L}_{ur}/\mathscr{L}_0$$

As with the likelihood ratio test, $\mathscr{L}_{ur}$ denotes the log-likelihood of the unrestricted model. $\mathscr{L}_0$ on the other hand, is the log-likelihood function in the model with only the intercept. The notion is thus such that, if these two log-likelihoods are equal to each other the covariates have no explanatory power. This is rather similar to the typical R-squared measure.[61]

3.2.5 THE Z-STATISTICS

When utilizing Stata, the more common way of determining significance levels are through a *t*-statistic. However, when for instance running a logistic regression through the software, the significance levels are determined by a *z*-statistic that follows the standard normal distribution. Despite the different distributions related to the *t*-statistics and the *z*-statistics, the interpretations accompanying the assessments of the two statistics and their corresponding p-values are the same.[62]

[60] Wooldridge, *Introductory Econometrics*, p. 40
[61] Ibid., pp. 581f.
[62] Statacorp, Kristin MacDonald. One-sided tests for coefficients. 2011. http://www.stata.com/support/faqs/stat/oneside.html (Visited 2012-04-26)

4 ANALYSIS

4.1 RATIOS AND BASIC RESULTS

The ratios used have been taken straight out from Ohlson's study. The first model (Model A) is a replica of Ohlson's Model 1 where no changes have been made in terms of descriptive variables.[63] When presenting the second model (Model B), we once again use Ohlson's nine variables described above, but add the two new audit variables described below as variables 10 and 11:

10. *REV_2* = One if the financial statements have remarks from the auditor (code 2 in Affärsdata considering audit remarks), zero otherwise.
11. *REV_4* = One if the financial statements have comments made by the auditor (code 4 in Affärsdata considering audit remarks), zero otherwise.

The signs of *REV_2* and *REV_4* should be positive considering that a remark or comment on the financial statements by the auditor is not desirable and should thus have a negative impact on the firm. More thoroughly explained, variable 10 denotes whether or not the auditor has assured (by reasonable assurance) that there are no material misstatements and variable 11 whether the auditor did just leave a comment on the accounting or financial reports, considering the flaws as non-material.

Table 3 shows a profile analysis where mean and standard deviation of the predictors for the sample is presented. The results shown in this table are in all sense what we expect. First, it supports the reasoning behind the signs of the coefficients. Second, it shows significant differences in line with the expectations between the bankrupt and non-failing firms. We see that the sample of bankrupt firms has both higher mean values for the variables *TLTA, CLCA, FUTL, INTWO, OENEG, REV_2* and *REV_4* and lower mean values for *SIZE, WCTA, NITA* and *CHIN* compared to the non-failing firms. This follows the logic that each predictor will on average increase the predicted probability of financial distress for actual financially distressed firms than for surviving firms. When comparing the profile analysis to the data presented by Ohlson we experience a rough dimidiation of *SIZE,* ten folding of *CLCA* and also a positive divergence of similar magnitude in *FUTL.*[64] We expect that the main

[63] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", pp. 118f.
[64] Ibid.

explanation to this difference is due to the differences in sample and time period, but of course this is only an assumption and there are many other plausible explanations such as outliers, errors in data etc.

TABLE 3
Profile Analysis

	All Firms in Sample		Surviving Firms		Focus Group (Financially Distressed)	
Variable	***Mean***	***Standard Deviation***	***Mean***	***Standard Deviation***	***Mean***	***Standard Deviation***
SIZE	6.533	2.429	6.705	2.411	4.794	1.880
TLTA	0.791	6.071	0.623	5.166	2.486	11.796
WCTA	-0.0395	3.551	0.146	0.345	-1.912	11.728
CLCA	9.803	96.863	5.459	46.926	53.691	285.244
NITA	-0.290	2.070	-0.176	1.247	-1.436	5.568
FUTL	-4.953	87.650	-5.142	91.854	-3.040	8.389
INTWO	0.445	0.497	0.419	0.494	0.708	0.459
OENEG	0.0263	0.160	0.0144	0.119	0.146	0.357
CHIN	-0.0284	0.640	-0.0095	0.639	-0.219	0.633
REV_2	0.0356	0.186	0.0103	0.101	0.292	0.459
REV_4	0.0844	0.278	0.0660	0.249	0.271	0.449
N	533		485		48	

The estimates computed using the logistic regression analysis was done in two sets. Model A predicts financial distress within one year using the same predictors as Ohlson. Model B also predicts financial distress within one year but this time with all the previously described predictors. A summary of the results of Model A and Model B is presented in Table 4 and in order to make comparison easier, Ohlson's Model 1 is presented alongside with the results.[65]

[65] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", p. 121

TABLE 4

Prediction Results

	Variable											
	SIZE	***TLTA***	***WCTA***	***CLCA***	***NITA***	***FUTL***	***INTWO***	***OENEG***	***CHIN***	***REV_2***	***REV_4***	***CONST***
Ohlson (1980) Model 1												
Estimates	-0.407	6.03	-1.43	0.0757	-2.37	-1.83	0.285	-1.72	-0.521	-	-	-1.32
t-statistics	-3.78	6.61	-1.89	0.76	-1.85	-2.36	0.81	-2.45	-2.21	-	-	-0.97
Model A												
Estimates	-0.282	-0.077	-1.13	0.00194	-0.279	0.00171	0.458	-0.789	-0.496	-	-	-1.08
z-statistics	-3.39	-2.44	-2.64	2.67	-1.98	0.38	1.09	-0.74	-1.54	-	-	-1.56
Model B												
Estimates	-0.184	-0.0425	-0.844	0.00152	-0.165	0.00063	0.165	-1.03	-0.499	3.10	1.48	-1.93
z-statistics	-2.10	-2.27	-1.78	1.57	-2.59	0.48	0.34	-1.22	-1.49	4.62	2.73	-2.63

	McFadden's R-squared	**Percent Correctly Predicted**
Ohlson (1980) Model 1	n/a	58.23
Model A	0.2033	92.50
Model B	0.2906	93.43

Ohlson uses 2.00 as a limit for the absolute values of the *t*-statistics when classifying which coefficients that are "statistically significant at a respectable level", [66] Skogsvik uses 1.40 as a limit for the absolute values of the *t*-statistics to classify which ratios to include in an iterative estimation of his models, and in standpoint of the new estimation evaluate their significance.[67] Using Ohlson's absolute limit of 2.00 we classify *SIZE*, *TLTA*, *WCTA* and *CLCA* as significant coefficients in Model A. In Model B *SIZE*, *TLTA*, *NITA*, *REV_2* and *REV_4* are classified as significant. If we use 1.40 as an absolute cut off point for the *t*-statistics, all coefficients except *FUTL*, *INTWO* and *OENEG* are classified as significant in both Model A and Model B. Ohlson reports a very high significance in *TLTA*, and also a higher value of the coefficient than what we get in both Model A and Model B. This might simply be the result of differing samples as Ohlson only uses industrial companies where the effect of leverage most likely is a more homogenous factor compared to cross-industrial-samples where leverage most reasonably can have different meanings for different industries. This is of course only a possible explanation and is not presented as a fact in this case.

A way to compare the accuracy of the three different models is to use the statistics percent correctly predicted which is calculated as the percent correctly predicted companies by the models using a cutoff point of 0.5. This means that a company with a predicted probability of failure greater than 0.5 will be classified as a predicted financially distressed company and a company with a predicted probability lower than 0.5 will correspondingly be classified as a predicted surviving company. For a cutoff point of 0.5 to be accurate it implicitly assumes a symmetric relationship across Type-I and Type-II errors. Of course this is not the case, but it is common practice to use this cutoff point for this type of measures.[68] Table 4 shows the percent correctly predicted and in order to evaluate these we must first specify that if all firms were classified as surviving (a cutoff point of 0) the percent correctly predicted would equal 90.90 (485/533). This means that, if the percent correctly predicted for a model is less than 90.90 for this sample, one will on average have a higher percentage of correctly predicted firms if one simply classifies all firms as not being financially distressed than if one uses the model with the cutoff point of 0.5. Keeping this in mind and looking at the statistics presented in Table 4 we clearly see that both Model A and Model B manages to beat 90.90 by a few percentage points, but when we apply Ohlson's Model 1 on our sample the percent correctly

[66] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", p. 120
[67] Skogsvik (1990), "Current Cost Accounting Ratios as Predictors of Business Failure: The Swedish Case", p. 143
[68] Wooldridge, Introductory Econometrics, p. 581

predicted is as low as 58.23. Premature conclusions should not be drawn from this statistic; this is only a measure that gives an indication of how well the model is fitted to the sample and at most suggests that Ohlson's Model 1 is not optimally adapted to the sample. However, if we examine the results presented in Ohlson's own study regarding this subject, the percent correctly predicted for Model 1 amounts to 96.12. This value is also a few percentage points above the limit describing the percent correctly predicted if all firms were classified as non-bankrupt (equaling a cutoff point of 0). The limit Ohlson presents in his paper equals 91.15. However, this limit appears to be subject to a miscalculation as his sample consists of 105 bankrupt firms and 2 058 non-bankrupt firms. This implies that the correct limit should be 95.15 $[2058/(105 + 2058)]$. This further implies that our results are quite similar to his results as to the percentages of correctly predicted observations gained by relying on the models.[69]

Another way of determining how well the model and its predictors will describe the outcome is by calculating the R-squared. As mentioned earlier the R-squared applicable for this kind of studies is a pseudo R-squared and the one employed in this particular study is McFadden's R-squared. This pseudo R-squared is also used by Ohlson.[70] The values of this measure vary between zero and one. Since the first referral model where Ohlson's Model 1 variables and coefficients are used, is not directly derived from our sample no R-squared is reported. However, the two other models, Model A and Model B are. Thus, their values are displayed in Table 4. From Table 4 one can observe a rather significant difference between the two and Model B assumes a much higher R-squared which should imply a higher predictability. It thus seems as if the two audit variables, *REV_2* and *REV_4*, do improve the model and provides the model with important information. A second way, apart from the increased R-squared, to determine the usefulness of these two added variables is to examine the Wald statistics. Also these statistics suggest that the two variables contribute to the model. The Wald statistics for Model A and Model B are 55.50 and 93.38, respectively. However, they both present p-values very close to zero, indicating that the variables of each model are not simultaneously equal to zero and thus contributing with a statistically significant improvement to the fit of the model, compared with randomly assigning probabilities to each company regarding their likelihood of reaching a state of financial distress in one year. A third way to test the reliability of these two variables is to perform a likelihood ratio test comparing the extended (unrestricted)

[69] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", p. 120
[70] Ibid., p. 121

Model B with (the restricted) Model A. The indication of this test is the same as of the R-squared and Wald test. The likelihood ratio index amounted to 28.16 resulting in a p-value close to zero, also implying a statistically significant improvement to the fit of the model. There is thus substantial proof indicating that the audit information provided by these two variables does increase the performance of the model. The improvement perhaps becomes the most concrete and apparent from comparing the percent correctly predicted, however. As described above, the indication is nonetheless the same.

To make sure that the coefficient groups of the audit variables (*REV_2*, *REV_4*), financial state variables (*SIZE*, *TLTA*, *WCTA*, *CLCA*) and performance variables (*NITA*, *FUTL*, *INTWO*, *OENEG*, *CHIN*) all contribute independently and significantly to the models, we carry out an analysis of the correlation of the estimations presented in Table 5**.** The findings are similar to those of Ohlson and supports that all variable groups are important in the models.[71] Furthermore, the correlation between the audit variables is as low as -0.06 which indicates that these two variables do contribute significantly both jointly and independently.

We have done no attempts to change Ohlson's variables or find any new existing accounting predictors apart from the two audit variables. The idea with the model has always been that it should be easy to use and that the information should be easily accessible. Tests were made where we dropped variables with low significance (*t*-statistics lower than 1.40) but this overall worsened the models predictability. If the addition of other variables would have increased the models significance is unclear, but studies shows that market-based information can be most useful in this context.[72] Limitations in the collection of data has restrained us form controlling for any market-based variables.

[71] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", pp. 122f.
[72] Reisz, A. and Perlich, C. "A Market-Based Framework for Bankruptcy Prediction", *Journal of Financial Stability*, Vol. 3, No. 1, 2007, pp. 85f.

TABLE 5

Correlation Matrix of Estimations

	SIZE	***TLTA***	**WCTA**	***CLCA***	***OENEG***	***NITA***	***FUTL***	***INTWO***	***CHIN***	***REV_2***	***REV_4***
SIZE	1										
TLTA	*	1									
WCTA	*	-0.58	1								
CLCA	*	*	*	1							
OENEG	-0.25	0.41	-0.32	*	1						
NITA	*	-0.23	-0.35	*	-0.33	1					
FUTL	*	*	*	*	*	*	1				
INTWO	-0.39	*	*	*	*	-0.21	*	1			
CHIN	*	*	*	*	*	*	*	*	1		
REV_2	-0.21	*	-0.26	*	0.28	*	*	*	*	1	
REV_4	-0.23	*	*	*	*	*	*	0.22	*	*-0.06*	1

* = Absolute value of correlation is less than 0.20

4.2 Evaluation of Predictive Performance

There is no standard procedure for when evaluating the accuracy of a bankruptcy prediction model. The fact that there are two different types of errors (Type-I and Type-II) which cannot be seen as simply additive to one another given that they are of somewhat different properties, makes it even harder. On the other hand, looking at the model that has the lowest sum of percentage errors is one of few possibilities to compare models. This type of comparison cannot be seen as completely fair since the different models are often computed using different samples, with different time periods, predictors, data, etc. Due to difficulties when evaluating the model in any other way, this method of error minimization will be used, but we will not make any cross model comparisons by given reasons.

All firms can fairly be divided into two groups by $P(\mathrm{X_t}, \hat{\beta})$, estimated as financially distressed or estimated as surviving, not financially distressed. This makes it interesting to present the distribution of the estimated probabilities. Figure 1 shows the sample distribution $P(\mathrm{X_t}, \hat{\beta})$ one year before financial distress for the 48 companies in the focus group using the estimated coefficients from Ohlson's Model 1.[73] Figure 2 and Figure 3 display the same distribution as Figure 1, however instead using the estimated coefficients from Model A and Model B respectively. The mean for each figure and their corresponding probabilities are 0.77, 0.26 and 0.36, respectively. Figure 4 shows the sample distribution $P(\mathrm{X_t}, \hat{\beta})$ for the 485 non-failing firms, using the estimated coefficients from Ohlson's Model 1.[74] In a similar fashion, Figure 5 and Figure 6 show the same using the estimated coefficients from Model A and Model B, respectively. The distributions within the figures are grouped into two percentage intervals. Furthermore, the mean for Figure 4, Figure 5 and Figure 6 and their corresponding probabilities are 0.44, 0.07 and 0.06, respectively. The estimates related to Ohlson's model and its inherent coefficients are thus substantially larger than the estimates generated from our Model A and Model B. This is apparent within the whole sample; hence the lower estimated probabilities within both the failing and non-failing companies.

[73] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy"
[74] Ibid.

FIGURE 1

Probability Distribution of Focus Group (Financially Distressed) using Ohlsons Model 1 Estimates

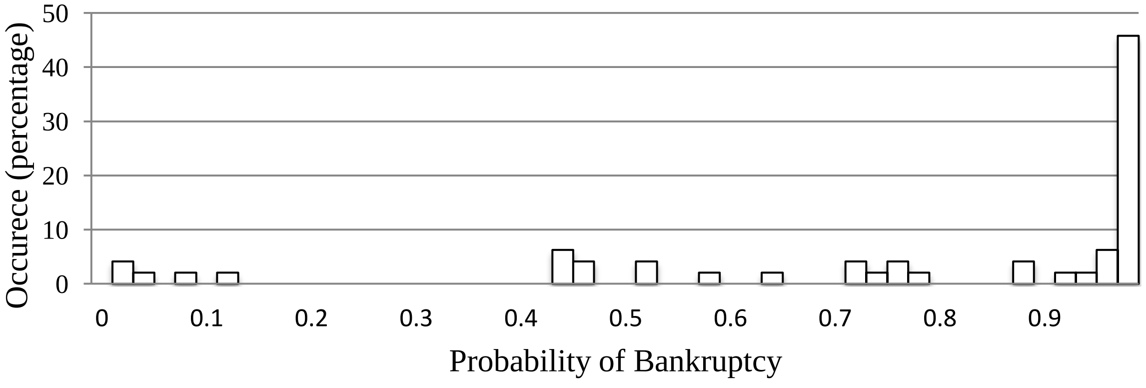


FIGURE 2

Probability Distribution of Focus Group (Financially Distressed) using Model A

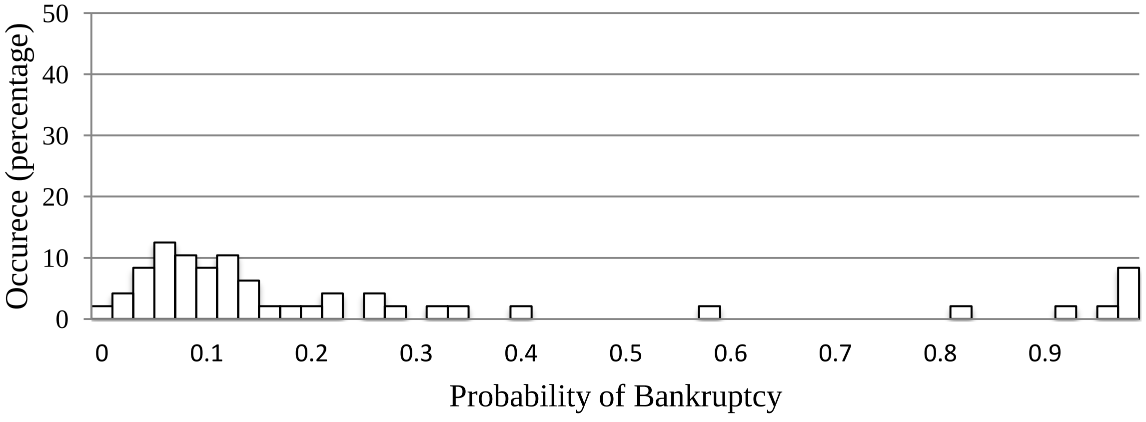


FIGURE 3

Probability Distribution of Focus Group (Financially Distressed) using Model B

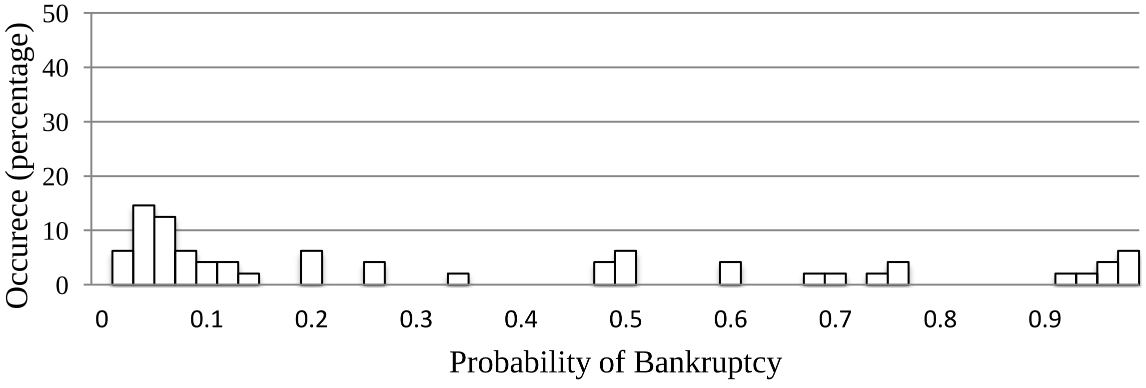


FIGURE 4

Probability Distribution of Surviving Firms using Ohlsons Estimates

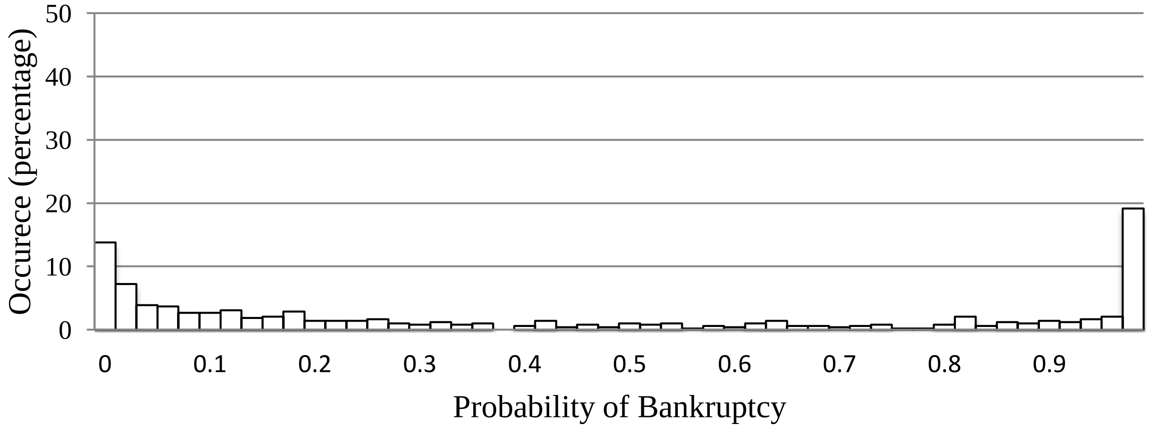


FIGURE 5

Probability Distribution of Surviving Firms using Model A

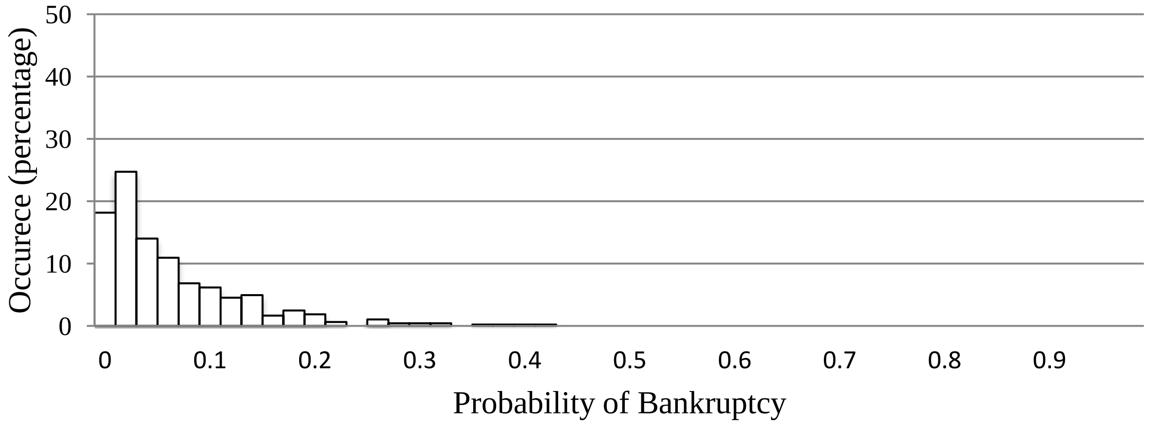
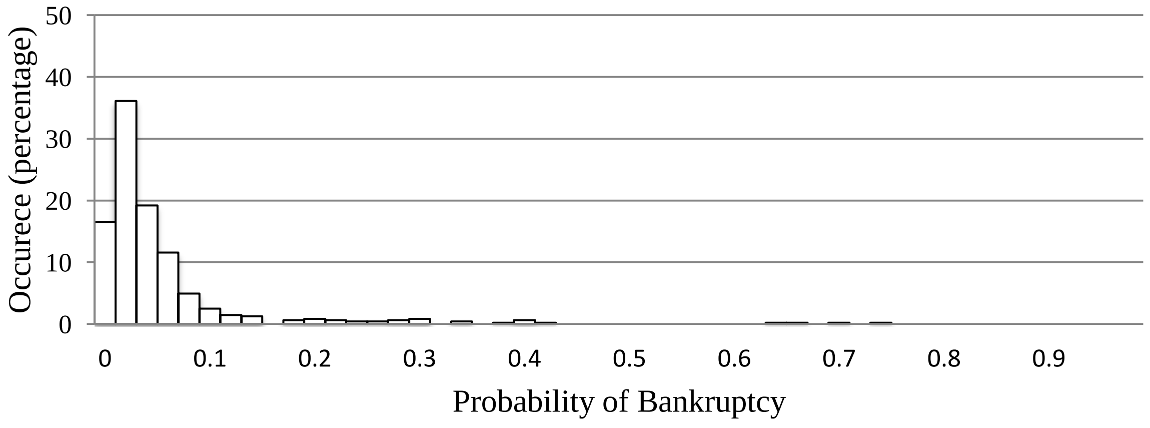


FIGURE 6

Probability Distribution of Surviving Firms using Model B



In order to classify errors for different cutoff points we examine the data underlying the probability distribution models, in more detail. A Type-I error is defined as when a non-failing firm has a probability $P(\mathrm{X_t}, \hat{\beta})$ greater than the cutoff point. A Type-II error is consequently defined as when a bankrupt firm has a probability $P(\mathrm{X_t}, \hat{\beta})$ smaller than the cutoff point. It would have been advantageous to perform this error analysis in an out-of-sample test, which would probably have been helpful in either strengthening or rejecting the models. Although, this was not possible to realize due to lack of data. We were neither able to divide the sample in order to use one part for estimations and another for testing, because of the size and ratio of financially distressed firms to surviving firms. Ohlson did not perform any out-of-sample tests in his study, reasoning that this would not be a serious problem considering that the sum of the percentage errors are quite stable over a wide range of cutoff points. This turns out to be the case in our study as well. He also states that using a sufficiently large sample should provide estimations which are not too sensitive to different samples. Regarding the size of our sample, we will not make any claims regarding whether it is sufficiently large as it is merely a fourth as big as Ohlson's. On the other hand, our sample is compiled from 533 observations and comprises a higher ratio of financially distressed companies in comparison to the bankrupt firms used by Ohlson. Evidently these arguments will be invalidated in a real-world application of the models, if the beta parameters are considerably different in the application period.[75]

When Type-I and Type-II errors are expressed as percentages, they are tradeoffs to one another. The cutoff points that minimize the percentage sum of errors are presented in Table 6. If there are X percent Type-I errors and Y percent Type-II errors at the cutoff point that minimizes the sum of the error rates, the expected error rate is calculated as (X + Y) / 2, given an infinite population where half of the firms are failing and the other half are non-failing.

TABLE 6

Cutoff Point that Minimizes Expected Error Rate

	Cutoff point	*Expected Error Rate*
Ohlson Model 1 (1980)	0.440	26.75%
Model A	0.050	28.07
Model B	0.066	22.58

[75] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", pp. 125f

The cutoff point that minimizes the expected error rate is substantially lower for Model A and Model B compared to as when we use Ohlson's estimates. This is not surprising considering what was reported in the probability distribution diagrams above (Figure 1-6). We experience a slight improvement of the expected error rates of our Model A and Model B compared to when we used Ohlson's estimates. On the other hand the results are not as low as in Ohlson's original study where he reports an expected error rate of 14.9 percent at a cutoff point at 0.038. The differences between the samples are most likely the reason to the difference in the expected error rate and as Ohlson states. Thus, it is not reasonable to make a direct comparison between the different models using this measure, considering that different samples and definitions of bankruptcy often are used as well as variables and modeling methods.[76]

Furthermore, Ohlson writes: "*Moreover, the accountants' reports would have been of little, if any, use. None of the misclassified bankrupt firms had a* 'going-concern qualification' *or disclaimer of opinion. A review of the opinions revealed that eleven of these companies had completely clean opinions, and the two that did not had relatively minor uncertainty exceptions. Curiously, some of the firms even paid dividends in the year prior to bankruptcy. Hence, if any warning signals were present, it is not clear what these actually were.*"[77] Although, our findings are different and we would actually want to stress the importance of the audit-based variables. Table 7 displays the ratio of Type-II errors and how many of the firms that are wrongly estimated to survive and that has either a *REV_2* or *REV_4*. Interestingly we find that when we use Olson's Model 1 estimates we almost do not misclassify any of these firms, and even manage to capture substantially more of them than what we do in model B where we control for them.

[76] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", p. 126
[77] Ibid., p. 129

T A B L E 7

Type II errors with REV_2 or REV_4 for Selected Cutoff Points

Estimates from:	*Ohlson Model 1 (1980)*			*Model A*			*Model B*		
Cutoff point	**Type II errors**	***REV_2****	***REV_4*****	**Type II errors**	***REV_2***	***REV_4***	**Type II errors**	***REV_2***	***REV_4***
0.00	0%	0%	0%	0%	0%	0%	0%	0%	0%
0.10	8.33	0	50.00	37.50	6	33.33	39.58	0	5.26
0.20	8.33	20.00	40.00	66.67	18.75	25.00	50.00	0	12.50
0.30	8.33	20.00	40.00	77.08	21.62	21.62	60.42	0	27.59
0.40	8.33	20.00	40.00	81.25	23.08	23.08	60.42	0	27.59
0.50	18.75	10.00	40.00	83.33	22.50	25.00	64.58	3.23	29.03
0.60	25.00	7.69	30.77	85.42	21.95	26.83	70.83	5.88	32.35
0.70	27.08	7.14	28.57	85.42	21.95	26.83	77.08	13.51	29.73
0.80	37.50	5.26	21.05	85.42	21.95	26.83	85.42	21.95	26.83
0.90	41.67	9.52	19.05	87.50	23.81	26.19	85.42	21.95	26.83
1.00	100	29.17	27.08	100	29.17	27.08	100	29.17	27.08

* Percent of Type-II errors where the wrongly estimated firm has a *REV_2*
** Percent of Type-II errors where the wrongly estimated firm has a *REV_4*

The rationale behind the very low Type-II error rates of Ohlson's Model 1 presented below is that it overall yields much higher estimated probabilities compared to Model A and Model B, as discussed above. This occurs at the expense of a much higher Type-I error rate. In Table 8 the Type-I and Type-II errors are presented for some selected cutoff points.

T A B L E 8

Type I-Type II Analysis for Selected Cutoff Points

Estimates from:	*Ohlson Model 1 (1980)*		*Model A*		*Model B*	
Cutoff point	**Type I***	**Type II****	**Type I**	**Type II**	**Type I**	**Type II**
0.00	100%	0%	100%	0%	100%	0%
0.02	86.19	0.00	81.86	2.08	83.51	0
0.04	78.97	4.17	57.11	6.25	47.42	6.25
0.06	75.05	6.25	43.09	14.58	28.25	20.83
0.08	71.34	6.25	32.16	27.08	16.70	33.33
0.10	68.66	8.33	25.36	37.50	11.75	39.58
0.20	56.08	10.42	5.57	66.67	5.98	50.00
0.30	49.07	10.42	1.65	77.08	3.09	60.42
0.40	45.15	10.42	0.41	81.25	1.65	60.42
0.50	41.44	20.83	0	83.33	0.82	64.58
0.60	37.73	27.08	0	85.42	0.82	70.83
0.70	33.61	29.17	0	85.42	0.41	77.08
0.80	31.34	39.58	0	85.42	0	85.42
0.90	25.57	43.75	0	87.50	0	85.42
1.00	0	100	0	100	0	100

*Type I: predict bancruptcy; actual nonbankrupt.
*Type II: not predicted bancruptcy; actual bankruptcy.

Once again we can observe the tradeoff relationship between Type-I and Type-II errors. A closer examination of Table 8 will show that Model A and Model B are essentially equivalent at different cutoff points whereas Ohlson's Model 1 has a higher Type-I error rate and a lower Type-II error rate than Model A and B systematically throughout the different cutoff points.

5 CONCLUSIONS

We have showed that when Ohlson's Model 1 is used to predict financial distress of Swedish listed firms, the estimated probabilities are generally large in comparison to the revised models. We also show that Model A and Model B, which we have modeled ourselves, display a slightly lower rate of errors and higher statistical significance, indicating that these models can be used with preference to Ohlson's Model 1 when predicting financial distress of Swedish listed firms. Furthermore, our results thus indicate that accounting information can very well be used to predict financial distress among companies, which is line with studies conducted by Altman and Ohlson among others. [78] [79] [80]

Results drawn form Model B also implies that remarks or comments made by the auditors on the financial statement add significant information in predicting the probability of financial distress in the models presented. These results are also in line with earlier studies including e.g. Hopwood et al. and Gaeremynck & Willekens.[81] [82]

As Ohlson concludes in his study, we also believe that significant improvements of the models presented, most likely require the addition of market-based predictors.[83]

[78] Altman (1968), "Financial Ratios, Discriminant Analysis and Prediction of Corporate Bankruptcy", p. 609
[79] Altman et al. (1977), "ZETA™ ANALYSIS, A New Model to Identify Bankruptcy Risk of Corporations, pp. 49f.
[80] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", p. 130
[81] Hopwood et al. (1989), "A Test of the Incremental Explanatory Power of Opinions Qualified for Consistency and Uncertainty", pp. 45ff.
[82] Gaeremynck et al. (2003), "The Endogenous Relationship Between Audit-Report Type and Business Termination: Evidence on Private Firms in a Non-Litigious Environment", pp. 77f.
[83] Ohlson (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", p. 130

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APPENDIX A: SUMMARY OF THE FINANCIALLY DISTRESSED COMPANIES

Company ID	Company Name	Exchange	NACE	Financial Distress Code	Last available report	Turnover	Net Income	Net Income, One Year Prior	Assets	Equity	Current Assets	Current Liabilities	Cash Flow from Operations	*SIZE*	*TLTA*	*WCTA*	*CLCA*	*OENEG*	*NITA*	*FUTL*	*INTWO*	*CHIN*	*REV_2*	*REV_4*
5566768726	Allokton AB	Delisted	6831	*	2010	21 192	213 404	-313 815	204 438	35 732	99 948	153 108	169 580	6.68	0.83	-0.26	1.53	0	1.04	1.01	0	1.00	0	1
5565560207	Alstrado AB	Delisted	7320	*	2010	0	-3 018	-46 652	2 502	-13 967	2 502	16 469	-3 006	2.28	6.58	-5.58	6.58	1	-1.21	-0.18	1	0.88	1	0
5566850375	Ancora Energispar AB	Delisted	2825	21	2007	32 715	-3 934	450	16 928	11 100	10 157	5 827	-8 929	4.19	0.34	0.26	0.57	0	-0.23	-1.53	0	-1.00	0	0
5565026563	Aqua Terrena International AB	OMX - Nordic Exchange Stockholm	1107	*	2010	400	-8 730	-7 183	15 651	4 971	15 398	10 680	-6 999	4.11	0.68	0.30	0.69	0	-0.56	-0.66	1	-0.10	1	0
5561962035	Audiodev AB	Delisted	2640	20	2008	88 260	-58 572	-44 310	154 892	99 751	118 005	55 141	-35 065	6.41	0.36	0.41	0.47	0	-0.38	-0.64	1	-0.14	0	0
5566609359	Bm Impex AB	Delisted	#N/A	20	2009	97 435	-1 706	-7 763	38 985	10 055	35 996	26 430	-2 457	5.08	0.74	0.25	0.73	0	-0.04	-0.08	1	0.64	0	0
5566603550	Brandworld Sverige AB (Publ)	OMX - Nordic Exchange Stockholm	4642	80	2010	114 486	2 034	17 907	51 283	31 089	40 829	14 218	-14 380	5.30	0.39	0.52	0.35	0	0.04	-0.71	0	-0.80	0	0
5562474386	Catech AB	Delisted	2849	20	2009	12 151	-2 304	3 492	21 927	9 871	4 350	2 419	-2 249	4.51	0.55	0.09	0.56	0	-0.11	-0.19	0	-1.00	0	0
5565523221	Catering Please I Skandinavien AB	OMX - Nordic Exchange Stockholm	5610	*	2009	61 706	-7 628	-2 115	22 217	-2 268	12 365	18 485	-9 786	4.52	1.10	-0.28	1.49	1	-0.34	-0.40	1	-0.57	1	0
5566372636	Cellpoint Connect AB	OMX - Nordic Exchange Stockholm	6190	*	2010	1 000	-44 958	-6 854	60 952	9 980	45 452	50 972	-56 374	5.47	0.84	-0.09	1.12	0	-0.74	-1.11	1	-0.74	1	0
5561534347	Cognos Technical Services AB	Delisted	#N/A	31	2008	62 244	57 154	16 948	135 564	98 505	134 079	34 005	-26 882	6.28	0.27	0.74	0.25	0	0.42	-0.73	0	0.54	0	1
5565418794	Countermine Technologies AB	Delisted	2892	32	2009	2 712	-22 173	-8 266	287 600	258 226	93 041	24 783	-21 477	7.08	0.10	0.24	0.27	0	-0.08	-0.73	1	-0.46	1	0
5566069323	Dacke Group Nordic AB (Publ)	Delisted	#N/A	20	2008	4 948	-157 276	-170 516	60 873	-41 723	238	102 596	-143 545	5.48	1.69	-1.68	431.08	1	-2.58	-1.40	1	0.04	0	1
5566768254	Ekomarine AB (Publ)	Delisted	#N/A	20	2010	1 161	-8 721	-5 538	5 826	5 216	5 042	609	-9 209	3.12	0.10	0.76	0.12	0	-1.50	-15.10	1	-0.22	0	0
5566620570	Eriksson Development And Innovation Company AB	Delisted	2811	*	2009	142	-2 244	-4 934	1 781	936	210	694	-1 911	2.00	0.47	-0.27	3.30	0	-1.26	-2.26	1	0.37	1	0
5566298914	Eurovip Group AB	Delisted	7022	*	2010	125	-10 789	2 276	9 324	2 446	1 437	6 878	-12 031	3.60	0.74	-0.58	4.79	0	-1.16	-1.75	0	-1.00	0	1
5566400411	Fasttv Net AB	Delisted	6020	80	2008	13 749	-37 706	-28 441	5 524	-14 456	4 016	19 980	-19 511	3.08	3.62	-2.89	4.98	1	-6.83	-0.98	1	-0.14	1	0
5562720358	Frontyard AB	Delisted	6209	20	2003	5 648	-2 513	-26 841	38 847	18 979	1 870	6 655	-5 512	5.17	0.51	-0.12	3.56	0	-0.06	-0.28	1	0.83	0	0
5565490363	Gamers Paradise Holding AB	Delisted	8292	20	2006	745	-86 905	-11 324	256 393	228 474	13 464	27 919	10 306	6.94	0.11	-0.06	2.07	0	-0.34	0.37	1	-0.77	0	0
5566802145	Gifttoday Sweden AB	Delisted	4791	20	2009	6 148	-7 210	-3 272	11 534	4 734	1 857	4 211	-2 202	3.86	0.59	-0.20	2.27	0	-0.63	-0.32	1	-0.38	1	0
5565515938	Global Gaming Factory X AB	OMX - Nordic Exchange Stockholm	7311	20	2009	3 560	-55 931	-856	3 309	-4 314	205	6 323	-53 909	2.62	2.30	-1.85	30.84	1	-16.90	-7.07	1	-0.97	0	1
5565837431	Globalfun AB	Delisted	5829	20	2009	8 871	-4 714	55	7 938	2 031	3 955	4 778	-1 038	3.49	0.74	-0.10	1.21	0	-0.59	-0.18	0	-1.00	0	0
5562850098	Hebi Health Care AB	Delisted	2120	20	2010	0	-32 099	-8 882	433 548	254 258	59	114 534	-21 913	7.43	0.41	-0.26	1941.25	0	-0.07	-0.12	1	-0.57	1	0
5563601821	Klippan AB	Delisted	1712	20	2004	837 104	-54 910	-53 555	571 641	118 764	203 894	293 917	30 043	7.82	0.79	-0.16	1.44	0	-0.10	0.07	1	-0.01	0	0
5566280656	LayerlAB AB	OMX - Nordic Exchange Stockholm	7211	*	2010	223	-3 280	-1 104	13 780	8 639	742	4 024	295	3.99	0.37	-0.24	5.42	0	-0.24	0.06	1	-0.50	0	0
5567022636	Metromark Hospitality Group AB (Publ)	Delisted	#N/A	20	2010	80	-37 349	-2 163	1 923	-2 785	1 923	3 058	-47 457	2.02	2.45	-0.59	1.59	1	-19.42	-10.08	1	-0.89	1	0
5565941787	Mfg Finance AB	Delisted	#N/A	32	2010	800	6 200	393 000	20 700	17 400	20 100	3 300	-169 200	4.39	0.16	0.81	0.16	0	0.30	-51.27	0	-0.97	0	0
5560226606	Micro Holding AB	Delisted	4519	32	2008	4 276	51	400	60 155	58 851	14 999	1 304	-4 576	5.47	0.02	0.23	0.09	0	0.00	-3.51	0	-0.77	0	1
5565320537	Micus Sverige AB	Delisted	#N/A	20	2009	17 332	1 804	-572	10 866	2 488	6 040	5 266	4 881	3.80	0.77	0.07	0.87	0	0.17	0.58	0	1.00	0	1
5564354693	Nordic Electronic Procurement Systems AB	OMX - Nordic Exchange Stockholm	6209	*	2010	2 035	1 587	-632	91	-7 387	91	7 478	1	-1.03	82.18	-81.18	82.18	1	17.44	0.00	0	1.00	1	0
5562110790	Novacast Technologies AB	Delisted	6201	20	2009	10 544	-29 835	1 348	171 989	91 454	20 444	63 534	10 387	6.57	0.47	-0.25	3.11	0	-0.17	0.13	0	-1.00	0	0
5563785632	Obducat AB	Nordic Growth Market (NGM)	2899	80	2010	10 233	-89 257	-51 549	43 124	20 771	3 100	22 353	-41 793	5.13	0.52	-0.45	7.21	0	-2.07	-1.87	1	-0.27	1	0
5565575965	Procast Media AB	Delisted	#N/A	80	2009	47 892	61	207	21 146	12 272	11 468	8 590	-1 592	4.47	0.42	0.14	0.75	0	0.00	-0.18	0	-0.54	0	0
5566263132	Pv Enterprise Sweden AB	Delisted	2611	32	2010	349 724	-11 332	-27 662	99 618	33 896	58 864	55 552	7 586	5.96	0.66	0.03	0.94	0	-0.11	0.12	1	0.42	0	0
5566196993	Rayclinic AB	Delisted	8610	20	2007	375	-13 536	-3 778	53 810	20 875	8 286	5 842	-13 008	5.35	0.61	0.05	0.71	0	-0.25	-0.39	1	-0.56	0	0
5567137947	Safe At Sea AB	OMX - Nordic Exchange Stockholm	3012	80	2010	3 949	-2 970	-2 644	4 969	2 567	3 942	2 339	-2 341	2.97	0.48	0.32	0.59	0	-0.60	-0.97	1	-0.06	0	0
5564451655	Scanmining AB	Delisted	2441	20	2006	156 217	-14 443	-22 875	543 346	489 435	44 541	21 411	-18 657	7.69	0.10	0.04	0.48	0	-0.03	-0.35	1	0.23	0	0
5566944954	Seanet Maritime Communications AB (Publ)	Delisted	6190	80	2010	16 762	-29 328	-32 876	54 155	7 697	16 409	31 856	-13 024	5.35	0.86	-0.29	1.94	0	-0.54	-0.28	1	0.06	0	1
5566734835	Snowolverine Group AB	Delisted	7490	32	2009	1 248	-15 713	-4 182	5 125	3 634	1 396	1 491	-18 687	3.05	0.29	-0.02	1.07	0	-3.07	-12.53	1	-0.58	0	1
5566092762	Stormfageln AB	Delisted	3012	32	2009	88	-2 280	-2 230	10 303	8 883	146	1 109	-1 967	3.75	0.14	-0.09	7.60	0	-0.22	-1.39	1	-0.01	1	0
5565740064	Svithoid Tankers AB	Delisted	5020	20	2007	4 100	2 600	-10 400	647 100	218 400	8 500	115 500	95 800	7.84	0.66	-0.17	13.59	0	0.00	0.22	0	1.00	0	0
5565425856	Tatura AB	Delisted	7112	20	2008	125	-19 862	-11 318	38 547	19 126	14 565	7 896	-30 158	5.02	0.50	0.17	0.54	0	-0.52	-1.55	1	-0.27	1	0
5563987154	Teligent AB	Delisted	6190	20	2007	262 800	-425 400	-142 300	539 900	167 000	246 000	299 100	-477 700	7.65	0.69	-0.10	1.22	0	-0.79	-1.28	1	-0.50	0	1
5564390341	Teligent Mobile Office AB	Delisted	6201	32	2008	3 824	-200 078	-38 500	8 873	7 762	4 984	1 110	-25 721	3.55	0.13	0.44	0.22	0	-22.55	-23.15	1	-0.68	0	1
5561769596	Tivox AB	Delisted	2849	21	2004	6 154	-27 440	-75 040	138 028	33 279	25 944	64 196	22 052	6.40	0.76	-0.28	2.47	0	-0.20	0.21	1	0.46	0	0
5562633098	Tmg International AB	Delisted	4520	20	2006	169	-64 953	-4 481	595 690	324 829	42 008	26 075	-91 096	7.78	0.45	0.03	0.62	0	-0.11	-0.34	1	-0.87	0	1
5566819149	Trimera AB	Delisted	2370	20	2009	773	-5 584	-1 020	6 291	5 773	4 994	518	-1 344	3.26	0.08	0.71	0.10	0	-0.89	-2.59	1	-0.69	0	1
5566329305	Xrf Analytical AB	Delisted	5829	20	2009	675	-4 931	-5 030	5 665	1 944	1 513	3 277	-1 958	3.15	0.66	-0.31	2.17	0	-0.87	-0.53	1	0.01	0	0

All values are in thousands SEK

* Default of Payment