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ENCOUNTER FINANCIAL DISTRESS IN THE CRISIS 2008-2009

A COMPREHENSIVE STUDY OF FACTORS WHICH POSSESS THE ABILITY TO PREDICT FINANCIAL DISTRESS AMONG THE FIRMS LISTED ON NASDAQ OMX FIRST NORTH

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ABSTRACT

Title: Encounter financial Distress in the crisis 2008-2009: *A comprehensive study of the factors which possess the ability to predict financial distress among the firms listed on Nasdaq OMX First North*

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Key Words: Credit rating**,** financial crisis, financial distress, financial flexibility, financial leverage, logistic regression, probability of financial distress.

Purpose: The purpose of this paper is to determine the factors which possess the ability to predict the probability to encounter financial distress during a financial crisis. It is of particular interest to test whether financial leverage has a significant effect on financial distress since prior studies as Graham et al. (2011) advocates that the likelihood of financial distress can be explained by a firm's indebtedness and credit rating.

Methodology: The firms listed on Nasdaq OMX First North 2007-12-31, are examined during the period; 2007-12-31 to 2011-12-31, to determine what pre-financial crises characteristics can predict the probability to encounter financial distress during a financial crisis and the subsequent economic downturn. The investigation is done using logistic regression analysis to asses the probability of financial distress.

Theoretical perspective: The theoretical framework is based on previous research within the field of financial distress prediction during times of stable and unstable macro-economical conditions.

Results and Conclusions: The obtained results determine age, liquidity and profitability to have the ability to predict the probability to encounter financial distress during a financial crisis. The result in this study differs from the results by Graham et al. (2011), as financial leverage surprisingly turned out to have an insignificant predictable power of financial distress.

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DEFINITIONS

Credit rating: A published rating by a credit rating agency based on a financial assessment of a firm's ability to meet its debt obligations. Lenders use this information to decide whether to approve a loan.

Financial crisis: Situation in with the supply of money is overtaken by the demand of money. Liquidity quickly disappears since available money is withdrawn from banks making the banks to sell other investments to make up for the shortfall or to collapse.

Financial distress: A firm enters financial distress when it cannot meet the financial obligations to its creditors.

Financial flexibility: A firm's ability to deal unexpected events depending on the firm's financial structure.

Financial leverage: The amount of debt used to finance a firm's assets.

Logistic regression: A method used to analyze whether an independent variable can predict the probability of a binary dependent variable to be classified into one of two groups.

Probability of financial distress: The likelihood of default over a particular time horizon.

1 INTRODUCTION

The introduction section provides a background to the research which further incorporates the purpose. Additionally, the delimitations of the research are explained and discussed.

1.1 BACKGROUND

Financial distress has been investigated frequently throughout the years applied both on times of relative stable economic conditions (Altman, 1968, Altman, Haldeman, Narayanan, 1977, Ohlson, 1980 Zavgren, 1985 and John, 1993) and during periods of financial crises (Bernanke,1983 Wiess, 1990 Graham et al., 2011 Opler and Titman, 1994). A firm's financial health is directly affected by the current market conditions thus the overall condition of the market has a major impact on the financial health of the firm. Consequently, a major interest of investigate a recession's impact on a firm's probability to encounter financial distress is present and in order to predict and further prevent the occurrence, the factors which possess the ability to predict financial distress need to be determined. During the latest century, numerous prediction models to financial distress are derived (Hing Ling Lau, 1987 Champbell et al., 2010 and Graham et al., 2011), mainly after the Great Depression in the US in the 1920s in order to prepare firms for macro economical effects during a future financial crisis. Throughout the century different factors have been determined and different results obtained, mainly dependent on different samples during different investigation periods. However, one factor which constantly recurs is financial leverage which is argued to hold a great ability to predict the probability of encounter financial distress.

According to theories as the Pecking Order Theory (Myres, 1984), the Traditional Trade-off theory (Kraus and Litzenberger,1973) and credit rating requirements, different approaches to financial leverage are discussed where both advocacy for and against a heavy borrowing capital structure is found. Even though these models hold different perspectives on debt, the common aim is to use debt in the sense that it enhances the market value of the firm such that it out-concurs the increase in the probability of encounter financial distress. Ibbotson (2011) implies that stock volatility tends to follow a financial crisis depending on the affection of the uncertainty on the market. During a financial crisis when markets are more volatile, a heavily leveraged firm is more likely to increase its probability to encounter financial distress. Consequently, the increased volatility on the market might change the underlying condition for a firm's capital structure. Opler and Titman (1994) states that highly leveraged firms lose substantial market share to their more conservatively financed competitors and are suffering the most in times of economic downturns. Additionally, their study shows that being heavily borrowed during a financial crisis will substantially increase a firm's probability to default on its obligations. Contrariwise, pursuant to the Pecking-order theory of capital structure (Myers, 1984) firms should, when considering external financing, prioritize debt before equity in the sense that it signals confidence for the firm, which in comparison with an equity issue would increase the risk for a drop in the share price. The Trade-off theory (Kraus and Litzenberger, 1973), which advocates for a balance between the dead-weight costs of bankruptcy and the tax saving benefits of debt, argues that according to the tax benefit of debt financing, debt financing would be of first priority until the increased probability of default has out concurred the benefit of debt financing. Due to a firm's sensitivity towards macro-economical changes, the optimal capital structure also changes when the market does.

Even though financial leverage has been the most talked-about factor to financial distress it might be other factors having the same or even more contribution to financial distress. Credit rating agencies evaluate and rate a firm's financial health and credit worthiness based on its ability to meet its credit obligations. Pursuant to Moody's Expected default frequency (EDF) model the firm's solvency is based on the distance between its market value of assets and the book value of debt. Thus, the firm's probability of default is directly linked to the net worth of the firm and the volatility of the firm's market value. This indicates that the more volatile market, the bigger chance of decreasing its distance to default. The credit score is hence directly linked to the firm's debt level, market value of assets and the asset volatility saying that in order to remain on the same credit score, the amount of new issued debt has to enhance the market value of the firm to the same extent. During a financial crisis, when the volatility is higher than normal, irregular movements in the firm's standard deviation might occur which consequently increases the distance between the value of debt and the market value of the firm. Consequently, during periods of financial instability on the market, credit rating agencies have to be up to date in order to not miss judge a firm's credit worthiness. Hence, the credit score is a potential factor to consider while investigating a firm's probability to encounter financial distress.

In an early study by Altman (1968) it is found that financial leverage, liquidity and profitability are factors which have the greatest ability to predict financial distress. Profitability possesses the ability to predict the health of the ongoing operation reflecting the future prospects of the firm hence the investors' confidence. Liquidity on the other hand, possesses the ability to predict whether the firm is able to convert its assets into cash in time during distressed conditions or if the firm holds too much fixed assets and liabilities. Liability of newness is an expression made by Stinchcombe (1965) meaning that age has a significant impact on the probability to encounter financial distress. He classifies financial distress as the inability to compete on the market in order to generate profits, meaning that new firms are exposed to a higher degree of competition and inefficiency and consequently experience a death rate higher than older firms. The theory by Stinchcombe has been tested and used frequently throughout previous studies and has for the most part been significant (Freeman et al., 1983). Dividend payouts and equity issues are also argued to possess the ability to predict financial distress meaning that in the case of dividends, firms tend to reduce or omit dividend payouts when facing financial constraints (DeAngelo and DeAngelo, 1990). Meanwhile equity issues are, according to the Pecking Order theory, classified as the financing of last resort it consequently symbolizes a firm's financial difficulties. Mentioned earlier, DeAngelo and Masulis (1980) advocate for an optimal debt level where a firm's capital structure should be in line with the industry average. In addition, Koller et al. (2010) state that the industry beta symbolizes the real risk exposure the firm should be facing within that particular industry.

A later study made by Graham et al. (2011) claims that, according to their result obtained applied on the Great depression (1920s) and the Recession (2008-2009), financial leverage and bond rating possess the best ability to predict financial distress during the investigation periods. It party consistent with the theory by Altman (1968) but the predication ability for liquidity and profitability in this latter case are not significant. According to the study by Graham et al. operating profit, age, investment and size can not explain the occurrence of financial distress. The result obtained contradicts the results by prior research but the study is also argued to be the first large-scale microeconomic analysis of corporate performance and survival during these eras.

1.2 PROBLEM DISCUSION

Graham et al. (2011) and Opler and Titman (1994) advocate for a positive relationship between financial leverage and financial distress during times of a financial crisis together with Moody's EDF model and the traditional Trade off Theory (Kraus and Litzenberger, 1973) which value a heavily borrowing capital structure during times of financial crisis as to reduce financial flexibility and increase the probability to encounter financial distress. A financial crisis creates uncertainty on the market which in turn drives volatility (Ibbotson, 2011). Consequently, heavily leveraged firms holding low financial flexibility, tend to be most financially affected by a financial crisis (Opler and Titman, 1994).

It is of particular interest to investigate the interchange between firm characteristics and financial distress during a financial crisis, since the effect is examined when it matters the most. Further, it is of interest to question the result obtained by Graham et al. where financial leverage and bond rating are the only explanatory factors to financial distress and test whether these results are applicable on a new set of sample or if the outcome leans more towards the result from the former study by Altman et al (1968). Nonetheless, the study by Graham et al. is applied on firms listed on the NYSE which are capable to fulfill the listing requirements of e.g. a minimum market capitalization of $500 million, revenues of $100 million the most recent 12-month period and an adjusted cash flow for the last three years of minimum $25 million (www.nyx.com). Hence, the conclusions made by Graham et al. are solely based on large capitalized firms on the American market. Bernanke (1983) however claims that small firms are less profitable and encountered financial distress more often than large firms during the Great Depression. Altman (1968) suggests in his study concerning the prediction of corporate bankruptcy among publicity held manufacturing corporations that future research should be extended to relatively smaller assets sized firms where the incident of business failure is greater than with larger corporations with the intention to obtain a different outcome.

Furthermore, Buttwill (2004) made a study of countries with the same economical situation (The EU countries, The US and Norway) and came to the conclusion that Sweden holds the highest bankruptcy frequently among all these countries in comparison to the US which holds the lowest. This might have an influence on the financial result since both the study by Altman (1968) and Graham et al. (2011) are applied on the American market. Using the conclusion made by Graham et al. (2011), Altman et al. (2011), Bernanke (1983) together with the research by Buttwill (2004), it is interesting to investigate the pre-crisis firm characteristics' ability to predict financial distress using a new set of sample.

1.3 PURPOSE

The main purpose of this paper is to determine the factors which possess the ability to predict the probability to encounter financial distress during a financial crisis. It is of particular interest to test financial leverage's ability to predict financial distress since the recent study by Graham et al. (2011) advocate that the likelihood of financial distress can be explained by a firm's indebtedness and bond rating. The question which is intended to be answered is:

- *Which pre-crisis firm characteristics possess the ability to predict financial distress during the crisis 2008-2009?*

1.4 DELIMITATIONS

According to Buttwill (2004) Scandinavian firms tend to have a higher bankruptcy frequency than American firms, creating an argument to why it is interesting to carry out a similar investigation as Graham et al. applied on the Scandinavian financial market. The sample is limited to firms listed on the Nasdaq OMX First North to restrict the investigation to smaller Scandinavian firms which do not meet the listing requirement for Nasdaq OMX Nordic. Bernake (1983) argues that small firms are less profitable and encounter financial distress more often than large firms during times of crisis, which strengthens the argument of investigating the firms listed on First North. It is not certain that a lager sample, including Nasdaq OMX Nordic, will result in stronger results due to the relative low bankruptcy frequency among larger firms. It is consistent with the extended research suggested by Altman (1968) meaning that it would be interesting to apply a bankruptcy prediction model on small assets sized firms facing a higher incident of failure. Consequently, the motive is to distinguish the sample from the one of Graham et al. who restricts their sample to firms with a market capitalization larger than $500 million, in order to investigate whether the factors contribute to financial distress is unaffected by the size and the origin of the firm. The investigation period (2007.12.31–2011.12.31) is chosen in order to capture the recent recession (2008-2009) and the following economical downturn. This research is consequently of interest for the investors of smaller firms with the ambition to consider which factors needed to be recognized in case of a future financial crisis.

2 THEORETICAL FRAMEWORK

In this section the explanatory factors which potentially contribute to financial distress are presented. The factors are micro economical, and have been chosen carefully with support by previous theory.

2.1 NASDAQ OMX FIRST NORTH

First North is an alternative exchange list for Nordic stock trading and for other securities. According to the EU-directive, First North is not a regulated market thus it is not allowed to be named stock market. It is an alternative choice for young, small firms with growth opportunities that are not required for Nasdaq OMX Nordic but still want to have access to the financial market. The firms listed on First North do not have to follow the legal provisions applied to firms listed on e.g. Nasdaq OMX Nordic or other authorized markets and gives the investors the possibility to invest early in a firm's lifecycle. However, such an investment have a higher risk to default and a profit potential which is classified as higher than for firms listed on the other Nordic stock exchanges (www.nadaqomxnordic.com).

2.2 BANKRUPCY REGULATION

In a paper by Buttwill (2004) sufficient evidence is found proving that Sweden has the highest frequency of liquidation bankruptcies among other European Union countries, Norway and the US. He compares the frequency of liquidation bankruptcies between countries with the same economic structure and among these Sweden has the highest frequency of liquidation bankruptcies followed by the other Scandinavian countries and the UK. Buttwill argues that these differences in bankruptcy frequency, between the countries, can be explained by differences in legal legislation, causing different kinds of incentives to debtors or creditors in respect to declaring firms bankrupt. The indication is that a country is classified as having too many bankruptcies when firms which is in financial distress but not in economical distress (still has a positive NPV) are closed. Contrariwise, a country is classified as having too few bankruptcies when a firm which is both in financial and economical distress continues to operate. The results based on the research by Buttwill (2004) show that Sweden has the largest frequency of liquidation bankruptcies of all the countries investigated whereas the US and Germany belongs to the low frequency group. One major reason for the low frequency for the US and Germany depends on the cost of filing for bankruptcy and the conditions to cover the proceeding costs.

2.3 EXPLANATORY FACTORS

In the prediction of financial distress risk, the factors which contribute to the occurrence have to be estimated. In a study by Altman from 1968, ratios of liquidity, profitability and financial leverage are the most important indicators of impending financial distress. A recent study by Graham et al. (2011) elaborate with the idea and test these ratios together with a new set of potentially factors: age, size, volatility, investment and macro economical factors and came to the conclusion that financial leverage and bond rating have the strongest relationship to financial distress. The results obtained by Altman and Graham et al. are considered hence the significant factors for their studies are included together with four other factors which might be relevant for this study. The factors investigated are displayed below:

(i) Financial leverage
(ii) Credit rating
(iii) Liquidity
(iv) Profitability
(v) Age
(vi) Industrial Affiliation
(vii) Dividends
(viii) Equity issue

2.3.1 FINANCIAL LEVERAGE

Using the same definition of financial leverage as Peterson (1994) financial leverage can be defined as the use of various financial instruments or borrowed capital to increase the potential return of an investment. Mentioned earlier in this paper, previous theory argues differently regarding the usage of financial leverage hence, this study tests the hypothesis:

H_A= Financial leverage possess the ability to predict the probability to encounter financial distress

Pecking Order Theory of Capital Structure

The pecking order theory by Donaldson (1961) further modified by Stewart Myers (1984) provides a description of observed corporate financing behavior. Myers means that firms prioritize their sources of financing according to the principle of least effort, preferring to raise equity as a financing means of last resort. According to his theory, managers prefer internal financing (equity financing through retained earnings) before external financing (issuance of debt or equity). However, in the case where no internal financing is available and external financing has to be made, managers tend to prefer the least risky security available i.e debt issue. Myers and Majluf (1984) formulate Myers's observation into a theoretical model that explains these corporate financial behavior aspects as a consequence of information asymmetry. Since the market is underinformed about the values of various projects it tends to undervalue these projects and consequently undervalue the securities issued to finance them, creating an effective cost of external financing. The asymmetric information between the shareholders and the managers favors the issue of debt over equity since the issue of debt signals confidence that an investment is profitable and that the stock is undervalued. Contrariwise, the issue of equity would signal lack of confidence among the board since it indicates an overvaluation of the stock price and the price will drop. A manager may thereby reject a profitable project if it must be financed with external equity since the project's NPV will not exceed the surrender cost.

The traditional Trade-Off theory

In the Traditional Trade-Off theory, a competitor theory to the Pecking Order theory (Myers, 1984 and Kraus and Litzenberger,1973) consider a balance between the dead-weight costs of bankruptcy and the tax saving benefits of debt. The Trade-Off theory refers to the idea that a firm chooses how much debt finance and how much equity finance to use to balance cost and benefits. Since interest on debt is tax deductible compared to other external financing a major advantage for debt financing is generated. Contrariwise, an increased risk to enter financial distress is related to debt financing and thereby additional bankruptcy and non-bankruptcy cost. Instead of ranking the different financing methods as the Pecking Order theory, the Trade-Off theory argues for an optimal capital structure consisting of a finite level of leverage. It considers both the positive and the negative effects of debt i.e. the tax shield earned due to debt financing and the present value of expected cost of future financial distress.

A study by Farma and French (2002), tests both the predictions of the traditional Trade-off theory and the Pecking Order theory for U.S nonfinancial firms during 1965-1999. The results of the study are that more profitable firms have less market leverage together with firms with more investment opportunities. This is consistent with the Traditional Trade-Off theory and not in particular with the Pecking Order theory since Myer (1984) predicts that short term variation in investment and those earnings is mostly absorbed by debt. Fama and French (2002) mean that profitable firms with many investment opportunities will not take on as much debt as less profitable firms. In conclusion, the Trade off theory states that debt financing has its benefits but it is important to carefully design the capital structure so that the distance between the tax benefit and the present value of cost of future financial distress is in optimum.

Financial distress in times of a financial crisis

Opler and Titman (1994) have reached a consensus on how financial distress affects corporate performance. They investigate industries that have experienced a financial crisis and investigate whether the firms in these industries with high financial leverage fare differently to the more conservatively financed firms. If financial distress is costly, a highly leveraged firm will experience greater operating difficulties during an economic downturn. Hence, Opler and Titman find a positive relationship between financial leverage and firm performance during a financial crisis. Highly levered firms tend to lose market share and lower their operating profits more than less leveraged firms. These losses in sales derives both from losses where customer are less willing to make business with potentially distressed firms and losses due to non-distressed competitors taking advantage of the distressed periods and drives out the vulnerable distressed competitors since their margins are mainly eaten up by their debt obligations. The same effect applies to market value of equity as a result of future prospect speculations since sales losses are clearly costly to shareholders. In conclusion, stock returns of more leveraged firms during a financial crisis are substantially lower than for less leveraged firms. Even though the operating income is not connected to leverage, it decreases more for highly leveraged firms during downturns supporting the argument that sales losses are customer or competitor driven. Graham et al. (2011) investigate the effects of financial distress during the Great Depression and the Recession 2008-2009. The study is applied on firms listed on the NYSE during 1928-1938 together with an out of sample period 2008-2009 to prove an overall understanding of financial economics. The study investigates the effects of taxes and debt bias and broadly examines the interplay between debt and financial distress where Graham et al. find that high financial leverage significantly increases the risk of entering financial distress during a depression era. The study consider firm characteristics assumed having different effects on firm performance during a financial depressed period and finds that among high valued firms the valuation of highly leveraged firms decreased by 40 percent more than for less leveraged firms. The factors which are tested by Graham et al. during the depressed eras are financial leverage, macroeconomic factors, age, liquidity, Size, profitability, investments and volatility. Their result indicates that a pre-depression leverage is a significant positive financial distress predictor since it is constraining corporate activity during an economic downturn. It also contributes to that the effect of leverage on shareholder wealth is negative during times of depression. Highly leveraged firms and firms with low bond rating had a high probability of becoming financial distressed during both sample periods. Thus, Graham et al. mean that credit ratings are significant predictors of financial distress during the Depression due to their provision of information above and beyond what the other factors can provide. Furthermore, operating profit, size, investment and age are not explaining the likelihood of financial distress and are only explained by leverage and bond ratings alone.

To capture the significant effects of financial leverage this study will measure financial leverage based on the debt-to-equity ratio which is consistent with the method used by Peterson (1999). The debt-to-equity ratio measures how the firm finances its operations with debt relative to the book value of shareholder's equity.

2.3.2 CREDIT RATING

According to Graham et al. (2011) bond rating possesses the explanatory power to financial distress meaning that the health of the firm is directly reflected in the rating of the firm. Rating agencies came to play a significant role for the appearance of the financial crisis 2008-2009 due to allegations of miss rating securities. According to the Financial Crisis Inquiry Commission (FCIC) subprime and mortgages were mostly held in residential mortgaged-backed securities (RMBS) and were together with the collateralized debt obligations (CDOs) rated by the rating agencies. Due to the massive rise in mortgage defaults in 2006, a mass downgrading of the RMBS and CDOs took place in the beginning of 2007. These losses for the investors and the write downs on these securities contributed to solvency and liquidity problems. Overvalued initial ratings on these securities trigged the financial crisis because of enabling the issuance of new securities by increasing investor demand for RMVS and CDOs.

If there would have been fewer AAA ratings the demand may have been less and less pension funds and depositary institutions would have invested in them. Moody's, one of the leading credit agencies in the world, states that default is normally a rare event with an average default probability of around 2 % in any year. A firm rated AAA have the odds of defaulting 2 in 10,000 annually compared to a CCC-rated firm with the odds 4 in 100, 200 times the odds of a AAA- rated firm. Moody's rating which is reflecting the financial health of the firm mainly depends on debt value in relation to firm value. A high rating is given to the firms with a high positive distance between firm value and debt value. Due to the rating systems major impact on the financial market, any incorrect ratings can cause undesirable consequences. For the determination of a firm's risk to default, many components have to be considered to generate a rating as accurate as possible. Moody's has developed the expected default frequency model (EDF), which is a credit measure showing the probability to default during the forthcoming year. The model is developed from the Vasicek-Kealhofer (VK) model which assumes an increase in a firm's default risk as the value of the assets approaches the book value of the liabilities. A firm is considered defaulted when the market value of its assets reaches the firm's default point i.e. when the firm is insufficient to repay its liabilities. The EDF model take three components into consideration when estimating the default probability of a firm; market value of assets, the asset volatility (industry/business risk) and the default point (normally the book value of debt). It is of great importance for a firm to receive a satisfying rating in order to obtain credit at favorable terms. In a paper by Craig et al. (2007) it is found that large banks are reluctant to supply small firms with credit. Small firms are thereby exposed to a higher degree of speculation and need to prove more than larger firms in order to obtain credit. With the purpose to test the credit ratings' relationship to financial distress, the hypothesis below is tested

H_A= Credit rating possess the ability to predict the probability to encounter financial distress

2.4 LIQUIDITY

Liquidity is defined as the ability to convert an asset to cash quickly at a price that is close to its fair value. Current asset is defined as those assets that are expected to be converted into cash within one year in the normal course of business and include cash, accounts receivable, inventory, marketable securities, prepaid expenses and other liquid assets that can be readily converted to cash (John, 1993). To test whether liquidity has a significant impact on the increased probability of financial distress the study tests the hypothesis below:

H_A= Liquidity possess the ability to predict the probability to encounter financial distress

Platt (1999) argues that current and fixed assets have different bankruptcy characteristics. The current assets usually yield a relatively lower return, but are at the same time exposed to a lower bankruptcy risk than fixed assets. The lower return potential of inventory and receivables depends on there main function to facilitate sales and the lower risk of the current assets steam from their ready convertibility into cash. Fixed assets have a higher bankruptcy risk because these are less liquid, but at the same time these are associated with a higher return potential. Platt argues that bankruptcy can eventuate from a firm’s asset mix being too heavily weighted towards either current or fixed assets. The problem of having weighted the asset mix too heavily towards current assets, the management may misinterpret the future product market. For example if product prices fall and situation where the value of work-in-progress and thereby the inventory of finished goods diminishes. Thus, the losses in inventory value cause losses in the firm’s equity which in the case of a large decline in product prices may contribute to the bankruptcy of the firm. Platt also advocates that a major problem is related to the quality of the firm’s receivables i.e. to what extent the credits and associated interests will be recovered by the firm. John (1993) analyzes the relationship of the costs of financial distress to the level of corporate liquidity maintained and leverage. She declares a firm to be financial distressed when the currently available liquid assets are severely inadequate to meet the current obligations of its hard financial contracts. Hence, the most important cost of asset liquidation is the destruction of going-concern value that occurs when assets are sold to pay down debt. Her overall result indicates a positive relationship between corporate liquidity and financial distress costs.

Graham et al. (2011) measure liquidity as the ratio of a firm’s current assets, also called liquid assets, to total assets. The ratio shows how much of a firm’s assets that are convertible into cash within one year in the normal course of business. Thus, this measure is used to capture the degree of liquidity for this study. However, Bromiley (1995) measures a firm’s liquidity by putting earnings before interest and tax (EBIT) in relation to its interest expense showing the firm’s ability is to pay the interest on its outstanding debt. Consequently, the interest coverage ratio is also chosen in order to capture the effect of liquidity.

2.4.1 PROFITABILITY

Opler and Titman (1994) argue that encounter financial distress is directly linked to the loss in sales indicating that a decrease in profitability contributes to a decrease in the overall confidence of the firm. Consequently, the reduced confidence in the firm results in costumer loss and increased competition, which thereby increases the probability to encounter financial distress. Sufficient evidence is found (Shumway, 2001) that the lack of profitability is strongly related to bankruptcy which goes along with Altman's (1968) theory that profitability is one of the major factors possessing the ability to predict financial distress. On the contrary, Graham et al. (2011) contend that their research do not find significant evidence that operating profit helps to explain the likelihood of financial distress.

A test of the relationship between profitability and size is further made by Storey et al. (1987) with purpose to determine whether profitability has the same effect on financial distress for both large and small firms. They determine an opposite effect where small firm's profitability decreases with a decrease in size, whereas large firms tend to increase their profitability with and decrease in size. Additionally, Storey et al. advocate that the current profitability of a small growing firm does not necessarily reflect its "true" profitability and therefore not contributes to an increased risk of encounter financial distress. The hypothesis which is further tested is:

H_A= Profitability possess the ability to predict the probability to encounter financial distress

Graham et al. measure the profitability of a firm as a ratio between earnings before interest and tax and total assets. This ratio is one of the most important measures since it captures the efficiency of operations regardless of how capital is financed as the financial costs are not included. It assess whether a firm is providing an acceptable return on the resources at disposal. Hence, the same measure is chosen for this study.

2.4.2 AGE

Stinchcombe (1965) imprinted the expression "liability of newness" meaning that new firms suffer a greater risk of failure than older firms. The reason is that younger firms depend on the cooperation of strangers, are not able to compete efficiently against established firms and possess low levels of legitimacy. Another study by Freeman, Carrol and Hannan (1983) is questioning the "liability of newness" and assert that due to heterogeneity in population the death rate for firms decline with age simple because the units with the highest death rates fail yearly. Consequently, the "liability of newness" might instead be a "liability of smallness" specifically since the smallest firms are screened out from the population and thus death rate declares with age instead of size. Freeman et al. (1983) concludes that their findings are consistent with the "liability of newness" when including both dissolution and absorption by merger in the reason for the death. When excluding absorption by merger, significant evidence is found that size has a large significant effect on rates of disbanding. In a study applied on the great depression (Bernanke, 1983) the findings are consistent with the "liability of size". They indicate that small firms are less profitable and encounter distress more often than large firms during the 1930s. Based on the above information the hypothesis below is developed.

H_A= Age possess the ability to predict the probability to encounter financial distress

2.5 INDUSTRIAL AFFILIATION

In the result of Graham et al. (2011) no significant evidence is found that industrial affiliation holds the ability to predict financial distress during the recent financial crisis. According to theory by Koller et al. (2010) the industry beta, which is a measure of the average systematic risk for the firms within the same industry, is an accurate measure for the risk the firms within the same industry are exposed to. For that reason, the difference between the firm betas depends only on each firm's individual leverage structure. In the context where DeAngelo and Masulis (1980) are discussing the existence of an optimal debt level, they are referring to where the firm can adjust its market value by changing its capital structure to the industry average. Their statement means that a firm which holds it debt level in line with the industry average will achieve the optimal mix of liabilities and assets. In the sense of Opler and Titman (1994) some industries are exposed to financial distress to a lager extent than other industries. The hypothesis tested is:

H_A= Industrial affiliation possess the ability to predict the probability to encounter financial distress

2.6 DIVIDEND PAYOUTS

Proved by DeAngelo and DeAngelo (1990) firms with an increased risk of financial distress tend to reduce or omit dividends due to liquidity constraints, restrictions imposed by debt covenants or strategic considerations such improving a firm's bargain position with trade unions. Hing Ling Lau (1987) also advocates that the changed dividend policy is reflecting the financial condition of a firm. Even Dielman and Oppenheimer (1984), and Gentry, Newbold, and Whitford (1985) came to the conclusion that a firm that reduces dividend is typically encountering some financial distress. Hence the hypothesis tested is:

H_A= Dividend payouts possess the ability to predict the probability to encounter financial distress

2.7 EQUITY ISSUES

The pecking-order theory (Myers, 1984) argues that managers tend to issue new equity as a financing choice of last resort when it cannot reach the requirements the banks impose for a debt issue. Hence, an issuing of new equity reflects a potential financial weakness within a firm. This further tend to signal an overvaluation of the stock price and the price will drop as result. Empirically, debt is treated favorably over equity in both tax and regulatory treatment, thus many firms chooses to issue debt instead of equity (Roe, 1991). The reason mainly depends on the monitoring effect and the reduced agency problems that come along with a debt issuing which for an equity issue has an opposite effect (Adler, 1993).

H_A= Equity issues possess the ability to predict the probability to encounter financial distress

These eight hypotheses are intended to be answered with the condition that all information is available.

3 METHODOLOGY

In this section a detailed description of the research methodology is presented. This includes a description of the data, where it was extracted, how it was processed and a discussion of its reliability and validity. This section also includes a description of how the statistical method, the Logistic Regression model, is used.

The methodology section describes the systematic modeling of whether pre-financial crisis characteristics predict distress during financial crises. The modeling is largely built upon the methodological approach suggested by Graham et al. (2011).

3.1 SOURCES OF INFORMATION

Information regarding the firms listed on the Nasdaq OMX First North is provided by Nasdaq OMX Nordic which provides information on corporate actions i.e. documentation of yearly delisting of firms and a description of the delisting cause. Where the information from Nasdaq OMX Nordic is sparse or unclear the information is supplemented with information from the Swedish Companies Registration Office, Bolagsverket, and the Danish Business Authority, Erhvervsstyrelsen. The databases used for this study is described below:

Database	**Description**
Retriever Business	*Extraction of financial information regarding Swedish firms*
Navne & Numre Erhverv	*Extraction of financial information regarding Danish firms*
Nasdaq OMX Nordic	*Information about corporate actions such as reason behind the delisting.*
Swedish Companies Registration Office	*Provided information of company status, if bankruptcy proceedings had been initiated*
Danish Business Authority	*Provided information of company status, if bankruptcy proceedings had been initiated*

The data received from these sources are in form of raw-data i.e. balance sheet items and income statement items. The raw data is further used to calculate the ratios considered appropriate for the hypothesis (presented above).

3.2 DATA COLLECTION AND PROCESSING

The collection and processing of necessary data can be illustrated as a six step process:

(i) Determine the firms listed on Nasdaq OMX First North at the start of the investigation period

(ii) Determine the firms that became delisted during the investigation period.

(iii) Determine the reasons behind the delisting

(iv) Determine and collect the pre-financial crisis variables

(v) Perform a logistic regression of the pre-financial variables

(vi) Ascertain the variables which have the ability to predict the probability to encounter financial distress during the investigation period.

3.2.1 DETERMINATION OF SAMPLE

To determine the firms that are listed on Nasdaq OMX First North 2007-12-31, the information is collected from the statement of “Corporate actions” by Nasdaq OMX Nordic. These firms are further investigated to determine which of these firms remained on First North throughout the investigation period. The firms which are absent by 2012-01-01 are further investigated for a determination of the delisting cause. The corporate actions information received from Nasdaq OMX Nordic provides most of the information and in the cases where the information is sparse or unclear the Swedish business registration office and the Danish business authority are used as a supplement for information. If a bankruptcy proceeding is initiated within a period of 12 month after the date of being delisted the cause of the delisting is assumed to be financial distress, a reasonable assumption with however imperfect accuracy. Ohlson (1980) states that bankruptcy is not an unexpected event, it is usually the result of an extended process of declines in financial health.

The majority of the firms are delisted due to other reasons than financial distress; either the firm goes private, switch to another stock market or is delisted due to a merger or an acquisition. It is reasonable to assume that at least in some cases the reason for the M&A are bankruptcy avoidance which is consistent with the theory by Ogden et al. (2011). However, for this study it is chosen not to include financial distress due to the difficulty to determine the reason behind a merger or an acquisition hence, a prudent approach is adopted and these events are ignored.

A SUMMARY OF THE HYPOTHESES THIS STUDY SETS OUT TO EXAMINE

Variable	Hypotheses	Measure
Financial Leverage	$\boldsymbol{H_A}$= *Financial leverage possess the ability to predict the probability to encounter financial distress*	Debt to equity ratio
Credit Rating	$\boldsymbol{H_A}$= *Credit rating possess the ability to predict the probability to encounter financial distress*	Credit rating
Liquidity	$\boldsymbol{H_A}$= *liquidity possess the ability to predict the probability to encounter financial distress*	CA-TA ratio and Interest Coverage ratio
Profitability	$\boldsymbol{H_A}$= *Profitability possess the ability to predict the probability to encounter financial distress*	Return on Total Assets
Age	$\boldsymbol{H_A}$= *Age possess the ability to predict the probability to encounter financial distress*	Age
Industry Affiliation	$\boldsymbol{H_A}$= *Industrial affiliation possess the ability to predict the probability to encounter financial distress*	Industry affiliation
Dividend Payouts	$\boldsymbol{H_A}$= *Dividend payouts possess the ability to predict the probability to encounter financial distress*	Dividend payout 2007
Equity Issues	$\boldsymbol{H_A}$= *Equity issues possess the ability to predict the probability to encounter financial distress*	Equity issue 2007

3.2.2 LOGISTIC REGRESSION

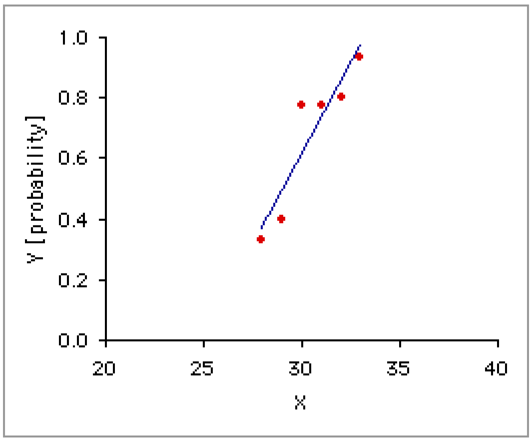
A logistic regression model is a regression analysis used when a binary dependent variable is to be classified into one of two groups using explanatory variables (Davidson et al., 2004). It is a method appropriate to examine the relationship between a binary dependent variable and a number of independent variables. The binary dependent variable is just able to have two values which for this study are 1 (distress) or 0 (non-distress). The explanatory factors includes; financial leverage, credit rating, liquidity, profitability, age, industrial affiliation, dividend payouts and equity issues. The model estimates the probability of the binary dependent variable to end up in distress using a linear function of predictors, i.e. the log-odds of the probability is the fit of the predictors using a linear regression (Davidson et al., 2004). The regression can be constructed either by using one explanatory variable or by multiple explanatory variables. The model can be described in the following way:

$$Y\ (1,0) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i + u$$

Y is the dependent variable, α is an intercept and the β's shows the loading on the independent variables X_1 and X_2. While estimating the logistic regression the accompanying probability measures are used to determine what pre-financial crises characteristics that possess the ability to predict the probability to encounter financial distress.

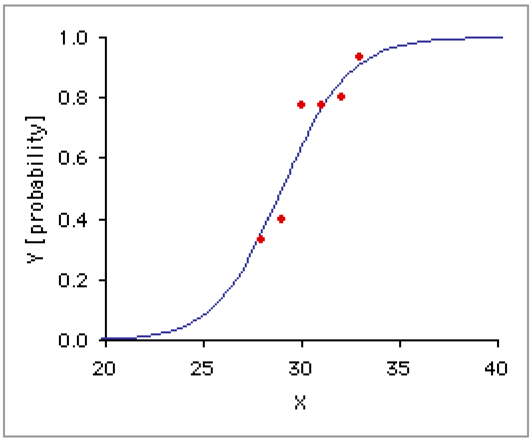
A problem with ordinary OLS techniques are that OLS is not mathematically constrained to remain within the probability range of 0,0 to 1,0. If the regression line happens to be extended a few units in ether direction there might be a risk of observing probabilities that falls outside the range of 0,0 to 1,0. The logistic regression is however mathematically constrained to remain within the range of 0,0 to 1,0. Below, an ordinary OLS regression and an S-shaped logistic regression are presented using the same observations.

Figure 1: OLS Regression



Source: (vassarstats.net)

Figure 1 : Logistic Regression



Source: (vassarstats.net)

The logistic regression is illustrated as the S-shaped curve in figure above and the mechanics of the logistic regression is the log-odds. The log-odds will equal 0,0 if the observed probability is less than 0,5 and it will equal 1,0 if the observed probability is equal to or greater than 0,5. The probability 0,5 can be seen as a cut-off point between the groups and the observed value between 0 and 1 is the probability of ending up in group 1 i.e. the probability of ending up in financial distress (Agresti, 2007):

$$\ln\left[\frac{P}{1-P}\right] = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i + u$$

Where:

$$\ln\left[\frac{P}{1-P}\right] = Y$$

The expression can be transformed into the probabilities of ending up in financial distress by the equation:

$$P = \left[\frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i + u)}}\right]$$

An additional positive characteristic of the logistic regression according to Mantel et al. (1974) is the non-requirement of normal distributed data, something that is rarely the case concerning financial data (Theodossiou,1998).

3.3 CRITISISM OF SOURCES

Using multiple databases for collecting financial information might cause accuracy problems since the different databases might employ different techniques for compiling and presenting the data. For this reason all financial information for each country is retrieved from the same database. The information for the Swedish firms is retrieved from the database Retriever Business and Navne & Numre Erhverv contributed with informaton about the Danish firms.

3.3.1 OFF-BALANCE SHEET FINANCING

Lim et al. (2003) presents off-balance sheet financing as large capital expenditures excluded from a firm's balance sheet through various methods. The motivation for off -balance sheet financing is the ability to reduce the reported book value of leverage and keeping debt to equity ratio and leverage ratios low. Leasing is the most common form of off–balance sheet financing. The firm only reports the rental expense of the asset which misleads investors due to a less levered approach. Lim et al. thereby indicates that operating lease debt is estimated to be comparable to balance sheet debt. To determine if off-balance sheet financing constitute a substantial source of financing for the companies on First North a hypothesis test is conducted. A simple random sample (SRS) of 10 firms is withdrawn from the population. The population refers to the 106 firms listed on Nasdaq OMX First North 2007-12-31. These 10 firms are further investigated to determine to what extent they use off-balance sheet financing. The approach for estimating the debt equivalent value of operating leases is a simplified method proposed by Steve et al. (2003). The debt equivalent value of operating leases is measured by comparing leasing expenses in relation to the total assets. Among the 10 firms the debt equivalent value of operating leases in relation to the total assets varies from 0% to 7,9%. Steve et al. conclude that the average usage of off-balance sheet is approximately 10-14% of total assets. An assumption is made that the usage of off-balance sheet financing is not of any big concern if the debt equivalent value of operating leases is lower than 6% of total assets. In order to draw any conclusions about the population the following hypothesis is examined.

H_A: The debt equivalent value of operating leases constitute of less than 6% of total assets.

ONE-SAMPLE HYPOTHESIS TEST: Off-balance sheet financing total assets ratio							
Test of mu = 0,06 vs. < 0,06							
Variable	**N**	**Mean**	**StDev**	**SE Mean**	**95% Upper**	**T**	**P**
Off-balance sheet financing total assets ratio	10	0,0350	0,0324	0,0102	0,0538	-2,44	0,019

The result of the hypothesis test can be seen in the table above. The p-value is below the 5% significant level and the null hypothesis is therefore rejected. Hence, it seams like the off balance sheet financing do not present a major source of error for this study.

3.3.2 VALIDITY AND RELIABILITY

During an investigation, it is important to be able to pronounce a result which during a replication obtains a similar result. It is therefore of great importance that potentially drawbacks with the investigation method is recognized. As mentioned earlier, a test is conducted to determine to what extent the investigated firms use off-balance sheet financing. It is of great importance to consider off-balance sheet financing since it is one of most critical sources of inaccuracy due to its underestimation of asset value. In order to reduce this potential problem, the already mentioned hypothesis test is performed. Additionally, the size of the sample might be a potential drawback since it reduces the ability to generalize the result to the total population. The investigation is limited to Nasdaq OMX First North and for natural reasons this will limit the number of investigated firms. However, it is not certain that a larger sample would have resulted in stronger results. Previous studies have found that distress probability decrease with firm size and Nasdaq OMX First North overall consists of small firms. A larger sample size would imply adding larger firms, something that would have affected the delimitations due to the potential negative relationship between size and financial distress. Due to the provision of insufficient information, this study assumes that a delisting due to M&A is not a consequence of financial distress. However, if that is not the case and that the M&A is a result of financial distress, the obtained result will be biased which also is a problem for the reliability of this study.

The used time period is also a potential interference to the generalization perspective since the time period reflects a severe financial crisis which obviously affects the generalizability against other time periods. Yet, the selected time period is made in order to capture the characteristic during such an event. The choice of how to measure the different factors in order to capture the core of the hypotheses can be questioned. For instance the measure for leverage, a reasonable measure would have been total debt to total assets instead as total debt to total equity and for liquidity where the measure should have been able to capture the bad effects of possessing too much current assets. However, the used measures are in all cases based on theoretical foundations from similar studies and in order to be comparable to the study by Graham et al. (2011) the same measure has to be used. Hence, it is considered that the measures variable problem is minimized. Finally, there is a risk of “human errors” in collecting and processing of the data. To minimize this risk computerized processes are used as extensively as possible.

4 EMPIRICAL RESULTS

This section begins with a presentation of the sample and some practical features regarding the variables. Then are the results of the logistical regressions displayed, first individually and than combined into a model of distress prediction

4.1 DATA DESCRIPTION

In 2007-12-31, 108 firms are listed on Nasdaq OMX First North, including two firms registered outside the EU. These two firms are excluded from the sample due to the inability to get access to relevant information. The remaining 106 firms are used in this investigation, including 8 Danish and 98 Swedish firms. During the period 2007-12-31 to 2011-12-31, 41 firms are delisted and 11 firms are considered to be delisted as a result of financial distress. 65 firms are still listed on 2011-12-31.

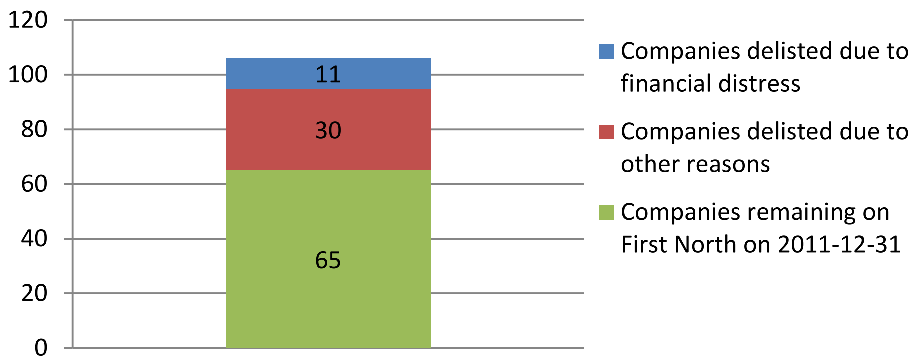
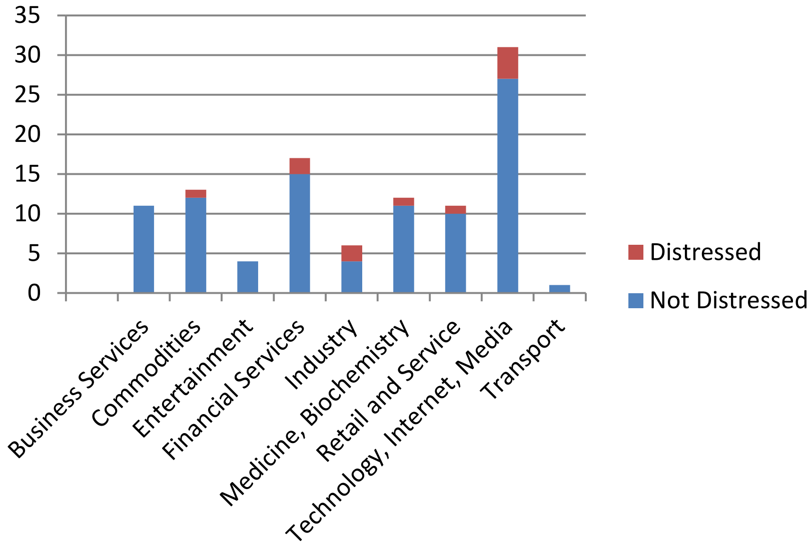


Table 1. The firm events during the period 2007-12-31 to 2011-12-31.

4.2 DATA MANAGEMENT

A detailed examination of the firms' dividend payouts and equity issues is carried out. Unfortunately only one firm evidently paid out dividends in 2007, and for that reason no further test can be made for dividend payouts. The same applies to equity issues where only 4 out of 106 firms issued new equity during 2007 hence the factor is no further used to predict financial distress. Credit ratings which according to Graham et al. (2011) have a great predictable power to financial distress can not further be investigated due to the absence of credit ratings for the firms listed on the First North. This may have its explanation in the cost of the credit rating issuance where many small firms choose not to invest in a credit rating until the economy is relatively stable. Due to insufficient data these three hypotheses cannot be tester nor answered.

The sample is divided into industry affiliation to check for potential relationships among the distressed firms. The classification is based on a simplified version of the Global Industry Classification Standard but due to limited number of sectors the sample is reduced down to nine different sectors: Business Services, Commodities, Entertainment, Financial Services, Industrial firms, Medicine & Biochemistry, Retail & Service, Technology/Internet/Media and Transport. According to the classification, the sector Technology/Internet/Media holds the predominant position for distressed firms but also the sector holding the largest number of firms. Due to a small sample size and a large number of sectors, no reliable relationship can be determined. Hence, no tests are further made on industrial affiliation's impact on financial distress.



4.3 ASSUMPTIONS UNDERLYING THE LOGISTIC REGRESSION

There are two underlying assumptions of the logistic regression. The first one is dealing with the distribution associated with the binary outcome, it presumes that each of the potential outcomes of the variable Y has a corresponding expected probability that varies as a function of the values of the independent variables. The second assumption is that the coefficents of the logsitic regression can be obtained through ML estimation. In some cases it is imposible to obtain the log-likelihood value or there may be more than one obtained log-likelihood value. In those cases it would not be appropriate to use ML estimation. An additional implication in the logistic regression is that no assumptions are made about the distributions of the explanatory variables. However, the explanatory variables should not be highly correlated with one another because this could cause problems with multicollinearity. The first assumption restict the probabilities to remain within the interval of 0,0 to 1,0. This is always accurate and will not cause any problems for the investigation. If concerns regarding the second assumption take place, this appears when running the regressions, if no log-likelihood values is obtained the model will fail and the statistical software Minitab will not be able to produce any results. If multiple log likelihood values are obtained, Minitab will choose one of these depended on the initial value. If no such problem arises when conducting the regressions, the second assumption is considered not to cause any problems. The correlation between the variables is examined by constructing a correlation matrix.

Finanlly only four out of eight hypotheses are qualified for investigation; financial leverage, liquidity, profitability and age.

4.4 CORRELATION BETWEEN VARIABLES

Multicollinearity is a statistical problem which occurs when high correlation exists between the independent variables in a multiple regression model. It does not affect how the overall independent variables predict the dependent variable, but it may give incorrect results about how the individual independent variable affects the dependent variable (Körner and Wahlgren, 2006). In order to avoid this problem a correlation matrix among the individual variables are constructed.

CORRELATION MATRIX INDEPENDENT VARIABLES

	Return on Total Assets	**Debt-to-Equity ratio**	**Interest Coverage ratio**	**CA-TA ratio**
Debt-to-Equity ratio	*0,109* *(0,264)*			
Interest Coverage ratio	*0,253* *(0,009)*	*0,010* *(0,920)*		
CA-TA ratio	*0,041* *(0,675)*	*0,021* *(0,832)*	*0,133* *(0,175)*	
Age	*0,124* *(0,205)*	*0,047* *(0,631)*	*0,061* *(0,538)*	*-0,002* *(0,982)*

The interpretation of the correlation matrix is done using a rule of thumb which states that correlation between the independent variables ranging between -0,7 and +0,7 will not affect the regression analysis (Rundqvist, 2011). The results of the correlation matrix range within this interval and the risk for Multicollinearity is therefore considered low.

4.5 LOGISTIC REGRESSION

This section determines the factors which possess the ability to predict the probability to encountering financial distress during a financial crisis. The first step is to investigate the predictable power of each of the individual factors. Hence, after the factors are examined, the ones who appear to have a significant predictable power are combined into the model of distress prediction.

4.5.1 FINANCIAL LEVERAGE

To investigate whether financial leverage possesses the ability to predict the probability of encounter financial distress, a series if logistic regression analyses is carried out, using the debt to equity ratio as explanatory variable of distress. Two tests are made, the first one uses the actual observed debt to equity ratios as explanatory variable. In the second test an adjusted series of debt to equity ratios are used. The motive behind the second test is that there is one extreme observation, one firm has a debt to equity ratio of 47,04 (the second highest debt to equity ratio is 16,8). This observation is considered to be abnormal and is therefore replaced by the sample's average debt to equity ratio. The complete results of the two tests can be found in appendix 3 and 4. The results of the two tests are similar hence, only the second test is displayed below.

LOGISTIC REGRESSION TABLE

Predictor	**Coef**	**SE Coef**	**Z**	**P**	**Odds Ratio**	**95 % CI Lower**	**Upper**
Constant	*-2,23611*	*0,370307*	*-6,04*	*0,000*			
Debt to Equity ratio Adjusted	*0,0515694*	*0,110799*	*0,47*	*0,642*	*1,05*	*0,85*	*1,31*

Log-Likelihood = -35,228
Test that all slopes are zero: G = 0,202, DF = 1, P-Value = 0,653

The logistic regression table displays the estimated coefficients, standard error of the coefficients, z-values and p-values together with the odds ratio and a 95% interval of the odds ratio. The p-value is not significant indicating that the debt to equity ratio does not possess the ability to predict the probability of encounter financial distress. Because the debt to equity ratio is insignificant the odds ratio is irrelevant to interpret. The statistics G refer to a hypothesis test, where the null hypothesis is that the predictor coefficient is equal to zero, versus the hypothesis that the predictor coefficient is not equal to zero. In this case the p-value of the statistics G is insignificant suggesting that there is not enough evidence to conclude that the coefficient is different from zero. The results of these two tests indicate that there is not sufficient evidence to reject the null hypothesis.

4.5.2 LIQUIDITY

Two different variables are used to investigate if liquidity possesses the ability to predict the probability of encounter financial distress. These two measures are the CA-TA ratio (Current Assets to Total Assets ratio) and the Interest coverage ratio. These two measures are investigated individually using logistic regression analysis.

4.5.2.1 CA-TA ratio

Two logistic regression analyses are done using the CA-TA ratios as explanatory variable of financial distress. In the first test the actual observed CA-TA ratios are used as explanatory variables. In the second test the average of the CA-TA ratios received from 2006 and 2007 are used as explanatory variables. The reason behind the second test is that the observed CA-TA ratios deviate noticeably from one year to the next for some of the examined firms. By using the average CA-TA ratio, the risk of that the potential findings is a result of temporary high or low observed ratios is reduced. The complete results of the two tests can be found in appendix 5 and 6. The results of the two tests are similar, however the average CA-TA ratios provides the strongest results. The second test is displayed below.

LOGISTIC REGRESSION TABLE

Predictor	**Coef**	**SE Coef**	**Z**	**P**	**Odds Ratio**	**95 % CI Lower**	**Upper**
Constant	*-0,997192*	*0,616163*	*-1,62*	*0,106*			
CA-TA ratio Average	*-2,32223*	*1,20805*	*-1,92*	*0,055*	*0,10*	*0,01*	*1,05*

Log-Likelihood = -33,381
Test that all slopes are zero: G = 3,898, DF = 1, P-Value = 0,048

The result indicates that the CA-TA ratio posses the ability to predict the probability to encounter financial distress at the 10% significance level. Because the coefficient is significant it is relevant to interpret the odds ratio. The odds ratio suggests that a 1% increase in the CA-TA ratio will decrease the probability of ending up in distress by 90%. However, the range of the confidence interval is 0,01-1,05. The confidence interval reflects the reliability of the estimated odds ratio. The confidence interval 0,01-1,05 implies that with 95% certainty one can expect to observed an odds ratio within this interval. This indicates that the observed odds ratio is imprecise. The statistics G is significant at the 5% level suggesting that there is sufficient evidence that the coefficient is different from zero. To conclude the finding in the two tests, the CA-TA ratio possess the ability to predict the probability to encounter financial distress.

4.5.2.2 Interest Coverage ratio

Two logistic regressions are conducted using the interest coverage ratios as explanatory variable of financial distress. In the first test the actual observed interest coverage ratios are used as explanatory variables. The results of the first test produced insignificant results, implying that the interest coverage ratio does not possess the ability to predict the probability to encounter financial distress. The complete results of the first test can be seen in appendix 7. In the second test the interest coverage ratios are redefined as a binary variable. A binary variable can take only one of two values; in this case those values are positive or negative. Firms which have a positive interest coverage ratio will be assigned the value positive, regardless of how positive the interest coverage ratio is. Firms which have a negative interest coverage ratio, regardless of how negative the interest coverage is will be assigned the value negative. The motive behind the second test is that the there are a substantial spread between the observed interest coverage ratios, something that may effect the findings in the first test. The idea behind the second test is to investigate if a firm with a negative interest coverage ratio have a higher probability of encountering financial distress than a firm with a positive interest coverage ratio. The results of the second test are displayed below.

LOGISTIC REGRESSION TABLE

Predictor	**Coef**	**SE Coef**	**Z**	**P**	**Odds Ratio**	***95 % CI*** **Lower**	**Upper**
Constant	*-2,77259*	*0,595113*	*-4,66*	*0,000*			
Interest Coverage ratio New 1 (financial distress)	*1,00188*	*0,707415*	*1,42*	*0,157*	*2,72*	*0,68*	*10,90*

Log-Likelihood = -34,220
Test that all slopes are zero: G = 2,218, DF = 1, P-Value = 0,136

Even the second test is insignificant according to the p-value. The finding in these two tests suggests that the interest coverage ratio does not possess the ability to predict the probability to encounter financial distress.

4.5.3 PROFITABILITY

In order to determine whether profitability possess the ability to predict the probability of encounter financial distress, a series if logistic regression analyses is carried out, using return on total assets as explanatory variable of distress. The same procedure is made for this variable where two tests are carried out. The first test uses the actual observed debt to equity ratios as explanatory variable. The test produces insignificant results which imply that return on total assets do not possess the ability to predict the probability to encounter financial distress. The complete results of the first test can be seen in appendix 9. In the second test an adjusted series of return on total assets are used. The motive behind the second test is that there are two extreme values, which may affect the results in the first test. One firm has a negative return on total assets of -414% and another have a negative return on total assets of -368%. These two observations are considered to be abnormal and are therefore replaced by the sample average return on total assets. The complete results of the two tests can be found in appendix 9 and 10. The results of the two tests are similar, therefore only the second test is displayed below.

LOGISTIC REGRESSION TABLE

Predictor	**Coef**	**SE Coef**	**Z**	**P**	**Odds Ratio**	**95 % CI Lower**	**Upper**
Constant	*-2,38424*	*0,372006*	*-6,41*	*0,000*			
Return on Total Assets Adjusted	*-1,60863*	*0,918558*	*-1,75*	*0,080*	*0,20*	*0,03*	*1,21*

Log-Likelihood = -33,926
Test that all slopes are zero: G = 2,807, DF = 1, P-Value = 0,094

The result indicates that the return on total assets posses the ability to predict the probability to encounter financial distress at the 10% significance level. The odds ratio suggests that a 1% increase in return on total assets, will decrease the probability of ending up in distress by 80%. The range of the confidence interval is 0,03-1,21, indicating that that the estimated odds ratio of 0,20 is imprecise. The p-value of the statistics G is significant at the 10 % level suggesting that there is sufficient evidence that the coefficient is different from zero. The result suggests that there is enough proof to reject the null hypothesis. Hence, return on total assets possesses the ability to predict the probability to encounter financial distress during a financial crisis.

4.5.4 AGE

To investigate if age possesses the ability to predict the probability of encounter financial distress, a logistic regression analysis is carried out, using age as explanatory variable of financial distress. The results of the logistic regression are shown below and a complete review can be found in appendix 11.

LOGISTIC REGRESSION TABLE

Predictor	**Coef**	**SE Coef**	**Z**	**P**	**Odds Ratio**	**95 % CI Lower**	**Upper**
Constant	*-1,34917*	*0,470966*	*-2,86*	*0,004*			
Age	*-0,115841*	*0,0646412*	*-1,79*	*0,073*	*0,89*	*0,78*	*1,01*

Log-Likelihood = -33,064
Test that all slopes are zero: G = 4,531, DF = 1, P-Value = 0,033

The result suggests that age is significant at the 10% level. The odds ratio indicates that a one year increase in age, will decrease the probability of ending up in distress by 11%. The confidence interval reflects the reliability of the estimate, the interval is 0,78-1,01. With 95% certainty one can expect to observe the odds ratio within this range. In this case the p-value of the statistics G is significant at the 5% level suggesting that there is sufficient evidence that the coefficient is different from zero. The result suggests that there is enough proof to reject the null hypothesis hence, age possess the ability to predict the probability to encounter financial distress during a financial crisis.

4.5.5 SUMMARY OF THE RESULTS OF THE HYPOTHESIS TESTS

The table below displays a summary of the empirical findings of the investigation which have been described previously in this chapter.

SUMMARY OF THE RESULT FROM THE HYPOTHESIS TESTS

Variable	**Alternative hypothesis**	**Measure**	**Action**	**P-value**
Financial Leverage	*Financial leverage possess the ability to predict the probability to encounter financial distress*	*Debt to equity measure*	*Rejected*	*0,642*
Credit Rating	*Credit rating possess the ability to predict the probability to encounter financial distress*	*A hypothesis test could not be due to too few available credit ratings*		
Liquidity	*Liquidity possess the ability to predict the probability to encounter financial distress*	*CA-TA ratio*	*Accepted*	*0,055*
		Interest Coverage ratio	*Rejected*	*0,157*
Profitability	*Profitability possess the ability to predict the probability to encounter financial distress*	*Return on Total Assets*	*Accepted*	*0,080*
Age	*Age possess the ability to predict the probability to encounter financial distress*	*Age*	*Accepted*	*0,073*
Industry Affiliation	*Industrial affiliation possess the ability to predict the probability to encounter financial distress*	*The industry affiliation hypothesis could be rejected without an hypothesis test just by studying the data material*		
Dividends	*Dividend payouts possess the ability to predict the probability to encounter financial distress*	*A hypothesis test could not be conducted due to insufficient number of firms which paid out dividends*		
Equity Issues	*Equity issues possess the ability to predict the probability to encounter financial distress*	*A hypothesis test could not be conducted due to insufficient number of firms that issued new equity*		

These findings form the foundation for the construction of the combined model of distress prediction.

4.5.6 COMBINED MODEL OF DISTRESS PREDICTION

The results of the individual tests indicate that age, CA-TA ratio and return on total assets individually possess the ability to predict the probability to encounter financial distress during a financial crisis. In this section these three variables are used to construct a model of distress prediction. [1] The model building is done using a forward selection approach. In this approach the variables are added one at a time, starting with the variable that has the highest correlation with the dependent variable (Agresti, 2007). The correlation matrix suggests that CA-TA ratio and return on total assets have the highest correlation with financial distress.

CORRELATION MATRIX BETWEEN FINANCIAL DISTRESS AND THE EXPLANATORY VARIABLES

	Financial distress	**Return on total assets adjusted**	**Age**
Return on total assets adjusted	*-0,177*		
Age	*-0,160*	*0,109*	
CA-TA ratio average	*-0,193*	*0,140*	*0,002*

Consequently, the first model of distress prediction uses the CA-TA ratios and return on total assets as explanatory variables of financial distress. The results of the logistic regression can be found in the table below.

LOGISTIC REGRESSION TABLE

Predictor	**Coef**	**SE Coef**	**Z**	**P**	**Odds Ratio**	**95 % CI Lower**	**Upper**
Constant	*-1,19756*	*0,662064*	*-1,81*	*0,070*			
Return on total asset	*-1,56953*	*0,946400*	*-1,66*	*0,097*	*0,21*	*0,03*	*1,33*
CA-TA ratio	*-2,40352*	*1,29975*	*-1,85*	*0,064*	*0,09*	*0,01*	*1,15*

Log-Likelihood = -32,118
Test that all slopes are zero: G = 6,424, DF = 2, P-Value = 0,040

A second logistic regression analysis is further made including age as explanatory variable. The results of the second test can be seen in appendix 12. To determine witch of the models

[1] The individual tests of the CA-TA ratios indicate that the average CA-TA ratios provides the strongest results, therefore the average CA-TA values are used in the combined test. The individual test of the return on total assets indicates that the highest predicative power is obtained by using the adjusted return on total assets. Thus, the adjusted return on total assets is used in the combined test.

that have the best fit the log-likelihood values and the Akaike Information Criterion (AIC) is used. The log-likelihood is preferable compared to other simple measures to compare the fit of two models when the numbers of variables are few. The Akaike Information Criterion (AIC) is similar to the r-square measure in OLS as it penalizes the statistic as extra variables are included in the model (Agresti, 2007). AIC is estimated in the following manner:

$$AIC = -2(maximized\ log\ likelihood - number\ of\ parameters\ in\ the\ model)$$

The second test exhibit higher log likelihood, however when the increased number of variables are taken into account, using the AIC, it appears to have a lower fit than the first test. An additional feature is that the return on total assets is no longer significant. Based on this observation a third test conducted where return on total assets is removed, using CA-TA ratio and age as explanatory variables. The third test can be seen entirely in appendix 14. A summary of the results from the three tests can be seen in the table below.

SUMMARY OF THE MODEL BUILDING TEST

Variables is the combined model of distress prediction	Log Likelihood	AIC
CA-TA ratio and return on total assets	*-32,118*	*68,236*
Age and CA-TA ratio	*-31,187*	*66,374*
Age, CA-TA ratio and return on total assets	*-30,139*	*66,278*

The results indicate that the best predictable power can be obtained by using the CA-TA ratio and the return on total asserts into a combined test of distress prediction (in has the highest AIC). The results of the combined model indicate that age and the CA-TA ratios are significant at a 10% level. However, the range of the confidence interval indicates that the odds ratios are imprecise. The p-value of the statistics G is significant at the 5% level, indicating that at least one of the coefficients is different from zero. The conclusion is that even though the model is significant it does an incomplete job explaining financial distress.

5 ANALYSIS AND FINAL DISCUSSION

In the analysis and discussion section, an analysis is carried out based on the results obtained from the logistic regressions. A discussion of whether the results are consistent with previous theory is provided followed by a discussion of the potential reasons for the obtained results.

The logistic regressions determine that age has the most sufficient explanatory power of financial distress followed by liquidity and profitability although non is significant at a 5 % level. Surprisingly, no significant relationship is found for financial leverage, hence a relationship between financial leverage and financial distress cannot be proven. It is of interest to further investigate the results and to specifically investigate the insignificant relationship obtained for financial leverage and financial distress among the firms listed on the First North during the recent financial crisis since it contradicts the statement from several prior studies.

The purpose of this paper is to determine the factors which possess the ability to predict the probability to encounter financial distress during a financial crisis. It is of particular interest to test whether financial leverage has a significant effect on financial distress since prior studies as Graham et al. (2011) advocates that the likelihood of financial distress can solely be explained by a firm's indebtedness and credit rating and neither age, profitability nor liquidity possesses the power to explain financial distress at this time. Consequently, the result for this study is confirmed to differ considerably from the result by Graham et al. when the list is changed from the New York Exchange to the Nasdaq OMX First North. During the investigation, four out of eight factors are excluded due to insufficient information, hence; credit rating, industrial affiliation, dividend payouts and equity issues are not further tested nor further analyzed as potential predictors to financial distress.

5.1 FINANCIAL LEVERAGE

Related to previous studies, financial leverage has been discussed and classified as a major contributing factor to financial distress. Credit rating agencies, which have the power to evaluate a firm's creditworthiness, base their judgment of a firm's financial health on the distance between a firm's market value of assets and book value of debt. Thus, taking on debt needs be beneficial for the firm and enhance the firm's market value to the same extent as the increased debt level in order to remain on the same credit score. This goes along with the traditional trade-off theory which argues for an optimal debt level where the trade off between the advantages and disadvantages of debt are balanced. In contrary, the Pecking-Order theory advocates that the financial health of the firm is reflected in its choice of financing method meaning debt financing are preferred before any other external financing methods although internal funds are to be exercised first.

Graham et al. (2011) advocate that according to their results, it is only financial leverage and credit rating which possess the ability to predict financial distress. However, their sample consists of large capitalized firms listed on NYSE including strict listing requirements indicating to an overall stable economic condition. This study on the other hand, focuses on small and risky firms which do not qualify to any of the lists on the stock exchange. Additionally the results received from the logistic regressions for this study determine no significant relationship between financial leverage and financial distress which contradicts both the argument by Graham et al. and the argument by Opler and Titman (1994) saying that heavily borrowed firms during a financial crisis possess a higher risk of encountering financial distress.

A reasonable explanation for the contradictory result is the change of list. According to Craig et al. (2007), banks tend to lower the probability for small firms to obtain credit since small firms are often classified to possess a higher risk of default which contributes to a higher degree of speculation. Consequently, it can be interpreted such that small firms which succeed to obtain credit instead possess a sufficiently strong financial position in order to convince the banks of their solvency. Additionally, the investigation is applied on the financial crisis where the market contains a shortfall in lending making the firms which are denied credit during normal economical conditions to be the ones to suffer during a crisis. Hence, in the case of this study, an increase in financial leverage does not necessarily have to increase the risk of financial distress and can instead symbolize stability and a lower risk of encountering financial distress. Although the argument that financial leverage ties up capital and makes the firm less liquid is sill valid thus, in the case of small firms the financial stability of the firm might out-concur the disadvantage of illiquidity.

Due to the ambiguous way to interpret the relationship between increased financial leverage and financial distress during the investigation period, holding a high degree of debt for the firms on the First North both symbolizes financial stability and an increased risk of encounter financial distress. It is therefore not irrational that this study determines the relationship insignificant. The firms which are not allowed to obtain debt from the commercial banks due to poor creditworthiness always find other sources of credit where the requirements are lower. Thus, high financial leverage does not necessarily have to symbolize stability to the same extent as it necessarily does not have to symbolize instability. Financial leverage affects the firms on First North in both ways where some highly leveraged firms encounter financial distress due to no sufficient power to meet its credit obligations and some highly leveraged firms managed not to encounter financial distress due to a stable pre financial crisis condition.

5.2 LIQUIDITY

Generally, liquidity is defined as the ability to convert assets into cash within one year at a price close to its fair value. Possess a high degree of tied up capital reduces liquidity and the firm gets more vulnerable during times of crisis (Altman, 1991). Platt (1999) further develops this argument and advocates that the risk of financial distress is directly related to the firm's mix of assets indicating that a firm increases its risk to encounter financial distress does not necessarily have to depend on being heavily weighted towards fixed assets but also towards current assets.

In order to make sure to capture the liquidity for the firms listed on First North, liquidity is measured from two perspectives. First, the current assets are weighted against total assets which go along with the traditional argument for liquidity. Secondly, liquidity is measured in the firm's ability to cover its financial expenses. According to the logistic regression, the CA-TA ratio is significant at the 10% level, further indicating that the more current assets the firm possesses in relation to its total assets, the less likely the firm is to end up in financial distress. The measure is consistent with the one used by Graham et al. (2011), but it also contradicts the argument by Platt meaning that an asset mix too heavily weighted towards current assets might make the management misinterpret the future product market. Hence, in the case of Platt, a large CA-TA ratio might also increase the risk of encounter financial distress. Graham et al. do not find a sufficient relationship between liquidity and financial distress and additionally contradict Altman's theory that liquidity is one important factor to influence financial distress. A reasonable explanation for the quite week relationship obtained in this study and the insignificant relationship obtained for Graham et al., might be influenced by the inaccuracy of solely focusing on the befit of current assets and not consider the disadvantage of the fact that the firm might loose market share and growing potential as a consequence of low investments. In the case of a financial crisis it is important to, specifically for small firms, to have additional capital to be able to deal with unpredictable situations. For this reason the benefits of possessing enough current assets in order to prevent financial distress might be of higher importance than the benefits of investment and increased market share during this time. For large and mature firms it might be less critical to hold fewer current assets during a crisis due to the ability to easier obtain credit and receive backup and it is instead more important not to loose market share. For that reason, it is realistic that the relationship between liquidity and financial distress is determined insignificant for the firms listed on NYSE whereas a significant relationship is determined for the firms listed on First North.

A second explanation to the weak relationship might be industrial differences in liquidity. While testing industrial affiliation's influence on financial distress, it is established that First North contains too many industries to possible find a significant relationship among the delisted firms and industrial affiliation. It also makes it hard to construct a fair estimation of the level of liquidity since the meaning of the ratio differs substantially from industry to industry. For instance, liquidity is on average higher for the service industry than for the real estate industry, due to the different amount of fixed assets, but does not necessarily indicate that the real estate industry faces a higher risk to encounter financial distress. For that reason the risk of obtaining a biased result is large. A weak significant relationship is therefore predictable when the measure is compared among firms within different industries. Relating to the result by Graham et al., the insignificant relationship can therefore be related to the number of different industries listed on the NYSE.

The interest coverage ratio is further investigated with the reason that the ability to cover the financial expenses is of great importance for a firm's solvency. By performing a logistic regression for the interest coverage ratio, no sufficient evidence is found that a relationship between interest coverage ratio and financial distress exists. Due to the relation between interest coverage ratio and financial leverage, the same argument is applied here as for the relationship between leverage and financial distress. No sufficient evidence is found that a relationship between financial distress and financial leverage exist among the firms listed on First North due to the ambiguous argument of the impact of financial leverage. The relationship can also be discussed based on the relationship between risk and return. The interest rate reflects the return the investor require for the amount of risk taken meaning that if the firm contain high interest expenses in relation to its total value of debt it also reflect the questioned financial stability of the firm. There are too many ways of interpreting the reason for a high/low interest coverage ratio hence it is not surprising that the relationship is insignificant.

5.3 PROFITABILITY

Profitability is one of the main sources of funds available to the firm in order to satisfy its stakeholder's interests. Consequently, a low or negative profitability implies that the firm is less capable of satisfy these interests. If the firm encounters financial difficulties it is reasonable to assume that, if the stakeholder are not satisfied, they will be more reluctant to contribute with additional funds to solve the difficulties. Hence, it will result in more failures among firms with a history of low profitability. The result of the logistic regression renders, in contrast to Graham et al. (2011), a significant relationship between profitability and distress. The results indicate, although weak, that an increase in profitability decreases the probability of encountering financial distress which are consistent with the findings of Opler and Titman (1994) arguing for a relationship between financial distress and loss in sales.

One reasonable explanation for the contradictive result obtained for this study and the study by Graham et al. might once again be based on the choice of list. According to Storey et al. (1987) the current profitability of a small growing firm does not necessarily reflect the "true" profitability of the firm, due to high current investment expenses in the growing stage, but holds a high potential of increased future profits. Hence, the argument for an increased risk of encounter financial distress and low profitability does not have to be accurate in the case of small firms with growing potential. The argument is reasonable, and can therefore have weakened the significance for profitability's ability to predict financial distress. The findings are however significant, and determine profitability to be an approved measure to predict financial distress.

5.4 AGE

Evidence is found that age possess the ability to predict financial distress. These results are in line with the "liability of newness" by Stinchcombe, (1965) which is further confirmed by Freeman el al., (1983) proving that an increase in age reflects a firm's business model capability of standing the test of time. Thus, the findings in this paper may be the result of a survivorship bias. The firms with insufficient business models or those who are unable to construct efficient organization tend not to survive the hard competition on the market, resulting in a situation where only the strongest firms survive. Stinchcombe argue that the reason for this is that younger firms suffer a higher risk of failure because due to the absence of an equally developed organization and competitive capabilities compared with older firms. Freeman et al. confirms his argument and state that the highest frequency of death rates among firms tend to appear during the first year of operation. In order to capture the effect whether age possess the ability to predict financial distress, a test is performed using the years the firm has been listed on the stock market. In contrast to the result by Graham et al. (2011) age do possess a significant ability to predict financial distress among the firms listed on First North. The difference between the study by Graham et al. and this study can for that reason be traced back to the theory by Freeman et al. stating that the frequency of death rate is the highest during the first operational year. On First North an average firm holds an age of 9,5 years, indicating that a large proportion of the firms are in their early stages of operation. NYSE on the other hand, contains listing requirements requiring a positive result during the last three years meaning that NYES does not include firms during their first year of operation. For that reason, it is not surprising that age is significant for First North and not for NYSE.

5.5 COMBINED TEST OF DISTRESS PREDICTION

At the attempt to construct a combined model of distress prediction the variables that are significant individually yielded unsatisfactory results. The most likely cause behind this is missing variable bias where the combined model contains too few explanatory variables which in turn depends on that too few variables are included into the overall investigation. In addition to the missing variable bias, also the weak findings in the individual tests result in a weak combined test. This is evidenced by the fact that when the third variable age is included into the combined model, return on total assets is insignificant. The result goes inline with the individual tests for liquidity and profitability which however indicates that these factors affect the probability of financial distress.

Since the purpose is to determine the factors possessing the ability to predict financial distress, with a particular interest in financial leverage, using the paper by Graham et al as a benchmark seems reasonable due to a similar study obtaining contradictory results. The differences in the result have mainly been traced back to the sample specifically focusing on the size of the firms. What have not been discussed is whether the legal legislation differences have had an impact on the differenced results obtained. Referring back to the paper by Buttwill (2004) the Scandinavian countries have been classified as containing much higher bankruptcy frequencies in comparison to the US. This can be interpreted such that among all the factors investigated, a significant result is found for three out of four factors for the Swedish and Danish firms whereas only one out of four are significant for the American firms. The obtained outcome might be influenced by the fact that fewer firm on the NYSE got distressed compared to the First North, and for that reason the firms on the NYSE might be affected the same as the firms on First North but due to the differences in the legal legislation in bankruptcies the results determine the firms on First North to be affected by more factors.

6 CONCLUSIONS

The last chapter incorporates the conclusions made from the empirical findings, analysis and the theoretical framework. Additionally, suggestions of potential improvements of predicting financial distress are made for future research.

Financial distress has during the last decade been investigated by numerous studies for the reason to determine the factors which affect the risk of bankruptcy. The purpose of this study is to determine the factors which possess the ability to predict the probability of encounter financial distress during times of financial crisis. A particular interest is to determine the size of the firm influence on financial distress during a depression era. This incorporates both the theory by Graham et al. (2011) Bernanke (2004) and Altman (1968).

6.1 CONCLUSION

The factors which hold the ability to predict financial distress during the crisis 2008-2009 for the firms listed on Nasdaq OMX First North are determined to be age, liquidity, profitability. Age is the factors holding the best predicable power due to First North's low listing requirement, allowing firms younger than one year to become listed. These firms are considered to be the ones with the highest bankruptcy frequency according to Freeman et al. (1983). Graham et al. did however not find a relationship between financial distress and age among the firms listed on NYSE which may depend on the fact that firms listed on NYSE does not approve firms of such risky character. Profitability is determined, although weak, to hold the ability to predict financial distress, indicating that the current profitability for small firms does not necessarily reflect the true profitability due to growing opportunities. Hence, the result is significant but weak. The results determine liquidity, the CA-TA ratio, to weakly possess the ability to predict financial distress which mainly depends on the fact that during times of crisis the advantage of holding liquid assets, especially for small firms, is larger. The result is weak and for the firms listed on NYSE it is insignificant. The reason is concluded to depend on the inaccuracy of the CA-TA ratio which excludes the disadvantages of holding too much current assets. Larger firms possess the ability to easier obtain credit or other support during times of crisis reducing the importance of current assets the firms listed on the NYSE. Additionally, liquidity is also hard to compare among different industries which contributes to a weak relationship among the firms listed on the First North.

Contrariwise, financial leverage does not possess the ability to predict financial distress among the firms listed on First North for the reason that heavy debt financing in the context of small and risky firms are ambiguous. The factor symbolizes both financial stability due to the ability to convince their creditors of their creditworthiness along with instability due to reduced financial flexibility. This study contradicts the results obtained by Graham et al. meaning that financial leverage and bond rating are the only factors able to predict financial distress.

In conclusion, the size of the investigated firms does have an influence on which factors that possess the ability to predict financial distress due to the contradictory result obtained in comparison to Graham et al. (2011). Moreover, the different legal legislation policies for bankruptcy do also contribute. Scandinavia does have more favorable policies concerning bankruptcies compare to the US, meaning that Scandinavian firms are generally more affected by the factors, in the context of financial distress, than the US. It also have to be considered that the results obtained by Graham et al. are significant at a 5 % level whereas for this study the conclusions are based on a significant level of 10%. This truly has an impact on the comparison between this study the study by Graham et al.

6.2 EXTENDED RESEARCH

Increasing the sample by including the whole Nasdaq OMX Nordic would make it possible to draw conclusions about the relationship between industrial affiliation and financial distress during the same time period. Additionally, an investigation can be made on whether the factors have different impact on financial distress within different industries. For instance liquidity, the amount of current assets within a firm differs exceptionally between financial services and the real estate industry. A real estate firm which possesses a low CA-TA ratio does not necessarily have to have a higher probability to encounter financial distress than a firm possessing a high CA-TA within the financial services industry. In that way, the study will be more reliable since the assumption that all industries reacts the same to a factor is not made. By including more ratios for each factor, the reliability of the investigation will be higher. Consequently, the drawbacks with each ratio will be covered by the advantages in another. In this way it is easier to determine the factors' impact on financial distress. Additionally, by further investigate the firms which were subject of M&A will make it possible to establish whether the M&A were carried out due to financial difficulties or other reasons. The sample period could perhaps be extended to other recent crises in order to make the research findings more robust.

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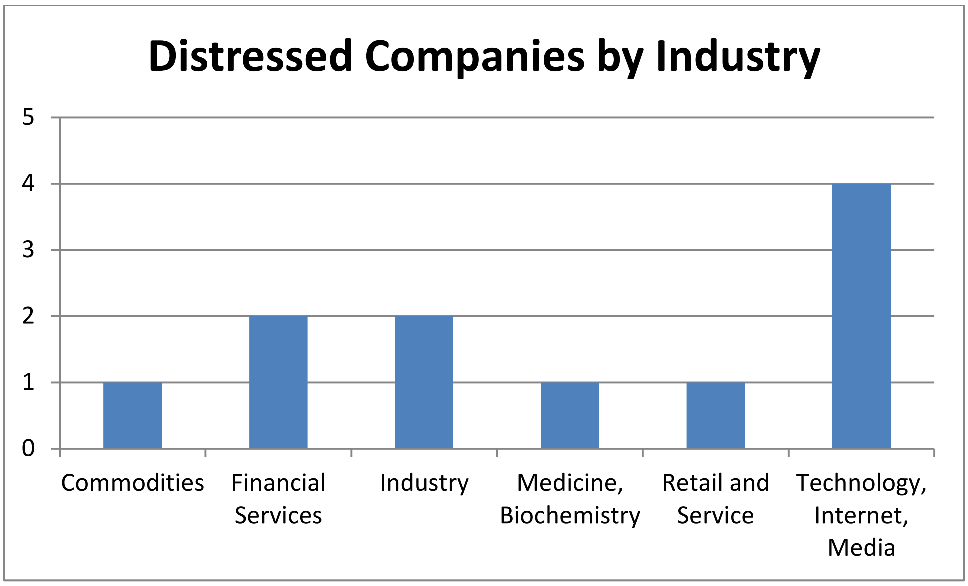
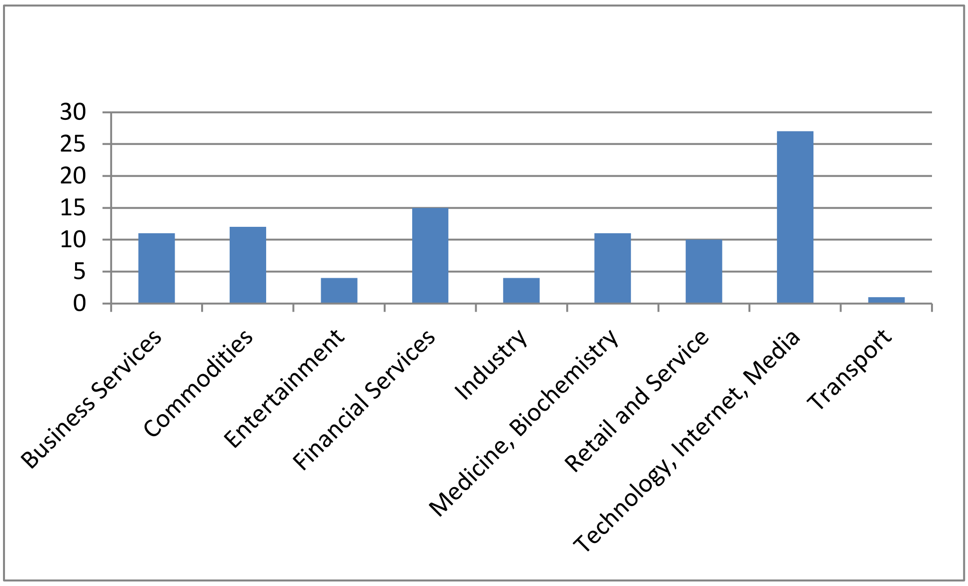
APPENDIX

Appendix 1

Industry affiliation, data description



The table above display the number of distressed companies acording to there industry affiliation.



The table above display the number of the companies listed on Nasdaq OMX First North on 2007-12-31 according to there industry affiliation.

Appendix 2

Hypothesis test of off-balance sheet financing

ONE-SAMPLE T: OFF-BALANCE SHEET TO TA RATIO

Test of mu = *0,06 vs < 0,06*

Variable	**N**	**Mean**	**StDev**	**SE Mean**	**Bound**	**T**	**P**	**95 % Upper**
Off-balance sheet to TA	*10*	*0,0350*	*0,0324*	*0,0102*	*0,0538*	*-2,44*	*0,019*	

Appendix 3

Logistic regression using the debt to equity ratio as explanatory variable

Binary Logistic Regression: Distress versus Financial Leverage

Link Function: Logit

Response Information

Variable	Value	Count	
Distress	1	11	(Event)
	0	95	
	Total	106	

Logistic Regression Table

					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Constant	-2,14892	0,338962	-6,34	0,000			
Debt to equity	-0,0039146	0,0657462	-0,06	0,953	1,00	0,88	1,13

Log-Likelihood = -35,328
Test that all slopes are zero: G = 0,004, DF = 1, P-Value = 0,952

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	98,8780	85	0,144
Deviance	66,8360	85	0,927
Hosmer-Lemeshow	16,1275	8	0,041
Brown:			
General Alternative	0,1835	2	0,912
Symmetric Alternative	0,0011	1	0,974

Table of Observed and Expected Frequencies:
(See Hosmer-Lemeshow Test for the Pearson Chi-Square Statistic)

	Group										
Value	1	2	3	4	5	6	7	8	9	10	Total
1											
Obs	2	2	0	0	1	0	1	0	1	4	11
Exp	1,0	1,1	1,0	1,1	1,1	1,3	1,0	1,0	1,1	1,1	
0											
Obs	8	9	10	11	10	12	9	10	10	6	95
Exp	9,0	9,9	9,0	9,9	9,9	10,7	9,0	9,0	9,9	8,9	
Total	10	11	10	11	11	12	10	10	11	10	106

Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	540	51,7	Somers' D	0,13
Discordant	408	39,0	Goodman-Kruskal Gamma	0,14
Ties	97	9,3	Kendall's Tau-a	0,02
Total	1045	100,0		

Appendix 4

Logistic regression using the adjusted debt to equity ratio as explanatory variable

Binary Logistic Regression: Distress versus Financial Leverage

Link Function: Logit

Response Information

Variable	Value	Count	
Distress	1	11	(Event)
	0	95	
	Total	106	

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Constant	-2,23611	0,370307	-6,04	0,000			
Debt to equity Adjusted	0,0515694	0,110799	0,47	0,642	1,05	0,85	1,31

Log-Likelihood = -35,228
Test that all slopes are zero: G = 0,202, DF = 1, P-Value = 0,653

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	101,129	85	0,112
Deviance	66,638	85	0,930
Hosmer-Lemeshow	17,029	8	0,030
Brown:			
General Alternative	15,181	2	0,001
Symmetric Alternative	13,656	1	0,000

Table of Observed and Expected Frequencies:
(See Hosmer-Lemeshow Test for the Pearson Chi-Square Statistic)

Value	Group 1	2	3	4	5	6	7	8	9	10	Total
1											
Obs	4	1	0	1	0	1	0	0	2	2	11
Exp	0,9	1,1	1,0	1,3	1,0	1,0	1,0	1,1	1,2	1,5	
0											
Obs	6	10	10	12	10	9	10	10	9	9	95
Exp	9,1	9,9	9,0	11,7	9,0	9,0	9,0	8,9	9,8	9,5	
Total	10	11	10	13	10	10	10	10	11	11	106

Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	444	42,5	Somers' D	-0,12
Discordant	569	54,4	Goodman-Kruskal Gamma	-0,12
Ties	32	3,1	Kendall's Tau-a	-0,02
Total	1045	100,0		

Appendix 5

Logistic regression using the CA-TA ratio as explanatory variable

Binary Logistic Regression: Distress versus CA-TA ratio

```
Link Function: Logit


Response Information

Variable  Value  Count
Distress  1         11  (Event)
          0         95
          Total    106


Logistic Regression Table

                                                   Odds     95% CI
Predictor           Coef   SE Coef      Z      P   Ratio  Lower  Upper
Constant        -1,19576  0,580936  -2,06  0,040
CA-TA ratio     -1,96782   1,13442  -1,73  0,083   0,14   0,02   1,29


Log-Likelihood = -33,763
Test that all slopes are zero: G = 3,133, DF = 1, P-Value = 0,077


Goodness-of-Fit Tests

Method                 Chi-Square  DF      P
Pearson                   77,0394  67  0,188
Deviance                  54,3425  67  0,867
Hosmer-Lemeshow            2,5705   8  0,958
Brown:
General Alternative        0,0399   2  0,980
Symmetric Alternative      0,0399   1  0,842


Table of Observed and Expected Frequencies:
(See Hosmer-Lemeshow Test for the Pearson Chi-Square Statistic)

                              Group
Value    1     2    3     4     5    6     7    8    9   10  Total
1
  Obs    0     1    1     0     1    1     2    1    2    2     11
  Exp  0,4   0,6  0,6   0,8   0,9  0,9   1,3  1,4  1,7  2,4
0
  Obs   10    10    9    11    10    9    10    9    8    9     95
  Exp  9,6  10,4  9,4  10,2  10,1  9,1  10,7  8,6  8,3  8,6
Total   10    11   10    11    11   10    12   10   10   11    106


Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs       Number  Percent  Summary Measures
Concordant     690     66,0  Somers' D              0,33
Discordant     349     33,4  Goodman-Kruskal Gamma  0,33
Ties             6      0,6  Kendall's Tau-a        0,06
Total         1045    100,0
```

Appendix 6

Logistic regression using the average CA-TA ratio as explanatory variable

Binary Logistic Regression: Distress versus average CA-TA ratio

```
Link Function: Logit


Response Information

Variable  Value  Count
Distress  1         11  (Event)
          0         95
          Total    106


Logistic Regression Table

                                                   Odds      95% CI
Predictor       Coef      SE Coef      Z      P    Ratio  Lower  Upper
Constant       -0,997192  0,616163   -1,62  0,106
CA-TA ratio    -2,32223   1,20805    -1,92  0,055   0,10   0,01   1,05
Average

Log-Likelihood = -33,381
Test that all slopes are zero: G = 3,898, DF = 1, P-Value = 0,048


Goodness-of-Fit Tests

Method                 Chi-Square  DF      P
Pearson                   57,7109  57  0,449
Deviance                  42,1205  57  0,930
Hosmer-Lemeshow            5,0967   8  0,747
Brown:
General Alternative        0,0330   2  0,984
Symmetric Alternative      0,0119   1  0,913


Table of Observed and Expected Frequencies:
(See Hosmer-Lemeshow Test for the Pearson Chi-Square Statistic)

                               Group
Value    1     2     3     4     5    6    7    8    9   10  Total
1
  Obs    0     1     1     0     1    1    3    1    1    2     11
  Exp  0,4   0,5   0,7   0,9   1,0  1,0  1,4  1,6  2,0  1,5
0
  Obs   10    11    11    13    11    9    8    9    9    4     95
  Exp  9,6  11,5  11,3  12,1  11,0  9,0  9,6  8,4  8,0  4,5
Total   10    12    12    13    12   10   11   10   10    6    106


Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs       Number  Percent  Summary Measures
Concordant     705     67,5  Somers' D               0,36
Discordant     328     31,4  Goodman-Kruskal Gamma  0,36
Ties            12      1,1  Kendall's Tau-a         0,07
Total         1045    100,0
```

Appendix 7

Logistic regression using the interest coverage ratio as explanatory variable.

Binary Logistic Regression: Distress versus Interest coverage ratio

Link Function: Logit

Response Information

Variable	Value	Count	
Distress	1	11	(Event)
	0	95	
	Total	106	

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	Upper
Constant	-2,15696	0,318795	-6,77	0,000			
Interest coverage ratio	-0,0000477	0,0004282	-0,11	0,911	1,00	1,00	1,00

Log-Likelihood = -35,323
Test that all slopes are zero: G = 0,013, DF = 1, P-Value = 0,910

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	96,2567	94	0,416
Deviance	64,1443	94	0,992
Hosmer-Lemeshow	9,0954	8	0,334
Brown:			
General Alternative	0,2858	2	0,867
Symmetric Alternative	0,0145	1	0,904

Table of Observed and Expected Frequencies:
(See Hosmer-Lemeshow Test for the Pearson Chi-Square Statistic)

	Group										
Value	1	2	3	4	5	6	7	8	9	10	Total
1											
Obs	1	0	0	2	1	0	1	2	3	1	11
Exp	1,0	1,1	1,0	2,1	1,0	1,0	1,0	1,0	1,0	0,6	
0											
Obs	9	11	10	18	9	10	9	8	7	4	95
Exp	9,0	9,9	9,0	17,9	9,0	9,0	9,0	9,0	9,0	4,4	
Total	10	11	10	20	10	10	10	10	10	5	106

Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	482	46,1	Somers' D	0,26
Discordant	206	19,7	Goodman-Kruskal Gamma	0,40
Ties	357	34,2	Kendall's Tau-a	0,05
Total	1045	100,0		

Appendix 8

Logistic regression using the interest coverage ratio, designed as a binary variable, as explanatory variable.

Binary Logistic Regression: Distress versus Interest coverage ratio

```
Link Function: Logit


Response Information

Variable  Value  Count
Distress  1         11  (Event)
          0         95
          Total    106


Factor Information

Factor                  Levels  Values
Interest coverage ratio      2  0; 1


Logistic Regression Table

                                                Odds     95% CI
Predictor      Coef   SE Coef      Z      P  Ratio  Lower  Upper
Constant   -2,77259  0,595113  -4,66  0,000
Interest coverage ratio
 1          1,00188  0,707415   1,42  0,157   2,72   0,68  10,90


Log-Likelihood = -34,220
Test that all slopes are zero: G = 2,218, DF = 1, P-Value = 0,136

* NOTE * No goodness of fit test performed.
* NOTE * The model uses all degrees of freedom.


Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs        Number  Percent  Summary Measures
Concordant      384     36,7  Somers' D              0,23
Discordant      141     13,5  Goodman-Kruskal Gamma  0,46
Ties            520     49,8  Kendall's Tau-a        0,04
Total          1045    100,0
```

Appendix 9

Logistic regression using the return on total assets as explanatory variable.

Binary Logistic Regression: Distress versus Return on Total Assets (ROTA)

Link Function: Logit

Response Information

Variable	Value	Count	
Distress	1	11	(Event)
	0	95	
	Total	106	

Logistic Regression Table

					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Constant	-2,17938	0,331643	-6,57	0,000			
ROTA	-0,0013177	0,0046374	-0,28	0,776	1,00	0,99	1,01

Log-Likelihood = -35,293
Test that all slopes are zero: G = 0,074, DF = 1, P-Value = 0,786

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	100,287	101	0,501
Deviance	67,813	101	0,995
Hosmer-Lemeshow	10,831	8	0,211
Brown:			
General Alternative	1,816	2	0,403
Symmetric Alternative	0,019	1	0,890

Table of Observed and Expected Frequencies:
(See Hosmer-Lemeshow Test for the Pearson Chi-Square Statistic)

	Group										
Value	1	2	3	4	5	6	7	8	9	10	Total
1											
Obs	1	0	0	0	3	2	0	2	1	2	11
Exp	1,0	1,1	1,0	1,1	1,1	1,0	1,1	1,0	1,2	1,3	
0											
Obs	9	11	10	11	8	8	11	8	10	9	95
Exp	9,0	9,9	9,0	9,9	9,9	9,0	9,9	9,0	9,8	9,7	
Total	10	11	10	11	11	10	11	10	11	11	106

Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	603	57,7	Somers' D	0,22
Discordant	377	36,1	Goodman-Kruskal Gamma	0,23
Ties	65	6,2	Kendall's Tau-a	0,04
Total	1045	100,0		

Appendix 10

Logistic regression using the adjusted return on total assets as explanatory variable.

Binary Logistic Regression: Distress versus Return on Total Assets (ROTA) w/o extreme values

Link Function: Logit

Response Information

Variable	Value	Count	
Distress	1	11	(Event)
	0	95	
	Total	106	

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Constant	-2,38424	0,372006	-6,41	0,000			
ROTA adjusted	-1,60863	0,918558	-1,75	0,080	0,20	0,03	1,21

Log-Likelihood = -33,926
Test that all slopes are zero: G = 2,807, DF = 1, P-Value = 0,094

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	50,6016	52	0,529
Deviance	43,2433	52	0,801
Hosmer-Lemeshow	3,3448	8	0,911
Brown:			
General Alternative	0,0341	2	0,983
Symmetric Alternative	0,0000	1	0,996

Table of Observed and Expected Frequencies:
(See Hosmer-Lemeshow Test for the Pearson Chi-Square Statistic)

	Group										
Value	1	2	3	4	5	6	7	8	9	10	Total
1											
Obs	1	0	0	1	2	1	1	2	1	2	11
Exp	0,6	0,8	0,8	1,1	1,2	0,9	1,0	1,2	1,6	1,9	
0											
Obs	10	11	10	12	12	9	9	8	9	5	95
Exp	10,4	10,2	9,2	11,9	12,8	9,1	9,0	8,8	8,4	5,1	
Total	11	11	10	13	14	10	10	10	10	7	106

Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	685	65,6	Somers' D	0,33
Discordant	343	32,8	Goodman-Kruskal Gamma	0,33
Ties	17	1,6	Kendall's Tau-a	0,06
Total	1045	100,0		

Appendix 11

Logistic regression using age as explanatory variable

Binary Logistic Regression: Distress versus Age

```
Link Function: Logit


Response Information

Variable  Value  Count
Distress  1         11  (Event)
          0         95
          Total    106


Logistic Regression Table

                                                  Odds      95% CI
Predictor       Coef    SE Coef      Z      P    Ratio  Lower  Upper
Constant    -1,34917   0,470966   -2,86  0,004
Age         -0,115841  0,0646412  -1,79  0,073   0,89   0,78   1,01


Log-Likelihood = -33,064
Test that all slopes are zero: G = 4,531, DF = 1, P-Value = 0,033


Goodness-of-Fit Tests

Method                 Chi-Square  DF      P
Pearson                   20,6085  25  0,714
Deviance                  15,6981  25  0,924
Hosmer-Lemeshow            5,9614   7  0,544
Brown:
General Alternative        0,0226   2  0,989
Symmetric Alternative      0,0007   1  0,980


Table of Observed and Expected Frequencies:
(See Hosmer-Lemeshow Test for the Pearson Chi-Square Statistic)

                             Group
Value    1     2     3     4     5    6     7     8    9  Total
1
  Obs    0     1     0     2     0    2     3     3    0     11
  Exp  0,1   0,4   0,8   1,0   1,5  1,4   3,0   2,4  0,4
0
  Obs   10    10    15    11    14    8    15    10    2     95
  Exp  9,9  10,6  14,2  12,0  12,5  8,6  15,0  10,6  1,6
Total   10    11    15    13    14   10    18    13    2    106


Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs       Number  Percent  Summary Measures
Concordant     679     65,0  Somers' D              0,38
Discordant     287     27,5  Goodman-Kruskal Gamma  0,41
Ties            79      7,6  Kendall's Tau-a        0,07
Total         1045    100,0
```

Appendix 12

Logistic regression using the CA-TA ratio and return on total assets as explanatory variables in a combined model of distress prediction.

Binary Logistic Regression: Distress versus Return on to; CA-TA Average

Link Function: Logit

Response Information

Variable	Value	Count	
Distress	1	11	(Event)
	0	95	
	Total	106	

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	Upper
Constant	-1,19756	0,662064	-1,81	0,070			
Return on total assets	-1,56953	0,946400	-1,66	0,097	0,21	0,03	1,33
CA-TA Average	-2,40352	1,29975	-1,85	0,064	0,09	0,01	1,15

Log-Likelihood = -32,118
Test that all slopes are zero: G = 6,424, DF = 2, P-Value = 0,040

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	101,464	101	0,468
Deviance	61,463	101	0,999
Hosmer-Lemeshow	2,534	8	0,960
Brown:			
General Alternative	1,288	2	0,525
Symmetric Alternative	0,233	1	0,629

Table of Observed and Expected Frequencies:
(See Hosmer-Lemeshow Test for the Pearson Chi-Square Statistic)

	Group										
Value	1	2	3	4	5	6	7	8	9	10	Total
1											
Obs	0	1	0	1	1	1	1	1	2	3	11
Exp	0,2	0,4	0,4	0,6	0,8	0,9	1,3	1,5	1,9	3,1	
0											
Obs	10	10	10	10	10	9	10	9	9	8	95
Exp	9,8	10,6	9,6	10,4	10,2	9,1	9,7	8,5	9,1	7,9	
Total	10	11	10	11	11	10	11	10	11	11	106

Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	732	70,0	Somers' D	0,41
Discordant	306	29,3	Goodman-Kruskal Gamma	0,41
Ties	7	0,7	Kendall's Tau-a	0,08
Total	1045	100,0		

Appendix 13

Logistic regression using age, CA-TA ratio and return on total assets as explanatory variables in a combined model of distress prediction.

Binary Logistic Regression: Distress versus Average CA-TA ratio; Age; ROTA w/o extreme values

Link Function: Logit

Response Information

Variable	Value	Count	
Distress	1	11	(Event)
	0	95	
	Total	106	

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Constant	-0,375368	0,801561	-0,47	0,640			
CA-TA Ratio avg	-2,36540	1,33637	-1,77	0,077	0,09	0,01	1,29
Age	-0,121343	0,0726359	-1,67	0,095	0,89	0,77	1,02
ROTA adjusted	-1,47062	0,980736	-1,50	0,134	0,23	0,03	1,57

Log-Likelihood = -30,139
Test that all slopes are zero: G = 10,381, DF = 3, P-Value = 0,016

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	96,9153	102	0,624
Deviance	60,2776	102	1,000
Hosmer-Lemeshow	10,1064	8	0,258
Brown:			
General Alternative	3,6472	2	0,161
Symmetric Alternative	0,2462	1	0,620

Table of Observed and Expected Frequencies:
(See Hosmer-Lemeshow Test for the Pearson Chi-Square Statistic)

	Group										
Value	1	2	3	4	5	6	7	8	9	10	Total
1											
Obs	0	0	0	1	2	1	0	3	0	4	11
Exp	0,0	0,2	0,3	0,5	0,7	0,9	1,2	1,4	2,3	3,6	
0											
Obs	10	11	10	10	9	9	11	7	11	7	95
Exp	10,0	10,8	9,7	10,5	10,3	9,1	9,8	8,6	8,7	7,4	
Total	10	11	10	11	11	10	11	10	11	11	106

Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	787	75,3	Somers' D	0,51
Discordant	252	24,1	Goodman-Kruskal Gamma	0,51
Ties	6	0,6	Kendall's Tau-a	0,10
Total	1045	100,0		

Appendix 14

Logistic regression using age, the CA-TA ratio and return on total assets as explanatory variables in a combined model of distress prediction

Binary Logistic Regression: Distress versus Age; CA-TA Average

Link Function: Logit

Response Information

Variable	Value	Count	
Distress	1	11	(Event)
	0	95	
	Total	106	

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Constant	-0,152898	0,761444	-0,20	0,841			
Age	-0,121056	0,0700997	-1,73	0,084	0,89	0,77	1,02
CA-TA Average	-2,35399	1,25304	-1,88	0,060	0,09	0,01	1,11

Log-Likelihood = -31,187
Test that all slopes are zero: G = 8,285, DF = 2, P-Value = 0,016

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	89,2581	102	0,812
Deviance	62,3737	102	0,999
Hosmer-Lemeshow	8,8928	8	0,351
Brown:			
General Alternative	1,0053	2	0,605
Symmetric Alternative	0,7100	1	0,399

Table of Observed and Expected Frequencies:
(See Hosmer-Lemeshow Test for the Pearson Chi-Square Statistic)

	Group										
Value	1	2	3	4	5	6	7	8	9	10	Total
1											
Obs	0	0	0	1	1	1	0	1	5	2	11
Exp	0,1	0,2	0,4	0,5	0,8	1,1	1,3	1,5	2,0	3,3	
0											
Obs	10	11	10	10	10	10	10	9	6	9	95
Exp	9,9	10,8	9,6	10,5	10,2	9,9	8,7	8,5	9,0	7,7	
Total	10	11	10	11	11	11	10	10	11	11	106

Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	802	76,7	Somers' D	0,54
Discordant	240	23,0	Goodman-Kruskal Gamma	0,54
Ties	3	0,3	Kendall's Tau-a	0,10
Total	1045	100,0		