MASTER THESIS

BUSINESS ADMINISTRATION – FINANCIAL MANAGEMENT

ACCURACY RATE OF BANKRUPTCY PREDICTION MODELS FOR THE DUTCH PROFESSIONAL FOOTBALL INDUSTRY

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MANAGEMENT SUMMARY

Bankruptcy and financial distress are chronicle problems for the Dutch professional football industry. Since the establishment of Dutch's professional football in 1954 nine clubs have been declared bankrupt (four since 2010) and many others were facing financial distress last few years. Club failure identification and early warnings of impending financial crisis could be very important for the Dutch football association in order to maintain a sound industry and to prevent competition disorder. As financial ratios are key indicators of a business performance, different bankruptcy prediction models have been developed to forecast the likelihood of bankruptcy. Because bankruptcy prediction models are based on specific industries, samples and periods it remains a challenge to predict with a high accuracy rate in other settings. Therefore, the aim of this study is to assess the accuracy rate of bankruptcy prediction models to an industry and period outside those of the original studies namely, the Dutch professional football industry. The study draws on the information from financial statements (e.g. annual report and season reports) as publicly provided by the Dutch professional football clubs since 2010. The accuracy rate of three best suitable (i.e. commonly used and applicable to the Dutch football industry) accounting-based bankruptcy prediction models of Ohlson (1980), Zmijewski (1984), and Altman (2000) were tested on Dutch professional football clubs between the seasons of 2009/2010 - 2013/2014. The sample size on the Dutch professional football industry throughout the different seasons fluctuates between 30 and 36 depending on the available data in a particular season. The study assumed that there is no difference in accuracy rate between the three accounting-based bankruptcy prediction models. Alternatively is assumed that the Z" model of Altman (2000) will outperform the other models and hereby follows the studies of Vazquez (2012) and Barajas & Rodríguez (2014) who claim that the Z" model is the best choice for football clubs. The accuracy rates for the Dutch professional football industry on Ohlson (1980), Zmijewski (1984) and Altman (2000) are depending on the prediction time frame between 17% and 19% (Ohlson), 61% and 66% (Zmijewski), 38% and 49% (Altman Z'), and 23% and 26% (Altman Z"). Overall, Zmijewski's probit model (1980) performed most accurate on the Dutch professional football industry within the five seasons of investigation. This implies that Zmijewski's model is the best predictor for bankruptcy likelihood for the Dutch professional football industry. However, the accuracy rates are quite low and therefore should be set into perspective and studied cautiously. Furthermore this study shows that the Dutch professional football industry has some huge financial problems. The majority of the clubs have liquidity, profitability and leverage problems and are based on the results of the different bankruptcy prediction models facing bankruptcy since they are having financial distress.

LIST OF ABBREVIATIONS

Table 1. List of abbreviations used in this master thesis

Abbreviation	Written entirely	Description and/or English Translation
AGOVV	Alleen Gezamenlijk Oefenen Voert Verder	Only Exercising Together Performs Further
AMM	Amortization	Amortization of a club's intangible assets
BV	Betaald Voetbal	Professional Football
BE/TL	Book Value Equity / Total Liabilities	Leverage ratio
CHIN	Change Net Income	= (NIt - Nit-1) / (NIt + Nit-1), where t is the year
CA/CL	Current Assets / Current Liabilities	Liquidity ratio
CL/CA	Current Liabilities / Current Assets	Liquidity ratio
DEP	Depreciation	Depreciation of a club's tangible assets
EBIT/TA	Earnings Before Interest and Taxes / Total Assets	Profitability ratio
FC	Football Club	-
FU/TL	Funds from Operations / Total Liabilities	FU = NI + DEP + AM - GSP, Liquidity ratio
FRS	Financial Rating System	Rating system developed by the KNVB in 2010
GSP	Gains on Sales of Property	-
HFC	Haarlemsche Football Club	Name of Dutch football club
INTWO	INTWO	1 If NI was negative for the last 2 years, 0 otherwise
KNVB	Koninklijke Nederlandse Voetbal Bond	Royal Dutch Football Association
MDA	Multiple Discriminant Analysis	Statistical method
MVE/TL	Market Value Equity/Total Liabilities	Leverage ratio
N.A.	Not Available	-
NI/TA	Net Income / Total Assets	Profitability ratio
NI/TL	Net Income / Total Liabilities	Profitability ratio
NWC/TA	Net Working Capital / Total Assets	Operating liquidity ratio
OENEG	OENEG	= 1 If TL > TA , 0 otherwise
OSIZE	Ohlsen Size	= LOG(total assets/GNP price-level index)
RBC	Roosendaalse Boys Combinatie	Roosendaalse Boys Combination
RE/TA	Retained Earnings / Total Assets	Profitability ratio (RE = net profit – dividends, where dividends in Dutch football are null)
RFS	Russia Football Union	-
SALES/TA	Sales / Total Assets	Profitability ratio
TL/TA	Total Liabilities / Total Assets	Profitability ratio
UEFA	Union of European Football Associations	Leverage ratio
WC/TA	Working Capital / Total Assets	Liquidity ratio

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1. INTRODUCTION

This chapter starts with an introduction and some necessary background information of the Dutch professional football industry. Next, a problem statement follows that lead up to the objective and research questions of the study. The chapter ends with the contribution and justification of the thesis.

Bankruptcy and financial distress are chronicle problems in the global professional football industry, one of the world's most popular sport.[1] Recently internationally well know professional football clubs such as England's Portsmouth in 2010, Scotland's Glasgow Rangers in 2012, and Italian's Parma FC in 2015 have been declared bankrupt. It is striking to see that the study of A.T. Kearny[2] (2010) about the top football leagues in Europe shows that, when running as normal companies, the top leagues in England, Spain and Italy would be bankrupt within two years. Two years later in 2012 one can conclude that this did not actually happen because football clubs are not running as normal companies and seem to have their own set of rules regarding bankruptcy. Still there is an unquestionable financial problem in European football, Szymanski (2012) underlined that sixty-six English professional football clubs have been involved in insolvency proceedings during the period 1982-2010. The evidence in the study of Barajas & Rodriquez (2014) suggests that Spanish football is in very poor financial condition and that an injection for more than €900 Mill. in total is required as a financial health therapy for a sound Spanish football industry. This is in line with previous studies within Spanish football of García & Rodríguez (2003), Boscá, Liern, Martínez & Sala (2008) and Barajas & Rodríguez (2010) who all assert that the economic situation of Spanish football clubs presents an important fragility. According to the study of Syzmanski (2010), in Spain, most clubs have significant debt exposure, only Real Madrid and FC Barcelona have real financial strength, and the rest of the clubs struggle to compete. For Spain's neighbor Portugal this isn't much different. According to Mourao (2012) most Portuguese football teams had increased their debt ratios during the previous two decades. But also other professional football clubs all over world face similar problems. Russia's Football Union (RFS) has financial problems due to the collapse of their

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[1] Generally known as 'football' in most of the world, but also often referred to as 'soccer', especially in North America. Not to be confused with American football which is a complete different ballgame.

[2] A.T. Kearny is a global management consulting firm that focuses on strategic and operational CEO-agenda issues facing, business, governments and institutions around the globe.

monetary unit the Russian Ruble, and according to the NOS[3], the debt of the football clubs in Brazil is so high that eight of the twelve clubs barely can pay their taxes and salaries. The UEFA[4] acknowledged the financial problems of the football industry in one of their reports called UEFA Club Licensing Report (2012). According to this report 56% of European clubs participating at the highest level of national competition were loss-making in 2010 and 36% reported negative net equity. In order to prevent professional football spending more than they earn, often in the pursuit of success and in doing so getting into financial problems, which might threaten their long-term survival, UEFA started the UEFA Financial Fair Play Regulations program in 2011.

In the top division of Dutch football 'the Eredivisie' none of the clubs have ever been declared bankrupt while they were playing in the highest division. Bankruptcy is more common for clubs that play in the second highest and also the lowest Dutch professional football division 'the Jupiler League'. Since the establishment of Dutch's professional football in 1954 nine clubs participating in the second highest division have been declared bankrupt, of which four since 2010. When one keeps in mind that the average amount of clubs playing in one of the two professional divisions was thirty-eight last decade, four since 2010 (more than 10%) is quite a striking number. Because of the competitive nature of Dutch football with the possibility to promote and relegate it can and does happen that a club which has been declared bankrupt has a recent history in the highest division. Financial distress however is something that both first and second highest division clubs faced now and then, especially since the last decade.

To maintain a sound Dutch professional football industry the Royal Dutch Football Association[5] made together with the clubs an agreement in 2010 to communicate in a transparent way about the financial situation of Dutch professional football industry and the individual clubs. Since this agreement clubs are forced to make their financial statements publicly available. An important part of this transparency is the publicly announcement of the category-division by the KNVB[6]. This category-division is based on the financial information from annual reports of the clubs. These,

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[3] NOS is the abbreviation of Nederlandse Omroep Stichting, which is the Dutch translation of Dutch Broadcast Foundation. It has a special statutory obligation to make news and sports programmes for the three Dutch public television channels and the Dutch public radio services. See references for exact source.

[4] UEFA is the governing body of European football (Union of European Football Associations – UEFA).

[5] The Royal Dutch Football Association is the governing body of football in the Netherlands. It organizes the main Dutch football leagues.

[6] KNVB is the abbreviation of Koninklijke Nederlandse Voetbalbond, which is the Dutch translation of Royal Dutch Football Association.

mostly financial figures, are filled in into a model called the Financial Rating System[7], which is developed by the KNVB in 2010. The individual score of a club will put them in one of the category-divisions. The division consists of three different categories: category I (insufficient), category II (sufficient) and category III (good). Every year there are several clubs categorized in the insufficient category I, which means that a club is likely to head to financial distress and that it needs to work on financial recovery. The recovery is at the clubs own responsibility and they need to develop a plan of approach that has the goal to belong to category II or III on a structural bases. The clubs are supposed to stick strictly to this plan to avoid sanctions of the KNVB. Sanctions could be warnings, money fines or deduction of league points. The KNVB strives to get all the club at least in category II within the upcoming years. This is to provide an early warning, for monitoring to avoid bankruptcy and to maintain a sound industry.

When bankruptcy occurs it has an effect on the followers and supporters of a professional football club. A ‘die hard’ supporter for example will feel robbed from their love for a club or his/her hobby. Besides this it has also an effect on the league’s ranking, since in cases of bankruptcy it might happen that all previous matches of the concerning club during that particular season are counted as non-played games. This will cause a competition distortion. Business failure identification and early warnings of impending financial crisis are important to analysts, practitioners, the suppliers of capital, investors, creditors, management, employees, auditors and in case of the professional football industry the concerning football association, since these parties are all severely affected by business failures (Deakin, 1972; Charitou, Neophytou, & Charalambous, 2004). The demand to predict financial problems such like bankruptcy and financial distress has led to the development of several bankruptcy prediction models to forecast the likelihood of it. Two approaches; accounting-based bankruptcy prediction models and market-based bankruptcy prediction models, imply different views of a club/firm and use financial ratios to estimate the possibility of bankruptcy or financial distress. Because bankruptcy prediction models are based on specific industries, samples and periods it remains a challenge to predict with a high accuracy rate in other settings. This master thesis draws on the information from financial statements (e.g. annual reports, season reports) as publicly provided by the Dutch professional football clubs since 2010. The goal is to assess the accuracy rate of the best suitable (i.e. commonly used and applicable to the Dutch football industry) bankruptcy prediction models for the Dutch professional football industry.

[7] An explanation and example of the Financial Rating System (FRS-model) is shown at appendix II.

1.1 Dutch Professional Football Industry and Financial Issues

The Dutch professional football industry, like any other professional football industry, is an industry that relies on money from ticket sales, merchandising, broadcast income (demand), sponsorships and extreme wealthy business people (Szymanski, 2012). The income of a professional football club is dependent on each of the above mentioned variables. However Szymanski (2010) claims that the impact of the economic cycle on the professional football clubs is limited, there are still a lot of things that could happen that influence the income of a club in a negative way. So can there be for example negative productivity shocks to the investment-performance relationship (bad luck on the field) or negative demand shocks to the performance-revenue relationship (Szymanski, 2012). The investment-performance relationship in this case is the relation between the amount of money which is invested in the player squad (player budget) and the performance on the field which is measured by the amount of league points or league ranking. Generally the higher the player budget the higher the position on the league's ranking. The performance-revenue relationship in this case is the relation between the performance of a club (position league ranking) and a club's revenue. Generally the higher the position on the league's ranking the higher the revenue (prize money, more sponsors, more sold tickets etc.).

Furthermore Szymanski (2012, p. 16) found in his study about English professional football clubs that "*negative shocks to productivity or to demand cause wage expenditure to rise relative to income, a deteriorating balance sheet and a higher probability of insolvency*". Bankruptcy and financial distress have shocked the Dutch professional football industry several times the last few years. BV Veendam was in 2013 the 9th Dutch professional football club which has been declared bankrupt since the establishment of Dutch's professional football in 1954. Four of these bankruptcies occurred since 2010. These were HFC Haarlem in 2010, RBC Roosendaal in 2011, AGOVV in 2013 and BV Veendam in 2013. So far all Dutch professional football clubs which went bankrupt acted in the second highest football division which is called 'Jupiler League'. But also the premier league of Dutch football which is called, 'Eredivisie' had some unexpected cases of financial distress within their league. Last decade a number of teams playing in both leagues have had financial problems, but they all have been bailed out by local government or local businesses[8]. Latest case is the weak financial position of FC Twente which has to cope with extreme financial distress at the moment, only five years after their first 'Eredivisie' championship in 2010. At the moment the club is upheld by wealthy local business people who lend FC Twente money to pay short term debts. Their

[8] Among others; FC Emmen in 2012 and 2013, FC Twente in 2003, Feyenoord in 2005 and 2010, NAC Breda in 2003, 2011 and 2013, and RKC Waalwijk in 2009, 2014 and 2015.

financial distress has led to a deduction of minus six points for FC Twente in the 'Eredivisie' leagues performance ranking of 2014/2015. This penalty (e.g. deduction of points) was the result of a violation of the rules from the Financial Rating System as drafted by the KNVB in 2010. Unfortunately FC Twente is not the only club who is facing financial distress last decade. Every year there are several clubs categorized by the KNVB in the insufficient category I which means that a club is likely to head to financial distress and that it needs to work on financial recovery. In chapter 3.1.1. the FRS-model of the KNVB will be elaborated.

1.2 Problem Statement

As mentioned in the introduction, four Dutch professional football clubs went bankrupt since 2010. These bankruptcies are a major concern for the stakeholders of the organization, the supporters, the employers and the Dutch football association. Every bankruptcy or moment of financial distress of a Dutch professional football club is quite a shock for the whole Dutch professional football industry. The likelihood of financial bankruptcy can be predicted in order to take appropriate actions before an actual bankruptcy takes place. In literature several models have been developed to predict cases of potential bankruptcy. Different bankruptcy prediction models that are able to forecast business failure have been developed after Beaver´s pioneering work in 1966. The problem with those bankruptcy prediction models is that they have been developed with another methodology and are dated. Some common used bankruptcy prediction models are even more than forty years old. Since the accuracy and structure of the models change over periods of time and when the setting of the study differs (e.g. country, industry, etc.) from the original methodology, it is likely that the accuracy rate of the bankruptcy prediction models change as well (Grice & Dugan, 2003). Furthermore none of the found studies have performed a research about the accuracy rate of the bankruptcy prediction models for a professional football industry. Therefore the professional football industry of the Netherlands might be a good place to start.

1.3 Objective

The objective of this master thesis is to assess the accuracy rate of bankruptcy prediction models for the Dutch professional football industry. This objective is achieved by comparing the results of each club according to the different bankruptcy prediction models to the FRS based category-division of the KNVB from t_{+1}, t_{+2} and t_{+3}. The goal is to find out if there are differences between the different bankruptcy prediction models in order to track down which bankruptcy prediction model performs best for the Dutch professional football industry.

1.4 Research Questions

The focus of this study will be on the best suitable (i.e. can be used in the Dutch football industry) bankruptcy prediction models. In order to assess the performance of these bankruptcy prediction models, finding out which one to use and measuring the accuracy rate of them is crucial. The higher the accuracy rate of a model, the less error it will have. Less error also means that the predictive power of a certain model is better or worse than the other. This underlying problem lead to the following research question and sub-questions:

What is the accuracy rate of bankruptcy prediction models for the Dutch professional football industry?

Accompanying sub-questions are formulated in order to answer the research question and eventually reach the research goal:

1. Which bankruptcy prediction models exist in literature?

2. Which bankruptcy prediction models can be used for the football industry?

3. What is the Financial Rating System of the KNVB?

4. What is the accuracy rate of the different bankruptcy prediction models?

1.5 Contribution and Justification

1.5.1 Theoretical Contribution

Numerous studies have been conducted to analyze bankruptcy prediction models since the development of Beaver's (1966) pioneering work. Examples are among others[9] the study of Oude Avenhuis (2010), Wu *et al.* (2010) and Bae (2012). The focus of those studies differentiates from firm characteristics (e.g. legal status and firm size) to particular industries and countries. None of the found studies have conducted a research concerning bankruptcy prediction models and a professional football industry. Only the study of Barajas & Rodriquez (2014) used Altman's models to classify Spanish professional clubs according to their Z-score values, but they did not assess the accuracy rate of the used models. Therefore this research contributes to the literature because the accuracy rate of bankruptcy prediction models for the Dutch football industry is assessed.

1.5.2 Practical Contribution

It will be interesting to see if the (Dutch) professional football industry is comparable with other industries and if the bankruptcy prediction models give justice to this industry. This may help the KNVB and other similar football associations to discover future 'problem' clubs at an earlier stage. The better bankruptcy or financial distress can be predicted the less damage one of the occasions will cause to all the interested parties of the football industry.

1.5.3 Justification

The topic of this master thesis *"Accuracy rate of bankruptcy prediction models for the Dutch professional football industry"* was chosen because of the personal experience in the world of Dutch professional football and interest in the field of bankruptcy prediction of the researcher. The financial data for this industry before 2010 is very limited. This because since 2010 it became obliged for Dutch professional football clubs to make their financial statements publicly available. Therefore the timeline of this research is set from the seasons of 2009/2010 until 2013/2014. The most commonly used and most cited account-based bankruptcy prediction models have been selected to conduct this research. This because AFC Ajax is the only publicly listed Dutch professional football club which means that the market-based models are not applicable for the Dutch professional football industry due to a lack of market data of all the other clubs.

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[9] Among others; Pongsatat *et al.* (2004), Canbaş *et al.* (2006), Gang & Xiaomao (2009) Kumar & Kumar (2012), Strand (2013), and (Kleinert, 2014)

2. LITERATURE REVIEW

This chapter starts with the typology and important definitions of this research. Furthermore an introduction about bankruptcy prediction models in general is given. Next some influential works from the accounting –and market based models are reviewed. In the end, both accounting –and market based methods are compared and an end conclusion on the literature review is given.

2.1 Terminology and Definitions

2.1.1 Default, Failure, Insolvency and Bankruptcy

In existing literature, one will find different terms describing business failure. Some authors have used the term 'failure' interchangeably with 'bankruptcy', whereas some others use the term ‘insolvency’. Basically there are four generic terms that are commonly found in the literature namely: *default*, *failure*, *insolvency* and *bankruptcy*. Although authors define these terms somewhat different and use them interchangeably, they are distinctly different in their formal usage.

Default is a term which is inescapably associated with the above mentioned terms. It can be seen as a precursor of failure and occurs when a debtor violates a condition of an agreement with a creditor (Altman & Hotchkiss, 1993). Default is most of the time rather innocent and rarely the catalyst for formal bankruptcy declaration and filing. According to the definition of Altman & Hotchkiss (1993, p. 4) *Failure*, by economic criteria, means that the realized rate of return on invested capital is significantly and continually lower than prevailing rates on similar investments. They also state that it should be noted that “*a company may be an economic failure for many years, yet never fail to meet its current obligations because of the absence or near absence of legally enforceable debt*”. Beaver (1966, p. 71) defined failure somewhat different, according to his paper failure is “*the inability of a firm to pay its financial obligations as they mature*”. Altman (1968) and Ohlson (1980) used the term failure in their papers in a legal perspective on companies that have filed for bankruptcy. Many academic studies to which are referred from in this study are from US authors or written in American English. Most of them use the term bankruptcy to identify business failure. *Business failure* which include the term failure are simply businesses that cease operation following assignment or bankruptcy (Dun & Bradstreet, as in Altman & Hotchkiss, 1993). Furthermore Altman (1968, p. 591) stated in his paper that “*bankruptcy is used in its most general sense, meaning simply business failure*”.

Insolvency is the state of being that prompts one to file for bankruptcy. An entity (a person, family, or firm) becomes insolvent when it cannot meet its current obligations, signifying a lack of liquidity

(Altman & Hotchkiss, 1993). *Bankruptcy* is a legal declaration of a person's or other entity's inability to pay off debts, in most jurisdictions imposed by a court order, often initiated by the debtor[10]. According to Karles & Prakash (1987, p. 575) bankruptcy "*is a process which begins financially and is consummated legally*". They underline that it is difficult to pinpoint the precise moment that bankruptcy occurs and that it is a subjective decision in which financial failure persists. For example the moment when the firm or creditor decides to file a legal action. Because of this legal status aspect financial failure is a necessary, but not sufficient, condition of bankruptcy. There can be noted the difference between bankruptcy and insolvency is born through legal differences. Moreover in the United States, where the majority of bankruptcy prediction literature originates, the term bankruptcy refers to the legal insolvency procedure used for companies and individuals. In the UK, bankruptcy is a process for individuals only; companies in the UK will enter one of several legal insolvency processes (Wood, 2012).

Concluding, when reviewing existing literature one can say that different conditions were applied to define a firm as bankrupt or non-bankrupt. This study will stick to the assumption that the term 'bankruptcy' is applied to Dutch professional football clubs which have been declared bankrupt by court, removed from the competition and lost its license. Clubs that meet these requirements are easy to find in the news and the leagues rankings.

2.1.2 Financial Distress and Bankruptcy Prediction

As Grice & Dugan (2003) also encountered, it is not clear whether the prediction models in the literature are specifically useful for identifying firms that are likely to go bankrupt or for identifying firms experiencing financial distress. Platt & Platt (2002, p. 185) also recognize this problem and state that, "*while there is abundant literature describing prediction models of corporate bankruptcy, few research efforts have sought to predict corporate financial distress*". If the words bankruptcy and prediction together with the bankruptcy prediction literature are analyzed one can make the conclusion that; *Bankruptcy prediction* is the art of predicting bankruptcy and various measures of financial distress of (public) firms. As mentioned in the introduction the importance of predicting bankruptcy is relevant for creditors and investors in evaluating the likelihood that a firm may go bankrupt. The definition of financial distress is somewhat more difficult to form. As Platt & Platt (2002, p. 185) also stated "*The lack of work on financial distress results in part from difficulty in*

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[10] Among others; Beaver (1966), Altman (1968), Altman & Hotchkiss (1993), Karles and Prakash (1987), and the Oxford dictionary of Finance and Banking (4 rev. ed.)

defining objectively the onset of financial distress". So it has been found that it is not simple to define the term financial distress. In Oxford Dictionary, the word distress means inability, pain, sorrow, lack of financial resources and poverty. There seems to be many definitions of financial distress which, economically approximate bankruptcy and these include extreme liquidity problems (Altman, 2000). Something that can be concluded is that existing literature agrees on the fact that financial distress is related to bankruptcy and liquidity[11]. Because the relation with liquidity there is also a similarity with insolvency, which is explained in chapter 2.1.1. Some of the found definitions of financial distress, such as Platt & Platt (2002, p. 184), who define financial distress as "*a late stage of corporate decline that precedes more cataclysmic events such as bankruptcy or liquidation*", imply several stages that can be recognized of corporate decline. However, these stages are not elaborated in the article, this is in line with what McKee (2003) stated about a firm going through various stages of financial distress. McKee (2003) claims that financial distress is a process that a firm undertakes before it goes bankrupt. McKee (2003) mentioned insufficient income and insufficient liquid asset position as the two stages before bankruptcy. After reviewing literature about financial distress one can conclude that *financial distress* is one of the stages an organization will go through before filing for bankruptcy. In this stage, the organization is running out of liquidity and has difficulties with paying their debt, invoices and other short term obligations. To determine which Dutch professional football club is facing/has faced financial distress the category-division as announced by the KNVB in the studied years will be leading. Clubs from category I (insufficient), which means according to the KNVB that a club is likely to head to financial distress is marked as financially distressed at that particular moment.

2.2 Bankruptcy Prediction Models

The history of bankruptcy prediction includes application of numerous statistical tools which gradually became available, and involves deepening appreciation of various pitfalls in early analyzes. The literature on bankruptcy prediction goes back to the 1930's beginning with the initial studies concerning the use of ratio analysis to forecast future bankruptcy. For example FitzPatrick (1932) who published a study of 20 pairs of firms, one failed and one surviving, matched by date, size and industry. He investigated the differences between ratios of successful industrial enterprises with those of failed firms. This was not a statistical analysis as is now common, but he thoughtfully interpreted the ratios and trends in the ratios. Up to the mid-1960's research focused on univariate

[11] Among others; Altman (2000), Grice and Dugan (2003), Platt and Platt (2002), and Suarez & Sussman (2006)

(i.e. single factor/ratio) analysis and the most widely recognized univariate study is that of Beaver (1966) (Bellovary, Giacomino, and Akers, 2007). In 1966 Beaver published his study about financial ratios as predictors of failure who is seen as the forefather of modern bankruptcy prediction literature. A few years later it was Altman who based his work the Z-score model on the study of Beaver (1966) and published the first multivariate study in 1968. Altman (1968) applied multiple discriminant analysis within a pair-matched sample and revolutionized corporate bankruptcy prediction. Powered by advancements and technological developments a multitude of bankruptcy prediction models have flooded the literature since Altman's (1968) model. Some were completely new and some were adjusted versions or derivative of Altman's (1968) work.

The variety in bankruptcy prediction models is great. Some models are more narrowly focused (e.g. developed for particular industries, firm size and countries) than other models. Different factors are considered and different methods are employed to develop a bankruptcy prediction model. The number of factors considered in the different models ranges from one to 57 factors (Bellovary *et al.*, 2007). Examples of these factors are different variables (e.g. net profit, total assets, total liabilities etc.) that measure for instance the profitability, leverage and liquidity of a firm. Discriminant analysis was a very popular method of model development in the early years of bankruptcy prediction followed by multivariate discriminant analysis (MDA). After this period several more complex techniques such as logit analysis, probit analysis, recursive partitioning, hazard models and neural networks were developed and became in play (Bellovary *et al.*, 2007). Several studies have been conducted to summarize the existing literature about bankruptcy prediction models. One of the most extensive ones is that of (Bellovary *et al.*, 2007). They conducted a review of 165 bankruptcy prediction studies from 1930 until 2007. They concluded that an analysis of accuracy of the different models suggests that multivariate discriminant analysis and neural networks are the most promising methods for bankruptcy prediction. Furthermore their findings suggest that a greater number of factors does not guarantee higher model accuracy. "*Some models with two factors are just as capable of accurate prediction as models with 21 factors*" (Bellovary *et al.*, 2007, p. 1).

In exiting literature, there are two major groups of models for predicting bankruptcy: accounting- and market based bankruptcy prediction models. For the first group the models can be used to predict business failure empirically based on the accounting data of companies; whereas the market-based models do not only rely on accounting data but includes current data from the market such as stock shares and macroeconomic variables.

2.3 Accounting-based Bankruptcy Prediction Models

Accounting-based bankruptcy prediction models use information from financial statements, normally in the form of ratio's to describe the risk of failure of a firm. Therefore they take into account the firm´s past performance as a base to predict future performance. Beaver (1966) was one of the first researchers which explored the predictive ability of these financial ratios and applied a statistical method called 't-tests' to predict bankruptcy for a pair-matched sample of firms. He applied this method to evaluate the importance of each of several accounting ratios based on univariate analysis (i.e. analysis with the description of a single variable) using each accounting ratio one at a time. He examined a sample of seventy-nine failed companies five years before the bankruptcy occurred and compared them with the ratios of solvent companies. He included both bankrupt companies and companies with other financial problems. He analyzed thirty financial ratios and found out that three financial ratios were significant in predicting bankruptcy of a firm. Namely net income / total assets, cash flow / total debt and total assets / total debt, whereas the first two ratios were the best predictors of failure. Beaver's (1966) pioneering work was the start of all kind of bankruptcy prediction models.

2.3.1 Altman's Z-score Model (1968)

In 1968 only two years after Beaver's work Altman presented the first multivariate (i.e. analysis of more than one statistical outcome variable at a time) model for bankruptcy classification based on accounting data. Altman (1968) extended the univariate analysis of Beaver (1966) by using more financial ratios in his analysis. This model, called Altman's Z-score prediction model, was based on a statistical method called multiple discriminant analysis (MDA), which was developed by Fisher (1936). The objective of the MDA technique is to *"classify an observation into one of several a priori groupings dependent upon the observation's individual characteristics"* (Altman, 1968, p. 591). According to Altman (1968) there is at least one primary advantage of MDA in comparison with Beaver's (1966) and others traditional univariate ratio analysis. This is the fact that the MDA technique has the potential to analyze an entire set of explanatory variables simultaneously, as well as the interaction of these variables, whereas the univariate analysis can only consider the measurements used for group assignments one at a time. Altman's (1968) discriminant function[12] is as follows:

[12] Altman (1968) used this function to transform individual variable values to a single discriminant score or Z-value which is then used to classify the object.

$$Z = V_1 X_1 + V_2 X_2 + \dots + V_n X_n \qquad (eq.\ 1)$$

Where; $V_1, V_2, \dots V_n$ = Discriminant coefficients

$X_1, X_2, \dots X_n$ = Independent variables

Altman (1968) performed his research with the objective to find out which combinations of financial ratios predict bankruptcies best. In his sample he used thirty-three bankrupt manufacturing firms and thirty-three non-bankrupt manufacturing firms of which all publicly held and headquarted in the USA. Altman (1968) used the model validation technique called 'cross-validation' to validate his function. This technique is used for assessing how the results of a statistical analysis will generalize to an independent data set and it's commonly used where the goal is prediction (Kohavi, 1995). Altman (1968) used an estimation sample and a hold-out sample. The estimation sample is used to estimate the function and the hold-out sample is used to validate the estimated function. The time frame was set from 1946 to 1965. Firms were defined as bankrupt when they filed bankruptcy in the period within the time frame. Firms were defined as non-bankrupt if they were still in existence in 1966. Altman (1968) evaluated twenty-two variables. These variables/ratios are chosen on the basis of their popularity in the literature and potential relevancy to the study. The result was a model with five different financial explanatory variables and a qualitative dependent variable (i.e. bankrupt within 1-2 years or non-bankrupt). These five variables are not the most significant variables when they are measured independently. This because the contribution of the entire variable profile is evaluated by the MDA function (Altman, 1968). The constructed discriminant function with the variables and estimated coefficients from the study of Altman (1968) is as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + .6X_{4a} + .999X_5 \qquad (eq.\ 2)$$ [13]

Where;
X_1 = Working capital / Total assets
X_2 = Retained earnings / Total assets
X_3 = Earnings before interest and taxes / Total assets
X_4 = Market value of equity / Total liabilities
X_5 = Sales / Total assets
Z = Overall Index

The calculation of this Z-score is compared to a predetermined cut-off value which classifies the concerning firm. This cutoff point is based on the number of minimal Type I (bankrupt but predicted non-bankrupt) and Type II (non-bankrupt but predicted bankrupt) errors. If the Z-score is higher than

[13] For a detailed explanation of the financial ratios see Altman (1968) or Altman (2000)

the cutoff point the firms are classified as non-bankrupt. Altman's Z-score model proved to be extremely accurate in predicting bankruptcy correctly. When using the initial sample 95% one year prior to bankruptcy and 72% two years prior to bankruptcy of all firms in the bankrupt and non-bankrupt groups were assigned to their actual group classification. This 'original' Z-score model was based on the market value (X_{4a}) of the firm and is thus applicable only to publicly traded companies. Therefore to be applicable to private firms Altman (2000) developed a re-estimation of the model substituting the market value of the equity for the book value, by using the same data as used in 1968. This new estimation implies that all the coefficients have to change (not only X_{4a}) and that there also will be new values in order to set the areas of safety and risk. The result was a revisited five-variable Z'-score model (Altman, 2000) for private firms:

$$Z' = .717X_1 + .847X_2 + 3.107X_3 + .420X_{4b} + .998X_5 \qquad (eq.\ 3)$$

Where; X_{4b} = Book value of equity / Book value of total liabilities

Altman's (2000) revisited Z'-score prediction model proved to be also accurate in predicting bankruptcy correctly. The Type I accuracy is only slightly less impressive than the model utilizing market value of equity (91% vs. 94%) but the Type II accuracy is identical (97%). In that same research, Altman (2000) offered a third version of the Z-score model, in order to minimize the potential industry effect. In this model, the X_5 ratio (Sales / Total assets) is excluded. This was done in order to minimize the potential effect related to the specific manufacturing industry since this industry is highly sensitive to the criteria of the size of business. Altman's (2000) four-variable Z"-score model for non-manufacturers & emerging markets is as follows:

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_{4b} \qquad (eq.\ 4)$$

Where; X_5 = Excluded

Altman's original and adjusted Z-score models have been used in many studies since their development. Altman's model has been persistently used by researchers and it is the most cited and used bankruptcy prediction model in literature (Grice & Ingram, 2001). Supportive Charitou *et al.* (2004, p 488) claim that Altman's model is commonly applied in finance and accounting research. "*it has been used extensively by both academics and practitioners as a standard of comparison for subsequent failure studies*". Other proponents of the model claim that it has the advantage of simplicity (Barajas *et al.*, 2014).

Studies that used Altman's Z-score model are mainly positive. The recent study of Anjum (2012, p. 12) for example concluded that "*It can be safely said that Altman's Z-score model can be applied to* *modern economy to predict distress and bankruptcy one, two & three years in advance.*" She also claims that when looking back to the past forty years Altman's revised Z'-score model is one of the most effective multiple discriminant analysis. The study of Hussain, Ali, & Ullah (2014, p. 114) concludes something similar. They claim that "*Altman's model can predict business bankruptcy one, two, three, even four years prior to failure with a higher rate of accuracy*" based on their study in the textile sector of Pakistan. Also Karamzadeh (2013, p. 2010) concluded positive when Altman's model is compared to the model of Ohlson (1980) "*in all three situations the Altman works better and it could be suggested to investors in order to predict bankruptcy of companies*".

The study of Wu, Gaunt, & Gray (2010) however shows something completely opposite. They tested the models of Altman (1968), Ohlson (1980), Zmijewski (1984), Shumway (2001), and Hillegeist, Keating, Cram, & Lundstedt (2004). Their sample consisted of listed US firms and their study covers the period from 1980 to 2006. Their distinctive conclusions was that the model of Altman (1968) "*performs poorly relative to other models in the literature*" (Wu *et al.*, 2010, p. 45). This conclusion is supported by Grice & Ingram (2001). They stated that the accuracy of the Altman's (1968) model declined when applied to their samples.

The main criticism on the Altman models are based on (1) the age of the original Altman (1968) model and (2) on the research design of the models. First, Altman's (1968) original model is more than fourty years old. As mentioned in the problem statement, it is likely that the accuracy rate of the bankruptcy prediction models change over periods of time when the setting of the study differs (Grice & Ingram, 2001). Second, the original parameters were estimated with the use of small and equal sample sizes (33 bankrupt and 33 non-bankrupt firms) this assumptions of normality and group distribution downgrades the representativeness of the sample[14]. Furthermore Grice & Ingram (2001) state that the hold-out samples are biased upward because the hold-out samples consisted of firms from the same industries as those in the estimation sample. Moreover Altman's (1968) original Z-score is based on manufacturing firms only. However, Altman (2000) recognized and tried to tackle this limitation by developing re-estimated models, the generalizability is still in question because other industries are excluded from the sample (Grice & Ingram, 2001). Regarding the use of the statistical technique MDA, the cut-off point for firms that are classified as bankrupt or non-bankrupt is very arbitrary and the accuracy rate of the model questionable (e.g. Joy & Tollefson, 1975 and Dimitras, Slowinski, Susmaga, & Zopounidis, 1999).

[14]Among others Eisenbeis (1977), Ohlson (1980), Jones (1987), and Boritz *et al.* (2007).

2.3.2 Ohlson's O-score Model (1980)

Another popular bankruptcy prediction model is the O-score model of Ohlson (1980). Ohlson (1980) was one of the first researcher who criticized Altman and other previous researchers that used the MDA method and came up with his own model based on a statistical method called 'logistic regression'. This method is an alternative to Fisher's (1936) classification method, linear discriminant analysis and is therefore related to Altman's Z-score model (Gareth *et al.*, 2014). According to Tabachnick & Fidell (1996, p. 575) "*Logistic regression allows one to predict a discrete outcome such as group membership from a set of variables that may be continuous, discrete, dichotomous, or a mix."* Therefore the logistic regression may be better suitable for cases when the dependant variable is dichotomous such as yes/no, pass/fail and bankrupt/non-bankrupt.

Ohlson (1980) chose the methodology of conditional logit analysis to avoid some fairly well known problems associated with multiple discriminant analysis (MDA). Ohlson (1980) highlighted several problems with the MDA studies, which were also extensively discussed by Eisenberg (1977) and Tollefson (1975). In short the criticism of Ohlson (1980) to the MDA method as used by Altman (1968) were:

1. There are two statistical requirements (key assumptions) imposed on the distributional properties of the predictors. First requirement is equal variance-covariance of the explanatory variables for the bankrupt and non-bankrupt firms and the second requirement is normally distributed predictables. According to Ohlson (1980) such requirements are hard to meet up and therefore the reliability and validity when using the MDA method may be doubtful.
2. The output of the MDA model is a score which has little intuitive interpretation, therefore it is basically an ordinal ranking device (Ohlson, 1980).
3. Bankrupt and non-bankrupt firms are matched according to criteria such as size and industry, and these tend to be somewhat arbitrary. According to Ohlson (1980) variables should be included as predictors rather than to use them for matching purposes.

Ohlson (1980, p. 112) "*stated that the use of conditional logit analysis, on the other hand, essentially avoids all of the above problems with respect to MDA"*. The logit function is suitable to model the probability of bankruptcy because the dependent variable has only two categories (bankrupt or non-bankrupt). The logit function maps the value to a probability bounded between 0 and 1. Furthermore the fundamental estimation problem can be reduced by using the following statement: *"What is the probability that the firm belongs to some pre-specified time period?"* (Ohlson, 1980, p. 112) When using this statement "*no assumptions have to be made regarding prior probabilities of bankruptcy and/or the distribution of predictors*" (Ohlson, 1980, p. 112).

In his study, Ohlson analyzed 105 bankrupt companies to 2058 non-bankrupt companies of which all US industrials. The boundaries for the population of the Ohlson (1980) model were restricted by the period (from 1970 to 1976), the equity of the firm (had to be traded on some stock exchange or over-the-counter market) and the firm must be classified as an industrial firm. The data collection started three years prior the date of bankruptcy. The cutoff point used by the original study of Ohlson (1980) is 0.38 because this should minimize the Type I and Type II errors. Concluding Ohlson (1980) came up with a nine factor linear combination of coefficient-weighted business ratios which are readily obtained or derived from the standard periodic financial disclosure statements provided by publicly traded companies. Two of the factors utilized are widely considered to be dummies (X_5 and X_8) as their value and thus their impact upon the formula typically is 0. Overall, his results showed that the factors: size, current liquidity and financial structure of a firm have a crucial role in detecting bankruptcy (Ohlson, 1980). The model of Ohlson (1980) is as follows:

$$O = -1.32 - .407X^1 + 6.03X^2 - 1.43X^3 + .0757X^4 - 2.37X^5 - 1.83X^6 + 0.285X^7 - 1.72X^8 - .521X^9 \qquad (eq.\ 5)$$

Where; X^1 = Log (Total assets / GNP price-level index)

X^2 = Total liabilities / Total assets

X^3 = Working capital / Total assets

X^4 = Current liabilities / Current assets

X^5 = 1 = If total liabilities > Total assets, 0 otherwise

X^6 = Net income / Total assets

X^7 = Funds provided by operations / Total liabilities

X^8 = 1 [1 If net income is negative for last two years, 0 otherwise]

X^9 = $X^9 = (NI_t – NI_{t-1})$ / (INItI + INIt-1 I), where NI_t = net income for recent period and $_t$ is the number of years.

As similar to Altman (1968) some of the predictors (X^1 until X^6) were chosen because they appear to be the ones most frequently mentioned in the literature (Ohlson, 1980). The result is four liquidity ratios (X^3, X^4, X^7 and X^8), two profitability ratios (X^6 and X^9) and two leverage ratios (X^2 and X^5). Ohlson's O-score model to be extremely accurate in predicting bankruptcy correctly. The overall accuracy rate of the estimation sample was 96% and for the hold-out sample 85%.

Ohlson’s (1980) model has been used in many (most comparing) studies within the field of bankruptcy prediction. In China Wang & Campbell (2005) found out that Ohlson’s model is applicable for predicting bankruptcy for Chinese firms. Pongsgat *et al.* (2004) compared Ohlson’s (1980) model to Altman’s MDA (1968) model and concluded that Ohlson’s model (1980) has a higher predictive ability in all three years preceding bankruptcy. Oude Avenhuis (2013) did something similar en included Zmiejevski’s model (1984) to his comparison to Dutch listed and large non-listed firms. He concluded that the model of Ohlson (1980) is the most accurate when all models use the same statistical technique. This implies that the explanatory variables of this model are the best predictors of the likelihood of bankruptcy. Kleinert (2014) did something similar for German and Belgian listed companies and concluded also that Ohlson´s model (1980) performs most accurate.

Some researches criticize the logit model of Ohlson because all parameters seem to be fixed in his method. As Hensher & Jones (2007, p. 243) stated “*the error structure is treated as white noise, with little behavioral definition*”. Therefore Hensher & Jones (2007) propose a mixed logit model instead of a simple logit model. The advantage of a mixed logit model is that it recognizes “*the substantial amount of heterogeneity that can exist across and within all firms in terms of the role that attributes play in influencing an outcome domain*” (Hensher & Jones, 2007, p. 243). Furthermore the logit approach averages data whereby a healthy firm is given the value of 0 and a non–healthy firm the value of 1. This means that non-healthy companies are treated as if they were bankrupt from the beginning onwards (Abdullah *et al*., 2008). According to Hillegeist *et al.* (2004) there are two economic problems with the single period logit model. The first problem is a sample bias due to the fact that only one and non-randomly observation is selected. The other problem is that Ohlson’s model fails by not including time varying changes, while researches such as Grice and Dugan (2003) state that that the effect on bankruptcy changes over industries and time. As a conclusion can be stated that Ohlson´s model (1980) seems to be inefficient and biased, but the results of his model suggests a high accuracy rate.

2.3.3 Zmiejewski’s Model (1984)

The following influential work came from Zmiejewski (1984), was based partly on Ohlson’s (1980) work and is called; ‘the probit model’. This name is related to the statistical method of probit analysis which is applied for this study. Similar to logistic regression the probit analysis is a type of regression where the dependent variable can only take two values (again bankrupt/non-bankrupt. The name comes from *prob*ability + un*it*. The purpose of the model, similar to those of Altman

(1968) and Ohlson (1980), is to estimate the probability that an observation with particular characteristics will fall into a specific one of the categories. The probit model is a type of binary classification model that estimates probabilities greater than 1/2. These are treated as classifying an observation into a predicted category.

Zmiejewski's model takes into account a set of independent variables as well as accounting data. He examines two estimation biases which can result when financial distress models are estimated on non-random samples. According to Zmiejewski (1984), the two biases are choice-based sample biases (i.e. oversampling distressed firms) and sample selection biases (i.e. using a complete data sample selection criterion). Zmijewski (1984) argues that with the choice-based sample bias the estimated coefficients will be biased, unless one builds a model based on the entire population. The estimation sample Zmijewski's (1984) study contained 40 bankrupt and 800 non-bankrupt firms, and the hold-out sample consisted of 41 bankrupt and 800 non-bankrupt firms. The population of his study consists of all firms listed on the American and New York Stock Exchanges between 1972 and 1978 with SIC-codes below 6000. This means that finance, service and public administration firms were excluded from the research. The accuracy rate of the Zmijewski (1984) model for the estimation sample was 99%, while the accuracy rate of the hold-out sample was not reported. Zmiejewski (1984) came up with three variables that should predict bankruptcy, namely; net income / total assets, total liabilities / total assets and current assets / current liabilities. The model of Zmiejewski (1984) is as follows:

$$\text{Zmijewski} = -4.3 - 4.5X_1 + 5.7X_2 + .004X_3 \qquad (\textit{eq.}\ 6)$$

Where; X_1 = Net income / Total assets

X_2 = Total liabilities / Total assets

X_3 = Current assets / Current liabilities

Zmiejewski's model (1984) accuracy rate scores pretty high (99%) according to the original (1984) study and high according to several other studies (e.g. Oude Avenhuis (2013), Mehrani *et al*. (2005), Grice and Dugan (2003)). Nevertheless there are some critics about the model. Shumway (2001, p. 120) argues that Zmiejewski's model (1984) is in fact only a "*one-variable model*" because the selected variables are highly correlated to each other. Shumway (2001) even claims that because of this correlation the model has no strong predictive power for bankruptcy. Additionally, Platt and Platt (2002, p. 186) state that "*Zmijewski (1984) could not test the individual estimated coefficients for bias against the population parameter*" since Zmijewski ran only one regression for each sample size. Another limitation is according to Grice and Dugan (2003) the selection of the ratios. They claim that the ratios were not selected on a theoretical basis, but rather on the basis of their performance in prior studies. However this will be the case for any bankruptcy prediction study that is based on or helped by prior work such as Beaver (1966).

2.3.4 Conclusion Accounting-based Bankruptcy Prediction Models

A lot of other researchers have performed similar studies after the above mentioned influential works. The methodologies of Beaver (1966) and Altman (1968) have been replicated and improved on for many different types of firms and in a number of foreign environments (Altman, 1984). Especially in the time before the 1980´s many other bankruptcy models built on Altman original Z-score model (1968). For example Balcaen & Ooghe (2004), the linear multiple approach by Deakan (1972) and Wilcox ´s model (1971). Other examples are Taffler (1984) who estimated a model for bankruptcies based in the UK and Bilderbeek (1977) who did something similar for the Netherlands. The models of Ohlson (1980) and Zmiejevski (1984) are also seen as venerable work. Together with Altman’s (1968,2000) models these three models are being the most popular accounting-based bankruptcy prediction models in literature and have been used in many bankruptcy prediction studies.[15]

2.4 Market-based Bankruptcy Prediction Models

As mentioned before, there are two major groups of models for predicting bankruptcy (accounting- and market-based). The second stream of prediction models includes market variables while the first stream include only accounting variables. Proponents of the market-based models claim that market-based variables have several reasons why they are valuable in predicting bankruptcy. One of the reasons is the availability of financial data, market-based variables are daily available whereas accounting-based variables are quarterly or sometimes even only yearly available. As Beaver *et al.* (2005, p. 110) state; market-based variables can be measured with “*a finer partition of time*”. Furthermore Agarwal & Taffler (2008, p. 3) state that market-based variables *“provide a sound theoretical model for firm bankruptcy; in efficient markets, stock process will reflect all information contained in accounting statements and will also contain information not in the accounting statements; market variables are unlikely to be influenced by firm accounting policies; market prices*

[15] Among others; Charitou, Neophytou, & Charalambous (2004), Kleinert (2014), Kumar & Kumar (2012), Oude Avenhuis (2013), and Wu *et al.* (2010)

reflect future expected cash flows, and hence should be more appropriate for prediction purposes; the output of such models is not time or sample dependent".

The latest modeling developments are the contingent claims models which are mainly based on option pricing theory as set out in Black and Scholes (1973) and Merton (1974). These three economists developed a formula to calculate the theoretical price of European put and call options, ignoring any dividends paid during the option's lifetime. The technique used in this 'option pricing model' is seen as a precursor of the new stream of market-based models. The amount of studies on the market-based bankruptcy prediction models is less extensive than the ones on accounting-based models. Therefore studies are limited on validating the quality of market-based bankruptcy prediction models. Most studies in this field are comparing studies between these 'contingent' models and traditional accounting number based models[16]. In common literature there are two market-based models that are called 'key' models (Wu *et al.,* 2010). These are Shumway´s hazard model (2001) and the Black-Scholes pricing model of Hillegeist *et al.* (2004).

2.4.1 Shumway's Hazard Model (2001)

Shumway´s (2001) discrete-time hazard model tries to predict's bankruptcy by using both accounting- and market variables. In one of his previous studies Shumway (2001) found out that accounting-based variables employed in previous studies are not significant in predicting failures. Therefore he included market–based data which are according to him better predictors of bankruptcy.

According to Wu et al., 2010 the main difference between this hazard model and the static logit model (e.g. Ohlson's model) is that the hazard model can use the entire life span of information (all firm-years) for each firm, wereas the logit model can only use one firm-year for each observation. Shumway stated that the market-based models (i.e as he reffered to as static models, with multiple-period bankruptcy data) ignored the fact that firms change troughout time. Therefore according to him static models are biased and produce inconsistent estimates of the probabilities that they approximate. "*Test statistics that are based on static models give incorrect inferences*" (Shumway, 2001, p. 101). He compared hazard to static model forecasts and estimate both hazard and static models and examine their out-of-sample accuracy. The final sample contained 300 bankruptcies between 1962 and 1992. The result was a new bankruptcy model that uses three market-driven variables to identify failing firms. Namely, a firm's market size, its past stock returns, and the

[16] For example; Bharath & Shumway (2004) , Hillegeist *et al.* (2004), Vassalou & Xing (2004), Campbell *et al*. (2006), Reisz & Purlich, (2007) and Agarwal & Taffler (2008).

idiosyncratic standard deviation of its stock returns. These market-driven variables combined with two accounting ratio's forecast failure quite accurate in out-of-sample tests.

2.4.2 Hillegeist et al's BSM-prop model (2004)

The following key work came from Hillegeist *et al.* (2004). They developed a market-based measure of the probability of bankruptcy that is based on the Black–Scholes–Merton option-pricing model, called 'BSM-Prob'. The BSM option-pricing model is used to price European options and was developed in 1973 by Fischer Black, Myron Scholes and Robert Merton. The study of Hillegeist *et al.* (2004) compared the relative information content of measures of the probability of bankruptcy based on the Altman (1968), Ohlson (1980), and Black–Scholes–Merton models. They used a comprehensive bankruptcy database and the discrete hazard rate methodology. The sample consisted of 65960 firms of which 516 went bankrupt between 1979 until 1997. Overall their results showed that the market-based BSM-Prob provides significantly more information about the probability of bankruptcy than the accounting-based models as used in this study. They even claim that this conclusion is *"is robust to various modifications of the Z- and O-Scores, including the use of updated coefficients based on our sample, adjusting for industry effects, and separating the measures into their lagged level and changes components"* (Hillegeist *et al.*, 2004, p. 28).

There are several critics about the BSM-Prob model. First as mentioned before the underlying theory for this model is the option-pricing theory of Black–Scholes–Merton (1973). This theory is a structural model and operationalizing requires the assumption of normality of stock returns (Saunders and Allen, 2002). It cannot distinguish between different types of debt and it assumes that the firm only has a single zero coupon loan (Agarwal & Taffler, 2008). Furthermore Agarwal & Taffler (2008) state that the option-pricing theory cannot differ between the asset value or volatility, while the measures of asset value and volatality are required.

2.5 Comparing Accounting-based and Market-based Bankruptcy Prediction Models

As outlined above, there are differences between the 'key' accounting- and market-based bankruptcy prediction models. Some well-known models include only accounting variables while other models include market variables and accounting variables.

Studies that compared both streams of models show contradictory results. The study of Shumway (2001, p. 123) for example concluded that "*the hazard model is theoretically preferable to the static models"*. The study of Hillegeist *et al.* (2004) concludes something similar in their paper. They made a comparison between the account-based models of Altman (1968), Ohlson (1980) and the market-based model of Black– Scholes–Merton. Their results demonstrate that the market-based BSM-Prob provides significantly more information about the probability of bankruptcy than do either of the popular accounting-based measures.

The study of Agarwal & Taffler (2008) claims something different. Their paper compared the performance of the accounting-based well-known and widely used UK-based Z-score model of Taffler (1984) with two market-based models, one following Hillegeist et al. (2004) and the other a naive market-based model following Bharath & Shumway (2004). The study covered all non-finance industry UK firms fully listed on the London Stock Exchange (LSE) at any time during the period 1985–2001. The final sample consisted of 2006 firms and 103 failures (0.67%). The results showed that in terms of predictive accuracy, there is little difference between the market-based and accounting models. One main benefit of the accounting-based approach is that it produces significant economic benefit over the market-based approach. "*The Z-score approach leads to significantly greater bank profitability in conditions of differential decision error costs and competitive pricing regime"* (Agarwal & Taffler, 2008, p. 1). Furthermore they also argue that accounting-based models are in favor because bankruptcy is not a sudden event but the result of several years of adverse performance, which is captured in the financial statement of the firm.

Agarwal & Taffler (2008) positive findings about the accounting-based models are strengthened by Das et al. (2008). They examined the information content of accounting-based and market-based metrics in pricing firm distress using a sample of Credit Default Swap (CDS) spreads. They used a sample of 2,860 quarterly CDS spreads available over the period 2001-2005. They found out that *"a model of distress which is entirely composed of accounting-based metrics performs comparably, if not better, than market-based structural models of default"* (Das et al., 2008, p. 1).

In the more recent study of Wu *et al.* (2010), where they compared the most relevant accounting-based and market-based bankruptcy models with each other, the conclusion is somewhat more towards the findings of Shumway (2001) and Hillegeist *et al.* (2004). Wu *et al.* (2010, p. 45) claim that the market-based models of Shumway (2001) and Hillegeist *et al.* (2004) *"generally outperforms models that are based on accounting information only"*. They argue that the performance of the accounting-based models has deteriorated over more recent periods.

Critics about both streams are also ranging. Agarwal & Taffler (2008) for example argue that the validity of the accounting-based models is doubtful since they present accounting information that include past performance. This numbers may be subject to manipulation by management and conservatism and historical cost accounting may cause that the true asset values may be very different from the recorded book values (Agarwal & Taffler, 2008). Furthermore they state that many accounting-based bankruptcy prediction models are too sample specific, which results a lack of generalization power. The market-based models also face some critics. Reisz & Perlich (2007) for example state that the market-based models need a longer time horizon and therefore are not a good predictor over a one-year period. Furthermore the market-based models are generally spoken time-consuming and more difficult to use. When looking to the literature the majority of international failure prediction studies employ multiple discriminant analysis[17]. One of the main reasons why accounting-based models are popular among practitioners is that the necessary data for the market-based models is not always available.

2.6 Conclusion Literature Review

To conclude, when comparing the conclusions, the limitations and the results towards market–based bankruptcy prediction models and accounting-based bankruptcy prediction model one can say that both streams of models imply advantages and disadvantages. As Collins & Green (1972, p.1) stated *"no technique is superior to other techniques".* Frequently heard arguments in favor of the market-based models are that they reflect market prices and that they take into account the partition of time. One important disadvantage is that they are time-consuming and therefore expensive. This time-consuming disadvantage is one of the advantages of the market-based models, since they have the advantage of simplicity. This is also the reason why the account-based approach has an economical benefit over the market-based models. Furthermore in contrast to the market-based models the quality and validation of the accounting based-models has been assessed in many studies throughout the years, while the studies on the market-based models are limited.

Going back to the industry were this study takes place, which is the Dutch professional football industry, AFC Ajax is the only club which is listed. The rest of the Dutch professional football clubs are non-listed private companies. Therefore the market-based models are not applicable to forecast the Dutch professional football industry, since they require market data such as stock returns. So the only option to perform this research is by using the accounting-based models. As mentioned before the most common used accounting-based bankruptcy prediction models are those of Altman (1968,2000), Ohlson (1980) and Ziejewski (1984). Therefore the conclusion after the literature review is that these models have been selected as the tools to perform this research. Appendix-A summarizes the most important findings of the key models as found during the literature review.

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[17] Among others; Altman (1984), Charitou *et al.* (2004), and Bellovary *et al.* (2007)

2.7 Derivation of Hypotheses

The original studies demonstrate that the accuracy rate of Altman (1968,2000), Ohlson (1980), and Zmijewski (1984) are all high and all models perform equally meaning that all results of accuracy rate lie close to each other. The question that arises is whether there is a difference towards the results of the bankruptcy prediction models of Altman (1968,2000), Ohlson (1980) and Zmijewski (1984) for the Dutch professional football industry. The variables, ratios and results of each model have been extensively analyzed in existing literature. The settings where these studies are performed differentiate from firm characteristics (e.g. legal status and firm size) to particular industries and countries. When keeping in mind that Grice & Dugan (2003) state that that the effect on bankruptcy changes over industries and time it will be interesting to see how these models perform in the Dutch professional football industry at present time. However according the original studies the models perform equally, some other studies show different. The study of Wu *et al.* (2010) for example shows that the result of accuracy lie close to each other with the following percentages; 86.1 % (Altman), 88.7 % (Ohlson), and 85.2 % (Zmijewski). This is similar to the studies of Grice & Ingram (2001) and Grice & Dugan (2003). Studies who claim differences between the different models show contradictory results. Grice & Ingram 2011 claim that Altman´s (1968) model declines over the years of observation. Other studies as Shumway (2001) reports a higher accuracy rate of the Ohlson model (1980) but opposite Mehrani *et al.* (2005) report that the accuracy rate for Zmijewski (1984) is higher when compared to Ohlson (1980). It may be assumed based on the above that there is a difference in accuracy rate between the three bankruptcy prediction models. Especially since they imply different financial ratios and therefore provide different information about a firm’s status of health. But, in common literature it is not clear which model performs best and regarding the accuracy rate no direction of the hypotheses can be determined yet.

When looking to the variables/ratios of the models there can be concluded that a lot of the same variables are used into the different models calculations. Unfortunately every model uses variables that might be a little bit questionable for the Dutch professional football industry. For example Altman’s (1968) model uses retained earnings which can be calculated by subtracting dividend from net income. Paying dividend is not quite common for the Dutch football industry. This implies that this model may perform less than the others. The models of Ohlson (1980) and Zmijewski also have some doubtful variables in their calculations. Ohlson (1980) uses funds from operations which can be calculated by adding depreciation and amortization to the net income and subtracting gains on sales of property. Amortization and sales of property are not quite common for the Dutch football industry. This also implies that this model may perform less than the others. The model of Zmijewski

(1984) uses the variable total liabilities in two of the three ratios. Professional football clubs tend to have large liabilities. This together with the fact that Shumway (2001, p. 120) argues that Zmiejewski's model (1984) is in fact only a "*one-variable model*" because the selected variables are highly correlated to each other, implies that this model may also perform. All the above taken into account one can conclude that based on the variables that are used in the different models no direction of the hypothesis can be determined. When looking to the amount that a model is used literature shows that the majority of international failure prediction studies employ multiple discriminant analysis[18]. This is in favor of the Altman (1968,2000) models which are also well known by their simplicity. As mentioned in chapter 2.3.1. the Altman (1968,2000) consist of three variations. One (Z; Altman, 1968) for manufacturing firms, one (Z'; Altman, 2000) for manufacturing private firms, and one (Z"; Altman, 2000) for private non-manufacturing firms. Because only one Dutch professional football club is listed (Z model) and football clubs are not manufacturing companies (Z') The most appropriate Altman's Z-score for football seems the Z" version for private non-manufacturing firms. This is in line with the study of Vazquez (2012) who states that the Z" model is the best choice for football clubs. The study of Barajas & Rodríguez (2014) supports this statement. They believe that Altman's (2000) Z" model would constitute an appropriate framework of analysis for the football industry and they use the same arguments as Vazquez (2012). When looking to the main criticism on the Altman models as mentioned in chapter 2.3.1. it seems that these do apply less for Altman's (2000) Z" model. Namely, Altman's (2000) Z" model is much more recent than the original Altman (1968) model and the assumption of normality and group distribution does not apply since the sample of Dutch professional football clubs has great variances (is not normally distributed). To conclude from the discussion above it seems that Altman's (2000) Z" model seems the best fit for the Dutch professional football industry since it is commonly applied in literature, well known for its simplicity, designed for non-manufacturing firms (football clubs are non-manufacturing), would constitute an appropriate framework of analysis for the football industry[19] and the mentioned criticism on the model make less sense for the Dutch professional football industry. Therefore the studies of Vazquez (2012) and Barajas & Rodríguez (2014) will be followed and the following hypotheses (which can be found on the next page) are formulated and will be tested:

[18] Among others; Altman (1984), Charitou *et al.* (2004), and Bellovary *et al.* (2007)

[19] According to Vazquez (2012) and Barajas & Rodríguez (2014)

Hypothesis 0 (null hypothesis)

H_0: There is no difference in the accuracy rate between accounting-based bankruptcy prediction models of Ohlson (1980), Zmijewski (1984), and Altman (2000) regarding the Dutch professional football industry.

Hypothesis A (alternative hypothesis)

H_A: The Z" model of Altman (2000) will outperform the models of Ohlson (1980), Zmijewski (1984) and the Z' model of Altman (2000) regarding the Dutch professional football industry.

3. METHODOLOGY AND DATA

This chapter presents the methods used in this study. The purpose is to provide the reader with an understanding of how data has been collected and analyzed in order to get the result.

3.1 Sample Selection and Data

The study covers all the Dutch professional football clubs from season 2009/2010 until 2013/2014. To determine which clubs are within the sample the leagues ranking of the 'Eredivisie' and the 'Jupiler League' will be used of all the above mentioned seasons. The study is focused on these seasons due to the fact that it became obliged for clubs to make their financial statements publicly available since 2010. Therefore the financial data from the years before is unavailable. News websites and KNVB's official website (with the FRS classification scores) are used to determine which club went bankrupt or were suffering financial distress. The accounting data (annual reports and financial statements) is collected from different sources. This is as suggested by the KNVB from the Dutch chamber of commerce, the clubs home websites, the KNVB itself and REACH. The calculations of the scores from the different bankruptcy prediction models are done by the help of SPSS and EXCEL (analytical quantitative analysis).

Table 2. Population of the study

Condition	Value
Status	Bankrupt, non-bankrupt, category I (distressed), II (sufficient) and III (good)
Size	38 Dutch professional football clubs
Bankrupt clubs	4 (financial data available of only three)
Distressed clubs	7 on average per season
Divisions	Only professional divisions: 'Eredivisie' and 'Jupiler league'
Seasons	2009/2010 until 2013/2014
Country	The Netherlands

3.2 Research Methodology

The research question of this master thesis is "*What is the accuracy rate of bankruptcy prediction models for the Dutch professional football industry?"* The accuracy rate is the percentage of correct classifications (bankrupt or non- bankrupt) to the total classification. Well-known researchers such as Altman (1968), Ohlson (1980) and Zmiejwski (1984) do it similarly. A club is defined as bankrupt if it has been removed from the competition and lost its license; this implies a declaration of bankruptcy by court order. Clubs that meet these requirements are easy to find in the news and the leagues rankings. The criteria for non-bankrupt clubs are obviously Dutch professional football clubs which are still in competition. The criteria for financial distressed clubs and healthy clubs are determined by the category-division (classification) according to the FRS-model as founded by the KNVB in 2010[20]. To be able to compare all the models, the three categories which are included in the FRS-model will be re-encoded into two categories; financial distressed, and safe (i.e. sufficient and good). For the sake of this research the assumption is made that this 'FRS classification' is always correct. Of each of the studied years (seasons 2009/2010 until 2013/2014) will be examined if a particular club is classified into the right group according to the results of the different models. This will be done by comparing these results to their category-division (classification) according to the FRS-model. The classification periods of t_{+1}, t_{+2} and t_{+3} will be used to compare the bankruptcy prediction models to the financial state a club is in according to this FRS-model. For example; for the accounting data of season 2009/2010 the comparing category-division (classification) according to the FRS-model of one year later is $t_{+1,}$ two years later is $t_{+2,}$ three years later is t_{+3} . This time frame is set because the literature of the selected bankruptcy prediction models claim that they perform best one year, two, and three years in advance.[21]

The research question will be answered by the outcome of the empirical results. The accompanying sub-questions will be answered by the conclusion of the literature review. The total population of this study is small and consists of thirty-eight clubs; therefore the full sample of all the available clubs will be used. Furthermore the full sample includes only three[22] bankrupt clubs. One of these clubs went bankrupt in 2011 and two in 2013. Due to the fact the sample of bankrupt clubs is very small per year, these clubs will be tested and included in the full sample and will be classified as bankrupt/financially distressed in that particular year.

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[20] In appendix II. the FRS-model is explained extensively.

[21] Among others; Altman (1968, 2000), Ohlson (1980), Zmijevski (1984), Anjum (2012), and Hussain *et al.* (2014)

[22] In total four clubs went bankrupt since 2010 but the data of only three clubs of them is available

This means that other than similar research, this study will use the full-sample instead of a holdout sample with an estimation. The number of data points is small enough to use the full-sample design and on the small side to use for a hold-out sample design. Furthermore a full-sample design will provide the better classifier according to Brun *et al.,* 2007. Moreover the goal of this study is simply assessing the accuracy rate of models and finding the best suitable bankruptcy prediction models for the Dutch professional football. To achieve this goal it is sufficient to compare the results of the different models and prediction time frames by accuracy rate. The first statistical test that this study will use is an ANOVA test including a test of homogeneity of variances (i.e. Levene's test). Levene's test is often used before a comparison of means. It assumes that all groups have the same or similar variance. A p value less than .05 indicates a violation of this assumption which simply means that the groups are not comparable. When this significance occurs, one should switch to more generalized tests that are free from homoscedasticity assumptions such as non-parametric tests (Levene's, 1960). If the groups are comparable an analysis of variance (two-way ANOVA) will be performed to analyze whether there are differences between or within the models (groups) by comparing their mean scores. When there is a difference in the accuracy rate between the used bankruptcy prediction models another test called multi comparisons post-hoc analysis two-way ANOVA (Bonferroni) test will be used as the statistical test that will show how the models differ and which one performs best. Altough it is unusual to use this kind of ANOVA testing in this reseach field, performing such test after calculating the accuracy rates for the different models, allows to compare the results of the three models (by their mean scores) for multiple predicting time frames. In this way it is possible to make inferences about the performances of the models with statistical evidence. Moreover studies from other fields with similar goals (i.e. comparing mean scores or assessing the best suitable model) do it similarly (e.g. Godfrey, 1985, Chellapilla *et al,* 2005 and, Kovatchev *et al,* 2008).

3.3 Selected Research Tools

Analytical quantitative research is adopted by this study. This type of research is primarily concerned with testing hypotheses, specifying and interpreting relationships by analyzing the facts or information already available. The tools which are selected to analyze are the most commonly used accounting-based bankruptcy prediction models. After literature review the venerable work of the following researchers is selected[23]:

1. Altman’s (1968,2000) multiple discriminant analysis; also called (revisited) Z-score models.
2. Ohlson’s (1980) logit regression analysis; also called O-score model.
3. Zmiejwski’s (1984) probit analysis; also called Zmiejewski’s probit model.

Using the data set, the performance of these models will be compared to the classification of the FRS-model as developed by the KNVB in 2010. Table 3 below shows examples of studies which used the above mentioned models. Table 4 on the next page provides a brief summary of each model.

Table 3. Examples of different (comparing) studies that used at least two of the models as used in this study.

Studies	**Altman (Z)**	**(Z')**	**(Z”)**	**Ohlson**	**Zmijewski**
Grice & Dugan (2001)				X	X
Muzir en Kaglar (2009)	X			X	X
Wu et. al. (2010)	X			X	X
Kumar & Kumar (2012)			X	X	X
Wood *et al.* (2012)	X			X	
Oude Avenhuis (2013)	X			X	X
Kleinert (2014)	X			X	X
Barajas & Rodríguez (2014)		X	X		

[23] In chapter 2.3. these models are explained and reviewed extensively.

Table 4. Summary of empirical models used in this master thesis. The first column lists the models that are examined. The second column summarizes the model specification. The final columns document the explanatory variables that are used in the models. For the explanation of the abbreviations see table 1.

Model	**Formula**	**Variable**	**Description**
Altman (1968, 2000)	$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + .6X_{4a} + .999X_5$	X_1	= NWC/TA
Multiple-	$Z' = .717X_1 + 0.847X_2 + 3.107X_3 + .420X_{4b} + .998X_5$	X_2	= RE/TA
discriminant	$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_{4b}$	X_3	= EBIT/TA
analysis	Cutoff points:	X_{4a}	= MVE/TL
	‘Safe’ Zone; $Z > 2.99$; $Z' > 2.90$; $Z'' > 2.6$	X_{4b}	= BVE/TL
	‘Distress’ Zone; Z 1.81; $Z' < 1.23$; $Z'' < 1.1$	X_5	= SALES/TA
	‘Grey’ Zone; Z, Z’ and Z” if score is between ‘safe’ and ‘distress’ zones		
Ohlson (1980)	$O = -1.32 - .407X^1 + 6.03X^2 - 1.43X^3 + .757X^4 - 2.37X5 - 1.83X6 +$	X^1	= OSIZE
Logit model	$.285X7 - 1.72X8 - .521X9$	X^2	= TL/TA
	$P = (1 + \exp\{- \beta' X\})^{-1}$, where P is the probability of bankruptcy and X	X^3	= WC/TA
	represents the variables listed. The logit function maps the value of $\beta' X$	X^4	= CL/CA
	to a probability bounded between 0 and 1.	X^5	= OENEG
		X^6	= NI/TA
	Cut off point:	X^7	= FU/TL
	‘Safe’ Zone; O-Score < 0.5	X^8	= INTWO
	‘Distress’ Zone; O-Score > 0.5	X^9	= CHIN
Zmijewski (1984)	$Zmijewski = - 4.3 - 4.5X_a + 5.7X_b + .004X_c$	X_a	= NI/TL
Probit model	$P = F(\beta' X)$, where P is the probability of bankruptcy and X represents	X_b	= TL/TA
	the variables listed, and F represents the cumulative normal distribution	X_c	= CA/CL
	function. The probit function maps the value of $\beta' X$ to a probability		
	bounded between 0 and 1.		
	Cut off point:		
	‘Safe’ Zone; Zmijewski-Score < 0.5		
	‘Distress’ Zone; Zmijewski-Score ≥ 0.5		

The first two models that will be used are the revisited Z-score models of Altman (2000). Altman (1968) applied the statistical method of discriminant analysis to a dataset of publicly held manufacturers. The estimation is originally based on data from publicly held manufacturers, but has since been re-estimated based on other datasets for private manufacturing and non-manufacturing/service companies. The usefulness of the Altman's (1968) original Z-score measure is limited by ratio X_4, the market value of equity divided by total liabilities. Obviously, if a firm is not publicly traded, its equity has no market value. As mentioned before AFC Ajax is the only Dutch professional football club which is listed. Therefore, Altman's (1968) original work will not be an applicable research tool for this study. To deal with this, Altman's (2000) revisited Z'-score for private companies will be used. Another limitation could be ratio X_5, sales divided by total assets (i.e. asset turnover). This ratio varies significantly by industry, but because of the original sample, the Z-score expects a value that is common to manufacturing a revisited version which excludes ratio X_5 is presented by Altman (2000). Therefore, Altman's (2000) more general revisited Z''-score for private non-manufacturing firms will also be used. The Dutch professional football clubs will be classified in a certain category according to the cut off points as suggested by Altman and mentioned in table 2. The explanatory variables that are required for these two models can all be retrieved from the annual reports of the clubs. Only retained earnings (included in variable X_2), which can be calculated by, net profit - dividends, is a variable that is not common in the Dutch professional football industry since none of the clubs pay's any dividend to their shareholders or owners. Therefore dividend in Dutch professional football is set to be null and retained earnings will be the same as net profit or net income. Furthermore the three categories which are included in the Altman (2000) models are re-encoded into two categories; financial distressed and safe (i.e. grey and safe combined) because the comparing models of Ohlson (1980) and Zmijewski (1984) categorize the clubs into two categories (financial distressed and safe).

The third model that will be used is Ohlson's O-score model. Ohlson (1980) applied the statistical method of logit regression analysis. Ohlson's O-Score is the result of a 9-factor linear combination of coefficient-weighted business ratios which are readily obtained or derived from the standard periodic financial disclosure statements provided by publicly traded corporations. Two of the factors utilized are widely considered to be dummies as their value and thus their impact upon the formula typically is 0. The logit function maps the value of the results between 0 and 1. The cut-off point is 1/2. A company facing a possibility above 1/2 is said to face bankruptcy whereas a possibility below it tells a firm that it does not face bankruptcy. For the first explanatory variable the assumption must be made that a base value of 100 for season 2009/2010 applies. Furthermore because not all accounting data from every club and season is available, it is not possible to calculate variable X^9 in the original way in a few cases (especially before 2010). Therefore this variable is set to be null (as if NI stays the same) when previous year NI is not available.

The fourth and last model that will be used is Zmiejewski's probit model. Zmijewski (1984) applied the statistical method of probit analysis. Zmijewski's model is the result of a 3-factor linear combination of coefficient-weighted business ratios which are also readily obtained or derived from the standard periodic financial disclosure statements. The purpose of the model is to estimate the probability that an observation with particular characteristics will fall into a specific one of the categories; moreover, probabilities greater than 1/2 are treated as distressed firms, the ones below 1/2 are considered to be healthy firms. The probit model is also a type of binary classification model. The explanatory variables that are required for this model can all be retrieved from the annual reports of the clubs and don't require any adjusting or explanation.

4. EMPIRICAL RESULTS

This chapter presents the results that were obtained from the study. First a section about descriptive statistics is presented, followed by an individual analysis of the accuracy rate of the bankruptcy prediction models, next the results are compared to prior studies and in the end the hypotheses will be tested

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4.1 Descriptive Statistics

Similar to other studies[24], the analysis of the data starts with some descriptive statistics. The following tables reports descriptive statistics of the entire sample but are divided by the seasons to prevent that a club will be counted double. Table 6 shows the required accounting ratios for the different bankruptcy prediction models per season. The aim of this table is to compare accounting ratios and to observe differences between the seasons and the status (e.g. healthy and distressed) of a club. In general this table shows that the scores of the different ratios as required by the models of Ohlson (1980), Zmijewski (1984), and Altman (2000) have low values for both healthy and distressed clubs. Were other studies such as Wu *et al.* (2010) and Kleinert (2014) show mainly positive scores for the ratios of their healthy companies, this study shows largely negative scores. In general compared to these studies the ratios are high when they should be low and are low when they should be high. Meaning that most of the scores show more resemblance with the scores from the sample of bankrupt companies from those studies. When looking to the standard deviation of all the seasons and ratios, one can conclude that these are quite large; this implies large variance in the sample. Moreover, the differences between the healthy and the distressed clubs are larger when compared to similar studies (e.g. Wu *et al.*, 2010 and Kleinert ,2014). This is due to the fact that the (financial) differences between the Dutch professional football clubs are also quite large. This implies that the sample consists of very small and very large clubs. This comes also forward into the large differences between the minimum and maximum of the different ratios (especially SALES/TA). In case of the Dutch professional football industry this is not an unusual outcome. It is generally known that the budget, the number of followers and the financial capabilities of the Dutch professional football clubs highly differentiates from each other. When looking to the median and mean scores one can conclude that these are also quite low. The differences between the median and mean scores differ somewhat less from each other. This implies that the sample is not severally affected by outliers.

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[24] Among others; Ohlson (1980), Beaver *et al.* (2005), and Kleinert (2014)

Table 6. Summary statistics for explanatory variables. This table reports summary statistics for all of the required accounting ratios dived by healthy (H) and distressed (D) clubs per season.

			Altman (1968,2000)					Zmijewski (1984)			Ohlson (1980)								
Season			WC/TA	RE/TA	EBIT/TA	BVEQ/BVTL	SALES/TA	NI/TL	TL/TA	CA/CL	Size	TL/TA	WC/TA	CL/CA	OENEG	NI/TA	FU/TL	INTWO	CHIN
Season 2009/2010 (N=36)	**Min**	H (N=20)	-0,854	-0,423	-0,595	-4,478	0,427	-0,907	0,300	0,511	0,880	0,300	-0,854	0,540	0,000	-0,423	-0,810	0,000	1,000
		D (N=16)	-2,996	-3,294	-2,765	-1,288	0,911	-0,512	0,756	0,097	0,681	0,756	-2,996	1,091	0,000	-3,294	-0,467	0,000	1,000
	Max	H (N=20)	0,281	1,114	0,838	2,338	4,026	0,494	2,470	1,851	3,056	2,470	0,281	1,958	1,000	1,114	0,523	0,000	1,000
		D (N=16)	-0,077	4,726	0,577	0,322	8,165	5,022	11,025	0,917	2,656	11,025	-0,077	10,344	1,000	4,726	5,154	0,000	1,000
	Median	H (N=20)	-0,102	-0,143	-0,144	0,136	1,463	-0,151	0,863	0,794	1,712	0,863	-0,102	1,261	0,000	-0,143	-0,015	0,000	1,000
		D (N=16)	-0,543	-0,163	-0,539	-0,512	1,904	-0,115	1,624	0,424	1,316	1,624	-0,543	2,782	1,000	-0,163	-0,078	0,000	1,000
	Mean	H (N=20)	-0,139	-0,020	-0,114	0,031	1,609	-0,094	0,989	0,905	1,834	0,989	-0,139	1,245	0,300	-0,020	0,005	0,000	1,000
		D (N=16)	-0,844	-0,134	-0,718	-0,532	2,302	0,180	2,401	0,440	1,421	2,401	-0,844	3,585	0,875	-0,134	0,231	0,000	1,000
	Std. Dev.	H (N=20)	0,264	0,375	0,286	1,317	0,986	0,334	0,580	0,361	0,674	0,580	0,264	0,403	0,470	0,375	0,323	0,000	0,000
		D (N=16)	0,739	1,550	0,849	0,398	1,772	1,308	2,446	0,269	0,531	2,446	0,739	2,601	0,342	1,550	1,328	0,000	0,000
Season 2010/2011 (N=31	**Min**	H (N=25)	-0,939	-1,440	-1,359	-3,924	-0,361	-2,194	0,424	0,316	0,733	0,424	-0,939	0,617	0,000	-1,440	-2,076	0,000	-5,587
		D (N=6)	-1,366	-6,262	-5,842	-2,300	1,207	-1,560	1,249	0,000	0,856	1,249	-1,366	0,000	1,000	-6,262	-1,287	0,000	-1,151
	Max	H (N=25)	0,319	0,365	0,309	1,314	4,572	0,247	3,028	1,620	3,058	3,028	0,319	3,162	1,000	0,365	0,512	0,000	5,100
		D (N=6)	-0,150	0,017	-0,078	-0,200	11,536	0,006	4,013	0,882	2,305	4,013	-0,150	6,465	1,000	0,017	0,058	0,000	0,358
	Median	H (N=25)	-0,231	0,002	-0,054	-0,041	1,697	0,002	0,892	0,713	1,534	0,892	-0,231	1,402	0,000	0,002	0,051	0,000	-0,989
		D (N=6)	-0,465	-0,204	-0,223	-0,522	2,195	-0,103	2,097	0,242	1,329	2,097	-0,465	2,484	1,000	-0,204	-0,068	0,000	-0,058
	Mean	H (N=25)	-0,255	-0,103	-0,156	-0,116	1,689	-0,167	1,145	0,743	1,724	1,145	-0,255	1,635	0,440	-0,103	-0,073	0,000	-0,967
		D (N=6)	-0,564	-1,168	-1,299	-0,769	3,485	-0,336	2,317	0,398	1,427	2,317	-0,564	2,848	1,000	-1,168	-0,255	0,000	-0,227
	Std. Dev.	H (N=25)	0,326	0,416	0,393	0,963	1,025	0,533	0,665	0,354	0,683	0,665	0,326	0,715	0,507	0,416	0,547	0,000	2,189
		D (N=6)	0,459	2,497	2,275	0,764	3,989	0,604	0,957	0,379	0,513	0,957	0,459	2,479	0,000	2,497	0,514	0,000	0,597
Season 2011/2012 (N=30)	**Min**	H (N=25)	-1,605	-0,932	-0,739	-1,413	0,459	-2,407	0,387	0,000	0,704	0,387	-1,605	0,000	0,000	-0,932	-2,363	0,000	-9,617
		D (N=3)	-0,539	-0,108	-0,204	-0,445	1,450	-0,060	1,117	0,304	1,104	1,117	-0,539	1,165	1,000	-0,108	0,012	0,000	-1,143
	Max	H (N=25)	0,317	0,398	0,429	1,589	10,449	0,698	7,284	1,611	3,045	7,284	0,317	4,187	1,000	0,398	0,797	1,000	27,714
		D (N=3)	-0,155	0,398	0,406	-0,105	1,647	0,288	1,801	0,859	1,983	1,801	-0,155	3,284	1,000	0,398	0,365	1,000	2,387
	Median	H (N=25)	-0,153	0,009	-0,003	-0,089	1,751	0,009	0,983	0,805	1,611	0,983	-0,153	1,225	0,000	0,009	0,065	0,000	-0,080
		D (N=3)	-0,289	0,005	0,008	-0,276	1,592	0,005	1,380	0,728	1,244	1,380	-0,289	1,373	1,000	0,005	0,088	1,000	1,000
	Mean	H (N=25)	-0,358	-0,012	-0,063	-0,055	2,469	-0,032	1,567	0,733	1,706	1,567	-0,358	1,602	0,444	-0,012	0,058	0,259	0,574
		D (N=3)	-0,328	0,098	0,070	-0,275	1,563	0,078	1,433	0,630	1,444	1,433	-0,328	1,941	1,000	0,098	0,155	0,667	0,748
	Std. Dev.	H (N=25)	0,512	0,302	0,280	0,641	2,267	0,513	1,748	0,366	0,695	1,748	0,512	0,976	0,506	0,302	0,536	0,447	5,876
		D (N=3)	0,195	0,266	0,310	0,170	0,102	0,185	0,345	0,290	0,473	0,345	0,195	1,168	0,000	0,266	0,186	0,577	1,779

Season 2012/2013 (N=34)	**Min**	H (N=32)	-1,422	-0,968	-1,157	-1,467	0,463	-3,310	0,293	0,315	0,308	0,293	-1,422	0,581	0,000	-0,968	-3,202	0,000	-2,559
		D (N=2)	-2,213	0,046	-1,390	-0,835	5,616	0,050	0,916	0,210	0,565	0,916	-2,213	1,009	0,000	0,046	0,074	0,000	-0,795
	Max	H (N=32)	0,269	0,242	0,349	2,430	7,870	0,382	5,447	1,720	3,081	5,447	0,269	3,175	1,000	0,242	0,784	1,000	9,330
		D (N=2)	-0,008	24,651	25,077	0,089	5,864	5,729	4,303	0,991	0,674	4,303	-0,008	4,769	1,000	24,651	5,766	0,000	1,000
	Median	H (N=32)	-0,184	0,004	-0,049	-0,208	1,782	0,002	1,097	0,739	1,484	1,097	-0,184	1,356	1,000	0,004	0,038	0,000	0,353
		D (N=2)	-1,110	12,349	11,843	-0,373	5,740	2,890	2,609	0,601	0,619	2,609	-1,110	2,889	0,500	12,349	2,920	0,000	0,103
	Mean	H (N=32)	-0,316	-0,080	-0,089	-0,030	2,348	-0,123	1,332	0,781	1,639	1,332	-0,316	1,558	0,531	-0,080	-0,021	0,188	0,924
		D (N=2)	-1,110	12,349	11,843	-0,373	5,740	2,890	2,609	0,601	0,619	2,609	-1,110	2,889	0,500	12,349	2,920	0,000	0,103
	Std. Dev.	H (N=32)	0,444	0,249	0,311	0,733	1,866	0,606	1,028	0,340	0,689	1,028	0,444	0,734	0,507	0,249	0,630	0,397	2,575
		D (N=2)	1,559	17,399	18,715	0,653	0,176	4,016	2,394	0,553	0,078	2,394	1,559	2,659	0,707	17,399	4,025	0,000	1,269
Season 2013/2014 (N=32)	**Min**	H (N=26)	-2,146	-1,908	-1,882	-1,297	0,346	-0,758	0,164	0,130	0,648	0,164	-2,146	0,221	0,000	-1,908	-0,691	0,000	-11,881
		D (N=6)	-1,329	-0,684	-0,812	-0,687	0,476	-0,721	0,950	0,337	0,672	0,950	-1,329	1,100	0,000	-0,684	-0,657	0,000	-1,054
	Max	H (N=26)	0,488	0,336	0,368	5,091	6,433	0,374	5,629	4,525	3,095	5,629	0,488	7,709	1,000	0,336	0,643	1,000	4,922
		D (N=6)	-0,028	0,614	0,622	0,032	4,807	0,192	3,201	0,909	2,918	3,201	-0,028	2,964	1,000	0,614	0,222	0,000	1,446
	Median	H (N=26)	-0,187	-0,021	-0,074	-0,052	1,981	-0,019	0,997	0,811	1,445	0,997	-0,187	1,234	0,000	-0,021	0,066	0,000	0,051
		D (N=6)	-0,345	-0,018	-0,002	-0,205	1,934	-0,017	1,216	0,492	1,424	1,216	-0,345	2,220	1,000	-0,018	0,021	0,000	0,224
	Mean	H (N=26)	-0,374	-0,164	-0,169	0,182	2,691	-0,099	1,294	0,951	1,601	1,294	-0,374	1,903	0,462	-0,164	0,017	0,231	-0,197
		D (N=6)	-0,491	-0,046	-0,030	-0,253	2,176	-0,118	1,512	0,551	1,554	1,512	-0,491	2,133	0,833	-0,046	-0,038	0,000	0,156
	Std. Dev.	H (N=26)	0,655	0,465	0,452	1,254	1,854	0,293	1,120	0,862	0,708	1,120	0,655	1,849	0,508	0,465	0,296	0,430	2,756
		D (N=6)	0,453	0,425	0,482	0,257	1,501	0,323	0,842	0,244	0,743	0,842	0,453	0,876	0,408	0,425	0,316	0,000	1,080

Until now the descriptive statistics showed that the scores of the different ratios are quite low compared to other studies. To understand the reason for this outcome table 7 is presented. This table shows the statistics of some negative accounting variables from the different bankruptcy prediction models per season.

Table 7. Descriptive statistics of the negative accounting variables from the different bankruptcy prediction models per season.

Negative accounting variables	**Season 2009/2010 (N=36) Amount**	**Season 2010/2011 (N=31) Amount**	**Season 2011/2012 (N=30) Amount**	**Season 2012/2013 (N=34) Amount**	**Season 2013/2014 (N=32) Amount**	**Seasons all (N=163) Mean**
Negative EQ	58.33%	61.29%	56.67%	61.76%	59.38%	59.49%
Negative WC	86.11%	83.87%	80.00%	76.47%	75.00%	80.29%
Negative EBIT	80.56%	67.74%	50.00%	52.94%	59.38%	62.12%
Negative NI	58.33%	54.84%	40.00%	41.18%	50.00%	48.87%

What one can conclude from this table is that the Dutch professional football industry is an industry that has huge liquidity, profitability and leverage problems. It is striking to see that the mean value of all seasons shows that; 59% of the clubs has a negative equity, 80% of the clubs has a negative working capital, 62% has negative earnings before interest, and 49% has a negative net income. In season 2009/2010 just after the start of Europe's economic recession these values are at their highest point. Until season 2013/2014 there is a small improvement notable but still these values are at a disturbingly low.

4.2 Analysis of the Bankruptcy Prediction Models

As mentioned in the literature review bankruptcy prediction models are designed to predict the risk that a (public) firm goes bankrupt. In table 8 the percentages of the clubs which might face bankruptcy according to the different models per season is showed. It is striking to see that the majority of the Dutch professional football clubs is facing bankruptcy, when their data is used for the most common accounting-based bankruptcy prediction models. Especially Ohlson's (1980) model and Altman's (2000) Z"score model classify almost every club into the 'is facing bankruptcy' category. The models of Zmijewski (1984) and Altman's (2000) Z'-score model are considerably milder in their judgment, especially Zmijevski's (1984) model.

Table 8. Descriptive statistics of the percentages of the clubs which face bankruptcy according to the different models per season and the actual percentages of distressed clubs per season according to the FRS-model.

Facing bankruptcy per model	Season 2009/2010 (N=36) Amount	Season 2010/2011 (N=31) Amount	Season 2011/2012 (N=30) Amount	Season 2012/2013 (N=34) Amount	Season 2013/2014 (N=32) Amount	Seasons all (N=163) Mean
Altman Z'	72.22%	67.74%	36.67%	38.24%	40.63%	51.10%
Altman Z''	86.11%	90.32%	83.33%	85.29%	84.38%	85.89%
Ohlson	91.67%	96.77%	93.33%	85.29%	93.75%	92.16%
Zmijevski	36.11%	38.71%	23.33%	35.29%	37.50%	34.19%
Actual Distressed	44.44%	19.35%	10.00%	5.88%	18.75%	19.68%

However the amount of clubs who are facing bankruptcy according to the models is quite a disturbing result, it is not one of the goals of the study. That is namely “assessing the accuracy rate of bankruptcy prediction models for the Dutch professional football industry”. To reach this, of each of the studied years (seasons 2009/2010 until 2013/2014) the accuracy rate is calculated for every model by dividing the amount of good predictions by the amount of clubs of which the data is retrieved that particular season. A good prediction is dependent on the category-division (classification) of the FRS-model and the particular bankruptcy prediction model, when both models are consistent in their judgment it is seen as a good prediction. So the results are compared to the classification according to the FRS-model. The classification periods of t_{+1}, t_{+2} and t_{+3} are used to compare the results of the bankruptcy prediction models to the financial state a club is in according to this FRS-model. For example; for the accounting data of season 2009/2010 the comparing category-division (classification) according to the FRS-model of one year later is $t_{+1,}$ two years later is t_{+2} and three years later is t_{+3}. The financial ratios (independent variable) of the models will determine the dependent categorical variable (financial distressed and safe) of each model. The correctness of the predicton of one of the models for a particular year and time frame has a base chance of 50/50 since there are only two categories; healthy and distressed, were clubs can be categorized in and abvious this prediction is wrong or right. This chance is the same when just gambling. Therefore for this study the accuracy rate of a prediction is seen low when below 50% since it then predicts worse than when gambling.

4.2.1 Analysis Altman's (2000) models

The two tables 9 and 10 summarize the results of Altman's (2000) revisited; Z', and Z"-score models for the Dutch professional football industry. To be able to say something about the prediction power the accuracy rate of one year later, two years later, and three years later from a particular season is calculated. Table 9 shows that Altman (2000) Z'-score model, which is originally developed for manufacturing firms, has an accuracy rate that is quite low for every season and predicting time frame.

Table 9. Results Altman's (2000) Z'-score model for Dutch professional football industry

Years later (t)	Season 2009/2010 (n=36) Altman Z'	Season 2010/2011 (n=31) Altman Z'	Season 2011/2012 (n=30) Altman Z'	Season 2012/2013 (n=34) Altman Z'	Season 2013/2014 (n=32) Altman Z'	Years later (n=163) Mean
t_{+1}	47.22%	41.94%	60.00%	23.53%	-	43.17%
t_{+2}	41.67%	38.71%	66.67%	-	-	49.01%
t_{+3}	27.78%	48.39%	-	-	-	38.08%

It is in line with similar studies that the accuracy rate declines when the amount of predicting years towards the future increases (e.g. Anjum, 2012). When looking to the results of Altman (2000) Z'-score one can conclude that the accuracy rate when compared to the classification of KNVB's FRS-model in t_{+2} is the highest with a mean score of 49.01%. The accuracy t_{+3} is much lower with a mean score of 38,08%. Strangely there seems to be a peak in season 2011/2012, were the accuracy rates are above 60% for t_{+1} and t_{+2} . Overall one can conclude that the accuracy rate of Altman's (2000) Z'-score model is pretty low. Especially when one keeps in mind that there is a 50/50 chance that the Z'-model categorizes a club into the same category as the FRS-model. This means that in almost every season and predicting time frame the Z'-model performs worse than the 50/50 chance when gambling.

Table 10. Results Altman's (2000) Z"-score model for Dutch professional football industry

Years later (t)	Season 2009/2010 (n=36) Altman (Z")	Season 2010/2011 (n=31) Altman (Z")	Season 2011/2012 (n=30) Altman (Z")	Season 2012/2013 (n=34) Altman (Z")	Season 2013/2014 (n=32) Altman (Z")	Years later (n=163) Mean
t_{+1}	38.89%	19.35%	20.00%	20.59%	-	24.71%
t_{+2}	27.78%	16.13%	33.33%	-	-	25.75%
t_{+3}	19.44%	25.81%	-	-	-	22.63%

When looking to table 10, the accuracy rate of Altman's (2000) Z"-model for non-manufacturing companies is even worse than the Z'-model. In all seasons and all predicting time frames the score is below 50%. This means that all the accuracy rates as can be seen in table 10 score below the 50/50 chance when gambling.

Overall one can conclude that this model performs very bad. To understand why Altman's (2000) Z-score models scores so low, the variables/ratios which are included in the model and the results from the descriptive statistics may be important. Namely, when looking to the five ratios which are included in the calculation one can see that ratios which measure liquidity (WC/TA), profitability, (RE/TA, EBIT/TA and SALES/TA) and leverage (BVEQ/BVTL) are determinative for the outcome. As table 7 shows most variables which are included in the ratios are negative and this may cause many 'facing for bankruptcy' classifications. This is also supported by table 8. Namely, when looking back to this table one can see that the Z'-score model classifies with a mean score of 51.10% of the clubs into the category 'is facing bankruptcy' and the Z"-score model even 85.89%. The reason why Altman's (2000) Z"-score model performs even worse is probably because ratio X_5 (SALES/TA) is excluded. Otherwise than expected the X_5 ratio, which is originally excluded in order to minimize the potential effect related to the specific manufacturing industry since this industry is highly sensitive to the criteria of the size of business, seems to be an important ratio for the Dutch professional football industry. This is mainly because the net sales for almost every club are much higher than the amount of total assets. These total assets are sometimes deliberately kept low so that in case of bankruptcy the important assets such as training ground and stadium are protected. However this may be a possible explanation, for most of the clubs the total assets are just on the low side, because they are small 'poor' professional football clubs. Most of the time they do not own the stadium where they play their matches. This stadium may be owned by a third party such as a municipality, town or investor or is financially rented by the particular professional football club.

4.2.2 Analysis Ohlson (1980 model)

The table below shows the accuracy rates of the logit regression of Ohlson (1980) on the Dutch professional football industry. The results suggest that Ohlson's (1980) model performs even worse than the Altman (2000) models. When looking back to table 8 this probably is because Ohlson's (1980) model classifies more than 90% as facing bankruptcy in every season and time frame. This is a very high score and therefore it is not surprising that it bears little resemblance to the category-division (classification) of the FRS-model. This result suggests that Ohlson's (1980) model is very strict in assessing the Dutch professional football clubs since almost every club should be already bankrupt or in the next few years. Obviously this has not quite been the case, therefore these results are questionable.

Table 11. Results Ohlson's (1980) model for Dutch professional football industry per season.

Years later (t)	**Season 2009/2010 (n=36) Ohlson**	**Season 2010/2011 (n=31) Ohlson**	**Season 2011/2012 (n=30) Ohlson**	**Season 2012/2013 (n=34) Ohlson**	**Season 2013/2014 (n=32) Ohlson**	**Years later (n=163) Mean**
t_{+1}	33.33%	12.90%	3.33%	26.47%	-	19.01%
t_{+2}	22.22%	9.68%	23.33%	-	-	18.41%
t_{+3}	13.89%	19.35%	-	-	-	16.62%

4.2.3 Analysis Zmijewski (1984 model)

The table below shows the accuracy rates of the probit model of Zmijewski (1984) on the Dutch professional football industry. In contrast to Ohlson's (1980) and Altman's (2000) models this model performs much better. The Zmijewski model classifies the Dutch professional football clubs in the same category as the FRS-model with an accuracy rate of more than 60% for almost every season and time frame. Although this is a promising result related to the other models which have been discussed above, it is compared to the results in literature (e.g. Wu *et al.*, 2010 and Kleinert, 2014) still much lower. When looking back to table 8 one can conclude that about 1/3 of the Dutch professional football clubs was facing bankruptcy last few years. This is pretty close to the actual amount which went bankrupt a few years later (8.33%) and which were in financial distress (36.11%). Overall with keeping in mind that the possibility of a good prediction/classification when gambling is 50/50, the result of Zmijewski's (1984) model can be termed as 'the best of the worst'.

Table 12. Results Zmijewski (1984) model for Dutch professional football industry

Years later (t)	Season 2009/2010 (n=36) Ohlson	Season 2010/2011 (n=31) Ohlson	Season 2011/2012 (n=30) Ohlson	Season 2012/2013 (n=34) Ohlson	Season 2013/2014 (n=32) Ohlson	Years later (n=163) Mean
t_{+1}	61.11%	64.52%	73.33%	64.71%	-	65.92%
t_{+2}	61.11%	61.29%	66.67%	-	-	63.02%
t_{+3}	63.89%	58.06%	-	-	-	60.98%

4.2.4 Comparison with prior studies

The table 13 below puts the accuracy rates of the Dutch professional football clubs into perspective with the accuracy rates of some similar research of different industries. This has the aim to show in how far the findings of this master thesis can be put into perspective. When the results of this study are compared to prior studies one can conclude that the accuracy rates as found in this study are on the low side as can be seen in table 13. Only the accuracy rate based on the model of Zmijewski in t+3 perform better than two of the three comparison studies.

Table 13. Overview of accuracy rates observed in the different time frames from similar research (based on own assessment).

	Accuracy rate observed in t+1			
Studies	**Altman (Z)**	**Altman (Z")**	**Ohlson**	**Zmijewski**
Oude Avenhuis (2013)	69,70%	-	97,50%	89,00%
Kleinert (2014)**	68,30%	-	97,40%	86,00%
Kleinert (2014)***	52,10%	-	98,50%	96,90%
Own study	43,17%*	24,71%	19,01%	65,92%

		Accuracy rate observed in t+2		
Studies	**Altman (Z)**	**Altman (Z")**	**Ohlson**	**Zmijewski**
Oude Avenhuis (2013)	75,80%	-	96,70%	45,00%
Kleinert (2014)**	68,00%	-	97,20%	79,00%
Kleinert (2014)***	53,10%	-	98,50%	96,90%
Own study	49,01%*	25,75%	18,41%	63,02%

		Accuracy rate observed in t+3		
Studies	**Altman (Z)**	**Altman (Z")**	**Ohlson**	**Zmijewski**
Oude Avenhuis (2013)	78,60%	-	96,90%	42,00%
Kleinert (2014)**	67,90%	-	97,00%	38,00%
Kleinert (2014)***	52,00%	-	98,50%	96,90%
Own study	38,08%*	22,63%	16,62%	60,98%

*. Z'

**. Accuracy rate from Belgium listed firms

***. Acurracy rate from German listed firms

4.3 Hypotheses and Discussion

4.3.1 Testing hypotheses

After taking note of the empirical results above it will be interesting to see what the effect of these results are on the hypotheses as formulated in chapter 2.7. The following hypotheses were formulated and will be tested:

Hypothesis 0 (null hypothesis)

H_0: There is no difference in the accuracy rate between accounting-based bankruptcy prediction models of Ohlson (1980), Zmijewski (1984), and Altman (2000) regarding the Dutch professional football industry.

Hypothesis A (alternative hypothesis)

H_A: The Z'' model of Altman (2000) will outperform the models of Ohlson (1980), Zmijewski (1984) and the Z' model of Altman (2000) regarding the Dutch professional football industry.

To be able to test these hypotheses the statistical program SPSS is used to determine whether there exists homogeneity of variances within the models (groups), whether there is a difference between the models, which model performs best and whether this all is significant. First the test of homogeneity of the variances within the models is important because when these variances are too high and significant the models are not comparable. Table 14 shows the results of this test which implies that the homogeneity of variances within the models is not significant (.319 for t_{+1}, .070 for t_{+2} and .070 overall). This means that the variances within the groups do not differ from each other and that the models are comparable.

Table 14. Test of homogeneity of variances

Years later (t)	Levene Statistic	df1	df2	Sig.
t_{+1}	1,302	3	12	.319
t_{+2}	3.490	3	8	.070
t_{+3}	*	3	*	*
Overall	2.744	3	32	.059

*. Too few cases to perform calculation

Because the models are comparable, a two-way ANOVA is calculated in table 15. This table shows the differences between the models and within the models. The results imply that the models statistically significant (.000 for t+1, .002 for t+2, .019 for t+3 and .000 overall) differ from each other regarding the Dutch professional football industry.

Table 15. Results two-way ANOVA

Years later (t)		Sum of Squares	df	Mean Square	F	Sig.
t+1	Between Groups	.537	3	.179	13.570	.000
	Within Groups	.158	12	.013	-	-
	Total	.695	15	-	-	-
t+2	Between Groups	.384	3	.128	13.436	.002
	Within Groups	.076	8	.010	-	-
	Total	.460	11	-	-	-
t+3	Between Groups	.235	3	.078	11.846	.019
	Within Groups	.026	4	.007	-	-
	Total	.262	7	-	-	-
Overall	Between Groups	1.146	3	.382	43.466	.000
	Within Groups	.281	32	.009	-	-
	Total	1.427	35	-	-	-

When looking back to hypothesis 0, one can conclude now that this hypothesis can be rejected and that there is a difference in the accuracy rate between accounting-based bankruptcy prediction models of Ohlson (1980), Zmijewski (1984), and Altman (2000) regarding the Dutch professional football industry. Because the models statistically significant differ from each other, it is interesting to perform a Bonferroni post-hoc analysis to find out how the models differ from each other. The results of these multi comparisons analysis is shown at table 16 on the next page.

Table 16. Multi comparisons post-hoc analysis two-way ANOVA (Bonferroni)

(I) Model	(J) Model	t_{+1} Mean Difference (I-J)	Sig.	t_{+2} Mean Difference (I-J)	Sig.	t_{+3} Mean Difference (I-J)	Sig.	Overall Mean Difference (I-J)	Sig.
Z'	Z''	18.43%	.255	23.30%	.115	15.50%	.776	19.40%*	.000
	Ohlson	24.15%	.070	30.63%*	.029	21.45%	.346	25.71%*	.000
	Zmijewski	-22.75%	.096	-14.00%	.701	-22.90%	.288	-19.87%*	.001
Z''	Z'	-18.43%	.255	-23.30%	.115	-15.50%	.776	-19.40%*	.000
	Ohlson	5.73%	1.000	7.33%	1.000	5.95%	1.000	6.31%	.660
	Zmijewski	-41.18%*	.002	-37.30%*	.009	-38.40%	.055	-39.27%*	.000
Ohlson	Z'	-24.15%	.070	-30.63%*	.029	-21.45%	.346	-25.71%*	.000
	Z''	-5.73%	1.000	-7.33%	1.000	-5.95%	1.000	-6.31%	.660
	Zmijewski	-46.90%*	.001	-44.63%*	.003	-44.35%*	.033	-45.58%*	.000
Zmijewski	Z'	22.75%	.096	14.00%	.701	22.90%	.288	19.87%*	.001
	Z''	41.18%*	.002	37.30%*	.009	38.40%	.055	39.27%*	.000
	Ohlson	46.90%*	.001	44.63%*	.003	44.35%*	.033	45.58%*	.000

*. The mean difference is significant at the 0.05 level.

When looking back to hypothesis A, it should be the case that the Z”-model will outperform the other models. Table 15 shows that this is not quite the case. Based on the mean differences the Z”-model performs worse than the Z’-model and Zmijewski’s model and better than Ohlson’s model at all time frames (e.g. t_{+1}, t_{+2}, t_{+3} and overall). When looking closer to table 15 one can see that not all of these mean differences are significant. For time frame t_{+3} this can be explained by the fact that the initial sample for that time frame is too small to calculate in a proper way, which also has been mentioned in table 13. When comparing the Z” model to the other models it seem that only the mean differences between Z” and Zmijewski are significant for the other time frames (t+1, t+2 and overall). When comparing Zmijewski’s model to the other models one can conclude that Zmijewski’s model by far outperforms the other models. It performs significantly better than the Z” model and Ohlson’s model. It seems that Zmijeski’s model also outperform the Z’ model but these accuracy rates are not significant and therefore they can be based on chance. Nevertheless based on the above mentioned evidence hypothesis A can be rejected and the Z” model of Altman (2000) does not outperform the Z’ model of Altman (2000), Ohlson (1980) model and Zmijewski’s (1984) regarding the Dutch professional football industry.

5. DISCUSSION AND CONCLUSION

This chapter presents the discussion and conclusion of this study. Next the limitations of the study follow. The chapter ends with some suggestions for future research.

5.1 Discussion

The results on the three different accounting-based bankruptcy prediction models were evaluated to answer the two hypotheses of this study. The study has tried to assess the accuracy rate of the Dutch professional football industry with the use of the most common accounting-based bankruptcy prediction models. The results of the models showed to be inconsistent with the hypothesis 0 and inconsistent with the hypothesis A. Hypothesis 0 stated that there is no difference between the accuracy rates of the three accounting-based bankruptcy prediction models whereas hypothesis A claimed that Altman's (2000) Z"-score model for non-manufacturing companies would outperform the other contestants. The findings indicated clearly that the accuracy rate of the models of Ohlson (1980), Zmijewski (1984) and Altman (2000) differ across the models. The accuracy rate for the Dutch professional football industry for the models of Ohlson (1980), Zmijewski (1984) and Altman (2000) are depending on the prediction time frame respectively between 17% and 19% , 61% and 66%, 38% and 49% (Z'), and 23% and 26% (Z").

That means that the model of Zmijewski (1984) performs best. Furthermore these findings also indicated clearly that the Z"-score model of Altman (2000) does not outperform the other models since Zmijewski's (1984) model is the best predictor. Based on the literature review and derivation of hypotheses this is not an outcome as expected. However some authors claim that the bankruptcy prediction models perform almost similar (e.g. Wu *et al.*, 2010) and others claim that they perform highly different in their accuracy rate (e.g. Grice & Ingram, 2003), the differences found in this study deviate much more from each other as they should be based on literature. The reason for this unusual outcome might be the specific characteristics of a professional football industry. Other than 'normal' firms, professional football clubs are seeking for success on the field (e.g. winning prizes and cups) instead of maximizing their profits like any 'normal' firm would do. This sometimes causes them to take irresponsible risk in order to win prizes or satisfy their supporters. The results are financial statements which show different figures/ratios than even unhealthy firms would have. The findings of the descriptive statistics support this possible explanation. In particular the amount of negative variables which were found. Namely, the amount of clubs who have a negative equity (59%), working capital (80%), EBIT (62%) and net income (49%) is far from usual. This indicates that professional football clubs are managed differently and are struggling to act as ‘normal’ firms. The reason why professional football clubs do not fall so frequently is because they are often saved by for example their municipality or wealthy supporters (often because of the sentiment) when having real financial distress. Overall it seems that the original models of Ohlson (1980), Zmijewski (1984) and Altman (2000) are too strict in predicting bankruptcy for the Dutch professional football industry. This is also supported with the findings of the descriptive statistics. Namely, when acting as ‘normal’ firms, the majority of the Dutch professional football clubs are facing bankruptcy (e.g. are financially distressed) and should be already bankrupt or should be bankrupt next few years according to de models of Ohlson (94%), Zmijewski (38%), Altman Z’ (41%), and Z” (84%). Of course it is not very likely that this would happen and therefore the findings of this study should be interpreted with caution.

5.2 Conclusion

In this study the accuracy rate of a number of bankruptcy prediction models is examined in order to assess their accuracy rate for the Dutch professional football industry. The models have been selected on their applicability and the relevance in literature. The models use a range of different independent variables (accounting information and firm-characteristics) and a range of statistical methods specifications (multiple-discriminant analysis, logit and probit analysis). This study shows that the Dutch football industry has some huge financial problems. The majority of the clubs has liquidity, profitability and leverage problems and based on the results of the different bankruptcy prediction models are facing bankruptcy. Generally this is due to the fact that the club’s have very little or even negative equity, negative working capital, little assets, and negative EBIT. When looking to the hypotheses one can conclude that hypothesis 0 can be rejected and that hypothesis A can be rejected as well. First other than expected there is a difference between the accounting-based bankruptcy prediction models of Ohlson (1980), Zmijewski (1984), and Altman (2000). Second the Z” model of Altman (2000) does only outperform Ohlson’s (1980) model and therefore not the other models.

Regarding the accuracy rate, the study found that none of the most common used accounting-based bankruptcy prediction models, which are used for this study, performs well. When there need to be a winner selected; Zmijewski’s (1984) model performs best in the Dutch professional football industry. This model has a mean accuracy rate between 61% and 65% depending on the selected predicting time frame. This is substantial better than the model of Ohlson (1980) which has a mean accuracy rate between 17% and 19% and is therefore the most inaccurate. In contrast to what one would expect for a non-manufacturing industry such as professional football, Altman’s (2000) Z’-

model outperforms his Z”-model. The mean accuracy rates are respectively between 38% and 49% for Altman’s (2000) Z’-score model and between 23% and 26% for Altman’s (2000) Z”-score model. Overall the conclusion can be made that the most common used accounting-based bankruptcy prediction models of Altman (1968,2000), Ohlson (1980) and Zmijewski (1984) are not well applicable for the Dutch professional football industry.

5.2.1 Limitations

Similar to other studies this study has some limitations. To start the first limitations are some common limitations of the accounting-based bankruptcy prediction models. Namely, the accounting variables in those models can be manipulated (e.g. depreciation method, window dressing etc.). Dutch professional football clubs which are motivated to belong to the healthy categories according the FRS-model in order to prevent penalties form the KNVB might manipulate their figures in order to achieve their goal. Moreover the data was retrieved from different sources and consists of the annual reports of the different clubs. The financial data included in these reports came most of the time with the footnote that these figures are drafted by the clubs themselves, not controlled by an auditor and still may deviate due to compression and classification. Furthermore the calculations of the used models require variables which are not quite common and/or logic for a professional football industry. As mentioned in chapter 3, this is for example the variable dividend. Taken this together with the fact that the data was manually entered into the calculations may cause that the data has some flaws and that the reliability of this study is not optimal. There are also some limitations regarding the sample size. While enough data was found throughout the seasons/years, unfortunately the amount of bankrupt clubs are only four (financial data available of only three). A larger bankrupt sample size would make it possible to work with a hold-out sample and would give a clearer and more defined representation to verify the validity of the accounting-based bankruptcy prediction models. The biggest limitation if this study is the assumption that has been made that the classification by the KNVB (with use of the FRS-model) is always right. When following the news it really seems that a club really is financially distressed when it’s categorized by the FRS-model in the insufficient category. Nevertheless this is a limitation of the validity of this study.

5.2.2 Suggestions for Future Research

While performing this study new questions have emerged. For example how would the models perform in other country's professional football industry. Of course to perform similar research someone must be able to retrieve all the necessary data. But when possible it would be interesting to see how the models perform in the professional football industry from other countries. When this is not possible another suggestion is to search for European professional football clubs which are listed. When enough one could perform a similar research and include some market-based models to compare both streams of models within for example the European football industry. Probably there won't be enough bankrupt/distressed clubs but, nevertheless it might be interesting to see how the clubs are categorized. Is professional football really a branch on its own and do all the clubs have financial problems according to the models or are the models just not applicable for this branch. When one of the above mentioned studies comes to a similar conclusion that none of the models performs adequate the question rises; which variables are necessary to predict a football industry?

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APPENDIX I – OVERVIEW KEY BANKRUPTCY PREDICTION MODELS

Table 17. Overview of the key bankruptcy prediction models.

Study of	Statistical Technique	Period	Pro's and Con's
Altman (1968)	Accounting-based: • Multi-discriminant analysis	1946-1965	+ Simplicity, adjusted versions, commonly applied, extensively tested – Assumptions, biased due equal distribution of the sample, small sample
Ohlson (1980)	Accounting-based: • Logit model	1970-1976	+ Less assumptions, 2 categories (0-1), large sample – Fixed parameters, only one and non-randomly observation
Zmiejewski (1984)	Accounting-based: • Probit model	1972-1978	+ Entire population – Variables are highly correlated
Shumway (2001)	Market-based • Hazard model	1962-1992	+ Combining accounting and market variables. – Not extensively tested, time consuming
Hillegeist *et al.* (2004)	Market-based • BSM-prob model	1979-1997	+ Used in practice – Same limitations as option-price theory, time consuming

APPENDIX II – KNVB'S FRS-MODEL REVIEWED

The Royal Dutch Football Association (in Dutch: Koninklijke Nederlandse Voetbalbond or abbreviated KNVB) is the governing body of football in the Netherlands. It organizes the main Dutch football leagues; premier league and first division, the amateur leagues, the KNVB Cup, and the Dutch men's and women's national teams. Along with its Belgian counterpart, the KNVB also organizes the BeNe League, the top women's league in both countries. The KNVB is based in the central municipality of Zeist. It is the single largest sports association in the Netherlands

In 2010 professional football clubs and the KNVB made an agreement to communicate in a transparent way about the licensing system and the financial policy of the clubs. An important part of this is the announcement of the category-division, on three pre-determined moments in the year. The division consists of three different categories: Category I (insufficient), Category II (sufficient) and Category III (good). This financial division of the clubs is based on the Financial Rating System (FRS). The FRS consists of ten core variables, with each a different scale and weight. The result of the core variables will be based on the information which can be retrieved from the financial reports of the different football clubs. All scores of the ten core variables are summed up and determine in which of the three categories the financial position of the club is classified. Below is shown a summary of the variables and an example.

Table 18. Variables Financial Rating System

Variable	Multiplier	Definition
1	6	Buffer liquid resources (cash) based on history
2	6	Buffer liquid resources (cash) based on future
3	8	Working capital position
4	8	Solvability
5	4	History net margin
6	6	History gross margin
7	2	Future net margin
8	4	Future gross margin
9	8	Labor cost ratio
10	8	Budgeting discipline

Source: KNVB

Example

A professional football club has a working capital position (variable 3) of 65%. At this outcome it will belong to category 2 (50% till 70%) of the working capital position of the club. The multiplier (the weight) of variable 3 is 8. De score of the concerning club for the working capital position is: 2 (scale/category) x 8 (multiplier) = 16 points. All scores (points) of the ten core variables are summed up and determines in which of the three categories the financial position of the club is classified. The points per category are:

I. Category I (insufficient): -16 until 64 points;
II. Category II (sufficient): 65 until 129 points;
III. Category III (good): 130 until 240 points;

When a club belongs to category I, it needs to work on financial recovery. This is at the clubs own responsibility and they need to develop a plan of approach that has the goal to belong to category II or III on a structural bases. This must be within maximum nine measurement points (a term of three years). The clubs are supposed to stick strictly to the plan to avoid sanctions of the KNVB. These sanctions could be warnings, money fines or a deduction of league points. The KNVB strives to get all the club at least in category II within the upcoming years.

APPENDIX III – EXTRA DESCRIPTIVE STATISTICS

Table 21. Results from the different bankruptcy prediction models, season 2013/2014 (N=32).

Club	Z'-score	Z"-score	Ohlson-score	Zmijewski-score
Ado Den Haag	1,836	-0,986	0,907	0,348
AFC Ajax	2,498	5,801	0,262	0,104
Almere City	5,559	0,372	0,717	0,212
AZ	0,765	-0,964	0,970	0,295
Cambuur Leeuwarden	3,625	-4,191	1,000	0,747
FC Den Bosch	-4,909	-33,687	1,000	0,985
FC Dordrecht	0,723	-4,274	0,995	0,523
FC Eindhoven	3,216	-4,298	0,998	0,571
FC Emmen	5,770	-2,819	0,990	0,311
Excelsior Rotterdam	1,081	-0,427	0,993	0,502
Feyenoord	2,893	3,709	0,902	0,234
Fortuna Sittard	6,050	-3,255	1,000	0,932
Go Ahead Eagles	4,580	4,795	0,612	0,303
De Graafschap	0,496	-4,454	0,968	0,483
FC Groningen	1,066	-0,897	0,977	0,327
SC Heerenveen	0,622	-1,000	0,999	0,289
Helmond Sport	1,558	-1,908	0,902	0,417
Heracles Almelo	2,122	1,737	0,563	0,175
MVV	3,195	-3,454	0,997	0,476
NAC Breda	3,179	-0,977	0,962	0,413
N.E.C.	2,176	-10,363	0,999	0,638
FC/TOP Oss	N.A	N.A	N.A	N.A
PEC/FC Zwolle	1,877	-4,941	0,929	0,505
PSV	0,823	0,702	0,632	0,203
RKC Waalwijk	1,485	-22,038	1,000	1,000
Roda JC	-0,965	-11,707	1,000	0,811
Sparta Rotterdam	2,187	0,767	0,950	0,421
Telstar	N.A.	N.A.	N.A.	N.A.
FC Twente	0,124	-2,236	0,922	0,386
FC Utrecht	-1,451	-5,868	0,924	0,538
Vitesse	1,092	4,675	0,035	0,273
FC Volendam	1,334	-2,462	0,974	0,312
VVV Venlo	-1,465	-11,713	0,995	0,537
Willem II	3,639	-8,936	0,998	0,349

Table 22. Status according the results from the different bankruptcy prediction models from season 2013/2014 (N=32).

Club	Status Z'-score	Status Z"-score	Status Ohlson-score	Status Zmijewski-score
Ado Den Haag	Safe (grey)	Risk of Bankruptcy	Risk of Bankruptcy	Safe
AFC Ajax	Safe (grey)	Safe (good)	Safe	Safe
Almere City	Safe (good)	Risk of Bankruptcy	Risk of Bankruptcy	Safe
AZ	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy	Safe
Cambuur Leeuwarden	Safe (good)	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy
FC Den Bosch	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy
FC Dordrecht	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy
FC Eindhoven	Safe (good)	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy
FC Emmen	Safe (good)	Risk of Bankruptcy	Risk of Bankruptcy	Safe
Excelsior Rotterdam	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy
Feyenoord	Safe (grey)	Safe (good)	Risk of Bankruptcy	Safe
Fortuna Sittard	Safe (good)	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy
Go Ahead Eagles	Safe (good)	Safe (good)	Risk of Bankruptcy	Safe
De Graafschap	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy	Safe
FC Groningen	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy	Safe
SC Heerenveen	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy	Safe
Helmond Sport	Safe (grey)	Risk of Bankruptcy	Risk of Bankruptcy	Safe
Heracles Almelo	Safe (grey)	Safe (grey)	Risk of Bankruptcy	Safe
MVV	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy	Safe
NAC Breda	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy	Safe
N.E.C.	Safe (grey)	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy
FC/TOP Oss	N.A	N.A	N.A	N.A
PEC/FC Zwolle	Safe (grey)	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy
PSV	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy	Safe
RKC Waalwijk	Safe (grey)	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy
Roda JC	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy
Sparta Rotterdam	Safe (grey)	Risk of Bankruptcy	Risk of Bankruptcy	Safe
Telstar	N.A.	N.A.	N.A.	N.A.
FC Twente	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy	Safe
FC Utrecht	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy
BV/SC Veendam	Bankrupt	Bankrupt	Bankrupt	Bankrupt
Vitesse	Risk of Bankruptcy	Safe (good)	Safe	Safe
FC Volendam	Safe (grey)	Risk of Bankruptcy	Risk of Bankruptcy	Safe
VVV Venlo	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy	Risk of Bankruptcy
Willem II	Safe (good)	Risk of Bankruptcy	Risk of Bankruptcy	Safe