U.S. CORPORATE BANKRUPTCY PREDICTING MODELS

How accurate are the bankruptcy predicting models of Altman(1968), Ohlson(1980) and Zmijewski(1984) after recalibration, when they are applied to U.S. listed firms in the period after the BACPA change in bankruptcy law?

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Abstract

Being able to predict bankruptcy can be very valuable for debtors, creditors, shareholders and other stakeholders. Historically, different models that predict corporate bankruptcy have been constructed. Three bankruptcy predicting models are used in this thesis; the models of Altman(1968), Ohlson(1980) and Zmijewski(1984). The relatively old original models are applied to U.S. listed firms after the BACPA change in bankruptcy law in 2005. It became clear that when the original models are applied to a more recent sample of 2005-2007, the predictive power of the models is very low, and bankruptcy is overpredicted. In order to be able to use the relatively old models in more recent periods, especially after the BACPA change in bankruptcy law in 2005, the results show that the models have to be recalibrated. The original models with the original variables are used, only the coefficients and the interpretation of the outcome of the models change by recalibrating. The recalibrated models show that especially variables of short term liquidity are more important nowadays in predicting bankruptcy than in the original models. After recalibrating the models, the accuracy rates of all models increased. Especially applying the recalibrated models of Altman(1964) and Ohlson(1980) to the sample of 2005-2007 result in high percentages of correctly classified observations and high areas under Receiver Operating Curves.

Key words: bankruptcy predicting models, Altman(1964), Ohlson(1980), Zmijewski(1984), classification matrix, Receiver Operating Curve

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1. Introduction

For a wide range of stakeholders, it can be of value to know whether a company will go bankrupt or will survive. Historically different bankruptcy models have been developed, of which Altman(1968), Ohlson(1980) and Zmijewski(1984) are studied in detail in this thesis. They mutually differ on input variables, statistical methods and weight of different parameters. *The question now is how good these relatively old models are in predicting bankruptcy in today's environment, and whether some calibration of the model will improve predictive power.*

In order to do so, a sample of US companies that went bankrupt in the period of 2005-2007 is selected, and they are compared to non-bankrupt companies in the same period. This research applies original bankruptcy predicting models to a sample of 2005-2007. Also, recalibrated models are applied to the recent sample. Recalibrated models use the same statistical method and explanatory variables, but the importance of each variable and the interpretation of the outcome changes. Especially the role of short-term liquidity became more important in the recent sample than in the original models. By recalibrating the models, the relatively old models are still accurate in predicting corporate bankruptcy in a more recent sample.

1.1 Research question

The main research question of this thesis is the following:

How accurate are the bankruptcy predicting models of Altman(1968), Ohlson(1980) and Zmijewski(1984) after recalibration, when they are applied to US listed firms in the period after the BACPA change in bankruptcy law?

This thesis also applies the original models without recalibration to the recent sample, in order to check whether the original models predict bankruptcy for companies that did not go bankrupt, and vice versa. It is expected that the original models overpredict bankruptcy, since the BACPA change in 2005 made it less advantageous for companies to file for bankruptcy. It is also checked, whether all the models are equally future proof, or whether there are some models better than others in predicting bankruptcy in current circumstances.

1.2 Sample and results

The sample that is used in this thesis is restricted to the period of 2005-2007. The reason for the demarcation 2005-2007 is twofold. (1) In 2005 a new Bankruptcy Act came in place. This made it more difficult for companies to file for bankruptcy, settle their matters with their creditors, and continue the business afterwards. So, one may assume that compared to past periods companies would be more reluctant to take the bankruptcy route. Since the main goal of this thesis is to find out whether relatively old bankruptcy predicting models can still be used after the change in bankruptcy law, 2005 is taken as starting point of the sample. All companies that filed for bankruptcy after October 17th in 2005, are affected by the new law. (2) the financial crisis of 2008 has created a discontinuity on macro level, for which the old models possibly are not fitted. It is expected that the Financial Crisis started affecting bankruptcies after the first quarter of 2007. Hence, the lower limit of the sample is a result of change in Bankruptcy act in 2005, the upper limit is a result of the Financial Crisis.

To create the sample for this thesis, first all bankruptcy filings are found on www.bankruptcydata.com and on the UCLA-LoPucki database. These databases include the exact date of filing for bankruptcies. A firm is only included in the sample if it filed for bankruptcy between October 17 2005 and April 1 2007, and did not file for bankruptcy the two years before October 2005. In total, 104 bankruptcies of U.S. listed firms are found, only public companies are taken into account in this thesis. All 104 bankrupt firms are looked up on COMPUSTAT in order to obtain data needed for all variables of the three models. Quarterly data is obtained and all variables are gathered on time t, which is the quarter in which the firm filed for bankruptcy. Also for every firm data is gathered for t-1, t-2 and t-3, which are 4 quarters, 8 quarters and 12 quarters before the quarter in which a firm filed for bankruptcy. Complete data is found for 64 firms.

The next step in constructing the sample is including non-bankrupt firms in the sample. A list of all listed firms between 2005 and 2007 that did not file for bankruptcy between 2002 and 2009 is made. In order to make clear which companies in the sample went bankrupt and which companies did not go bankrupt, a binary variable is created which is 1 if a firm is defined as bankrupt and 0 if a firm is defined as non-bankrupt. The procedure of adding non-bankrupt firms to the sample is different for the recalibration of Altman(1968), than for the recalibration of the model of Ohlson(1980) and Zmijewski(1984).

First the sample which is used to recalibrate the model of Altman(1968) is constructed. Because Altman(1968) uses Multiple Discriminant Analysis(MDA) to predict bankruptcy, equal group sizes are needed. For every bankrupt firm, one non-bankrupt firm is randomly selected, based on industry and size, which results in a matched –pair sample. Data is gathered for the same quarters as for the matched bankrupt firm. In total, for 63 bankrupt firms and the same amount of non-bankrupt firms, data has been gathered, so the final sample that is used to recalibrate the model of Altman(1968) consists of 63 bankrupt firms and 63 non-bankrupt firms.

For the sample that is used for the recalibration of the models of both Ohlson(1980) and Zmijewski(1984), 20 non-bankrupt firms are randomly selected for every bankrupt firm, and data is gathered for the same quarters as the matched bankrupt firm. The ratio of 20 non-bankrupt firm for every bankrupt firm is chosen because the original models used the same ratio. In total, for 64 bankrupt firms and 1336 non-bankrupt firms, data has been gathered to construct all variables of the original models. The total sample that is used to recalibrate the models of Ohlson(1980) and Zmijewski(1984) consists of 64 bankrupt firms and 1336 non-bankrupt firms.

The samples that are described above are used to check the accuracy of relatively old models, when they are applied to US listed firms in the period after the BACPA change in bankruptcy law. First, the original models are applied to the above described sample. It became clear that all three models have little predictive power in predicting bankruptcy when the models are not recalibrated. The total amount of correctly classified companies is low and the original models of Altman(1968) and Ohlson(1980) predict bankruptcy often for firms that did not go bankrupt. Since the original models were constructed in periods long before the BACPA change in law in 2005, the original models do not capture the effect of this law change. Because it became less attractive for companies to file for bankruptcy after the BACPA change in law, the original models were expected to overpredict bankruptcy, and for the models of Altman(1968) and Ohlson(1980) this can be seen in the results. When the original model of Zmijewski(1984) is applied to the new sample, the opposite happens. Non-bankruptcy is overpredicted, which is in contrary to what was expected and contrary to the classification of Ohlson(1980) and Altman(1968).

In order to make the models more accurate in a different period, the next step was recalibrating the models, and applying these to the above described sample. The recalibrated models consist of the same variables as the original models, and the same statistical technique is used, but the importance of variables changes. In all three recalibrated models short term liquidity became more important than in the original models. It turned out that both the models of Altman(1968) and Ohlson(1980) have high predictive power, and even though the accuracy rate was lower when bankruptcy is predicted three years in advance than for predicting 2 or 1 year in advance, the models still have predictive power at t-3. The recalibrated model of Zmijewski(1984) underperformed the other models, because at t-2 and t-3 the model had low predictive power.

1.3 Relevance

Even though more recent bankruptcy predicting models exist, old models are still used and turn out to be still accurate. It is very remarkable that the models which are based on samples that are more than 30 years old, still seem to predict bankruptcy well, even though the bankruptcy law and the economic circumstances dramatically changed. This research does not just investigate the predictive power of old models in a different period. This research focusses on bankruptcies between 2005 and 2007, since in 2005 the bankruptcy law changed dramatically. Because it is expected that the financial crisis had a big impact on bankruptcies, the sample of this thesis does not include observations after the first quarter of 2007.

1.4 Outline

This research starts with a literature review, which contains the background information that is used for this thesis. It is explained how corporate bankruptcies work, and the three original bankruptcy predicting models are explained in further detail. The next section is the research method, which explains how the research is done. First it is made clear how the sample looks like. Also the variables that are used in this thesis are summarized. Moreover, it is explained how the recalibrated models can be interpreted and the expected signs of the re-estimated models is added to this section. The last part of this section consists of the hypotheses. Section 4 includes the results of this thesis. It starts with applying the original models to the new created sample. Then, the models are re-estimated and evaluated. The last section includes the conclusions and the limitations of this research.

2. Literature review

This section consists of the theoretical background that is used to re-estimate bankruptcy predicting models. First, the main principles of corporate bankruptcies will be discussed. Also the bankruptcy law and the most recent change in the law will be discussed. Finally, bankruptcy predicting models will be discussed.

2.1 Corporate bankruptcy in the U.S.

The definition of bankruptcy found in the businessdictionary is:

'Legal procedure for liquidating a business (or property owned by an individual) which cannot fully pay its debts out of its current assets. Bankruptcy can be brought upon itself by an insolvent debtor (called 'voluntary bankruptcy') or it can be forced on court orders issued on creditors' petition (called 'involuntary bankruptcy'). Two major objectives of a bankruptcy are (1) fair settlement of the legal claims of the creditors through an equitable distribution of debtor's assets, and (2) to provide the debtor an opportunity for fresh start.'[1]

The first national federal bankruptcy law in the United States became effective in 1800, and got updated several times because of changes in the financial market. Around 100 years later, the first provision in the law that protects firms which are unable to pay their debts against their creditors, became effective.[2] This gave financially distressed firms an option to reorganize their firms, in order to be able to pay back their creditors later.

In 1978 the US bankruptcy Reform Act took effect. This was the first time a Chapter 11 was constructed. The main principle of Chapter 11 is reorganizing firms in order to give them an opportunity to pay their creditors later, which is different from Chapter 7, since chapter 7 has the main goal of liquidation instead of reorganizing.

The most recent big impact change in the bankruptcy law of the United States is the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005; BACPA. This change in law affected bankruptcy filings which filed after October 16, 2005. The changes in the bankruptcy law affected personal bankruptcies, and the changes also had a big impact on corporate bankruptcies. According to Bohn (2007), the changes '*have made it more costly for businesses to reorganize and more difficult for existing management to control the troubled company's destiny. As a result,*

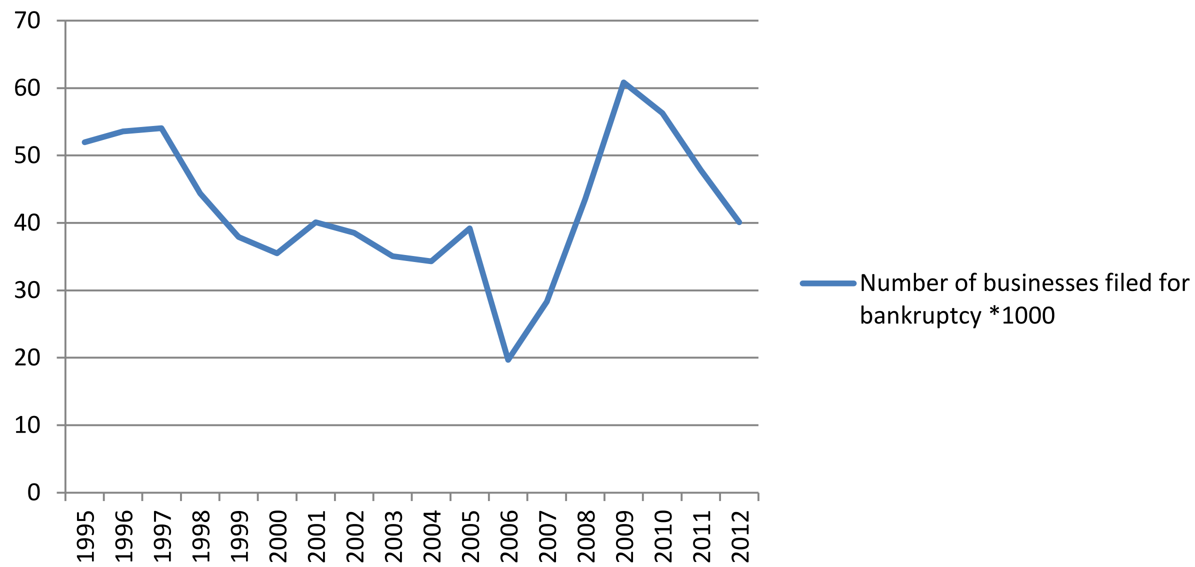
[1] Retrieved from: http://www.businessdictionary.com/definition/bankruptcy.html (2014)
[2] Source: www.bankruptcydata.com, 'A brief history of bankruptcy' (2014)

business reorganizations are down (more than 50 percent in 2006) and restructuring outside of bankruptcy has increased'(p.61).

The main changes of BACPA are a shorter exclusivity period and lower retention payments, as written by Bohn(2007). The exclusivity period is made shorter, and there is less allowance to extend this period, in order to make the process shorter and more efficient. Excessive retention payments are discouraged, since managers often got paid a lot so they would stay at the firm, and those payments became absurdly high, which was usually not the best solution for the creditors.

As can be seen in figure 1, the amount of bankruptcies declined in 2005, which was the year the BACPA took effect, and the financial crisis of 2007-2008 has led to an increase in the amount of corporate bankruptcy filings. Figure 1 shows a graphical overview of U.S. firms that filed for bankruptcy between 1995 and 2012.

Figure 1 Corporate bankruptcy filings 1995-2012



Source: data retrieved from http://www.abiworld.org/AM

The first step for financially distressed companies, is finding out whether they want, and are able, to solve their financial troubles out of court, or in formal bankruptcy. Gilson, John, & Lang(1990) found that significant determinants for this choice are: amount of lenders, amount of intangible assets, and amount of debt owed to bank. Resolving financial problems out of court is usually the least expensive option and it has the best outcome for stockholders, but it is not always possible to avoid formal bankruptcy. Franks & Torous(1994) state that more solvent firms, and firms with less negative stock returns prior to restructuring, are more likely to restructure out of court. Most firms restructure in formal bankruptcy, because they cannot come to an agreement with their creditors (a private workout), or because they want to be protected by the Bankruptcy Code. Another problem of restructuring out of court is known as the holdout problem, which holds that when firms ask their creditors to voluntarily participate to be paid back later, most creditors will wait and hope that other creditors will participate, which is also known as the free-rider problem. Also a solution between in court and out of court exists; prepackaged reorganization. In this situation, a firm already finished its reorganization plan before it files for Chapter 11. The main advantage is that this procedure lowers costs, since firms will be in Chapter 11 for a shorter time than a normal Chapter 11 filing.

Firms solving their financial distress within court have the choice between Chapter 7 which has the goal of liquidation, and Chapter 11 which has the goal of reorganization of the U.S. Bankruptcy Code. In theory, a firm should file for Chapter 11 when the firm's value is higher than its liquidation value. Chatterjee et al (1995) find that firms that are highly leveraged, have poor operating performance and creditor coordination problems, are more likely to file for Chapter 11 than for Chapter 7. Gilson S. (2012) states that the main advantages of Chapter 11 are automatic stay and 'debtor-in-possession'(DIP) financing. Automatic stay means that as soon as a firm files for bankruptcy, the firm is protected by the Code against creditors that claim their collateral. Due to DIP financing, a new source of cash can be found more easily. DIP financing gives a potential lender, which lends money to a firm while it is in Chapter 11, the advantage of getting priority in getting paid back by the financially distressed firm.

Due to the DIP financing and the automatic stay, it becomes clear that even though the associations with bankruptcies are very negative, filing for bankruptcy can help firms resolving their financial distress, but it is important to note that filing for bankruptcy is expensive. Altman (1984) found that the total bankruptcy costs(direct and indirect) are between 11% and 17% of the total firm value, and after the BACPA change the costs even increased.

2.2 Bankruptcy and financial distress prediction models

Being able to predict bankruptcy can be very valuable and a lot of research is done in the area of bankruptcy predicting models. A lot of different models exist, some predict bankruptcy and some predict financial distress. The main advantage of predicting bankruptcy is that is has a clear date on which a firm goes bankrupt, but it is harder to set a hard date or find a good criterion on which you define a firm being in financial distress. The models used in this thesis, Altman, Ohlson and Zmijewski, are summarized in table 1.

Table 1: Original models summarized

	Altman(1968)	Ohlson(1980)	Zmijewski(1984)
Statistical technique	MDA	Logit	probit
Sample size	N=66, 33 bankrupt and 33 non-bankrupt	N= 2163, 105 bankrupt and 2058 non-bankrupt	N=840, 40 bankrupt and 800 non-bankrupt
Explanatory variables profitability	* EBIT/TA * Sales/TA	*Net Income/TA * Change in Net Income	*Net income/TA
Explanatory variables liquidity	* Working Capital/TA	*Working Capital/TA * Current Liabilities/Current Assets * Funds provided by operations/Total Liabilities *INTWO[a]	*Current assets/ Current liabilities
Explanatory variables leverage	* Retained Earnings/TA * Marketvalue of Equity/book value of total debt	*Total liabilities/TA * OENEG[b]	Total Debt/TA
Other explanatory variables		* Size = log(total assets/GNP price-level index)	

TA= Total Assets

a) INTWO is a dummy variable which is 1 if net income was negative in the last two years and 0 otherwise

b) OENEG is 1 if Total Liabilities > TotalAssets, 0 otherwise.

The original models will be discussed in more detail in the next three sections.

2.2.1 Altman(1968)

Altman E. (1968) states that most of the bankruptcy predicting models at that time used univariate analysis. Since outcomes of univariate methods (like traditional ratio analysis) are often interpreted wrong, Altman decided to use a different method; Multiple Discriminant Analysis (MDA). The MDA technique is used for situations where two groups are identified and the dependent variable can only take two values. In this example, the dependent variable is bankrupt or non-bankrupt. MDA creates a linear combination that can discriminate the different groups, by using all variables simultaneously, which is different from traditional ratio analysis where the effect each variable is measured separately.

The sample of bankrupt firms used for this model consists of U.S. manufacturers which filed for bankruptcy between 1946 and 1965. Manufacturers have a SIC-code between 2000 and 3999. Each bankrupt firm is matched to a non-bankrupt firm, based on its industry and size. All non-bankrupt firms still exist in 1966. The final sample consists of 33 bankrupt firms and 33 non-bankrupt firms. In the final model, the 5 most important variables out of the 22 variables that Altman tested are used. The following is Altman's final model:

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

where X1 = Working capital/Total assets (WC/TA), X2= Retained earnings/Total Assets (RE/TA), X3= Earnings before interest and taxes/Total assets (EBIT/TA), X4 = Market value equity / Book value of total debt (MVE/BVD), X5= Sales/Total assets (S/TA) and Z= overall index.

The model classifies 95% correct one year prior bankruptcy, and 83% two years prior bankruptcy. The model is also applied to the sample of bankrupt firms, three, four and five years before went bankruptcy and predicts 48%,29% and 36% respectively correctly. Since the predictive power drastically goes down after the second year, Altman concludes that the model is unreliable for predicting more than two years in advance.

A firm with a Z-score ≥ 2.675 is expected not to go bankrupt, and a firm with a Z-score <2.675 is expected to go bankrupt. Alman also introduced a grey area, to make the classification even more accurate. In this case, Altman is inconclusive for firms with a Z-score between 1.81 and 2.99, but firms with a Z-score lower than 1.81 are predicted to go bankrupt, and firms with a Z-score higher than 2.99 will not go bankrupt.

2.2.2 Ohlson(1980)

Another model used in this research to predict bankruptcy is the model described by Ohlson(1980). Since Ohlson(1980) states that there are problems when using the MDA methodology like Altman(1968) did, Ohlson(1980) uses conditional logit technique to build his model. The main problems of the MDA methodology noted by Ohlson(1980) are that even though the sample of Altman(1968) is constructed by matched pair sampling, the variables differ across bankrupt and non-bankrupt companies, the output is not easily interpretable and some statistical assumptions that are made by Altman(1968) may not be valid.

To avoid the problems of using MDA, Ohlson(1980) uses logistic regressions to predict corporate bankruptcy. The sample includes public industrial companies from 1970 to 1976. 105 bankrupt firms and 2058 non-bankrupt firms are used to build three models; the first model predicted bankruptcy within one year, the second model predicted bankruptcy of firms that did not go bankrupt in the first year, but will go bankrupt in the second year. The third model predicted bankruptcy within one or two years. The models consist of 9 different predictors and the first model has the following estimates:

$$O - score = -1.32 - 0.41X_1 + 6.03X_2 - 1.439X_3 + 0.08X_4 - 2.37X_5 - 1.83X_6 + 0.285X_7 - 1.72X_8 - 0.52X_9$$

where: X_1=log(total assets) corrected for inflation, X_2=total liabilities/total assets, X_3=working capital/total assets, X_4=current liabilities/current assets, X_5=one if total liabilities>total assets, zero otherwise, X_6=net income/total assets, X_7=operations funds/total liabilities, X_8=one if net income was negative for the last two years, zero otherwise, X_9=change in net income

The logit model can be interpreted as follows:

$$P(x) = \frac{1}{1 + e^{-(ß0+ß1X1+\cdots+ßnXn)}}$$

The outcome of a logit model is easy to interpret, since it is a probability, so it is a number between 0 and 1. In logistic models, it is assumed that the errors are standard logistically distributed. This is different from the probit model, where it is assumed that the errors are normally distributed. The percentage of correctly predicted observations of the first model is 96.12%, but this number should be interpreted with caution. The percentage correctly classified is high, but this number is not corrected for having 20 times more non-bankrupt than bankrupt firms in the sample. So even when the model predicts bankruptcy in all cases, the percentage correctly classified is 2058/(2058+105) = 95.15%. In order to get a more useful accuracy rate, Ohlson plotted type I and type II errors[3], and found that the optimal cut-off point, which minimizes the sum of the percentages of type I and type II errors, is 0.038. This means that in his model, firms with a probability smaller than 0.038 are predicted not to go bankrupt and firms with a probability higher than 0.038 are predicted to go bankrupt. When using the cutoff-point of 0.038, Ohlson's first model classifies 87.6% of the bankrupt firms and 82.6% of the non-bankrupt firms correctly at t-1.

This research shows both the coefficients of the regression and the odds ratio for the logit model. This is done because the odds ratio is used for easier interpretation for the logit model. When drawing conclusions based on the coefficients of the logit regression, only changes in the log odds of the dependent variable can be interpreted. In this case, where the dependent variable is 1 if a firm went bankrupt and 0 when a firm did not go bankrupt, an increase in X_1 (SIZE) leads to a decrease in the log odds of going bankrupt, since the sign of X_1 is negative. Since it is not very intuitive to study the effects on the log odds, all coefficients are exponentiated. The exponentiated coefficients are called the odds ratios, and are easier to interpret since the dependent variable does not contain log anymore. This disappearing of the log can be easily seen in the following formula:
If ßX = log(Y), then $e^{ß}X$ = Y.

[3] Type II errors are non-bankrupt firms that are classified as bankrupt, type I errors are bankrupt firms that are classified as non-bankrupt

The odds ratios are used for interpretation of logistic models. Every variable with a positive coefficient will have an odds ratio greater than 1, and variables with a negative coefficients have odds ratios smaller than 1.

2.2.3 Zmijewski(1984)

Zmijewski (1984) used the probit method to predict bankruptcy. The outcome of a probit regression is similar to the outcome of a logit regression between 1 and 0. Most bankruptcy predicting models select the independent variables based on theory, and select the variables with most predictive power. Zmijewski(1984) however, based his selection of independent variables purely on how well the variables predicted in previous models.

Zmijewsk(1984) included firms in his sample which were listed on NYSE between 1972 and 1978, and have a SIC code smaller than 6000. The restriction on SIC-codes excludes firms in the financial and service sector, which usually have a distinct balance sheet. Consequently, firms from the financial and service sector are hard to compare with firms from other industries. Financial distress is defined as the act of filing a petition for bankruptcy. Zmijewski(1984) mentions that there are two problems with the way other bankruptcy predicting models are constructed. The first problem arises in the way some researchers match the samples of non-bankrupt and bankrupt firms. When bankrupt firms are chosen first, and then based on some criteria a match is chosen, the sample is not a random sample anymore. The second problem is that firms with incomplete data are often removed from the dataset, which can only be done if the subsample of firms with incomplete data is a random sample of the total sample. Zmijewski(1984) tries different sample sizes, and the sample with 40 bankrupt companies and 800 non-bankrupt is used.
Zmijewski(1984) uses the three variables that are most used in previous bankruptcy predicting models, and the model is as follows:

$$Zm = -4.336 - 4.513\, X_1 + 5.679X_2 - 0.004X_3$$

Where X1 = net income/total assets, x2= total debt/total assets and x3= current assets/current liabilities.

A firm with a probability greater than 0.5 is classified as bankrupt, and a firm with a probability smaller than 0.5 is classified as non-bankrupt. The overall out-of-sample accuracy rate of Zmijewski’s model is 95.29%, but it is important to note that none of the bankrupt firms are predicted to go bankrupt in this classification, and in 99.39% of all non-bankrupt firms the model classified the firms as non-bankrupt. In fact, the cut-off point here is not corrected for the different numbers of bankrupt and non-bankrupt firms. Since for every bankrupt firm, Zmijewski has 20 non-bankrupt firms in his sample, the classification matrix shows that almost all observations are predicted to go bankrupt, since 95% of the total sample consists of non-bankrupt firms.

The interpretation from the coefficients of probit models is not straightforward. For example if $ß_2$ is the coefficient belonging to variable X1 is 0.2, if X1 changes one unit, the Zmijewski-score increases by 0.2. Instead of knowing an increase/decrease in the Zmijewski score, the effect of a change on the probability can also be calculated. To interpret changes of a variable on the probability of going bankrupt, the marginal effect of each variable is needed. The marginal effect indicates how much the probability of bankruptcy changes, when one of the independent variables increases/decreases by one unit, ceteris paribus.

3. Research method

This section starts with explaining how the sample is created. First the total sample is created, which is used to recalibrate the model of Ohlson(1980) and Zmijewski(1984). Then all bankrupt firms are matched to one non-bankrupt firm in order to re-estimate the model of Altman(1964), since equal group sizes are needed for the MDA model. Furthermore, all variables are discussed in detail. Then the original and re-estimated models are discussed. Also, the hypotheses and main research question are included in this section.

3.1 Sample selection

Even though the models of Altman, Ohlson and Zmijewski use different samples, this thesis only uses one sample. First the total sample will be constructed, and out of that sample, a matched-pair sample will be made. Matched-pair sampling will be used since Altman uses equal group sizes for bankrupt and non-bankrupt firms, and matched every bankrupt firm with a non-bankrupt firm, based on size and industry. Table 2 gives an overview of which sectors/industries Altman, Ohlson and Zmijewski included in their samples, and what criterion they use in order to make a difference between bankrupt and non-bankrupt firms.

Table 2: Samples of original models

	Years	**Defined as bankrupt when**	**Sectors included**[4]
Altman(1968)	1964-1965	A firm filed for bankruptcy	Manufacturers SIC between 2000 and 3999
Ohlson(1980)	1970-1976	A firm filed for bankruptcy between 1970 until 1976 ‘in the sense of Chapter X, Chapter X1 or some other notification indicating bankruptcy proceedings’ (Ohlson, 1980, p.114).	Public industrial companies SIC between 1-3999 and 5000-5999. 4000-4999 are excluded; transportation and public utilities
Zmijewski (1984)	1972-1978	Firmst listed on NYSE which filed a petition for bankruptcy	SIC code < 6000. Only excludes finance, services and public administration

[4] Standard Industrial Classification (SIC) code classification is retrieved from http://siccode.com/en/siccode/list/directory/code/

First, it will be explained which sectors/industries are included in the sample of this thesis. A sample of U.S. listed companies with a Standard Industrial Code (SIC) smaller than 6000 and excluding firms with a SIC code between 4000 and 5000 is used. This differs from the industries that Altman used for his original model, since Altman only used manufacturing firms. Altman did adapt his original model to make it also applicable to non-manufacturing firms and to emerging markets, which is known as the four variable Z'' score model (Altman, 1993).

This research does include non-manufacturing firms, but still the original model of Altman is used. This is done because other research, for example (Grice & Ingram, 2001), (Wu, Gaunt, & Gray, 2010) and (Begley, Ming, & Watts, 1996) also re-estimated the original model of Altman while including non-manufacturing firms in their samples, which still resulted in high accuracy rates. Also because this research only includes listed companies from the U.S., which is not an emerging market, it is expected that the original model of Altman can be used.

Even though Ohlson (1980) does not exclude firms with SIC codes between 4000 and 5000, the sample of this thesis does not include these public utility firms in the sample, since it is expected that public utility firms are structurally different from the rest of the sample. To summarize the above, the sample of this thesis includes U.S. listed companies with a SIC code smaller than 4000 and codes between 5000 and 6000. Now the industries/sectors which are included in the sample, the sample has to be split up in bankrupt and non-bankrupt firms.

This thesis includes firms in the bankrupt sample if a bankruptcy filing date was found in the UCLA-LoPucki bankruptcy research database, or on www.bankruptcydata.com, and could be found in COMPUSTAT. Only firms with a bankruptcy filing date between October 17 2005 and April 1, 2007 are included in the sample of bankrupt firms, and are only included if they did not file for bankruptcy in the two years before. [5] Data is retrieved from 17th of October because the American Bankruptcy Institute[6] notes that this is the date on which the BACPA change became effective. Numbers after the quarter of 2007 are not retrieved, because it is expected that the financial crisis had a big impact on the US corporate bankruptcies. Including numbers from during the financial crisis could possibly lead to drawing conclusions on the change of the financial environment instead of the change of the bankruptcy laws. For each bankrupt firm, data is gathered for the quarter in which the firm filed for bankruptcy and 1, 2 and 3 years before the filing date.

[5] This is done because predicting bankruptcy for a firm that already went bankrupt in the last two years is too obvious.

[6] Source: American Bankruptcy Institute, the essential resource for today's busy insolvency professional retrieved from: http://www.abiworld.org/Content/NavigationMenu/OnlineResources/LegislativeNews/NewBankruptcyLaw/New_Law1.htm

Non-bankrupt firms are retrieved from COMPUSTAT. For each bankrupt firm, 20 non-bankrupt firms are randomly chosen and data is gathered for the same quarters as the bankrupt firm. Non-bankrupt firms are only included in the sample if they did not file for bankruptcy between 2002 and 2009. After deleting observations with missing data points, the sample consists of 64 bankrupt firms and 1336 non-bankrupt firms. The total sample is divided in two parts; 1/3 of the total sample is used to recalibrate the original models, and the remainder of the total sample is used as a control sample. The reason for dividing the total sample in an estimation sample and a control sample is that when the classification is constructed from the same sample as the estimation sample, the accuracy rate of the models would be very high, but when you want to apply the re-estimated model to another sample from the same period and industries, the accuracy decreases. So dividing the total sample in an estimation sample and a control sample gives a more fair accuracy rate. The estimation sample is obtained by randomly selecting 22 bankrupt firms and 695 non-bankrupt firms from the total sample. The remainder of the total sample is the control sample which consists of 42 bankrupt firms and 1308 non-bankrupt firms. In order to recalibrate the models of Ohlson(1980) and Zmijewski(1984), the estimation sample is used to re-estimate the coefficients of the original models. In order to check in how many cases the model predicted bankruptcy successfully, the re-estimated model is applied to the control sample. The ratio of 64 bankrupt firms to 1336 non-bankrupt firms is used because both Ohlson and Zmijewski use about 20 non-bankrupt firms for every bankrupt firm in their samples.

The sample that is used to re-estimate Altman's model is different from the sample that is used to re-estimate the models of Ohlson(1980) and Zmijewski(1984). Because Altman uses equal group sizes for bankrupt and non-bankrupt groups, all bankrupt firms in the sample are matched to a non-bankrupt firm based on industry and size, and data from the same quarters as from the bankrupt firm are gathered. The final sample that is used to test the model of Altman(1968) consists of 63 bankrupt firms and the same amount of non-bankrupt firms. In order to create a robust model, half of the total sample is used to re-estimate the model, and the other half is used as control sample, which are obtained by randomly selecting pairs of firms. The estimation sample consists of 31 bankrupt and 31 non-bankrupt companies and the control sample consists of 32 bankrupt and 32 non-bankrupt firms.

3.2 Variables

All three models use measures of profitability, liquidity, leverage, and Ohlson is the only model which uses size to predict bankruptcy. For each model all variables will be explained in more detail below. Altman uses EBIT/TA(earnings before interest and taxes/total assets) and S/TA(sales/total assets) as profitability variables, which measure how efficient assets are used in terms of earnings and in terms of sales respectively. To measure liquidity, Altman used WC/TA(working capital[7]/total assets) as a variable in his model. This variable is often used by investors to check how much of a company's assets are used to invest in the company. Altman also used two leverage variables; RE/TA(retained earnings/total assets) and MVE/TD(market value of equity/book value of total debt), where RE/TA measures how much of the earnings are reinvested in the firm to grow or expand, scaled by its total assets and MVE/TD is a solvency ratio.

Ohlson's model is the only model considered in this thesis which uses size to predict bankruptcy; SIZE(log(total assets/GNP price-level index). This thesis does not correct for GNP price-level index since this thesis uses only a short period of time. Ohlson used two different variables to measure profitability; NITA(net income/total assets) and CHIN(change in net income, which is calculated as follows; $(NI_t - NI_{t-1})/(|NI_t| + |NI_{t-1}|)$). Liquidity is measured by four different variables; WCTA (working capital/total assets), CLCA(current liabilities/current assets), FUTL(funds provided by operations[8]/total liabilities) and INTWO(a dummy variable which is 1 if net income was negative in the last two years and 0 otherwise). Leverage is measured by using two different variables; TLTA(total liabilities/total assets) and OENEG(1 if total liabilities>total assets, 0 otherwise).

Zmijewski uses only three variables to predict bankruptcy. Profitability is measured by NITA(net income/total assets). The variable CACL(current assets/current liabilities) is used as measure for liquidity. The last variable used is TLTA(total liabilities/total assets), which is used as a measurement for leverage.

All variables are winsorized at 99%, in order to make the effect of extreme values smaller, which is also done by Wu et al.(2010). The sample that is used to re-estimate Altman's model consists of 63 bankrupt firms and the same amount of non-bankrupt firms since it is a matched sample. Since Zmijewski and Ohlson both use about 20 non-bankrupt firms for every bankrupt firms, 20 non-bankrupt firms are randomly selected for each bankrupt firm. The descriptive statistics of all variables from the three models can be found in table 3. In table 3 it can be seen that for most variables the group means for bankrupt firms are significantly different from the means of the non-bankrupt groups, since significantly different group means are marked with *,** or *** which indicate significant differences at 10%, 5% and 1% respectively. A clear difference can be noted for the

[7] Working capital = current assets – current liabilities

[8] Ohlson used Funds provided by operations/Total Liabilities. Funds provided by operations is operating revenue which was not available in Compustat. As a proxy, Pretax Income + depreciation and amortization is used, following Ho, C.Y., McCarthy, P. Yang and Ye (2012)

variable ‘OENEG’, which is a dummy variable that is equal to 1 when total liabilities are larger than total assets, 0 otherwise. Non-bankrupt firms have a significantly lower mean for this variable which indicates that in the group of non-bankrupt firms, fewer firms had larger liabilities than assets, compared to the bankrupt firms, of which more firms had more liabilities than assets.

Correlations between independent variables are shown in correlation matrices for each model and can be found in Appendix A. correlation between independent variables that is larger than 0.8 is a warning for multicollinearity, following (Retherfor & Choe, 1993). There are two high correlations in the variables used to re-estimate Ohlson(1980), between O2&O3 and between O3&O4. Since the Variation Inflated Factors (VIFs) are not larger than 10, it is assumed that even though some multicollinearity exists, the model can still be used. Following (O'Brien, 2007) it is important to check the VIFs, because when VIFs are too high a model can have a high R^2 even when none of the variables is significant.

Table 3 Descriptive statistics

This table contains the summary of the explanatory variables for the models used in this thesis. Firms are classified as non-bankrupt if they did not file for bankruptcy between 2000 and 2009. Firms are classified as bankrupt if a bankruptcy filing date between October 17 2005 and April 1, 2007 is found in the LoPucki bankruptcy research database or on www.bankruptcydata.com, and if they did not file for bankruptcy in the two years before. All variables are measured at t-1.

Independent variables	Non-bankrupt firms					Bankrupt firms					
	Mean	SD	Min	Max	Median	Mean	SD	Min	Max	Median	T-test[a]
Ohlson(1980)											
Size	2.3980	1.1686	-.6421	4.7786	2.4812	1.8238	.9590	-1.1605	4.2693	1.9115	0.0001***
TL/TA	.6334	1.0084	.0315	8.45180	.4585	1.3352	1.4835	.0589	8.4518	.9157	0.0000***
WC/TA	.1724	.7067	-5.3237	.8644	.2459	-.2279	1.0988	-5.3237	.8644	.0952	0.000***
CL/CA	1.0218	2.8275	.0496	21.9755	.4909	1.9118	3.2190	.0589	18.0551	.7880	0.0146**
OENEG	.0771	.2668	0	1	0	.42190	.4978	0	1	0	0.0000***
NI/TA	-.1530	.8996	-6.7383	.3826	.0426	-.1307	.3385	-1.7236	.3826	-.0476	0.8439
FUTL	.0197	1.1816	-6.6071	2.7757	.1995	-.0416	.4537	-1.2771	2.7757	-.0235	0.6795
INTWO	.3211	.4671	0	1	0	.7969	.4055	0	1	1	0.0000***
CHIN	.03196	.5253	-1	1	.0617	.1221	.5981			.0867	0.1829
	N=1336					**N=64**					
Altman(1968)											
WC/TA	.2157	.5154	-1.5589	.8985	.2903	-.2694	1.2730	-6.4163	.8925	.0936	0.059*
RE/TA	-2.3613	5.5208	-29.1321	.7845	-.0479	-7.1187	16.0469	-79.763	.7845	-.8638	0.0279**
EBIT/TA	-.0724	.3847	-1.3705	.2206	.0884	-.1142	.2507	-1.3705	.0927	-.0192	0.4708
MVE/TD	2.6457	4.7108	0	28.7240	1.4342	1.2658	3.8931	0	28.7240	.3285	0.0755*
S/TA	1.2463	.8566	0	2.9982	1.1733	.3225	.2614	0	1.1925	.2824	0.0000***
	N=63					**N=63**					
Zmijewski(1984)											
NI/TA	-.1530	.8996	-6.7383	.3826	.0426	-.13075	.3385	-1.7236	.3826	-.0476	0.8439
TD/TA	.1572	.2196	0	1.3773	.0884	.3528	.4366	0	1.3773	.1778	0.0000***
CA/CL	3.0140	3.1310	.0455	20.1805	2.0370	1.5704	2.1592	.0554	16.9827	1.2695	0.0003***
	N=1336					**N=64**					

[a] P-values of twosided t-test are shown, which tests whether the means of the variables are different for the bankrupt and the non-bankrupt firms.

*, ** and *** indicate significant difference at 10%, 5% and 1% respectively.

Size=log(total assets),TL/TA= Total liabilities/ Total assets. WC/TA=Working capital/Total assets. CL/CA=Current liabilities/Current assets. OENEG= 1 if total liabilities>total assets, 0 otherwise. NI/TA=Net income/Total assets. FUTL=Funds provided by operations/total liabilities, where pretax income + depreciation and amortization is used as a proxy for funds provided by operations. INTWO is 1 if net income was negative in last two years and 0 otherwise. CHIN=change in net income.WC/TA=working capital/total assets. RE/TA = retained earnings/total assets. EBIT/TA = earnings before interest and taxes/total assets. MVE/TD= market value of equity/book value of total debt. S/TA=sales/total assets. NI/TA=net income/total assets. TD/TA=total debt/total assets. CA/CL=current assets/current liabilities

3.3 Original model and recalibrated models

The original models will be applied to the created sample. It is expected that when applying the original models to the new sample, the models will have little predictive power. Also it is expected that when applying the original models to the new sample, bankruptcy will be over-predicted, because the BACPA change in bankruptcy law made it less attractive for companies to file for bankruptcy. The models will have to be recalibrated in order to improve the accuracy, because the used models are from 1968, 1980 and 1984, so the effect of most variables on the likelihood of bankruptcy might have been changed. Begley et al., (1996) point out that the effect of debt on the probability of going bankrupt has changed because a higher level of debt is accepted. This change in accepted capital standards leads to a lower effect of high amounts of debt, than it did 30 years ago. Also it is pointed out that the choice of filing for bankruptcy might be less driven by financial variables and more by strategic reasons, while only financial variables are taken into account in the models of Ohlson and Altman. So it is interesting to see how the coefficients of variables change due to the recalibration, and whether the recalibrated models are accurate or not.

All models will be recalibrated to check whether the accuracy of the models increase when using new coefficients instead of the coefficients from the original models. The sign of coefficients show whether the probability of bankruptcy increases or decreases when the variable of interest increases, all else equal. Because by recalibrating the coefficients of the variables change, and the same variables are used, the importance of each variable in the original model can be compared to the importance of the variable in the recalibrated model. By doing this, it can be seen what is the most important factor that drives companies to bankruptcy nowadays, compared to the most important factor that lead to bankruptcy 30 years ago.

In Altman's original model, all coefficients have a positive sign, which in this case of means that when the variable of interest increases, the probability of bankruptcy decreases, ceteris paribus. A greater coefficient in the MDA model means a lower probability of bankruptcy, since the outcome of the model, Z, is greater for non-bankrupt firms and lower for firms that are predicted to go bankrupt. So for example, firms with a lower WC/TA (X_1) have a lower liquidity ratio and have lower ability to pay their bills, and all else equal, lower X_1 leads to a lower Z-score, which indicates higher probability of bankruptcy. It is expected that the coefficient for X_1 in the re-estimated model will be positive, since more liquid firms are expected to have a lower probability of bankruptcy. X_2 (RE/TA) is also expected to have a positive sign in the re-estimated model. High retained earnings are common for firms that are longer in existence, which makes firms less vulnerable to bankruptcy. Also X_3 (EBIT/TA) is expected to have a positive sign, since firms whith higher earnings, corrected for total assets, have a lower probability of bankruptcy. X_4 (MVE/TD) is higher for firms of which investors think that they have high potential. Also this variable is expected to have a positive sign since higher potential firms have a lower probability to go bankrupt. The last variable in Altman's original model is X_5 (Sales/TA). Firms with more sales compared to what the firms needs in order to be able to sell, are less likely to go bankrupt so also the last variable is expected to have a positive sign in the re-estimated models.

After Altman's model is re-estimated, also Ohlson's model will be re-estimated. With 9 coefficients, each belonging to one variable, the O-score is calculated. The probability of logistic models is calculated as $1/e^{-o}$ where O indicates the outcome of the equation. A higher O-score indicates higher probability of bankruptcy .Ohlson(1980) predicts the signs of all 9 coefficients of the logit regression. Since it is a bad signal when firms have higher liabilities than assets, it is expected that TLTA and CLCA both have a positive sign, which means that an increase in TLTA and CLCA leads to a higher probability of bankruptcy. Also INTWO is expected is expected to have a positive sign, because firms that had negative net income in the past two years are more likely to go bankrupt. Ohlson(1980) expects that SIZE, WC/TA, NI/TA, FUTL and CHIN all have a negative sign. Intuitively, the signs of SIZE, WC/TA and NI/TA are easily interpretable since larger companies, more liquid companies and companies with higher net income, are less likely to go bankrupt. Higher operating revenue is also a sign for financially healthy firms, so also FUTL is predicted to have a positive sign. The variable CHIN is negative when the net income is lower in year t than in year t-1. It is expected that firms with decreasing income are more likely to go bankrupt, so higher CHIN leads to lower probability of bankruptcy. Ohlson(1980)notes that OENEG is included in the model, in order to make the effect of an extreme TL/TA smaller.

The model of Zmijewski(1984) consists of three different variables only; NI/TA, TL/TA and CA/CL. Since NI/TA is already used in Ohlson's model, the same intuition is used for the expectation of the sign. It is expected that firms with higher net income are less likely to go bankrupt, so NI/TA is expected to have a negative sign. Also TL/TA is the same as in the previous model. Higher liabilities than assets lead to a higher probability of bankruptcy, so the sign of the coefficient TL/TA is expected to be positive. CA/CL is the opposite, since assets are here in the numerator and liabilities in the denominator, so the expected sign of CA/CL is negative.

3.4 Evaluation of recalibrated models

For each recalibrated model a classification matrix will be constructed, which will have the following form:

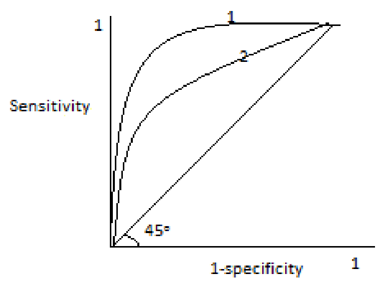
Figure 2: Classification matrices

		Actual	
Predicted		Actually went bankrupt	Actually did not go bankrupt
	Classified as bankrupt	A = true positive (sensitivity)	C = false positive (=1-specificity)
	Classified as non-bankrupt	B = false negative (=1-sensitivity)	D = true negative (specificity)

A model with high predictive power has high true positive and true negative rates, and low false negative and false positive rates. Because the sample for the re-estimation of Ohlson(1980) and Zmijewski(1984) contain more non-bankrupt firms than bankrupt firms, it is important to look at the percentages instead of looking at the numbers in the table. For each re-estimated model, the total percentage predicted correctly is calculated, which is: (A+D)/(A+B+C+D). It is important to note that this number depends on the cut-off point that is chosen, which is used to predict a firm as bankrupt or as non-bankrupt. The cut-off point of each model is chosen, as the intersection of the sensitivity and specification, in a graph with possible cut-off points on the X-axis and sensitivity/specificity on the Y-axis. This is done, because the classification now includes the effect of having more observations in the non-bankrupt group than in the bankrupt group, and the sum of the percentages of type I and type II errors is minimized.

Zhou, Obuchowski, & McClish (2011) note that the overall accuracy depends on the cut-off point that is chosen, and that there is also a way to check the predictive power of a model without having a fixed cut-off point; Receiver Operating Curves (ROC). ROCs are plotted in a graph that looks as the graph in figure 3.

figure 3: Receiver Operating Curves



The graph that is used to calculate the area under ROC has sensitivity on the Y-axis, which is in this case the fraction of bankrupt firms that the model correctly classifies as bankrupt. On the X-axis, 1-specificity is plotted, which is the probability that the model predicts that a company will go bankrupt, given that the company did not file for bankruptcy. The 45^o line is a model that cannot distinguish bankrupt firms from non-bankrupt firms. The larger the area under the ROC, the better the model can discriminate between bankrupt and non-bankrupt companies. So a model with area under ROC of 0.5 is a useless model, and a model with area under ROC of 1 is a perfect model. In the case of figure 3 it is clear that model 1 has more predictive power than model 2, but it is not always true that the model with the largest area under ROC is the best model. In some cases researchers are more interested in a low false negative rate than in a low false positive rate. For example, it can be more costly when a firm is predicted as not going bankrupt, while it actually did go bankrupt, than when a firm that did not go bankrupt was predicted as going bankrupt. In order to be able to compare models, this thesis does not have a preference for low false positive rate or low false negative rate, hence they are equally treated.

3.5 Hypotheses

In this thesis, original models will be applied to the new sample. It is expected that all three models, when using original estimate coefficients, will over-predict bankruptcy since it became less attractive for firms to file for bankruptcy after the BACPA change. Therefore, the first null hypothesis is as follows:

$H1_0$: when the original models are applied to the new sample, non-bankruptcy will be overpredicted.

Both Grice & Dugan (2001) and (Platt & Platt, 1990) suggest that the coefficients of the original models should be re-estimated to have more predictive power in different time periods than the original studies. The models that are used in this thesis are all at least 30 years old and in those years a lot has changed in the business environment since 1984. This makes it very remarkable that all three models are still used to predict bankruptcy. The model of Altman (1968) is even able to predict bankruptcy of Jordan listed companies in the period of 1989-2008, which is a completely different time period and business environment than the sample that Altman used to estimate his original model (Alareeni & Branson, 2013). This thesis investigates the predictive power of recalibrated models, when they are applied to U.S. listed firms in the period after the BACPA change in 2005. Therefore, the second null hypothesis is as follows:

$H2_0$: All three models will achieve a low accuracy rate after re-estimating the models by using the recent sample of this thesis.

The main research question is: How accurate are the bankruptcy models of Altman(1968), Ohlson(1980) and Zmijewski(1984) after recalibration, when they are applied to US listed firms in the period after the BACPA change in bankruptcy law?

The main objective of this thesis is testing the predictive power of three bankruptcy models, of which the most recent one is already 30 years old, for U.S. firms after the BACPA change in law. This will be done before and after recalibrating the models. It will also be checked how the variables change when the models are recalibrated, in order to be able to show which variables became more important predictors for bankruptcy, and which variables became less important in predicting corporate bankruptcy.

4. Results

This section first describes the results of applying the original models, without re-estimated coefficients, to the sample that contains firms in the period 2005-2007. Next, the three models will be re-estimated by using the original statistical techniques and the sample used for this thesis. Then, the original models will be compared to the re-estimated models and the differences in predictive power between the re-estimated models will be discussed.

4.1 Original models

Even though other researches advice to re-estimate the bankruptcy predicting models before using them (Grice & Dugan, 2001), it is interesting to see what their predictive power is without recalibrating. The created sample for the re-estimation of Altman's model consists of 63 bankrupt firms and 63 matched non-bankrupt firms. The model with the original coefficients is applied to this new sample. The observations with a calculated Z-score greater than 2.675 are expected not to go bankrupt, and the observations with a Z-score smaller than 2.675 are expected to go bankrupt. The cut-off point of 2.675 is chosen by Altman since it minimized the classification error rate. When using this single cut-off point and applying it to the new sample, the following classifications are made:

Table 4: Classification rates original model of Altman(1968) without grey area

The original coefficients are applied to the new sample at t-1. Firms with Z-scores greater than 2.675 are expected not to go bankrupt and firms with Z-scores smaller than 2.675 are expected to go bankrupt. N=1400, 64 bankrupt firms, 1336 non-bankrupt firms.

	True bankrupt	**True non-bankrupt**
Classified bankrupt	62 (98.5%)	47
Classified non-bankrupt	1	16 (25.4%)
Total correctly classified	61.90%	
Total classified wrong	38.10%	

Table 4 shows that the original model, when applied to another time period, predicts bankruptcy in too many cases. The number of type II errors is very high which means that the model predicts bankruptcy often for firms that did not go bankrupt. When changing the cut-off point from 2.675 to 0.1, 49 bankrupt firms and 48 non-bankrupt firms are classified correctly, which means that the total correctly classified is 76.98%. The cut-off point of 0.1 is chosen, because it minimized the classification error rate. Since only the cut-off point is changed, the same sign and importance of each variable still give a good predictive power, even though the model is based on a sample which is more than 40 years old. Altman found that most of the wrong classifications came from firms with a Z-score between 1.81 and 2.99. By using new cut-off pints, Altman is inconclusive about firms with a Z-score between 1.81 and 2.99, which is called the grey zone. Firms with a Z-score smaller than 1.81

are expected to go bankrupt, and firms with a Z-score greater than 2.99 are expected not to go bankrupt. Out of 126 firms in this sample, 12 are in the grey zone. When making use of the grey zone, the amount of observations that is classified wrong decreases, as can be seen in table 5, but it is important to note that when the grey area is used, the model is inconclusive for more than 10% of all companies in the sample. So the total classified wrong decreases, but that is mainly because the model is inconclusive for more than 10% of the companies.

Table 5:Classification rates original model of Altman(1968) with grey area

The original coefficients are applied to te new sample at t-1. The grey area consists of Z-scores between 1.81 and 2.99. N=1400, 64 bankrupt firms, 1336 non-bankrupt firms.

	True bankrupt	**True non-bankrupt**
Classified bankrupt	62	35
Classified non-bankrupt	0	14
Classified inconclusive	1	14
Total correctly classified	60.32%	
Total classified wrong	27.78%	
Total inconclusive	11.90%	

Also the original model of Ohlson(1980) is applied to the new sample. A cut-off point of 0.038 is used in his original model, since it minimized the sum of the type I and type II errors. In table 6 the classification of the original model and cut-off point of 0.038 when applied to the new sample can be found. Also in this model, bankruptcy is predicted in too many cases, since for only 65 from 1336 non-bankrupt firms the model predicted non-bankruptcy.

Table 6: Classification rates original model of Ohlson(1980) original cut-off point

Original coefficients are applied to the new sample at t-1, and a cut-off point of 0.038 is used. N=1400, 64 bankrupt firms, 1336 non-bankrupt firms.

	True bankrupt	**True non-bankrupt**
Classified bankrupt	35(54.69%)	1271
Classified nonbankrupt	29	65 (4.78%)
Total correctly classified	7.14%	

The total classification rate when using the same cut-off point as in the original model, is very low. When a new cut-off point is used, which maximizes the sums of the correctly classified observations, the original model becomes more useful, as can be seen in table 7. Especially the classification of non-bankrupt firms improved, since with the original cut-off point only 4.78% of the non-bankrupt firms was classified correctly, and with the new cut-off point, 68.64% of the non-bankrupt firms is classified correctly.

Table 7: Classifications original Ohlson(1980) model, optimal cut-off point

Original coefficients are applied to the new sample at t-1, and a cut-off point of 0.6 is used. N=1400, 64 bankrupt firms, 1336 non-bankrupt firms.

	True bankrupt	True non-bankrupt
Classified bankrupt	44 (68.75%)	419
Classified nonbankrupt	20	917 (68.64%)
Total correctly classified	68.64%	

The last model used in this thesis is Zmijewski(1984). Table 8 shows the results of the application of the original model to the new sample. Contrary to the expectations, without re-estimation, the model predicts non-bankruptcy in too many cases. From the 64 firms in the sample that went bankrupt, only 22 are predicted to go bankrupt by the original model. Even though the percentage of total correctly classified is 84.93%, the model is not very useful if it is not re-estimated. Because there are more non-bankrupt firms in the sample, and the model predicts non-bankruptcy in too many cases, the total classification seems good, but the classification for bankrupt firms is only correct for 34.4% of the observations. So contrary to what was expected, when the original model of Zmijewski(1984) is applied to the new sample, non-bankruptcy is overpredicted.

Table 8: Classifications of original Zmijewski(1984) model

Original coefficients are applied to the new sample at t-1. A probability greater than 0.5 indicates that a firm is expected to go bankrupt, a probability of smaller than 0.5 indicates that a firm is expected not to go bankrupt. N=1400, 64 bankrupt firms, 1336 non-bankrupt firms.

	True bankrupt	True non-bankrupt
Classified bankrupt	22(34.4%)	169
Classified nonbankrupt	42	1167(87.35%)
Total correctly classified	84.93%	

Tables 4 until 8 show that when the original models with the original coefficients are applied to the new sample, they have low predictive power. It is expected that the models become more useful after re-estimation of the coefficients.

4.2 Recalibration of original models

In order to be able to use the models in different time periods, they have to be re-estimated (Grice & Dugan, 2001). It is checked how the magnitude and sign of each variable changes, in order to find out which factors became more important in predicting bankruptcy and which factors became less important, compared to the time periods of the original models.

4.2.1 Re-estimation of Altman(1968)

For the re-estimation of the Altman(1964) model, a sample of 63 bankrupt firms and 63 matched non-bankrupt firms is used. This sample is pairwise randomly split up in an estimation sample and a control sample. The estimation sample is used to re-estimate the model and consists of 31 bankrupt firms and 31 non-bankrupt firms. The holdout sample is used to check the accuracy rate of the model by using the coefficients that are obtained from the estimation sample, and consists of 32 bankrupt and 32 non-bankrupt firms. The cut-off point is set as the average of the discriminant score of the bankrupt companies and the discriminant score of the non-bankrupt companies in the estimation sample. This cut-off point is found for t-1, t-2 and t-3 in the estimation samples, and this cutoff point is also used to classify the companies in the control samples at t-1, t-2 and t-3. The results of the recalibrated model at 1, 2 and 3 years before bankruptcy are shown in table 9.

Table 9: Re-estimation Altman t-1, t-2 and t-3

In-sample prediction results, N=62, 31 bankrupt and 31 non-bankrupt companies. Standardized canonical discriminant function coefficients are shown for t-1, t-2 and t-2. P-values are *shown in brackets.*
, **, * indicate significance at 10, 5 and % respectively. t-1, t-2 and t-3 indicate one, two and three years before bankruptcy respectively.*

	Altman(1968)	***Discriminant coefficients Recalibrated models***			***Canonical structure***
	t-1	*t-1*	*t-2*	*t-3*	*t-1*
WC/TA (X1)	0.012 ***	.9343** (0.0142)	.7532 (0.1303)	2.4261 (0.9014)	0.3337
RE/TA (X2)	0.014***	-.2629 (0.1725)	-.4051 (0.8748)	-3.86625 (0.7428)	0.1824
EBIT/TA (X3)	0.033***	-.1851 (0.6650)	.1540 (0.5994)	-.8188 (0.7306)	0.0575
MVE/TD (X4)	*0.006****	.5883 (0.1489)	-.6005 (0.4342)	-.25492 (0.8977)	0.1932
S/TA (X5)	*0.999*	.9714*** (0.0000)	.9479*** (0.0000)	1.1164 (0.0000)	0.6518
F ratio		*10.699*	*7.2106*	*8.2749*	
Likelihood ratio		*0.5114*	*0.6083*	*0.5751*	
Correctly classified [9]	*94.45%*	*84.38%*	*84.38%*	*81.25%*	

WC/TA=working capital/total assets. RE/TA = retained earnings/total assets. EBIT/TA = earnings before interest and taxes/total assets. MVE/TD= market value of equity/book value of total debt. S/TA=sales/total assets

The signs in the original model are all positive and the signs of the significant variables remain positive. Altman(1968) notes that the difference between bankrupt and non-bankrupt firms for X5 is not significant, so when univariate analysis would have been used, X5 would not have been included in the model. Because Altman(1968) looks at variables simultaneously, he found that S/TA turned out to be an important variable in predicting bankruptcy, even though the variable on its own does not seem to be an important variable which should be included in the model. Altman(1968) notes that the relative contribution of each variable can be measured. Altman ordered the contribution from

[9] Classification rates for the control sample are used. The percentages correctly classified for both estimation and control samples can be found in Appendix B.

high to low: X3, X5, X4, X2, X1. The relative importance for each variable in the re-estimated model at t-1 is from high to low: X5, X1, X4, X3, X2, which can be seen in the canonical structure. An overview of the importance all individual variables in the original model and in the recalibrated model is shown in Appendix B table 1. WC/TA became more important in predicting bankruptcy than it was in 1964. EBIT/TA had most contribution in the original model, but the canonical structure shows that EBIT/TA became the least important variable in the recalibrated model. So short term liquidity became more important in predicting corporate bankruptcy, and profitability became a less important predictor for bankruptcy in the recalibrated model, when they are compared to the relative contribution of the original model of Altman(1968). The variable Sales/TA was ordered high in relative contribution in the original model, and is still important in predicting corporate bankruptcy in the recalibrated model.

The classification matrix of the recalibrated model at t-1 can be found in table 10, and the classification matrices of the recalibrated models at t-2 and t-3 can be found in Appendix B. The total correctly classified is calculated as the correctly classified observations divided by the total correctly classified observations plus the Type I and Type II errors.

Table 10: Classification matrix re-estimated Altman t-1

This classification does not include a grey area. Cut-off point is based on the estimation sample and set as the average of the discriminant score of the bankrupt firms and the discriminant score of the non-bankrupt firms. Cutoff point =1.83

	Estimation sample		**Control sample**	
	True bankrupt	True non-bankrupt	True bankrupt	True non-bankrupt
Classified bankrupt	29	5	29	7
Classified non-bankrupt	2	26	3	25
Total correctly classified	88.71%		84.38%	

The percentage of correctly classified observations of the control sample decreases when estimating longer periods in the original model of Altman. For t-1, t-2 and t-3 the percentage correctly classified are 95%, 72% and 48% respectively. It is interesting to see that the re-estimated model at t-1 has lower classification accuracy than the original model, but for t-2 and t-3 the recalibrated model classifies better than the original model.

4.2.2 Re-estimation of Ohlson(1980)

For the re-estimation of Ohlson, the sample consisting of 64 bankrupt firms and 1336 non-bankrupt firms is used. The sample is randomly split up in a way that the ratio of bankrupt to non-bankrupt firms is the same for both samples. The estimation sample consists of 22 bankrupt firms and 462 non-bankrupt firms. The hold-out sample consists of the remainder of the sample; 42 bankrupt firms and 874 non-bankrupt firms. The results of the logistic re-estimations for t-1, t-2 and t-3 are shown in table 10.

The coefficients in table 11 are the regression coefficients, but the interpretation of the coefficients is not as straightforward as with an OLS-regression. Appendix C includes table 1 with the odds ratios, which are used to interpret the effect of a one unit increase/decrease of each variable. The second table of Appendix C shows which variables were significant or insignificant in the original model, and which variables are (in)significant in the recalibrated models. By comparing the significance between the original and the recalibrated models, it can be seen which variables became more important and which variables became less important in predicting bankruptcy.

Table 11 Re-estimation of Ohlson(1980)

In-sample prediction results Ohlson, N=484. (22 bankrupt, 462non-bankrupt)

t-statistics are shown in brackets. *, ** and *** indicate significance at 10%, 5% and 1% respectively. *t-1, t-2 and t-3 indicate one, two and three years before bankruptcy respectively.*

Variable	Ohlson (1980) model 1[a]	Ohlson(1980) model 3[b]	Recalibrated Ohlson t-1	Recalibrated Ohlson t-2	Recalibrated Ohlson t-3
Size	-.407 ***	-.478***	-.2514	-.4211	-.0602
	(-3.78)	(-6.23)	(-0.78)	(-1.59)	(-0.25)
TL/TA	6.03***	5.29***	-0.0684	1.4109*	.1447
	(6.61)	(7.72)	(0.11)	(1.70)	(0.35)
WC/TA	-1.43*	-.990*	-.5032	.4929	-.0033
	(-1.89)	(-1.74)	(-0.68)	(0.544)	(-0.01)
CL/CA	.0757	0.062	-.0899	.0639	.0369
	(0.761)	(.738)	(-0.73)	(0.46)	(0.88)
OENEG	-1.72***	-1.91***	1.8587 **	0.2799	.0328
	(-2.450)	(-3.11)	(2.36)	(0.28)	(0.76)
NI/TA	-2.37*	-4.62***	1.3804	2.7287**	.6096
	(-1.85)	(-3.60)	(1.45)	(2.17)	(0.76)
FUTL	-1.83***	-2.25***	.7874	.4574	.1708
	(-2.36)	(-3.42)	(1.23)	(0.84)	(0.54)
INTWO	0.285	-.521*	4.2588***	2.4364***	1.3178**
	(0.812)	(-1.73)	(4.07)	(3.25)	(2.26)
CHIN	-.521**	.212	0.9160*	-.5740	-.1340
	(-2.21)	(1.30)	(1.78)	(-1.19)	(-0.33)
Intercept	-1.32	1.13	-5.5813***	-4.4864***	-3.7044***
	(-.970)	(1.15)	(-4.77)	(-4.90)	(-4.80)
Pseudo R2	0.8388	0.719	0.3936	0.2518	0.0543
Area under ROC			0.8393	0.7671	0.7616
Correctly classified[10]	96.12%	92.84%	85.59%	79.91%	70.74%

[a] *The first model of Ohlson predicts bankruptcy within one year.*

[b] *The third model of Ohlson predicts bankrupty within one or two years.*

Size=log(total assets),TL/TA= Total liabilities/ Total assets. WC/TA=Working capital/Total assets. CL/CA=Current liabilities/Current assets. OENEG= 1 if total liabilities>total assets, 0 otherwise. NI/TA=Net income/Total assets. FUTL=Funds provided by operations/total liabilities, where pretax income + depreciation and amortization is used as a proxy for funds provided by operations. INTWO is 1 if net income was negative in last two years and 0 otherwise. CHIN=change in net income

The variable INTWO, which is 1 if net income was negative for the last two years and zero otherwise, is not significant in the original model at t-1. In the re-estimated model, INTWO is highly significant

[10] The percentages correctly classified of the recalibrated models can be found in Appendix C

for all three time periods. It is not surprising that INTWO is significant and the sign is positive. Intuitively it makes sense that firms that had a negative income in the past two years, are more likely to go bankrupt. Since a higher O-score means a higher probability of bankruptcy, the sign is thus positive. So INTWO was not an important factor in predicting bankruptcy in the original model, but in the recalibrated models it is turns out to be very significant. Hence, having a negative net income seems to drive companies more to bankruptcy nowadays than it did in 1980. Also the variable FUTL is not significant in the original model, and highly significant in the recalibrated models. Both FUTL and INTWO are measures for liquidity. So liquidity became a more important predictor for bankruptcy nowadays than in 1980. It can also be seen that in the original model, SIZE is a highly significant predictor for the likelihood of going bankrupt. SIZE has a negative sign in the original models, so smaller companies are more likely to go bankrupt. However, in the re-estimated models, SIZE is still negative but insignificant for all three time periods. Hence, size became a less important factor in predicting bankruptcy, because it was significant in the original models, and insignificant in the recalibrated models. Also the variable TL/TA has a very different role in the original model than in the recalibrated model. Whereas long term solvency used to be an important predictor for bankruptcy in 1980, in the recalibrated model the variable is insignificant at all three time periods. Since OENEG serves as a discontinuity variable in order to balance the effect of TL/TA, the sign and magnitude is not discussed in further detail.

By filling in the coefficients for each variable for each firm, O-scores are calculated. A higher O-score indicates a higher probability of bankruptcy. In the original model, Ohlson(1980) finds that when a cut-off point of 0.038 is used, the model has the lowest misclassification rate. The cut-off points for the re-estimated models are set as intersection of sensitivity and specificity for the estimation sample. This means that the cut-off point is set such that the sum of the percentages of type I and type II errors is minimized. When using the cutoff-point of 0.038, Ohlson's first model classifies 87.6% of the bankrupt firms and 82.6% of the non-bankrupt firms correctly at t-1, which is a total accuracy rate of 82.84% at t-1. The classification matrix of the recalibrated model can be found in table 12. The classification matrices of the recalibrated models at t-2 and t-3 can be found in Appendix C.

Table 12: Classification matrix re-estimated Ohlson t-1

An optimal cut-off point is based on the intersection between the sensitivity and specificity in the estimation sample. The same cut-off point is used in the control sample. Cut-off point is set at 0.062

	Estimation sample N=484		Control sample N=916	
	True bankrupt	True non-bankrupt	True bankrupt	True non-bankrupt
Classified bankrupt	20 (90.91%)	54	25 (59.52%)	115
Classified non-bankrupt	2	408(88.31%)	17	759 (86.84%%)
Total correctly classified	88.43%		85.59%	
Area under ROC curve	0.9186		0.8393	

When taking into account that a fair cutoff point should be used, the recalibrated model has almost the same accuracy rate as the original model. Even though the original model is based on a data 30 years before, the model does not lose predictive power when it is applied to the new sample, as can be seen in the total accuracy rates for the re-estimated models.

4.2.3 Re-estimation of Zmijewski(1984)

To re-estimate the model of Zmijewski(1984), the same sample is used as for the re-estimation of the model of Ohlson(1980). The results of the re-estimated probit models for t-1, t-2 and t-3 are summarized in table 13.

Table 13: Re-estimation of Zmijewski(1984)

In-sample prediction results Zmijewski, N=484. (22 bankrupt, 462non-bankrupt) .

t-1, t-2 and t-3 indicate one, two and three years before bankruptcy respectively.

	Zmijewski (1984)[a]	Recalibrated t-1	Recalibrated t-2	Recalibrated t-3
NI/TA	-4.513***	.16603	.1440	-.0131
		(1.16)	(0.63)	(-0.07)
TD/TA	5.679***	.9502***	1.0816***	.2189
		(2.98)	(3.22)	(0.50)
CA/CL	.004	-.3298***	-.0850	-.1864**
		(-2.78)	(-1.32)	(-2.15)
Intercept	-4.336***	-1.2577***	-1.7298***	-1.3291***
		(-5.25)	(-8.62)	(-5.91)
Pseudo R2		0.1385	0.0850	0.0494
Area under ROC		0.7704	0.6641	0.6963
Correctly classified[11]	97.4%	60.31%	71.07%	61.03%

[a] the coefficients of the model with 800 nonbankrupt firms and 40 bankrupt firms are used at t-1.

z-statistics are shown in brackets

*** , **, *indicate significance at 1%, 5%, 10% respectively

NI/TA = net income/total assets, TD/TA= total debt/total assets and CA/CL= current assets/current liabilities.

[11] Percentages correctly classified of the recalibrated models can be found in Appendix D.

It can be seen that TD/TA is significant and positive at t-1 and t-2. The positive sign is as expected, since firms with higher total debt than total assets are more prone to bankruptcy. So when TD/TA increases, the Zmijewski-score increases and the higher the Zmijewski-score, the higher the likelihood of going bankrupt. The interpretation of a coefficient of the probit model is not very intuitive, so marginal effects are shown in Appendix D. The marginal effects show the effect of a change in a variable on the probability instead of on the Zmijewski-score. Because TD/TA was a significant variable in the original model, and it still is significant in the recalibrated models at all time periods, it can be concluded that highly leveraged were more likely to go bankrupt 30 years ago, and nowadays leverage is still an important factor in predicting bankruptcy.

The individual importance of each variable in the original and in the recalibrated model is shown in Appendix D table 2. It is remarkable to see that NI/TA was a very important predictor for bankruptcy in 1984, whereas it is insignificant in the recalibrated models at one, two and three years before bankruptcy. Also CA/CL has a different role in the original model compared to its role in the recalibrated models. CA/CL was not significant in the original model, but it is the most important factor in predicting bankruptcy in 2005-2007. This importance of variables of the original models compared to the importance of variables in the recalibrated models show that 30 years ago it was more likely that a firm would go bankrupt if its profitability was low, whereas nowadays the short term liquidity is a more important factor in predicting corporate bankruptcy.
In order to classify firms as bankrupt or non-bankrupt, the cut-off point is set as the intersection of the sensitivity and specificity, which is also done for the logit regression. This is done because there are 20 non-bankrupt firms in the sample for every bankrupt firm. So even if the model classifies every observation as non-bankrupt, the total accuracy rate is 95%, even though 0% of the bankrupt firms is classified as bankrupt. In order to avoid this, the cut-off point is set such that the percentages of Type I and Type II errors are minimized. The classification matrix at t-1 can be found in table 14 below. The classification matrices at t-2 and t-3 can be found in Appendix D.

Table 14: Classification matrix of the recalibrated model of Zmijewski(1984) at t-1

An optimal cut-off point is based on the intersection between the sensitivity and specificity in the estimation sample. The same cut-off point is used in the control sample. Cut-off point is set at 0.056

	Estimation sample N=484		**Control sample N=916**	
	True bankrupt	True non-bankrupt	True bankrupt	True non-bankrupt
Classified bankrupt	16 (72.73%)	121	26(61.90%)	256
Classified non-bankrupt	6	341(73.81%)	16	618 (70.71%)
Total correctly classified	73.67%		60.31%	
Area under ROC curve	0.7881		0.7704	

4.3 Evaluation of the models

To evaluate the models, the areas under Receiver Operating Curves are used, because contrary to the overall accuracy, the area under ROC does not depend on a specific cutoff point. Because the model of Altman(1968) uses MDA, the outcome of the model is not 0 and 1, the total percentage correctly classified is used as a measure of accuracy, whereas the accuracy of the recalibrated models of Ohlson(1980) and Zmijewski(1984) are measured by area under ROC. So area under ROC is used when possible, since this does not depend on one specific cutoff point. Since this thesis does not distinguish between false positive rates and false negative rates, models with a larger area under ROC are better. As noted by (Fischer, Bachmann, & Jaeschke, 2003) models with an area under ROC smaller than or equal to 0.5, are useless, the accuracy of models with are under ROC between 0.5 and 0.7 is low, the accuracy of models with area under ROC between 0.7 and 0.9 is moderate, and when the area under ROC is greater than 0.9 the accuracy is high. Since the original models show the percentage of correctly classified observations, and do not present the area under ROC, all re-estimated models also include the percentage correctly classified, in order to be able to compare the classification of the original models with the classification of the recalibrated models. When comparing accuracy rates it is important to note that all recalibrated models are classified by using an optimal cutoff point which minimizes the sum of the percentages of type I and type II errors, but the original models of Ohlson(1980) and Zmijewski(1984) report overall accuracy without correcting the cutoff point. The optimal cut-off point of each model is chosen as the intersection of the sensitivity and specification, in a graph with possible cut-off points on the X-axis and sensitivity/specificity on the Y-axis. By choosing this cutoff point, it does not matter anymore that there are more non-bankrupt companies than bankrupt companies in the sample. When the cutoff point is not corrected, the model might have a very high total accuracy rate, even when the model does not classify any of the bankrupt companies correctly, because there are 20 times more non-bankrupt than bankrupt companies.

Areas under ROC and percentages correctly classified can be found in Appendix B, C and D for the recalibrated models of Altman(1968), Ohlson(1980) and Zmijewski(1984) respectively. All accuracy rates of original and recalibrated models are also summarized in Appendix E, in order to have an overview which makes it easier to compare accuracy between models and between time periods. The recalibrated Ohlson(1980) models have greater areas under ROC than the recalibrated Zmijewski(1984) model. The accuracy of the recalibrated Ohlson(1980) model is highest one year before bankruptcy. It is remarkable that the accuracy rate for the recalibrated Ohlson(1980) model is the same for two and three years before bankruptcy. This means that the recalibrated model predicts bankruptcy three years in advance as good as it predicts bankruptcy two years in advance.

When comparing the original model of Ohlson(1980) to the recalibrated model, the total accuracy rate is compared, because the original model does not include area under ROCs. When an optimal cutoff point is used in Ohlson(1980), the total accuracy rate is 82.84%. This number can be compared to the accuracy rates of the recalibrated models, since these models also used an optimal cut-off point. The accuracy rates of the recalibrated models are 85.59%, 79.91%, 70.74% at t-1, t-2 and t-3 respectively.

The areas under ROC of the recalibrated Zmijewski(1984) models, are lower than the areas under ROC of the recalibrated models of Ohlson(1980). The total percentage correctly classified of the recalibrated models of Zmijewski(1984) are lower than the percentage correctly classified of the recalibrated modesl of Altman(1964). The percentage correctly classified is also much lower for the recalibrated model than for the original model. It is remarkable that at t-2 the total percentage correctly classified is 71.07%, whereas it is 60.31% at t-1.

For the recalibrated model of Altman(1964), no ROC's are available, so the percent correctly classified is used to evaluate the models. The recalibrated model has the same accuracy rate for t-1 and t-2. Even though Altman(1964) notes that the predictive power of the original model decreases dramatically after t-2, the recalibrated model can also be used at t-3.

It is interesting to see that relatively old models are not very useful when they are applied to the new sample, but after recalibration the models are still accurate. To check where the difference in accuracy between the original models and the recalibrated models comes from, the coefficients of the original models and the recalibrated models are compared. In the previous section it is discussed for each model which variables became more important in predicting bankruptcy and which variables became less important. In this section it is discussed what the change of importance of variables means for all three models together.

It became clear that in all three models, measures of short term liquidity (CA/CL and WC/TA) became much more important predictors for bankruptcy in the recalibrated models than in the original models. So having short term cash constraints is what drives companies to bankruptcy nowadays. In the recalibrated models of both Zmijewski(1984) and Altman(1968), measures of profitability(NI/TA and EBIT/TA) became less important in predicting bankruptcy nowadays, compared to the importance of profitability in the original models. So it seems that having short term liquidity problems is a more important predictor for bankruptcy than low profitability nowadays. Not having enough cash can be an immediate problem for firms, whereas low profitability in the longer term can lead to problems for firms. So 30 years ago firms filed for bankruptcy because in the longer term they were not going to be able to meet their obligations, whereas firms nowadays go bankrupt because of immediate problems. So it looks like filing for bankruptcy became more a last possibility for firms than it was 30 years ago.

5. Discussion

This section consists of the main results of this thesis. Also the limitations and suggestions for further research are discussed.

5.1 Conclusion

This study investigated the predictive power of the bankruptcy predicting models of Altman(1968), Ohlson(1980) and Zmijewski(1984), when they are applied to U.S. listed firms in the period after the BACPA change in law in 2005.

The first hypothesis that is tested, is that when the original models are applied to the new sample, firms will be classified as non-bankrupt too often. The null hypothesis is rejected for the model of Altman(1964) and the model of Ohlson(1980). The predictive power of all three models is low, but for Altman(1964) and Ohlson(1980) bankruptcies are overpredicted, as was expected. For the model of Zmijewski(1984), the amount of non-bankruptcies was overpredicted, which is contrary to what was expected.

After recalibration of the models, the second hypothesis is tested. The second null hypothesis stated that all three models will achieve a low accuracy rate after re-estimating the models by using the recent sample of this thesis. The original models had accuracy rates at t-1 of 94.45%, 96.12% and 97.4% for the model of Altman(1964), Ohlson(1980) and Zmijewski(1984) respectively. It is important to note that both Ohlson(1980) and Zmijewski(1984) did not correctly adjust their cut-off points in order to correct for the differences in group sizes. Ohlson(1980) predicted 100% of his non-bankrupt firms correctly, but only 53% of the bankrupt firms. Since there are 20 times more non-bankrupt firms in his sample than non-bankrupt firms, the overall percentage correctly predicted is very high. When a cut-off point is used which minimizes the sum of the percentages of type I and type II errors, 87.6% of the bankrupt firms and 82.5% of the non-bankrupt firms are classified correctly, which in total is an accuracy rate of 82.84%, which seems more fair to use. Also the total correctly classified of Zmijewski(1984) should be interpreted carefully.

An optimal cut-off point, which minimizes the sum of the percentages of the type I and type II errors, is used for the classification matrix of the recalibrated models of Ohlson(1980) and Zmijewski(1984). For the recalibrated model of Altman(1964), the group sizes were equal, so the cut-off point is not adjusted. The recalibrated models of Zmijewski(1984) clearly underperforms when comparing the percentage correctly classified with the recalibrated models of Altman(1964) and Ohlson(1980). It is remarkable that the accuracy of both the recalibrated models of Altman(1964) and Ohlson(1980) do not dramatically decrease after t-2, since the original models were not useful at t-3. To conclude the above, the models of Altman(1964), Ohlson(1980) can still be used to predict bankruptcy, but it is strongly recommended to recalibrate the models first. The accuracy of the recalibrated model of Zmijewski(1984) is not high at t-1 and decreases at t-2 and t-3, so this model is less useful nowadays to predict corporate bankruptcy.

The accuracy of the models increases when the models are recalibrated. Because the statistical method and the variables remain the same for original and recalibrated models, the sign and magnitude of the variables are compared, in order to see what actually changed in the recalibrated models, and what made the recalibrated models more accurate when applied to the current sample than the original models. The most noticeable change between the original and the recalibrated models is that measures of short term liquidity became much more important in the recalibrated models, and profitability became less important. Hence it looks like that in the past, companies filed for bankruptcy if they had longer term problems (like low profitability), whereas in 2005-2007 companies file for bankruptcy for more immediate problems like liquidity issues.

5.2 Limitations

Readers should read the results with caution, since the sample size that is used for this thesis is small. No data is taken after the first quarter of 2007 because it is expected that the financial crisis had a big impact on corporate bankruptcies in the U.S., which is why the period of the crisis should be investigated separately. Mainly because of this limitation, the sample size that is used is small. Besides, there may be omitted variables in the models. The original models that are used are based on very old data and the variables that are chosen depend on this data. It may be better to exclude variables that are insignificant in the recalibrated models, and it is might also be true that there are variables that are not taken into account in this thesis, but that might have a significant influence on the probability of bankruptcy.

5.3 Suggestions for future research

It is very interesting to investigate the prediction of bankruptcies during the financial crisis. Even though the characteristics and causes of every crisis are different, it is interesting to see whether there are still models which had predicted the bankruptcies during the crisis correctly. The results of the predicting of bankruptcies in the recent crisis can also be compared to bankruptcies in 1980 in the United States. Also it would be interesting to see how an aggregate model of Ohlson(1980) and Altman(1968) works, to see if the prediction increases if the results of both models are combined.

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Appendix A

This Appendix includes the correlation matrices of the explanatory variables

Table 1 Correlation matrix Altman t-1

This table shows the correlation between the independent variables used to re-estimate Altman's model at t-1.

	Z1	Z2	Z3	Z4	Z5
Z1	1.0000				
Z2	0.6220	1.0000			
Z3	0.4212	0.5662	1.0000		
Z4	-0.3310	-0.4125	-0.4423	1.0000	
Z5	0.1225	0.2065	0.3435	-0.0953	1.0000

Table 2 Correlation matrix Ohlson t-1

This table shows the correlation between the independent variables used to re-estimate Ohlson's model at t-1.

	O1	O2	O3	O4	O5	O6	O7	O8	O9
O1	1.000								
O2	-0.3246	1.000							
O3	0.2717	-0.8794	1.000						
O4	-0.3125	0.6722	-0.7928	1.000					
O5	-0.3459	0.6651	-0.5647	0.4670	1.000				
O6	0.4497	-0.7600	0.6854	-0.5589	-0.4804	1.000			
O7	0.3526	-0.0890	0.0698	-0.1121	-0.1100	0.3755	1.000		
O8	-0.4492	0.2417	-0.1870	0.1956	0.3341	-0.3747	-0.5383	1.000	
O9	0.0259	-0.0294	-0.0022	0.0050	-0.0104	0.1297	0.1921	-0.4352	1.000

Table 3 Correlation matrix Zmijewski t-1

This table shows the correlation between the independent variables used to re-estimate Zmijewski's model at t-1.

	Zm1	Zm2	Zm3
Zm1	1.0000		
Zm2	-0.0048	1.0000	
Zm3	0.0256	-0.0395	1.0000

Appendix B

This Appendix includes information of the recalibrated models of Altman(1968)

Table 1: individual importance of each variable

The importance of each variable of the original model of Altman(1968) is compared to the importance of each variable of the recalibrated model, both at t-1.

Importance of variables	Original model at t-1	Recalibrated model at t-1
1	EBIT/TA	Sales/TA
2	Sales/TA	WC/TA
3	MVE/TD	MVE/TD
4	RE/TA	EBIT/TA
5	WC/TA	RE/TA

Table 2: Classification matrix re-estimated Altman t-1

This classification does not include a grey area. Cut-off point is based on the estimation sample and set as the average of the discriminant score of the bankrupt firms and the discriminant score of the non-bankrupt firms. Cut off point = 1.83

	Estimation sample		**Control sample**	
	True bankrupt	True non-bankrupt	True bankrupt	True non-bankrupt
Classified bankrupt	29	5	29	7
Classified non-bankrupt	2	26	3	25
Total correctly classified	88.71%		84.38%	

Table 3: Classification matrix re-estimated Altman t-2

This classification does not include a grey area. Cut-off point is based on the estimation sample and set as the average of the discriminant score of the bankrupt firms and the discriminant score of the non-bankrupt firms. Cut off point = 0.81

	Estimation sample		**Control sample**	
	True bankrupt	True non-bankrupt	True bankrupt	True non-bankrupt
Classified bankrupt	27	9	29	7
Classified non-bankrupt	4	22	3	25
Total correctly classified	79.03%		84.38%	

Table 4: Classification matrix re-estimated Altman t-3

This classification does not include a grey area. Cut-off point is based on the estimation sample and set as the average of the discriminant score of the bankrupt firms and the discriminant score of the non-bankrupt firms. Cut off point = 1.92

	Estimation sample		**Control sample**	
	True bankrupt	True non-bankrupt	True bankrupt	True non-bankrupt
Classified bankrupt	27	7	29	9
Classified non-bankrupt	4	24	3	23
Total correctly classified	82.26%		81.25%	

Appendix C

This Appendix includes information of the recalibrated models of Ohlson(1980)

Table 1: Odds ratios re-estimated Ohlson at t-1, t-2 and t-3

Odds ratios are used for interpretation of the logit model

	Odds ratios		
	t-1	t-2	t-3
O1	.7771	.6563	.9416
O2	1.0708	4.0995	1.1557
O3	.6046	1.6371	.9967
O4	.9140	1.0660	1.0376
O5	6.4154	1.3230	1.0334
O6	3.9763	15.3131	1.8347
O7	2.1977	1.5760	1.1863
O8	70.7220	11.4320	3.7352
O9	2.4993	.5633	.8772
Constant	.0038	.0113	.0246

Table 2: individual importance of each variable

<table>
<tr><th rowspan="4">Recalibrated model</th><th colspan="3">Original model</th></tr>
<tr><td></td><td>Good individual predictor</td><td>Insignificant individual predictor</td></tr>
<tr><td>Good individual predictor</td><td>NI/TA, CHIN</td><td>FUTL, INTWO</td></tr>
<tr><td>Insignificant individual predictor</td><td>Size, TL/TA, WC/TA</td><td>CL/CA</td></tr>
</table>

OENEG is not included since it serves as a discontinuity variable

Table 3: Classification matrix re-estimated Ohlson t-1

An optimal cut-off point is based on the intersection between the sensitivity and specificity in the estimation sample. The same cut-off point is used in the control sample. Cut-off point is set at 0.062

	Estimation sample N=484		**Control sample N=916**	
	True bankrupt	True non-bankrupt	True bankrupt	True non-bankrupt
Classified bankrupt	20 (90.91%)	54	25 (59.52%)	115
Classified non-bankrupt	2	408(88.31%)	17	759 (86.84%%)
Total correctly classified	88.43%		85.59%	
Area under ROC curve	0.9186		0.8393	

Table 4: Classification matrix re-estimated Ohlson t-2

An optimal cut-off point is based on the intersection between the sensitivity and specificity in the estimation sample. The same cut-off point is used in the control sample. Cut-off point is set at 0.053

	Estimation sample N=484		**Control sample N=916**	
	True bankrupt	True non-bankrupt	True bankrupt	True non-bankrupt
Classified bankrupt	18 (81.82%)	91	25 (59.525%)	167
Classified non-bankrupt	4	371 (80.30%)	17	707 (80.89%)
Total correctly classified	80.37%		79.91%	
Area under ROC curve	0.8741		0.7671	

Table 5: Classification matrix re-estimated Ohlson t-3

An optimal cut-off point is based on the intersection between the sensitivity and specificity in the estimation sample. The same cut-off point is used in the control sample. Cut-off point is set at 0.053

	Estimation sample N=484		**Control sample N=916**	
	True bankrupt	True non-bankrupt	True bankrupt	True non-bankrupt
Classified bankrupt	14 (63.64%)	160	29 (69.05%)	255
Classified non-bankrupt	8	302 (65.37%)	13	619 (70.82%)
Total correctly classified	65.29%		70.74%	
Area under ROC curve	0.6948		0.7616	

Appendix D

This Appendix includes information of the recalibrated models of Zmijewski(1984)

Table 1: Marginal effects of recalibrated model of Zmijewski(1984)

	t-1	t-2	t-3
NI/TA	0.0076	0.0111	-.0010
TD/TA	0.0437**	0.0833***	0.0160
CA/CL	-0.0152***	-0.0065	-0.0136***

Table 2: individual importance of each variable

		Original model	
Recalibrated model		Good individual predictor	Insignificant individual predictor
	Good individual predictor	TD/TA	CA/CL
	Insignificant individual predictor	NI/TA	

Table 3: Classification matrix of the recalibrated model of Zmijewski(1984) at t-1, in and out of sample.

An optimal cut-off point is based on the intersection between the sensitivity and specificity in the estimation sample. The same cut-off point is used in the control sample. Cut-off point is set at 0.056

	Estimation sample N=484		Control sample N=916	
	True bankrupt	True non-bankrupt	True bankrupt	True non-bankrupt
Classified bankrupt	16 (72.73%)	121	26(61.90%)	256
Classified non-bankrupt	6	341(73.81%)	16	618 (70.71%)
Total correctly classified	73.67%		60.31%	
Area under ROC curve	0.7881		0.7704	

Table 4: Classification matrix of the recalibrated model of Zmijewski(1984) at t-2, in and out of sample.

An optimal cut-off point is based on the intersection between the sensitivity and specificity in the estimation sample. The same cut-off point is used in the control sample. Cut-off point is set at 0.049

	Estimation sample N=484		Control sample N=916	
	True bankrupt	True non-bankrupt	True bankrupt	True non-bankrupt
Classified bankrupt	12 (54.55%)	128	19 (45.24%)	242
Classified non-bankrupt	10	334(72.29%)	23	632 (72.31%)
Total correctly classified	71.49%		71.07%	
Area under ROC curve	0.6751		0.6441	

Table 5: Classification matrix of the recalibrated model of Zmijewski(1984) at t-3, in and out of sample.

An optimal cut-off point is based on the intersection between the sensitivity and specificity in the estimation sample. The same cut-off point is used in the control sample. Cut-off point is set at 0.054

	Estimation sample N=484		**Control sample N=916**	
	True bankrupt	True non-bankrupt	True bankrupt	True non-bankrupt
Classified bankrupt	14 (63.64%)	165	30 (71.43%)	345
Classified non-bankrupt	8	297 (64.29%)	12	529 (60.53%)
Total correctly classified	64.26%		61.03%	
Area under ROC curve	0.6779		0.6963	

Appendix E

This appendix gives an overview of the accuracy of original models and recalibrated models

Table 1: Accuracy Altman(1968)

	Total percentage correctly classified in estimation sample
Altman original t-1	95%
Altman original t-2	83%
Recalibrated Altman t-1	84.38%
Recalibrated Altman t-2	84.38%
Recalibrated Altman t-3	81.25%

Table 2 Accuracy Ohlson(1980)

	Total percentage correctly classified in estimation sample	Area under ROC in estimation sample
Ohlson original t-1	82.84% [a]	n.a.
Recalibrated Ohlson t-1	85.59%	0.8393
Recalibrated Ohlson t-2	79.91%	0.7671
Recalibrated Ohlson t-3	70.74%	0.7616

[a]) This accuracy is calculated by making use of a cut-off point of 0.038, so 87.6% of the bankrupt firms is classified correctly and 82.6% of the non-bankrupt firms is classified correctly.

Table 3: Accuracy Zmijewski(1984)

	Total percentage correctly classified in estimation sample	Area under ROC in estimation sample
Zmijewski original t-1	82.84% [a]	n.a.
Recalibrated Zmijewski t-1	85.59%	0.8393
Recalibrated Ohlson t-2	79.91%	0.7671
Recalibrated Ohlson t-3	70.74%	0.7616