Aalto University
School of Business

Synthesis of research studies examining prediction of bankruptcy

Accounting

Master's thesis

Heikki Linden

2015

Department of Accounting
Aalto University
School of Business

Aalto University
School of Business

Aalto University, P.O. BOX 11000, 00076 AALTO
www.aalto.fi

Abstract of master's thesis

Author Heikki Petteri Linden

Title of thesis Synthesis of research studies examining prediction of bankruptcy

Degree Master's Degree

Degree programme Accounting

Thesis advisor(s) Assistant Professor Henry Jarva

Year of approval 2015 **Number of pages** 88 **Language** English

Abstract

The purpose of this study is to synthesize the findings of prior bankruptcy prediction research studies by compiling and classifying the independent variables used as predictor variables in the studies. The objective is to find out the popularity of the different types of the predictor variables by classifying the variables into the categories describing the fincancial function of the variables, and by assessing the popularity of the significant variables in the categories. This work studies elementary theories on firm failure and bankruptcy to discuss and seek justitication for what might be the reasons for using the most popular financial function measures in the bankruptcy prediction.

Bankruptcy prediction research literature covers vast amount of studies in which various different predicton models are developed for predicting bankruptcy. Usually these studies use a prediction model with a set of some financial and/or non-financial variables that are presumed to be relevant proxies for financial distress and eventually business failure and bankrupcty. However, there seems to be no consensus or unified theory on how the variables predicting bankrupcty should be selected, thus the numerous bankruptcy prediction research studies include vast number and various different types of variables that are presumed to be applicable in predicting bankruptcy.

This study includes a systematic literature review where 51 bankruptcy prediction research studies were collected from well-recognized scientific journals. The studies included into the review were such that included a single or multiple bankruptcy prediction models, the detailed description of the independent variables, and the information about the statistical significances of the independent variables. The variables were then classified according to their financial function and a meta-analysis were conducted on those variables which were significant in bankruptcy prediction, to find out the popularity of the different variable categories.

The findings of this study suggest that the most popular predictor variables included into the banktuptcy predicton models are accounting-based financial ratios, particurarly ones measuring liquidity, profitability, and financial leverage, and that there exists also theoretical foundation for using these variables in the bankruptcy prediction.

Keywords business failure, bankruptcy, financial ratios, bankruptcy prediction, systematic literature review, meta-analysis

Aalto University School of Business

Aalto-yliopisto, PL 11000, 00076 AALTO
www.aalto.fi

Maisterintutkinnon tutkielman tiivistelmä

Tekijä Heikki Petteri Linden

Työn nimi Synteesi konkurssiennustemallien tutkimuksista

Tutkinto Maisterin tutkinto

Koulutusohjelma Laskentatoimi

Työn ohjaaja(t) Apulaisprofessori Henry Jarva

Hyväksymisvuosi 2015 **Sivumäärä** 88 **Kieli** englanti

Tiivistelmä

Tämän tutkimuksen tarkoitus on yhdistää konkurssiennustemalleja käsittelevien aikaisempien tutkimuksien tuloksia. Tässä tutkimuksessa kerätään ja luokitellaan konkurssiennustemalleissa selittävinä eli konkurssia ennustavina muuttujina käsiteltyjä muuttujia. Luokittelu määritetään tutkimuksessa kuvaamaan muuttujien taloudellista toimintoa, ja tavoitteena on selvittää eri muuttujaluokkien suosiota aikaisempien tutkimusten konkurssiennustemalleissa, sekä etsiä mahdollisia teoreettisia perusteita kyseisten muuttujaluokkien suosioon.

Konkurssien ennustamiseen tähtäävä tieteellinen tutkimuskenttä käsittää laajan määrän tutkimuksia, joissa on kehitetty erilaisia ennustemalleja hyödyntäen erilaisia laskentamalleja. Yleensä ennustemallit käsittävät tietyt taloudelliset ja/tai ei-taloudelliset muuttujat, joiden on oletettu olevan oleellisia yritysten konkurssin ennustamisessa. Kuitenkaan yleistä ja yleisesti hyväksyttyä teoreettista mallia ei näiden ennustavien muuttujien valintaan ole tunnistettu, ja täten konkurssiennustemallit käsittävätkin paljon erityyppisiä muuttujia konkurssin ennustamiseen.

Tämä tutkimus sisältää systemaattisen kirjallisuuskatsauksen, jossa on kerätty 51 aikaisempaa konkurssiennustemallitutkimusta yleisesti tunnetuista tieteellisistä julkaisuista. Kirjallisuuskatsaukseen on valittu tutkimuksia, joissa on kehitetty yksi tai useampia konkurssiennustemalleja, ja joista on voitu erotella malleissa käytetyt selittävät muuttujat, sekä tulkita yksittäisten muuttujien tilastolliset merkittävyydet konkurssin ennustamisessa. Tämän jälkeen muuttujat on luokiteltu niiden taloudellista toimintoa kuvaaviin luokkiin ja eri luokkien suosion selvittämiseksi tilastollisesti merkittävien muuttujien määriä eri luokissa tutkittu meta-analyysilla.

Tutkimuksen löydökset osoittavat, että konkurssiennustemalleissa ennustavina muuttujina on eniten käytetty taloudellisia tunnuslukuja, ja erityisesti niitä tunnuslukuja joilla mitataan yrityksen likviditeettiä, kannattavuutta ja rahoituksellista velkaantuneisuutta. Tutkimuksessa osoitetaan myös teoreettisia näkökulmia ja perusteita kyseisten muuttujien soveltuvuuteen konkurssien ennustamisessa.

Avainsanat konkurssi, konkurssien ennustaminen, taloudelliset tunnusluvut, systemaattinen kirjallisuuskatsaus, meta-analyysi

Contents

List of tables

List of figures

List of appendices

1 Introduction

1.1 Study objective and motivation

The objective of this thesis work is to synthesize the results of the research studies on the field of bankruptcy prediction. These research studies focus on developing and/or comparing models for predicting the probability of bankruptcy with some set of predictor variables that are deemed to predict financial weakness, financial distress, and a failure of a firm. The synthesis in this thesis work will focus on analyzing the origin and use of these predictor variables to assess the popularity and reasons for using specific types of variables. In addition, the work includes discussion on how the findings from the synthesis reflect to the theoretical justifications and how they compare to the prior findings made in the bankruptcy research literature.

Dimitras et al. (1996) describes that a firm failure has high cost to the firm, to its stakeholders, to the society, and eventually to the country's economy. Only in Finland, there were 3 131 bankruptcies during year 2013 and the number of persons working in these companies was over 15 000. And as the number of bankruptcies increased from the previous year by almost six percent, the development seems unfavorable. (Tilastokeskus 2014)

Aziz and Dar (2006) emphasize the importance of bankruptcy prediction to corporate governance as corporate responsibility and liability are observed nowadays more cautiously, especially after the large and costly failures of WorldCom and Enron. Bankruptcy involves usually high cost as Jordan et al. (2008, 568) write that the direct bankruptcy costs, i.e. costs for lawyers, accountants and consultants were as high as over one billion dollars in the Enron bankruptcy case from 2004. Although it is the largest bankruptcy in the history in the U.S., Jordan et al. continue with other examples such as WorldCom's direct bankruptcy costs of 600 million dollars and United Airline's 335 million dollars. In Finland, in a very recent case, bankruptcy of Talvivaara mining company, Finnish government may face losses up to 400 million euro in a form of investment loss and managing of the environmental impact (MTV Uutiset - STT 2014).

It seems that the motivation for research in corporate bankruptcy prediction is quite evident as the early detection of financial distress is crucial for taking corrective actions in time to prevent the realization of the costs of bankruptcy. Dimitras et al. (1996) state that bankruptcy prediction's role as an early warning system is important in preventing failure, but in addition bankruptcy prediction is useful for decision makers in financial institutions in evaluating whom to co-operate with or to where to invest in. Chen (2011) describes that more accurate financial distress prediction would provide useful information for stakeholders such as stockholders, creditors, governmental officials, and even the for the general public. Back (2001) suggests that a good bankruptcy prediction model could for example help auditors in making the statement about going concern as a good prediction model would give auditor better information about the company's vulnerability. And to summarize, Chen (2011) sees that the radical change for globalization require more accurate forecasting methods for corporate financial distress thus arguing that the current methods for corporate failure prediction should be continuously improved.

1.2 Background information and literature overview

Beaver (1966) describes that operationally a firm can be seen failed when any of the following events has occurred: bankruptcy, bond default, an overdrawn bank account, or nonpayment of a preferred stock dividend. The causes for firm failure and bankruptcy are often recognized to lie within the firm itself (Altman 1993, 180) in issues such as management defects and accounting system defects that are causing fatal mistakes in financial planning and control (Argenti 1976a). In addition, macroeconomic and external factors such as natural disasters, deregulation and international competition have also been suggested as possible causes for firms to go bankrupt (Argenti 1976b; Dambolema & Khoury 1980; Altman 1993, 15-17).

But as fundamental factor for business failure are suggested to be internal factors of the firm (Altman 1993, 180), the prediction of bankruptcy were first approached by empirically discovering financial ratios that are effective indicators and predictors of bankruptcy. However, Horrigan (1968) has emphasized that these empirical models lack a rigor theoretical background.

Jackson and Wood (2013) describe that the early research literature focusing on predicting firm failure and bankruptcy started the evolution of the bankruptcy prediction models in the 1960s. Dambolema and Khoury (1980) present that the first significant analysis on internal factors causing bankruptcy was Altman's (1968) statistical Z-score model.

Aziz and Dar (2006) have conducted an extensive literature review of bankruptcy prediction research studies where the use of different bankruptcy prediction models was surveyed. As it can be seen from their study, there is a wide diversity on the approaches to the bankruptcy prediction. The prediction models vary from traditional statistical models and modern models, to theoretical models.

The traditional statistical models such as the Altman's (1968) Z-score model are the most popularly applied in the field of bankruptcy prediction research. These models focus on statistical analysis of financial ratios using such techniques as multiple discriminant analysis and logistic regression. The modern models are technology-driven models utilizing novel prediction techniques such as decision trees, neural networks, genetic algorithms, and rough sets. Theoretical models on the other hand are based on some explicit theory on firm failure rather than on empirical research, and these models try to determine the qualitative causes of bankruptcy. Theoretical models evolve from such theories as credit risk theory, cash management theory and gambler's ruin theory. However, it should be emphasized that both modern models, and theoretical models are somewhat based on the traditional statistical models. Almost all of the modern models use financial ratios as input variables and some of the models can be considered as automated statistical approaches to bankruptcy prediction. And theoretical models usually accompany some traditional statistical model rather than being developed directly on the theoretical principles. (Aziz & Dar 2006)

As the statistical analysis of financial ratios is most often in the core of the bankruptcy prediction, it is evident that selecting which financial ratios among the hundreds of available are the best bankruptcy predictors. However, Karels and Prakash (1987) argue that the financial theories give only little support to the selection process of the financial ratios to obtain a best possible set of financial ratios for the purpose of bankruptcy prediction. Also Brezigar-Masten & Masten (2012) present that there is no generally accepted unified theory to the identification and selection of the financial variables and they continue describing that it is usually based on methods ranging from financial professionals' subjective opinions to various statistical procedures. In addition, novel modern techniques have been utilized in the financial ratio selection process. For example Brezigar-Masten & Masten (2012) have applied a novel classification tree algorithm into the selection process of financial ratios.

From the bankruptcy prediction studies included into the Aziz and Dar's (2006) review it can be seen that the research consists of such studies where new prediction models are developed based on some existing prediction method, or on some novel technology that has not yet been applied into a bankruptcy prediction. From the studies reviewed by Aziz and Dar, it can be also recognized that in many of the studies, new prediction models based both on older models and new technologies are developed and compared to assess the potentiality of the new technology in the bankruptcy prediction.

Dimitras et al. (1996) have conducted a similar study to this thesis work in which they assess the popularity of different financial ratios in bankruptcy prediction research studies. Their research covers 47 studies published between years 1932-1994 and the aim of the research was to find out the differences in the use of financial ratios by origin country of the studies, by industrial sector of the sample companies, and by period of the sample data. Differing from this thesis work, Dimitras et al. did not further assign the financial variables in categories and assess the popularity of the categories. However, they summarized the number of the most popular predictor variables thus providing a good benchmark when examining the results of this thesis work. In addition, this thesis work will include also a larger portion of the most recent bankruptcy prediction research than the study by Dimitras et al. (1996), thus providing an up-to-date view to the field of bankruptcy prediction research.

Akers et al. (2007) performed a historical summary of bankruptcy prediction studies where they have analyzed 165 bankruptcy prediction studies published from 1965 to 2007. In their work, they discuss how bankruptcy prediction studies have evolved and evaluate the prediction accuracy of the bankruptcy prediction models versus the number of individual predictor variables included into the model.

There are also many bankruptcy prediction studies in which different prediction models are compared by assessing the prediction accuracy of the models (see for example Tseng & Hub 2010). In addition, Hite (1987) conducted s study with meta-analysis on bankruptcy prediction research literature, where the analysis was performed to find out conflicts between the prediction accuracy of the different bankruptcy prediction models. However, the nature of these studies is different from this thesis work since the objective in these studies was to analyze the overall model, not the individual predictor variables used in the models.

Thus it can be concluded that there exists a research gap for this thesis work as it synthesizes the findings from prior bankruptcy prediction research by including a categorical analysis of the popularity of the financial variables used as predictor variables. And in addition, this work includes the assessment of the significance of the individual financial variables in the bankruptcy prediction when assessing the popularity of the variables.

1.3 Research question

There is research evidence suggesting that various methods have been introduced to the bankruptcy prediction. All of the methods include a set of variables, usually a combination of financial ratios which are used as predictor variables in a model constructed to predict a firm failure or bankruptcy (Aziz & Dar 2006). The prior bankruptcy prediction research literature shows that the financial variables measuring liquidity, solvency and profitability are seen as good candidates for this (see for example Altman 1968), and they seem to be popularly incorporated into the prediction models generated in the field of bankruptcy prediction research.

However, the bankruptcy prediction literature states that there is a lack of generally accepted theory on how the predictor variables should be chosen into the bankruptcy prediction model (Karels & Prakash 1987; Brezigar-Masten & Masten 2012). This thesis work seeks answers from elementary theories on firm failure and bankruptcy, and from prior research on bankruptcy prediction, to find out what is the popularity of the different types of predictor variables utilized in the bankruptcy prediction research and if there are theoretical premises and justification for favouring these variables. Thus the research questions in this thesis work are the following:

- Which variables and types of variables are used as a proxy for financial distress, firm failure and bankruptcy in the prior bankruptcy prediction research literature?
- What is the popularity of the different variable categories in the bankruptcy prediction research literature when the variables are categorized by their financial function? And how the popularity of the variable categories relates to the theories on firm failure and bankruptcy?

1.4 Research design

This thesis work is conducted as a synthesis of prior bankruptcy research studies, and it is carried out in three phases. First, the synthesis starts with an extensive systematic literature review covering the prior research in the field of bankruptcy prediction. Second, a simple meta-analysis of the bankruptcy predictor variables collected in the literature review is conducted. And finally, the results of the literature review and the meta-analysis are interpreted, and the conclusions of the research are presented.

The bankruptcy prediction research studies included into the systematic literature review are chosen from high quality scientific journals. Studies are selected so that a study is included in to the review if it comprises at least one specific model developed for bankruptcy prediction from where the independent variables can be identified and distinguished. This includes also the interpreting of the significance of the collected independent variables in the bankruptcy prediction model in which they were incorporated. The synthesis then includes a categorization of the financial variables into categories expressing the financial function of the variable. These categories are constructed for the systematic literature review based on the theoretical aspects presented in this thesis work. The findings of the systematic literature review are then summarized and a meta-analysis on the review findings is conducted. The analysis is performed by assessing the popularity of the categories constructed from the financial variables collected in the review, by counting the number of significant variables in each category. The results and the statistical significance of the analyses are then assessed to test the constructed hypotheses.

1.5 Contribution and findings in brief

This thesis work contributes to prior research by including an analysis of the variables used as bankruptcy predictors by aggregating these into categories describing the financial function of the variables, thus giving an overall view of the types of variables used in the prior bankruptcy prediction research. In addition, the possible theoretical foundation on the background of the developing of the bankruptcy prediction techniques and models is considered and scrutinized in relation to the findings of the analysis of the bankruptcy predictor variables.

The results of this work indicate that the findings are similar to the prior research and that the financial ratios determined from accounting information are the most popularly applied predictor variables in bankruptcy prediction. The systematic literature review conducted in this thesis work included 51 bankruptcy prediction studies and the meta-analysis of the review findings provide significant evidence that the financial ratios measuring liquidity, profitability, and financial leverage can be seen as the most popularly applied in the bankruptcy prediction studies, as the number of variables which were significant in predicting bankruptcy were the most highest among these financial function categories. In addition, the overall descriptive analysis of the findings on the systematic literature review revealed similar findings on the most applied bankruptcy prediction techniques and models as similar prior research.

1.6 Structure of the thesis

In this thesis work report, first a theoretical background is presented in the chapter 2. The chapter discusses findings from prior research literature relating to firm failure and bankruptcy, and to the prediction of bankruptcy. Theoretical background is put together to present background information on how financial distress, business failure and bankruptcy are linked together, and which kind of prediction techniques and models are developed and applied in predicting firm failure and bankruptcy. Background information includes also examination of which kind of variables are typically used as predictors for bankruptcy and what is the empirical and/or theoretical justification for using such variables in the field on bankruptcy prediction research.

After the theoretical part, chapter 3 consists of the description of the systematic literature review conducted on a population of the selected bankruptcy prediction research studies and the results of the review. The synthesis of the bankruptcy prediction studies includes a meta-analysis on the findings of the systematic literature review. The meta-analysis is presented in the chapter 4, and it includes the hypothesis development for the research questions and statistical tests to test the constructed hypotheses and the interpretation of the test results against the hypotheses. And finally, in the chapter 5, this report presents the discussion and conclusions on the systematic literature review and meta-analysis results regarding to the research setup and question.

2 Theoretical framework

2.1 Business failure and bankruptcy

Jordan et al. (2008, 579) write that the term ‘bankruptcy’ states for “*a legal proceeding for liquidation or reorganization a business*”. Altman (1993, 5) describes that the term ‘bankruptcy’ may refer to a situation where the firm’s net worth is negative, or to a more observable situation where the firm has formally declared bankruptcy by entering a judicial state of bankruptcy reorganization. Altman (1968) uses in his seminal work on bankruptcy prediction a legal definition for bankruptcy, as he defines failed firms to such that have filed a legal bankruptcy petition.

Karels and Prakash (1987) report, that many researchers use the term ‘failure’ interchangeably with the term ‘bankruptcy’. Dimitras et al. (1996) indentify bankruptcy prediction as a business failure prediction, which seems also to emphasize the interchange ability of these terms. Beaver (1966) uses term ‘failure’ in his bankruptcy prediction study and describes that operationally a firm can be seen failed when any one of the following events has occurred: bankruptcy, bond default, an overdrawn bank account, or non-payment of a preferred stock dividend. Deakin (1972) on the other hand, includes bankruptcy, insolvency, or liquidation for the benefit of creditors, when defining failed firm in his study. As Karels and Prakash (1987) demonstrate, the initial definition of the state when a company is considered failed usually varies in the bankruptcy prediction related research.

Although failure does not always lead to bankruptcy, Karels and Prakash (1987) state that financial failure is a necessary condition of bankruptcy. They add that bankruptcy research literature emphasize bankruptcy to be defined by following the legal criteria, which is similar to the Altman’s (1993, 5) judicial definition of bankruptcy presented earlier. Jordan et al. (2008, 579) describe legal bankruptcy as a situation where a firm or its creditors bring petition for bankruptcy to a court. Karels and Prakash (1987) argue that the reason for researchers to use failure instead of judicial definition of bankruptcy in the bankruptcy prediction research, might be that because a bankruptcy is a process which begins financially, and at the time of their study in U.S, there were no official financial criteria defined for bankruptcy and each case were judged by the court on an individual basis. In Finland, the judicial definition of bankruptcy is defined in the law so that the bankruptcy of the debtor can be initialized only by the court order if the debtor is found to be insolvent so that the insolvency is recognized not to be only a temporary condition for the debtor (Konkurssilaki, 2004).

Wruck (1990) describes financial distress as another term which is also used sometimes as a synonym for bankruptcy. However, she gives a broader and not so specific definition to financial distress than bankruptcy, as she defines financial distress as a situation where a firm's cash flow is insufficient to meet its financial obligations and it gives a possibility to creditors to start legally demand their rights.

Default is also another condition associated with business failure and caused by financial distress. Technical default is described as a situation where the company has violated a condition of an agreement with its creditor, such as a loan covenant which sets a specific limit for the value of the current ratio. A formal default, on the other hand, is likely to happen when a firm misses its scheduled loan payment. Both technical and formal default might lead to legal actions by creditor and to a distressed restructuring, and if the problem is persistent or restructuring is not successful, a bankruptcy will be evident. (Altman 1993, 5)

2.2 Elementary causes of failure and bankruptcy

Argenti (1976a) presents a firm failure as a process where defects and mistakes are causes to the symptoms of a firm failure. He lists the major defects to be management defects, defects in the accounting system, and the lack of responsiveness to the changes e.g. in market situation or technology. Management defects include such as internal communication problems, poor policies, and poor management knowledge on financial matters. Defects in the accounting systems include deficient budgetary control, insufficient cash flow management, and faulty costing system. Argenti (1976a) continues that major mistakes leading to a firm failure include too high leverage, overtrade i.e. setting challenging sales target without an equally challenging profit target, and starting a big project that becomes a burden when something goes wrong. He describes that these defects and mistakes are causes for financial symptoms, which then should be able to be identified from the financial information of a firm.

In addition to the internal factors of corporate failure mentioned above, Argenti (1976b) lists some external factors for a firm failure, such as labour unions demanding too high wage settlements, government regulations distorting the functioning of the market system, and natural causes such as natural disasters and demographic changes. Dambolema and Khoury (1980) describe that the analytical studies of causes of firm failure were first linked to the macroeconomic factors such as monetary policy, investor's expectations on economic conditions, and to the state of the economy.

Altman (1993, 15-17) also describes external factors such as deregulation, international competition, and relatively high new business formation rate for causes of business failures, but after all adds that overwhelming cause for individual failures is some type of managerial incompetence, and that the fundamental cause for business failure has been recognized to lie within the firm itself (Altman 1993, 180). Argenti (1976a) states that the three major mistakes he has listed are the most often causes for a firm to fail thus supporting Altman's perception as the mistakes Argenti has listed are also internally generated.

Discussion of whether the elementary cause of bankruptcies is due to a systematic or unsystematic risk is contradictory (Westgaard & van der Wijst 2001). Jordan et al. (2008, 413) describe that a systematic risk i.e. market risk, is a risk which influences large number of assets and has a market-wide effect, and they continue that an unsystematic risk is unique risk affecting only some of the assets. Opler and Titman (1994) see that the risk of financial distress is more of an unsystematic risk since it is mainly caused by idiosyncratic, firm-specific factors. They found out in their study that in industry downturn the bankruptcy risk is smaller on less leveraged firms than high leveraged firms in the same industry. However, Lang and Stulz (1992) argue that the factors affecting bankruptcy risk are industry-wide as they describe that a bankruptcy of a firm has a contagion effect and a competitive effect on the other firms in the same industry, and that the effect can be negative or positive depending on the degree of the competition and the common financial structure of the firms on the industry.

When expanding the scrutiny to economy-wide and macroeconomic factors, it seems quite intuitive that these factors have an impact to a bankruptcy risk as for example an economy-wide recession should increase the financial distress for a weak firm (Westgaard & van der Wijst 2001). However, this hypothesis includes also the idiosyncratic factor measuring the weakness of a specific firm thus expressing the diversity and the interconnectivity of the factors affecting to the bankruptcy risk.

2.3 Theories on business failure and bankruptcy

Scott (1981) describes a simple bankruptcy theory where the earnings the firm generates are seen as a stochastic variable and the firm goes bankrupt if it generates so high losses that causes negative equity i.e. the value of the firm is less than the amount it owes its creditors.

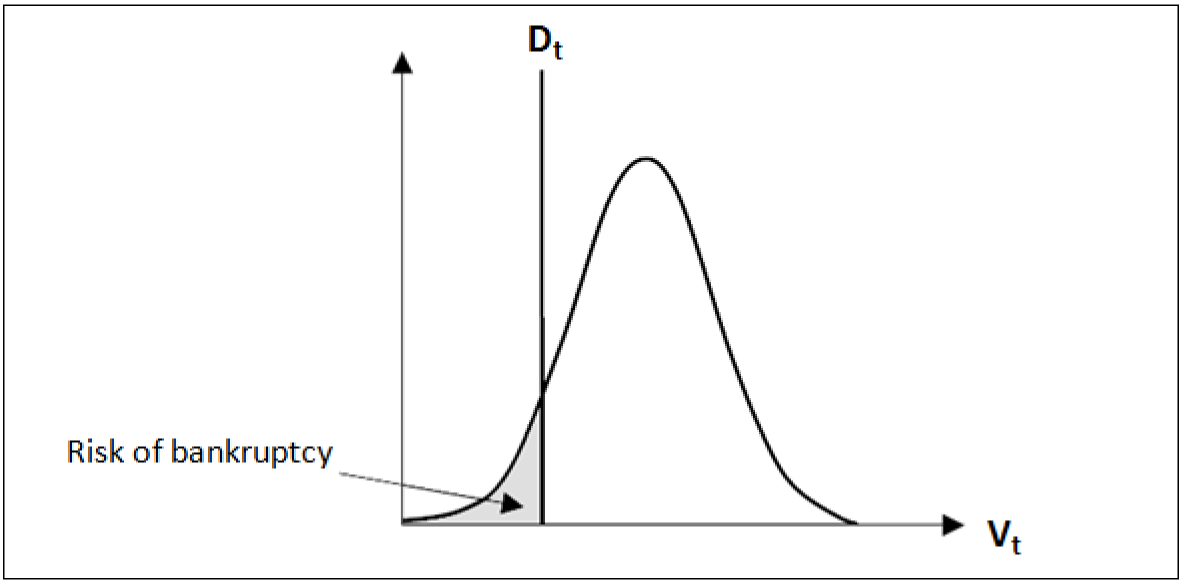

Figure 1: Risk of bankruptcy

The risk of bankruptcy by this theory is presented in the figure 1 where D_t stands for total debt of the company at time t, and V_t stands for the value of the company at time t which is equal to the value of the company at time t-1 added with net profit from time period t-1 to t. Hence essential factors affecting to the risk of bankruptcy by this theory are profitability, variance of profitability, and solvency.

Altman (1993, 4) also uses earnings in his definition, as he describes that firm failure is evident when a firm has insufficient revenues for covering costs. However, Altman adds that there are also two other situations causing a firm to fail. First, the firm's realized return on invested capital is significantly lower than the return rates of similar investments, or second, the firm's average return on investment is below its cost of capital. These situations described by Altman focuses on firm's return rate of investments, which is similar to the Prihti's (1975, 35-46) investment based theory. In Prihti's theory, a firm is seen as a series of investments financed with earnings, equity and debt, and a firm must generate enough earnings to cover financing costs of the investments. If a firm fails in this, it will face liquidity problems as the firm might lose the trust of its stakeholders and face difficulties in getting more financing.

Beaver (1966) has introduced his theory based on the cash-flow model to identify a firm failure. The theory views a firm as a reservoir of liquid assets supplied by inflows and drained by outflows. He demonstrates that if this reservoir of liquid assets exhausts, the firm will be unable to pay its obligations as they mature and the firm faces insolvency and the failure is evident. By this insolvency theory, the probability of insolvency increases as the reservoir of liquid assets reduces, and continues as that the lower profitability generate even lower cash inflows, and the higher financial obligations from required debt financing generate even higher cash outflows (Laakso et al. 2010, 17).

2.3.1 Insolvency

Altman (1993, 4-5) describes insolvency as a financial distress situation that can cause a formal bankruptcy. He separates insolvency to two different kind of situation. First, he describes technical insolvency as a situation where a company cannot meet its current financial obligations, which is similar to the Beaver's (1966) cash-flow model described earlier. Altman though points out that the technical insolvency might be only temporary condition and thus not necessary leading to firm failure or bankruptcy and as such considering more of a short-term liquidity issues. Second, Altman continues by describing a more serious and chronic type of insolvency in a bankruptcy sense where the real net worth of the company is negative i.e. total liabilities exceed fair valuation of total assets. This corresponds to the simple bankruptcy theory described by Scott (1981) where the value of the firm is less than the amount it owes its creditors thus considering more long-term solvency issues.

Wruck (1990) also describes insolvency as a situation where the company's cash flow is insufficient to cover its current obligations. She continues that the term insolvency might be often misinterpreted as the technical insolvency and insolvency in a bankruptcy sense described by Altman are often confused with each other. Wruck separates these two by describing the technical insolvency as flow-based insolvency as it is a situation where company is unable to meet its current cash obligations. She refers the Altman's insolvency in a bankruptcy sense as the stock-based insolvency where the company has negative economic net worth i.e. the present value of its cash flows is less than its total obligations, thus giving it a slightly different definition to what Altman (1993, 4-5) had. However, Altman (1993, 5) describes that assessing insolvency in a bankruptcy sense requires fair valuation of assets with thorough valuation analysis instead of using accounting net worth. And as the valuation can be done by using present value approach based on cash flows (Petersen and Plenborg 2012, 216-219), it seems that Altman's and Wruck's definitions are strongly related. Jordan et al. (2008, 579) use the term accounting insolvency for the insolvency in a bankruptcy sense as they describe it happens when the book value of total liabilities exceed the book value of total assets.

Wruck (1990) points out that a company that is insolvent on a stock-basis but solvent on flow-basis, can continue operating since it is capable of meeting its current obligations as the creditors' claims are paid on time. However, if the company becomes insolvent also on flow-basis, it faces a severe situation since it must resolve the distress situation by reducing fixed claims or by reorganizing to create enough value to meet the obligations and claims of the creditors. Wruck continues that if a company is solvent on a stock-basis and faces financial distress by becoming insolvent on a flow-basis, it should be able to resolve the distress situation by far more lower effort by for example renegotiating new payment schedules for the obligations.

Laakso et al. (2010, 18) describe that even though the prior research studies on insolvency have suggested multiple different definitions for an insolvent firm, there still are common and generalizeable results in the field of research. They state that common findings of these research studies indicate that an insolvent firm particularly has a low solvency, and little cash flow financing and liquid assets, in relation to the firm's current liabilities. Laakso et al. link these findings particularly to the cash-flow theory by Beaver (1966) as the cash flow financing is central to the theory, but in addition to the bankruptcy theory by Scott (1981) as profitability has also been seen low among the insolvent firms.

2.3.2 Factors of insolvency

Laakso et al. (2010, 18) describe that even though insolvency has a significant role when assessing financial health of a firm, it is difficult to be measured unambiguously in practice. On Gryglewicz's (2011) research study on connection between corporate illiquidity and insolvency, he argues that there is no common understanding how both of these are related to each other. He continues that by his research findings, persistent short-term liquidity insufficiency will affect long-term solvency risk, which can be measured by leverage and profitability. Gryglewicz describes that this effect works also other way around as a company is supposed to select an optimal capital structure i.e. level of leverage, to limit the exposure to the liquidity risk.

The connection between the factors described by Gryglewicz (2011) and how they relate to technical insolvency can be seen extended in the illustrative "healthy firm triangle" presented by Laakso et al. (2010, 38-41).

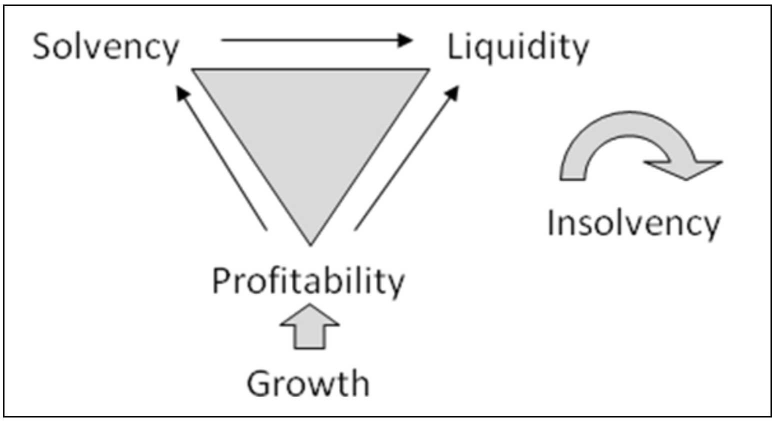

Figure 2: "Healthy firm triangle" and insolvency (Laakso et al. 2010, 39)

The "healthy firm triangle" presented in the figure 2 has three interconnected factors which together are factors of insolvency: profitability, solvency and liquidity. Laakso et al. establish their triangle to profitability as they state that it is the operational precondition for all healthy businesses. They continue that profitability affects positively also on the liquidity since a profitable firm generates enough cash flows to reduce the need for short-term liability, thus reducing the risk for flow-based insolvency. In addition, they describe that the sufficient cash flow financing increases financial assets, thus reducing the risk for stock-based insolvency as the decrease in the financial leverage improves the long-term solvency. Laakso et al. (2010, 39) describe similar connection between solvency and liquidity as Gryglewicz (2011): they state that a firm with good solvency is able to select a more optimal capital structure when gaining financial assets, and thus avoiding the use of short-term liability and preventing excessive liquidity risk.

In addition, Laakso et al. (2010, 39-40) argue that growth is also one critical factor for insolvency. They state that a high growth rate may lead to financial problems when a company is growing too fast compared to its profitability, and thus needing excess debt financing in order to support the growth. They continue that this might lead to unbalanced financing and to corporate illiquidity or insolvency. In addition, Laakso et al. describe that an unprofitable growth probably leads to liquidity problems as the cash flow financing becomes insufficient due to the weaken profitability.

Laakso et al. (2010, 41-42) note that insolvency is always related to a certain period in time so that a company might not need to be able to meet its financial obligations at every point during the time period, but it should have enough liquidity to be able to handle the financial obligations during the time period. In other words, if the company has enough liquidity at every point on the whole time period, it will be able to meet its financial obligations. Laakso et al. concludes that the road to insolvency usually begins due to the lack of liquidity, but often will be finally at hand when solvency and profitability have fallen to a level that will affect negatively in obtaining the necessary funding, and the company faces persistent troubles to meet its financial obligations.

Petersen and Plenborg (2012, 150) state that without liquidity a company cannot meet its short-term obligations as they fall due and that the liquidity risk is affected by company's ability to generate positive net cash flows in both short-term and long-term. They continue that solvency risk then refers to the company's ability to meet its long-term financial obligations and also all future obligations. Petersen and Plenborg (2012, 164) see that short-term funding problems are easier to overcome than long-term solvency related problems, as short-term problems are often solved by creating a convincing action plan enabling the troubled firm to gain the necessary funding from shareholders and lenders, as long-term solvency problems require more thorough long-term planning and restructuring. As a summary, Petersen and Plenborg conclude that companies having problems with both liquidity and solvency are likely bankruptcy candidates.

2.3.3 Financial leverage and bankruptcy costs

Petersen and Plenborg (2012, 158) describe that an indicator of solvency risk is financial leverage describing how much a firm relies on debt financing instead of equity financing. Jordan et al. (2008, 552-555) write that the more debt financing a firm uses, the higher the financial leverage is, and they state that the motive for firms to favor debt financing over equity is its leverage impact to the shareholders' earnings. However, they continue that the impact of the financial leverage is twofold as it magnifies both gains and losses to shareholders.

Jordan et al. (2008, 562) describe that the total systematic risk of a firm's equity consists of business risk and financial risk. They state that the business risk is affected by systematic risk of the firm's assets and is not depended on firm's capital structure as opposite to the financial risk, which is completely depended on the amount of financial leverage. This seems to be related to Opler and Titman's (1994) findings where they argue that the financial distress risk for a firm is a firm-specific risk rather than systematic risk: they found out in their study that in industry downturn the bankruptcy risk is smaller on less leveraged firms than high leveraged firms in the same industry, thus relating the financial distress risk to the financial risk. Jordan et al. (2008, 562) conclude that even though financial leverage gives the potentiality to magnify gains, the shareholder's required return increases along the invocation of financial leverage as the financial risk increases while the business risk stays the same.

In addition, other limiting factor for financial leverage is the bankruptcy costs, including direct and indirect bankruptcy costs. Direct costs occur when the value of the firm's assets is equal or less than the amount of its debt, and it goes bankrupt as Scott's (1981) simple bankruptcy theory suggests. And as the firm's equity then has no value, the firm is economically bankrupt but as the creditors are first to get their claims, the legal process to formally turn over the assets to the creditors include legal and administrative expenses i.e. direct bankruptcy costs, which can be sometimes very substantial, especially in large corporate bankruptcy cases. Indirect costs are the costs from actions done by the management to avoid bankruptcy filing, as the firm is trying by all means to avoid the legal bankruptcy which would mean moving over the control of the firm to the creditors. These actions done by management are all taken away from the actual running of the business, and for example potential investments cannot be carried out which will eventually reflect negatively to the firm value. (Jordan et al. 2008, 567-568)

2.4 Bankruptcy prediction research

Prihti (1975) describes that in overall, bankruptcy research can be divided in the three following categories:

a) Inductive research that focus on discriminating the qualities between bankruptcy and non-bankruptcy firms to identify significant predictors for bankruptcy.

b) Research focusing on constructing bankruptcy theories applied in creating theoretically-driven prediction models where the predictors for bankruptcy would have a solid theoretical justification.

c) Other bankruptcy research where the main focus is on the life span of companies or on the macroeconomic factors to identify their relevance as a reason for bankruptcy.

Dambolema and Khoury (1980) describe that the analytical studies of causes of firm failure were first linked to the macroeconomic factors such as monetary policy, investor's expectations on economic conditions, and to the state of the economy, which seems to relate to the other bankruptcy research category described by Prihti (1975).

However, as fundamental cause for business failure has been recognized to lie within the firm itself (Altman 1993, 180), the prediction of bankruptcy were approached by empirically discovering financial variables that can be identified as indicators and predictors for bankruptcy. Prihti (1975) describes this field of research as an inductive research. Dambolema and Khoury (1980) present that the first significant analysis on micro-level factors was Altman's (1968) Z-score model where he used statistical analysis techniques to identify financial ratios that seems to be the best predictors for corporate failure.

Akers et al. (2007) found out in their review of bankruptcy studies that since Altman's (1968) study, the number of the bankruptcy prediction studies and the complexity of the bankruptcy prediction methods and techniques i.e. bankruptcy prediction models utilized in the studies, have both increased dramatically. From Aziz and Dar's (2006) extensive literature review on bankruptcy prediction models it can be noticed, that there are a vast number of various models which are develop and applied in prediction of firm failure and bankruptcy. Jackson and Wood (2013) have identified 25 different models in their review of the bankruptcy prediction literature. They describe the evolution of the bankruptcy prediction models so that the traditional statistical methods such as univariate and multivariate analysis were first used in the 1960s and 1970s, then logistic regression analysis and its applications in the 1980s, then modern models based on the artificial intelligence in the 1990s, and finally to the emerge of the theoretical models in the 2000s.

Scott (1981) describes that there are no unified theory how the bankruptcy prediction model should be developed and that the first models were constructed on empirical basis by using statistical techniques to identify financial variables that seem to best discriminate bankrupt and non-bankrupt firms. However, Scott adds that these empirically-driven models does not have the full support of research professionals as they lack the underpinning to a solid theory, thus bankruptcy prediction models based on some financial theories are also developed in the research studies. Prihti (1975) separated this kind of research as to a research focusing on constructing bankruptcy theories.

However, Aziz and Dar's (2006) review points out that the empirical-driven models are still the most common prediction models existing in the research literature. They continue that each of the models has their strengths and weaknesses so choosing the model is not a straightforward and unambiguous process. It can be recognized from Aziz and Dar's review that in many of the bankruptcy prediction studies there are new prediction models developed that are utilizing some existing prediction method or novel technology that has not been applied into a bankruptcy predication. In many of the recent studies, multiple models based both on older models and new technologies are developed and compared to each other to assess the potentiality of the new technology in bankruptcy prediction.

Dimitras et al. (1996) describe that usually the technique for developing a bankruptcy prediction model consists of generating of sample of bankrupt and non-bankrupt firms, identifying and selecting the predictor variables and constructing the prediction model, and finally validating the model by assessing the statistical significance and accuracy of the prediction results the model generates. Choi and Lee (2013) emphasize that the empirically-driven prediction model should be constructed so that it represents the relationship between bankruptcy firms and the changes in the values of the predictor variables of these firms, so that the same model could be used to predict also the possible failure of other firms.

Brezigar-Masten and Masten (2012) describe that selection of financial variables as a predictors of bankruptcy is an important step when developing a bankruptcy prediction model. However, they add that there is no generally accepted unified theory to this, and various methods have been used for the selection process varying from rough methods based on financial professionals' knowledge to statistical step-wise procedures.

2.5 Bankruptcy prediction models

Aziz and Dar (2006) have conducted an extensive literature review on bankruptcy prediction models where they have categorized the models to a three different model category depending on type of the computational complexity and quantitative versus qualitative properties of the technique and method applied in the model. Similar categorization of models can be found in some other research studies on bankruptcy prediction, as for example Jackson and Wood (2013) use Aziz and Dar's classification in separating between statistical, artificially intelligent and theoretical models. Model categories and their main features are listed on the table 1.

Model category	*Main features*
Statistical models (traditional models)	Focus on symptoms of failure Drawn mainly from company accounts Could be univariate or multivariate (more common) in nature Follow classical standard modelling procedures
Artificially intelligent and expert system models (AEIS models)	Focus on symptoms of failure Drawn mainly from company accounts Usually, multivariate in nature Result of technological advancement and informational development Heavily depend on computer technology
Theoretical models	Focus on qualitative causes of failure Drawn mainly from information that could satisfy the theoretical argument of firm failure proposed by the theory Multivariate in nature Usually employ a statistical technique to provide a quantitative support to the theoretical argument

Table 1: Bankruptcy prediction model categories (Aziz & Dar 2006)

The traditional statistical models are the most popular and they focus on statistical analysis of financial ratios. The modern models are technology-driven models utilizing such techniques as decision trees, neural networks, genetic algorithms, support vector machines, and self-organizing maps. Theoretical models focus on determining the qualitative causes of bankruptcy by grounding on theoretical arguments of firm failure proposed in the theory. (Aziz & Dar 2006)

The main difference between the three models is that the traditional statistical and the modern AEIS models have a focus on firm's symptoms of failure, and the predictor variables are selected by using empirical methods to identify variables which greatly correlate with bankruptcy by utilizing statistical or more sophisticated modern methods. Theoretical models on the other hand, focus on the causes of failure, and the predictor model and its variables are justified by theoretical arguments of a specific financial theory used as a foundation for the model. (Aziz & Dar, 2006)

Scott (1981) describes the main difference between models by referring the statistical models as empirically-derived models, and the theoretical models to ones that derive their model and prediction formulas from the major bankruptcy theories. Scott points out, that empirically-derived models try to find such predictor variables through statistical search which successfully discriminate between bankruptcy and non-bankruptcy firms.

However, as Aziz & Dar (2006) state that even though there are major differences between the models, all of them are somewhat based on or utilize the traditional statistical models. They relate the modern models on the traditional statistical models as almost all of them use financial ratios as input variables, and some of the modern models can be considered as automated statistical approaches to the bankruptcy prediction. And on the other hand, Aziz & Dar continue that the theoretical models also origin on the statistical models, since they accompany some statistical model rather than being directly developed on the theoretical principles.

2.5.1 Traditional statistical models

The most popular bankruptcy prediction models are the traditional statistical models utilizing financial ratios with statistical prediction method (Aziz & Dar 2006). Altman (1993, 179) states that even though his seminal statistical bankruptcy prediction model, the Z-score model, was developed already in 1968, it is still very popular among the researchers and practitioners. He sees that one of the reasons for this might be that corporate financial distress has become more and more relevant issue and the Z-score model is fairly easy to understand and apply, and it has also proven to generate quite accurate predictions. However, Altman continues that because of the major changes in the corporate environment, he has been continuing to develop new versions of the statistical models to meet the needs of the changing environment and to sustain a good accuracy in his bankruptcy prediction models.

The basis for statistical models is in identification and selecting of financial ratios which significantly affect the probability of bankruptcy (Petersen and Plenborg 2012, 292). There is no generally accepted unified theory to this so the identification and selection is based on different kind of methods ranging from financial professionals’ subjective opinions to various statistical procedures (Brezigar-Masten & Masten 2012). Karels and Prakash (1987) argue that the theoretical models on firm failure and bankruptcy provide only little foundation for selecting which financial ratios among literally hundreds of potential candidates are the best for the prediction model.

However, it is questionable how much effort should be put on refining the choosing of the financial ratios to the final prediction model. Beaver et al. (2005) describe that most of the prior bankruptcy prediction studies show robust results on prediction accuracy even though various mix of financial ratios are used as predictor variables between the studies. So the precise combination of the financial ratios seems to be of minor importance in respect to the prediction accuracy. Beaver et al. (2005) argue that this is due to the fact that the financial variables used as independent variables are correlated.

The variable selection in statistical models usually follows similar procedure used in Altman's (1968) seminal work where the initial setup of variables is based on their popularity on research literature and potential relevancy. Then the ability of the initial variables to discriminate between bankrupt and non-bankrupt firms selected into the sample is tested, and the intercorrelation among the variables is evaluated to find out the potential final set of predictor variables to be used as independent variables in the final prediction model. The final variable set selected to the prediction model is then proofed by assessing the predictive accuracy and statistical significance of the developed model.

Aziz and Dar (2006) list that there are various statistical techniques used in the statistical bankruptcy prediction models. These include such as univariate analysis, multiple discriminant analysis, linear regression, logit model, and probit model. However, they add that from the single models, multiple discriminant analysis and logit are by far the most used statistical techniques in the prior bankruptcy prediction literature, which has been also noticed by Dimitras et al. (1996) in their survey of bankruptcy prediction methods.

Univariate analysis is the simplest form of statistical analysis and was used by Beaver (1966) to examine the predictive ability of the financial ratios, one at a time. Altman (1968) describes that using multiple discriminant analysis instead of univariate analysis as a statistical technique, he was able to combine several financial ratios into his model and consider the interaction between the variables. Altman (1968) describes that multiple discriminant analysis develops discriminant coefficients for each of the predictor variables so that the linear combination of the variables will best discriminate between *a priori* grouped bankrupt versus non-bankrupt firms.

Logistic regression analysis such as logit model and probit model were introduced to the statistical bankruptcy prediction in 1980s (Jackson and Wood 2013). Ohlson (1980) describe that by using a logit model, he were able to avoid the problems that were identified in applying multiple discriminant analysis to bankruptcy prediction. Ohlson continues that one of the problems is that the outcome of the multiple discriminant analysis is a discriminant score, which must be subjectively interpreted rather than with a logit model, where the outcome is a probability that a firm fails within some pre-specified time period.

As a critic for predicting bankruptcy with statistical models, Petersen and Plenborg (2012, 292-296) present that a statistical model cannot substitute for fundamental credit analysis and hard analytical work. They argue that financial ratios should be compared to peers from the same industry, and that the coefficients generated for the predictor variables in the prediction model should be revised on a regular basis as they are not stable across time. In addition, they emphasize that the statistical models are usually based purely on financial ratios considering only historical information without any forward-looking, qualitative information. Hence these models are lacking of information about the future issues which might affect the financial situation of a firm. Petersen and Plenborg give an example of such information in a form of an expiring patent, which expiration will have a negative effect on the firm's future cash flows. However, Petersen and Plenborg add that statistical models can be useful when selecting which financial ratios could be used in the analysis of company defaults, or when a quick and cost-efficient approach to risk analysis is needed rather than using a heavier fundamental analysis.

2.5.2 Modern artificially intelligent and expert system models

Rapid development of information technology since 1980s has introduced the development of more technology-driven bankruptcy prediction models (Aziz and Dar 2006). Chen (2011) describes that traditional statistical bankruptcy prediction models can be seen limited as they are based on assumptions such as linearity, normality, independence among predictor variables, and pre-existing functional forms relating to the predicted and the predictor variables. Chen continues that these limitations and the ambition to achieve higher prediction accuracy lead to application of artificial intelligent techniques into the bankruptcy prediction during the 1990s.

Artificial intelligence (AI) uses symbolic and non-algorithmic problem solving methods, and utilize heuristics to reduce the complexity of the problem solving process. And through machine learning, AI gives the ability to the system to monitor and adjust its behavior by itself thus allowing the system to automatically react to changes. (Delen et al. 2011, 534-535)

Expert systems (ES) are application of AI. In ES system, expert knowledge is attempted to be captured into the system in order to be computationally used in decision making process in a narrow problem solving domain requiring deep and specific knowledge. In ES, AI is utilized by using symbolic reasoning and machine learning as ES system is developed to automatically learn from the decision outcomes it ends up. (Delen et al. 2011, 542-544)

Aziz and Dar (2006) describe that AI research has much been emphasized on the features of expert systems and machine learning, and thus describing these modern technology-driven bankruptcy prediction models as artificial intelligence and expert system (AIES) models. They continue that these models have been successfully applied to the bankruptcy prediction, and they list the AIES models used in the bankruptcy prediction to include such modern techniques as neural networks, genetic algorithms, decision trees, case-based reasoning, and rough sets. Some of these techniques are described briefly in the following sections. The scope of this thesis work is to assess the usage of the predictor variables rather than the actual prediction techniques so these descriptions are kept on a general level.

Akers et al. (2007) describe that a neural network is basically analyzing inputs to find patterns and develop a model for decision-making process. They describe that a neural network must be “trained” by running a several sample cases in order to “teach” the neural network the decision-making process. Aziz and Dar (2006) continue that in the case of bankruptcy prediction, the inputs for the neural network are information about firms, and that the network consists of multiple nodes classifying the inputs and passing the outputs to other nodes, and that the process continues until the decision satisfies the pre-specified criteria of probability for firm failure.

Lee and Shin (2002) have applied a genetic algorithm to the bankruptcy prediction. They criticize that using neural networks has deficiencies related to selecting of a proper network architecture from a numerous and complex variety of available network architectures, and the fact that neural networks are often referred as “black boxes” since the user cannot “see” the final rules the neural networks generates. Instead, they point out that genetic algorithms are capable of extracting bankruptcy prediction rules that are easy to understand for the user of the system. Delen et al. (2011) describe genetic algorithms similar to a biological process of evolution as they demonstrate self-organization and adaption by following the rule of evolution: survival of the fittest. A genetic algorithm performs reproduction process where the solution is improved each round by producing new collection of feasible solutions using the best solutions of the current generation. Lee and Shin (2002) describe that genetic algorithms are suitable for multi-parameter optimization problems and as such are suitable for bankruptcy prediction using various different predictor variables.

Decision trees are a form of supervised learning where the algorithm is "taught" with expert knowledge to generate a recursive partitioning decision rules by using samples with "training" data. The decision tree contains multiple decision nodes and the final node of the tree then contains firms of only one type, bankrupt or non-bankrupt. Case-based reasoning solves a problem by using help from the previously solved similar cases and it self-evaluates the suggested solution and stores the case to be used as an internal help when solving a new problem. Rough sets then on the other hand, as the name suggests, use imprecise information presented in a table containing sets of condition and decision attributes that are used to derive decision rules. The derived rules are then matched to a firm to classify it as a bankrupt or non-bankrupt firm. (Aziz & Dar 2006)

These AIES models and techniques are applied in some of the bankruptcy prediction studies to the actual prediction model (see for example Alfaro et al. 2007; Gordini 2014; Kim et al. 2005). And in some of the studies they are applied in the selection process of the predictor variables (see for example Back et al. 1996; Brezigar-Masten & Masten 2012). For example, Brezigar-Masten and Masten (2012) use a modern non-parametric regression and classification tree method to select the final set of predictor variables, i.e. independent variables to a traditional statistical logit prediction model. AIES models, and statistical techniques and models are thus often used together in the bankruptcy research studies. Aziz and Dar (2006) emphasize this by stating that virtually all of the bankruptcy prediction models have a statistical heritage and that the AIES models can be seen as sophisticated, automated offspring of the statistical approach.

2.5.3 Theoretical models

Even though the majority of the bankruptcy prediction research is based on empirically-driven statistical models, Scott (1981) describes that statistical models have suffered from criticism because they lack of theoretical underpinning and are only focusing on the current state by reflecting firm's financial position at one point in time. Petersen and Plenborg (2012, 296) sees also that the problem with statistical models is that they rely purely on historical information thus neglecting such forward-looking and qualitative information which could improve the prediction of bankruptcy. Jackson and Wood (2013) continue that the problems seen in the empirically-driven model research are related to the ambiguity in the definition of bankruptcy and arbitrary selection of study samples, predictor variables and prediction models.

Scott (1981) sees that these reasons are on the background for the development of the theoretical bankruptcy prediction models i.e. models that rest on explicit theory rather than on empirical analysis. Aziz and Dar (2006) describe theoretical models focusing on determining the qualitative causes of bankruptcy by grounding on theoretical arguments proposed for firm failure.

The financial theories used as a foundation in the theoretical models include such as option pricing theory, gambler's ruin theory, cash management theory, and credit risk theories (Aziz and Dar 2006; Jackson and Wood 2013). The simplest theoretical model concerning bankruptcy is the simple bankruptcy theory described earlier in the section 2.3. The model simply assumes that firm goes bankrupt if its liquidation value is less than the amount it owes to its creditors (Scott 1981).

From Scott's (1981) summary of the predictor variables used in different theoretical models, it can be seen that each of the models incorporate at least variables measuring book or market value of the firm's equity, and the estimation of how the value will change measured by standard deviation of the firm's value or by standard deviation of the firm's earnings. These models incorporate estimation of the firm's future financial performance thus acknowledging the criticism for empirically-driven models and their focus only on the current financial state of the firm. Some of the theoretical models are described briefly in the following sections. The scope of this thesis work is to scrutiny the usage of the predictor variables rather than the details of the prediction model so these descriptions are kept on a general level.

Scott's (1981) describes gambler's ruin theory based model as a model where a firm is compared to a gambler playing with some probability for win and loss, and that the player continues to operate until his net worth goes negative i.e. firm's liquidation value measured from its physical assets is negative. Scott states that the gambler's ruin model assumes that a firm does not have access to external capital and that it is able to cover its losses only by selling its assets. He continues by reviewing other theoretical models which are assuming that firms have perfect or imperfect access to external capital. These are similar to the gambler's ruin model, but include also a market valuation of a firm as they assume that a firm can cover its losses by raising capital externally. Westgaard and van der Wijst (2001) point out that the basic idea in these Scott's (1981) theoretical models is that if firm's current cash flows can be seen as a predictor of firm's future performance, then past and present cash flows can be seen as indicators for the probability of bankruptcy.

Jackson and Wood (2013) describe theoretical, contingent claims models based on option pricing theory by Black and Scholes (1973) and Merton (1974). Jackson and Wood (2013) continue that the contingent claims models are usually constructed so that the shareholders of a firm is seen to hold an European call option on the firm, and if the option's exercise price on its expiry date is lower than the amount required to cover the firm's debt liabilities, the shareholders won't exercise the option and the situation can be interpreted as a default. Jackson and Wood's review on contingent claims models shows that all of these models incorporate similar predictor variables which are also similar to the models described by Scott (1981) being market value of a firm, volatility of the value, and expected earnings.

Aziz and Dar (2006) describe credit risk theories as one source for theoretical models. They describe that credit risk is a risk for default, and that the credit risk theory based models are usually utilized in credit rating companies' credit rating models. These include such as CSFB's CreditRisk+ and Moody's KMV credit rating models. Aziz and Dar (2006) collectively refer also option pricing theory as one of the credit risk theories as it predicts default, and they point out that JP Morgan's CreditMetrics and Moody's KMV credit rating models are based on the option pricing theory.

Laitinen and Laitinen (1998) present a prediction model based on cash management theory which links the financial failure to a firm's short-term cash management function. The theory they have used is founded on the Beaver's (1966) cash-flow based theory described earlier in the section 2.3. By the theory, the firm failure can be seen evident when the firm becomes illiquid and it will be unable to pay its obligations. This can be expressed in a single period version where the realized cash flow is less than debt obligations or as a multi-period model where the realized cash flow plus expected future cash flow is less than debt obligations.

Agarwal and Bauer (2013) describe the hazard bankruptcy prediction model being a mix of empirical and theoretical model. The model is based on survival analysis where time varying predictor variables are used to estimate the bankruptcy risk at each point in time, by assuming that bankruptcy in time *t+1* is conditional on survival until time *t*. The hazard models are constructed as a traditional statistical model such as logistic regression model, and they include both accounting-based financial ratios selected by empirical means and market-based ratios that origin from the survival theory.

Bankruptcy prediction models have been demonstrated empirically feasible in the research literature and their theoretical examination provides justification for the empirical models. This is because the results of the empirical models are more or less explainable in terms of well developed theory, and there exists also empirical support for the theoretical models. (Scott 1981)

2.5.4 Prediction accuracy of the models

The scope of this thesis work does not include assessing the overall accuracy of the bankruptcy prediction models i.e. how well an individual model is able to predict bankruptcy. However, as background information, it could be shortly described that even though there are multiple various models for bankruptcy prediction, there seems to be no major differences in the prediction accuracy of the different models. Aziz and Dar (2006) describe that the prediction accuracy of the 16 different models they have reviewed, varies mainly between 80-94 % excluding theoretical, cash management theory -based prediction models, which had only 67 % accuracy on average.

On the other hand, Jackson and Wood (2013) found larger differences between models when they compared traditional statistical models to theoretical contingent claim models. In their study, the overall prediction accuracy between 13 individual models varied from about 58 % to 84 %, and the higher accuracies were mostly achieved with theoretical prediction models. The average overall prediction accuracy for both model categories can be calculated from Jackson and Wood (2013) study, and for statistical models it was about 72 % and for theoretical models about 83 %, reflecting a quite similar difference between model categories that Aziz and Dar (2006) have demonstrated. In addition, it should be noted that the predictive ability to distinct between bankruptcy and non-bankruptcy firms was statistically significant at 1 % level in 12 of the 13 models Jackson and Wood (2013) tested and at 5 % level in the weakest model. This indicates a broad success in prediction ability in all the models employed in the Jackson and Wood study.

The prediction accuracy is usually reported as overall accuracy (Aziz & Dar 2006), which is the percentage of the correctly classified instances (Chen 2011). In addition, the bankruptcy studies usually report type I and II errors (Aziz & Dar 2006). Akers et al. (2007) describe that the type I error shows the percentage of the bankrupt firms which are classified as non-bankrupt by the prediction model, which is seen to be more severe as such misclassification can be costly for lenders. Akers et al. continue that the type II error, on the other hand, describes the portion of non-bankrupt firms which are classified as bankrupt firm and are thus not seen as severe as type I errors. Akers et al. (2007) found out in their review of prior bankruptcy prediction research studies from 1970 to 2003 that the predictive accuracy of the prediction models has not increased during the time period they have evaluated.

2.6 Predictor variables

Fabozzi et al. (2010, 243-244) describe that evaluating the performance and financial condition of a company can be based on analysis of economic, market, and financial information. They continue that some of the most important tools for the analysis include financial ratio analysis and cash flow analysis, which are both based on analyzing of financial information obtained from companies' annual and quarterly financial statements. Fabozzi et al. (2010, 243-244) describe that financial ratio analysis is an important tool for assessing issues such as company's operating performance, assets utilization efficiency, profitability, and company's ability to meet its financial obligations. They add that cash flow analysis is a tool for the valuation of a company as it brings out information about company's past and current cash flows and also a forecast of the future cash flows.

In the bankruptcy prediction studies, the most common type of variables used as indicators i.e. predictor variables for bankruptcy, are financial ratios based on accounting figures (Aziz & Dar 2006). Altman (1968) found out already in his seminal work that in general, financial ratios measuring profitability, liquidity, and solvency can be seen as good predictors of corporate failure.

Some bankruptcy research studies include also predictor variables which are non-ratio type financial variables measuring for example company size by its assets, and market-based variables such as volatility of the firm's stock price (see for example Altman et al. 1977; Campbell et al. 2008). In addition, some studies include predictor variables that can be seen as non-financial variables, as they measure changes in the macroeconomic conditions or factors such as experience level of the management and employee well-being (see for example Hall 1994; Derwall & Verwijmeren 2010).

2.6.1 Macroeconomic variables

Dambolema and Khoury (1980) describe first analytical studies on bankruptcy prediction were linked to macroeconomic factors such as monetary policy and economic conditions. Jackson and Wood (2013) suggest that global financial problems create high level of financial uncertainty thus creating the distinguishing between failing and non-failing firms exceptionally difficult. Hence they see that the variables measuring macroeconomic factors should be also included into the scrutiny when developing bankruptcy prediction models.

Bessler et al. (2013) describe that the relationship between business failures and macroeconomic conditions has been far less studied than the effect of firm-specific factors to the business failures. They list several studies where the relationship between macroeconomic factors and aggregate business failure rates were under scrutiny, rather than using macroeconomic factors on a firm-specific bankruptcy prediction. This relationship between macroeconomic factors and business failure rates was studied for example by Altman (1983). He found out that macroeconomic pressure caused by cumulative effects of slowed down real economic growth, stock market performance, credit market conditions, and increased formation of new firms, did increase business failure rates. Altman measured real economic growth with change in gross domestic product, stock market performance with changes in S&P 500 Index of stock prices, and credit and money market conditions with changes in nation's monetary stock, free reserves, and interest rates. In addition, Altman (1983) argues that inflation, especially unanticipated price increases, lowers business failure rates as leveraged firms are likely to be better in serving their debt with “cheaper” money, and the higher prices can be probably passed through to the consumer prices during the rising price thus increasing temporarily the contribution margins.

In addition to Altman’s (1983) study, Bessler et al. (2013) list a set of empirical studies where the influence of macroeconomic factors was also examined. They describe that all of these studies found out that aggregate measure of corporate profits and interest rates are affecting the business failure rates. They continue that the studies though had mixed findings in the effect of inflation and stock market performance on the business failure rates. Contrary to Altman’s

(1983) findings on inflation, some of the studies suggested that inflation leads to increased bankruptcy rates.

Bessler et al. (2013) studied themselves the effect of macroeconomic variables to business failure rates using essentially the same set of variables as Altman (1983). Their findings indicate that the business failure rates are not influenced much by these variables, except the high increase of interest rates which seems to cause a subsequent rise in the failure rates. Hence, they argue that the causality should be rather expressed how business failure rates influence macroeconomic conditions i.e. how business failure risk plays a structural role in economic fluctuations.

Using macroeconomic variables in a firm-specific bankruptcy prediction is studied for example by Mensah (1984). He argues that usually bankruptcy prediction models are constructed without considering the significant changes in economic conditions during the period from the data is pooled. Mensah however, constructed a statistical logit bankruptcy prediction model where he selected financial ratios which were hypothesized to be affected by the macroeconomic environment changes over the sample period he had chosen. Mensah lists these factors affecting macroeconomic environment as inflation, interest rates and credit availability, and business cycle indicating phases of recession and expansion. Mensah findings suggest that the accuracy and the structure of the bankruptcy prediction models are affected by these macroeconomic factors and to improve the accuracy, the models should be re-estimated over the time periods where the macroeconomic conditions have been changing.

Macroeconomic variable measuring price level has also been incorporated into some of the bankruptcy prediction models to adjust the financial variables used as predictor variables in the model, so that they are more comparable over time. For example Ohlson (1980) uses gross domestic product price-level index adjusted total assets of a firm as an indicator of firm size in his bankruptcy prediction model.

2.6.2 Financial ratios

Petersen and Plenborg (2012, 63) describe that financial ratio analysis is useful in assessing company's economic performance and financial health. They point out that financial ratios are important indicators of financial performance describing the level of company's profitability, growth and risk. Jordan et al. (2008, 56) describe financial ratios being measures for comparing relationship between accounting numbers of different sized firms. And because financial ratios are expressed in percentages, multiples, or time periods, they thus avoid the effect of firm size on the accounting numbers. Jordan et al. continue that because there are many different kind of accounting numbers, the number of possible financial ratios that can be constructed is huge.

Fabozzi et al. (2010, 244) describe that financial ratios can be classified by considering how they are constructed, what financial characteristics they are describing or capturing, and by the dimension of the company's performance or financial condition. Fabozzi et al. 2010, (244-245) emphasize that objective of the financial ratio analysis is to assess company's operating performance and financial conditions, hence presenting the following categories for financial ratios by using classification based on financial characteristics and function that the financial ratio is supposed to capture:

a) Liquidity
b) Profitability
c) Activity
d) Financial leverage
e) Return on investment

Jordan et al. (2008, 57-66) have listed most common financial ratios and use a grouping they describe as a traditional grouping for financial ratios. Their grouping is based on overall on what the different ratios are intended to provide information on and what they measure. Financial ratio classification presented by Jordan et al. (2008, 57-66) is presented in the table 2 and it seems to be based on the same principles as the classification presented by Fabozzi et al. (2010, 245-263).

Financial ratio group	*Description*	*Example financial ratios*
Short-term solvency, or liquidity ratios	Provides information about firm's ability to pay its short-term obligations i.e. liquidity	Current ratio, Quick ratio, Net working capital to total assets
Long-term solvency, or financial leverage ratios	Addresses firm's ability to meet its long-term obligations	Total debt ratio, Cash coverage, Equity multiplier, Times interest earned (TIE) ratio
Asset management, or turnover ratios	Measures efficiency of firm's asset utilization i.e. how efficiently a firm uses its assets to generate sales	Inventory turnover, Receivables turnover, Days' sales in receivables, Total asset turnover, Net working capital turnover
Profitability ratios	Measures how efficiently a firm uses its assets and manages its operations with focus on earnings	Return on equity (ROE), Return on assets (ROA), Profit margin
Market value ratios	Ratios including market-based valuation only available for publicly traded companies	Price-earnings ratio (P/E), Price-sales ratio (P/S), Market-to-book ratio

Table 2: Financial ratio grouping (Jordan et al. 2008, 57-66)

Principles of different financial ratios and their classification is discussed in the below sections by separating them in categories presented by Fabozzi et al. (2010, 245-263). After these sections with categories by Fabozzi et al., some of the market-based financial measures including market value ratios by Jordan et al. (2008, 65-66) are presented in their own chapter.

Liquidity ratios

Fabozzi et al. (2010, 247-252) describe that the assessment of company's ability to meet its short-term obligations can be based on financial ratios measuring liquidity. They continue by describing that the short-term obligations are the liquidity needs dependent on a company's operating cycle. So that the longer the operating cycle, the more liquidity is required. Operating cycle can be measured with cash conversion cycle describing how long it takes to receive cash back from investments in inventory and accounts receivables (Fabozzi et al. 2010, 250). This is related to the Beaver's (1966) theory based on the cash-flow model where the firm is viewed as a reservoir of liquid assets which is supplied by inflows and drained by outflows, and that the reservoir can be supplied by the net liquid asset flow from operations.

Fabozzi et al. (2010, 251) describe that financial ratios measuring liquidity include current ratio, quick ratio and net working capital to sales ratio. These ratios all include financial measures for current assets and current liabilities. Jordan et al. (2008, 57) state, that using these measures has the advantage that the book and market values of the measures are likely to be similar. However, they continue that as being near-cash measures, current assets and liabilities can change rapidly thus not being a good predictor of future situation. Petersen and Plenborg (2012, 156) emphasize also this by describing that it is doubtful that company's net working capital i.e. current assets less current liabilities is a good indicator of how much will be cash tied up in the working capital in the future.

Petersen and Plenborg (2012, 157-158) include cash flow from operations to short-term debt ratio into the liquidity ratios category, and they continue that using cash flow from operations seems to be a better measure of cash available than current assets when assessing a company's ability to serve its current liabilities. This is supported by Mills and Yamamura (1998) whom found out that ratios based on cash flow are useful indicator for solvency and liquidity, and that they provide insight on a company as a going concern. They argue that ratios determined from cash flow statement gives better information about company's ability to meet its obligations than the ratios derived from balance sheet figures. They justify this by describing that the cash flow based ratios test cash inflows over a period of time against the obligations, rather than just indicating how much cash the company had available on a single date, which working capital calculated from balance sheet figures does.

Profitability ratios

Fabozzi et al. (2010, 253) write that profitability ratios express how well a company manages its expenses. They mention profit margin ratios, which are measuring operating performance of the company, and comparing income to revenues. These ratios include such as gross profit margin, operating profit margin, and net profit margin.

In addition to profit margins, Jordan et al. (2008, 65) have included ROE and ROA in the profitability ratios category whereas Fabozzi et al. have separated them into the return on investment -category. Previously Courtis (1978) has described in his financial ratios categoric framework, that profitability include profit margin, capital turnover, and return on investment. This linkage can be also seen in the DuPont model (Jordan et al. 2008, 67-68) where the return on equity is broken up into three components i.e. three financial ratios. The first of these three components is ratio measuring operating efficiency with profit margin, and the second asset utilization with total asset turnover, thus linking ROE in profitability and capital turnover. In addition, the third component of the DuPont model is equity multiplier ratio linking also financial leverage into the components of ROE.

Activity ratios

Fabozzi et al. (2010, 255) describe that profit margin ratios do not include sensitivity for changes in sales prices and changes in sales volume. They add that in order to capture these and to assess the future profitability of the company, the activity ratios are needed. Fabozzi et al. (2010, 256-257) use term turnover ratio for activity ratio and describe that each of them express a turnover rate of the asset included in the ratio thus measuring how effectively a company is utilizing its assets. The overall asset management efficiency can be assessed with total assets turnover ratio i.e. revenues to total assets ratio. Jordan et al. (2008, 61) have described these financial ratios belonging to asset management, or turnover ratios group, and they explicitly state that these ratios assess how efficiently a company uses its assets to generate sales.

The total assets turnover ratio is also included in the DuPont model described earlier, thus establishing a link between profitability and asset management efficiency. In addition, Courtis (1978) has described ratios measuring credit policy management and inventory management as measures of managerial performance, thus emphasizing the effect of management defects on the company's operating performance and financial condition. Management defects were seen as a major cause for a firm failure and bankruptcy as described earlier in the chapter 2.2.

Financial leverage ratios

Financial leverage ratios measuring long-term solvency, assess company's ability to manage its long-term obligations (Jordan et al. 2008, 59). Fabozzi et al. (2010, 258-260) write that these ratios describe the financial structure of the company i.e. the balance between debt and equity, and are thus related directly to financial risk which describes company's ability to satisfy its debt obligations. They add that these include financial ratios that compare debt to equity or debt to assets thus indicating the amount of financial leverage in the company.

In addition to ratios measuring capital structure, financial leverage ratios include ratios for measuring company's ability to handle financial obligations caused by debt or other fixed financial commitments (Fabozzi et al. 2010, 260). These ratios are called coverage ratios and they include interest coverage ratio for assessing company's ability to serve its interest expense (Fabozzi et al. 2010, 260) and cash coverage ratio to assess the sufficiency of company's cash flows in serving its interest expense (Jordan et al. 2008, 60-1). These ratios seem to be related to the Beaver's (1966) theory based on the cash-flow model in which cash flow generates cash inflows and interest expense cash outflows.

Return on investment ratios

When the return on investment ratio compares earnings to total assets, it measures the return a company gets from its total investments i.e. ROA, and how well a company uses its assets in its operations. When the ratio compares earnings to equity, it measures ROE i.e. the return the company generates on shareholders investments. (Fabozzi et al. 2010, 262-263)

The DuPont model presented earlier breaks up ROE into three components from which each of can be associated to financial ratio categories presented earlier. However, Jordan et al. (2008, 63-64) and Courtis (1978) have both associated ROA and ROE into the profitability category. Courtis has justified this by describing that the profitability category is based on the "profitability triangle" where the components of DuPont model express the significant linkage between profit margin and asset turnover. He describes this linkage so that the number of times the assets were turned over into sales reflects to the return on total investment. Hence Courtis sees that profitability ratios measure profitability in relation to investments, and profitability in relation to sales, thus assessing returns on shareholders and assets.

2.6.3 Market-based financial ratios and variables

In addition to accounting based financial ratios, financial variables which are based on market values such as volatility of the company stock price, are also applied in bankruptcy prediction (see for example Altman et al. 1977; Campbell et al. 2008). As these ratios include market-based financial information, they can be only calculated for publicly traded companies (Jordan et al. 2008, 65). Altman (1968) has introduced market value based financial ratio already in his seminal work, where he had included into his bankruptcy prediction model a financial ratio comparing the market value of equity to the book value of total debt.

Cram et al. (2004) argue that stock market provides potential source for alternative and superior information for bankruptcy prediction by including information from other sources than only financial statements. Jordan et al. (2008, 65-66) include to their market value ratios category two ratios with company's stock price: stock price per earnings ratio and stock price per sales ratio, both for assessing the valuation and future growth of the company. The use of stock price as a predictor variable were earlier supported by both Beaver (1968) and Scott (1981) whom see that low stock price is a good predictor for bankruptcy, as they describe that stock price presents the amount of external capital the company might be able to raise to avoid bankruptcy. Beaver (1968) demonstrated this by stating that the financial failure predicted by investors should have been reflected to the stock price long before failure, and found out that stock price were in fact slightly better predictor for firm failure than accounting based ratios.

Jordan et al. (2008, 65-66) include in their market value ratios category the market-to-book ratio, which is basically comparing market value of company's investments to their costs. Dichev (1998) brings out that it has been hypothesized that book-to-market ratio, i.e. inverted market-to-book ratio, correlates positively to bankruptcy risk. However, their findings suggest that the relation is not full proof as they found out that companies with highest bankruptcy risk have lower book-to-market ratios than companies with not as high risk. They add that this might be due to the fact that book values of distressed company might be reduced for covering losses or that they can even fall negative.

Petersen and Plenborg (2012, 158-160) state that when determining financial leverage ratios and if market values are available, they should be used instead of book values since market values are closer to the realizable values. They demonstrate this with company's equity as they describe that if the market value of the equity is significantly higher than the book value, assessing long-term liquidity using book values show much higher long-term liquidity risk than using market values.

2.6.4 Other financial variables

In addition to accounting-based and market-based financial ratios and variables, variables measuring for example company size are applied in bankruptcy prediction. For example, Ohlson (1980) measures size by gross domain product price-level index adjusted total assets and argues that in his bankruptcy prediction model it seems to be one of the important predictors of bankruptcy. Jackson and Wood (2013) found out that simple statistical bankruptcy prediction model incorporating only single variable measuring size has a fairly good prediction accuracy compared to a more sophisticated and multi-variable bankruptcy prediction models.

Dichev (1998) describe that as the effects of company size and book-to-market financial ratio are seen probably as the two most powerful predictors of company's stock returns, these could be also valuable when predicting bankruptcy risk. They continue that the significance of the effect of the size measure was seen strong in the bankruptcy research in the 1960s and 1970s, as there were found correlation for negative relation between bankruptcy risk and company size. However, they argue that the strong significance of the size measure is no more recognized in the research field since there is no reliable evidence that the size effect could explain the relation between bankruptcy risk and company's returns.

Castanias (1983) has included company size measured by total assets in his bankruptcy prediction model even though it is not suggested in his initial theoretical hypothesis used for determining which predictor variables to use. He justifies the inclusion of the size measure by stating that a larger company has less business risk because of the reasons such as diversification, easier access to borrowing markets and less information asymmetries, thus making a larger company seem less risky from lenders' point of view. He also points out that due to the diversification larger companies have lower variance of earnings.

Laakso et al. (2010, 36-37) emphasize the importance of growth in assessing financial problems as they describe that a firm with uncontrolled fast growth will have difficulties in keeping the firm profitable. They continue that this is because the fast growth lowers the firm's relative cash flow financing and increases the need for external financing thus lowering solvency and liquidity. In addition, they continue that an unstable growth also increases firm's business risk as it increases the volatility of the firm's earnings. They describe that growth can be measured for example by using firm size, or by growth in turnover or total assets. Petersen and Plenborg (2012, 131-132) present that a firm growth can be assessed by measuring growth in such as revenues, operating profits, free cash flows, and dividends.

Donoher (2004) studied how the managerial ownership of equity and the board composition between outside and inside representation affected probability to bankruptcy. He hypothesized these by describing that high levels of outside equity ownership and board representation allegedly lead more probably to reorganization when firm faces financial problems than in the case of lower levels of outside equity ownership and board representation. He found out that firms with high level of inside equity ownership and secured indebtedness seem to be less reluctant to seek reorganization than firms with high outside ownership and current indebtedness, but no effect were found on the board composition on outside and inside representation of the board members.

Cram et al. (2004) describe asset volatility being a crucial variable and superior to the accounting-based financial ratios in the bankruptcy prediction because it includes a forward-looking view into the value of company's assets. They see that asset volatility captures the probability for such a decline in assets that could affect the company's ability to serve its debt thus increasing the bankruptcy risk.

2.6.5 Non-financial variables

Some bankruptcy prediction studies include predictor variables that can be seen as non-financial variables as they measure factors such as experience level of the management and employee well-being (see for example Hall 1994; Derwall & Verwijmeren 2010). As described in the previous section 2.6.4, variables measuring firm size could be interpreted as other financial variables if the size measure accompanies accounting or market based variable such as total assets or market value of assets. However, there are also size measures used as in bankruptcy prediction that are based solely on non-financial information. For example in the study by Chen et al. (2013), they use a average number of employees in a firm to measure the firm size.

As for example Mensah (1984) and Petersen and Plenborg (2012, 295) has argued that the bankruptcy prediction model should consider the industry type, some of the bankruptcy prediction studies include predictor variables which describe the industry type of a firm. For example, Hensher and Jones (2004) include dummy variables and various financial ratios in their bankruptcy prediction logit model where the function of the dummy variables is to classify a firm's industry sector between old economy sector, new economy sector, resources sector, and financial services sector.

Westgaard and van der Wijst (2001) use similar method to classify a firm between real estate and services, and hotel and restaurant industry. In addition, Westgaard and van der Wijst incorporate predictor variable describing the geographical location of a firm in their bankruptcy prediction logit model. They use a dummy variable to classify a firm's location to a Northern Norway or Mid Norway as their empirical study on Norwegian bankruptcy data revealed that there is significant distribution of the predictor variables in between these locations and the industry types.

2.6.6 Number of variables included into the prediction models

One of the earliest research on bankruptcy prediction is Beaver's (1966) study where he uses univariate analysis to find out which financial ratio is the best predictor for bankruptcy thus using approach to utilize only single predictor variable. Considering the number of financial ratios, Akers et al. (2007) have discovered in their review of bankruptcy prediction studies that the amount of predictor variables used in statistical and modern AIES bankruptcy prediction model has varied over time from one to 57, and has been about 10 in average.

As described earlier in the section 2.5.3, theoretical bankruptcy prediction models derive their predictor variables from the underpinned theory thus including highly similar set of predictor variables to the models that are based on the same theory. For example theoretical models reviewed by Jackson and Wood (2013) based on option pricing theory include set of predictor variables measuring similar type of financial factors thus usually incorporating such measures as the market value and the volatility of the firm's assets, and the expected return on the firm's assets. Thus the number of predictor variables is limited smaller than on the traditional statistical and modern AIES models, where the number of variables can be even dozens.

Akers et al. (2007) assessed the prediction accuracy of the bankruptcy prediction models compared to the number of predictor variables used in the models. They found out in their study that the higher number of predictor variables is not a guarantee of higher accuracy and that a bankruptcy prediction model with just two predictor variables were just as good in the terms of accuracy as a model with 21 variables.

2.6.7 Limitations of financial ratios

Though it seems evident by the literature review that financial ratios are the most applied predictor variables in the bankruptcy prediction studies, there have been also critic presented against using them. Petersen and Plenborg (2012, 165) list shortcomings for using financial ratios including the fact that with accounting-based financial ratios, the result is only backward-looking as ratios are based on the historical information. In addition, they highlight that financial ratios are less useful if they are not used together. Petersen and Plenborg (2012, 295) add that comparing financial ratios between companies should be done with peers from the same industry as the financial structure varies across industries. Petersen and Plenborg (2012, 277) demonstrate this by describing that for example companies offering commodities need to generate high activity ratios, for example high inventory turnover, in order to attract capital as the fierce competition in the industry sets an upper limit to the achievable profit margin. Similar issues have been brought out by Jackson and Wood (2013) whom suggests that as the accounting-based financial ratios contains only historical information, the accuracy of the bankruptcy prediction using only them varies over a period of time as the significant changes in general economic conditions cannot be captured into the prediction model.

Cram et al. (2004) argue that conservatism in preparing financial statements often leads to undervaluation of asset values relative to their market values thus causing financial ratios, particularly financial leverage ratios, to be overstated. In addition, they see that since financial statements are formulated on the going-concern basis assuming that companies will continue operating instead of going bankrupt, it limits the use of accounting-based financial ratios in the bankruptcy prediction.

The causes to the firm failure listed by Argenti (1976a) and described earlier in the chapter 2.2 could be well observed from the financial information. However, Argenti (1976a) continues that due to the possible “creative accounting” carried out in the company, the reported financial information might be such that the firm’s recovery from the failure situation can be seen certain. In addition, even though the time span of the failure process is usually in practice at least few years, Argenti sees that creative accounting performed by the company management might make the eventual failure to be seen as a sudden event by external viewers, thus limiting the use of financial ratios as indicators in an early-warning system. As a matter of fact, Beaver (1966) has already before Argenti presented that the most popular financial ratios for predicting bankruptcy may become the most manipulated by management, thus reducing the utility of these ratios. He calls this kind of management manipulation activity as “window dressing”.

However, as a summary Chen et al. (2013) state that even though several researchers have been trying to apply also other types of variables than financial ratios into the bankruptcy prediction, financial ratios are still irreplaceable. They argue that this is because the results of the bankruptcy prediction research using other types of variables than financial ratios are mixed and ambiguous, and that the use of financial ratios in the bankruptcy prediction is supported by a vast amount of well-recognized prior research with a long history.

3 Systematic literature review

3.1 Systematic literature review method

This study utilizes a systematic literature review where prior research literature examining prediction of bankruptcy are searched, evaluated and summarized. Petticrew and Roberts (2006, 2-3) describe systematic literature review as a tool for researchers for synthesizing and making sense of large bodies of information. They emphasize that systematic literature review focuses on issues that try to identify, select and synthesize research evidence relevant to the research question from the analyzed research studies. Systematic literature review includes the following five steps by Antes et al. (2003):

1. Framing the question for a review
2. Indentifying relevant work
3. Assessing the quality of the studies
4. Summarizing the evidence
5. Interpreting the findings

The systematic literature review is conducted by following these steps in this thesis work. The research questions introduced earlier in the chapter 1 frame the question for the review, and a simple meta-analysis technique is used as a tool for summarizing the evidence.

3.2 Study search for systematic literature review

The relevant studies for the review are studies focusing on the prediction of bankruptcy. Studies were searched from financial and scientific journals starting from the early days of the bankruptcy prediction studies in the 1960s to the most present and novel studies. The studies that were included into the systematic literature review were limited to those in which:

a) a certain predictive model or multiple models are used for bankruptcy prediction,

b) predictive model or models are traditional statistical models or modern AIES models,

c) the dependent variable in the predictive model is probability of bankruptcy or a dummy variable for bankruptcy,

d) the predictive model include financial and/or non-financial variables as independent variables i.e. variables that proxy financial weakness, distress and potential insolvency of firms, and

e) the independent variables and their significance can be individually identified from the predictive model by given statistical significance value, or by interpreting all the independent variables included in the model to be significant, if the study include such a sophisticated method for selecting independent variables that can be assumed to end up with a set of significant variables.

Theoretical models were excluded from the systematic literature review since most of the bankruptcy research studies considered as candidates did not include any information of the significance of the predictor variables for the variables included into the theoretical model. An exception to this is the bankruptcy research studies utilizing the hazard model such as Agarwal and Bauer (2013) and Beaver et al. (2005), where the model is traditional statistic model but it include accounting and/or market-based financial ratios derived from the theoretical framework as explained earlier in the section 2.5.3. These kinds of studies were included into to the systematic literature review.

There are also many bankruptcy prediction studies in which different prediction models are compared by assessing the prediction accuracy of the different models in overall (see for example Tseng & Hub 2010). The nature of these studies is different from the thesis work since the objective in these studies is to analyze the overall model, not the individual variables used in the models. However, these studies are taken as study candidates to the systematic literature review since they employ some already presented model or slightly adjusted model with different sample to test the model. This probably leads to different set of significant variables than in the former studies that utilize the same model, since it has been presented in the literature that the significance of the predictor variables on the probability of bankruptcy are sample specific (Becchetti & Sierra 2003).

To ensure high coverage of the literature review, there was no limitation set on the origin country of the research study or the sample of the companies used in the study. The samples used in the included literature thus cover companies from various countries, from various industries, and from various sizes ranging from small companies to publicly listed global corporations.

To ensure the quality of the research studies, they were selected from research journals which have a relatively high Impact Factor and Scientific Journal Ranking. The table 3 describes the research journals which were used as a source for the studies included into the systematic literature review. The Impact Factors (IF) and Scientific Journal Rankings (SJR) presented in the table 3 are for the year 2013.

Journal name	*Abbreviation*	*IF*	*SJR*
Computers and Mathematics with Applications	CMWA	1,996	1,343
Contemporary Accounting Research	CAR	1,533	2,544
Decision Support Systems	DSS	1,814	1,814
European Journal of Operational Research	EJOR	1,843	2,595
Expert Systems with Applications	ESWA	1,965	1,487
Journal of Accounting Research	JAR	2,449	5,155
Journal of Banking and Finance	JBF	1,362	1,423
Journal of Business Finance and Accounting	JBFA	1,261	1,007
Journal of Business Research	JBR	1,306	1,215
Journal of Finance	JOF	6,033	18,440
Journal of Management Studies	JOMS	3,277	3,806
Review of Accounting Studies	RAST	1,167	2,253
The Accounting Review	TAR	2,420	5,000
The Journal of Financial and Quantitative Analysis	JFQA	1,877	4,743

Table 3: Research journals used as a source for the studies

Dimitras et al. (1996) also found out in their survey that research journals Journal of Banking and Finance, Journal of Business Finance and Accounting, and Journal of Accounting Research are the most frequent sources for papers studying business failure and bankruptcy. These three journals were the also major ones they used as a source for the bankruptcy prediction studies they have included in their review. Also Aziz and Dar (2006) have also used many of the journals listed in the table 3 as a source for studies in their study examining the popularity of the different bankruptcy prediction models. They have included studies for example from journals Journal of Finance, Journal of Business Finance and Accounting, and European Journal of Operational Research.

The search for study candidates was done from the www-sites of the journals by using the keyword search embedded into the each journal's www-site. The search was done using keywords "bankruptcy", "bankruptcy prediction", "firm failure", "business failure", "corporate failure", "default", "insolvency", and "financial distress". In addition to keyword-based search from internet, studies were selected as candidates based on their existence in a prior research reviewing bankruptcy studies, such as the studies by Aziz and Dar (2006), and Ravi and Ravi (2007).

The study candidates found by the search were then included into the systematic literature review by evaluating each study independently if it meets the requirements listed in the beginning of this section. The reasons for excluding research studies were mostly related to some of the following issues:

a) The list of independent variables included into the bankruptcy prediction model was incomplete.

b) There were no reported statistical measures or written identification of the statistical significance of the independent variables included in the bankruptcy prediction model.

c) The statistical measures or written identification of the statistical significance of the independent variables in the bankruptcy prediction model were reported so unclearly or ambiguously that it was not possible to reliably interpreted the statistical significance from the research study.

3.3 Classification of financial variables

A classification of the predictor variables collected in the systematic literature analysis is performed to assess which types of variable categories is of the interest in the bankruptcy prediction research literature. In this thesis work, the classification is constructed as an upper-level classification, which is based on the classification of financial ratios presented by Jordan et al. (2008, 57-65) and Fabozzi et al. (2010, 245-263). The principles for their classification are described earlier in the section 2.6.2.

The classification is expanded here so that it is describing what the variable is measuring and on the function of the variable. If the variable is an accounting-based financial ratio, it derives its classification directly from grouping presented by Fabozzi et al. (2010, 245-263). However, the categories in the classification scheme constructed in this work are defined so that they can include also non-ratio type of financial variables, which measure the same financial measure as the financial ratio group described by Fabozzi et al. For example, profitability category can include non-ratio type financial variable measuring total net income. In addition, the financial ratios that can be associated with return on investment category presented by Fabozzi et al. (2010, 262-263), are all to be included here into the profitability category similarly like Jordan et al. (2008, 63-64) had done, thus excluding return on investment category from the constructed classification scheme.

Jordan et al. (2008, 65-66) had defined an own category for financial ratios which utilize market-based valuation, thus making it possible to determine them only for publicly listed companies. However, since many of the samples in the reviewed bankruptcy studies include also non-listed companies, and the classification constructed in this work is based on what the variable is measuring, these market-based ratios and variables are included here into categories which best described what they are deemed to measure. Hereby the classification scheme constructed here does not include explicit category for financial variables which include market-based values.

In addition, a specific size-category is constructed for variables that express the size of the firm in monetary assets, or in physical size, such as variable measuring the number of employees in the firm. Size category is added into the classification as it seems to have support in the research literature as described earlier in the section 2.6.4.

Own category is constructed also for other financial variables. The category includes for example macroeconomic variables, and financial variables which cannot be included in any of the explicitly defined financial variable categories mentioned earlier, yet it can be identified that they derive their value from financial information. The classification include also category for non-financial variables such as variables expressing the type of the industry the firm operates on or a variable measuring the experience level of the companies' employees (see for example Becchetti & Sierra 2003; Hall 1994).

The categories used in the classification scheme constructed for the systematic literature review are presented in the table 4.

Category name	*Category type*	*Measures*
Liquidity	Financial	Short-term solvency
Profitability	Financial	Quality and growth of earnings, ROE, ROA
Activity	Financial	Asset management, asset turnover
Financial leverage	Financial	Coverage and financial leverage, long-term solvency
Size	Financial/ non-financial	Asset size or physical size
Other financial	Financial	Various issues
Non-financial	Non-financial	Various issues
Unidentified	-	-

Table 4: Classification categories

In addition, the classification constructed in this thesis work includes also category for unidentified variables, in which all the variables that cannot be soundly identified to any of the other categories are to be included. Variables and ratios included into the unidentified-category are not included into the meta-analysis part in this thesis work since their function and purpose of use is not recognized.

3.4 Results of the review

3.4.1 Descriptive summary

The final set of studies included into the systematic literature review contained 51 studies. The number of studies included from each research journal is viewed in the table 5. The detailed list of the included studies is in the appendix A.

Journal name	*Abbreviation*	*Number of studies*
Expert Systems with Applications	ESWA	9
Journal of Banking and Finance	JBF	8
Journal of Business Finance and Accounting	JBFA	8
Journal of Finance	JOF	5
Review of Accounting Studies	RAST	4
Journal of Accounting Research	JAR	3
The Accounting Review	TAR	3
Decision Support Systems	DSS	2
European Journal of Operational Research	EJOR	2
Journal of Business Research	JBR	2
Journal of Management Studies	JOMS	2
Computers and Mathematics with Applications	CMWA	1
Contemporary Accounting Research	CAR	1
The Journal of Financial and Quantitative Analysis	JFQA	1

Table 5: Number of studies included from different research journals

The studies included in the review were published between 1966 and 2014. The number of studies from each decade is presented in the figure 3.

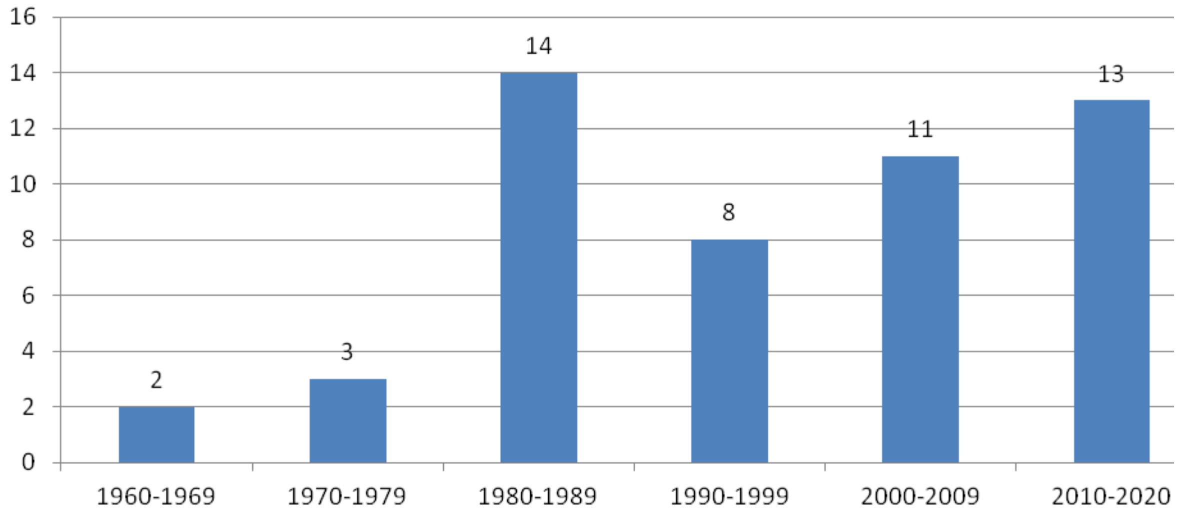

Figure 3: Number of reviewed studies by decades

The reviewed studies were from various countries as presented in the table 6. However, it can be seen that the majority of the studies originated from U.S. which has been often identified characteristic for the bankruptcy studies in the bankruptcy research literature.

Country of origin	*Number of studies*
USA	20
UK	4
Australia	3
Italy	3
Korea	3
Finland	2
Taiwan	2
USA and UK	2
Greece	2
UK and Spain	1
Japan	1
Canada and China	1
Norway	1
UK and Germany	1
Hong Kong	1
France	1
Slovenia	1
Australia and Netherlands	1
Portugal and China	1

Table 6: Number of studies by origin countries

The studies included into the review were constructed with a company sample sizes varying from smallest with 42 companies and largest with over 35 000 companies. 21 of the studies explicitly described their samples to include only publicly traded companies. Others described their samples to include mixed type of companies ranging from small and medium-sized companies to publicly traded companies. Eight of the studies did not include any description of the company sizes included in their sample.

In 19 of the studies, the company samples were described to represent companies only or mainly from manufacturing and retail industries. Nine of the studies did not describe the industry type of the sample companies at all, and the rest of the studies described their samples to include companies from mixed industries. However, companies from financial sector such as banks and insurance companies were usually explicitly expressed to be excluded from the samples in some of the studies, as financial sector companies are structurally different and have a different bankruptcy environment (Ohlson 1980).

3.4.2 Summary by applied techniques and methods in bankruptcy prediction

The number of the times the different techniques and methods were applied in the predictor variable selection process and/or as a prediction model method in the reviewed studies is summarized in the figure 4. The descriptions of the techniques and methods are presented in the figure 4 are in the table 7.

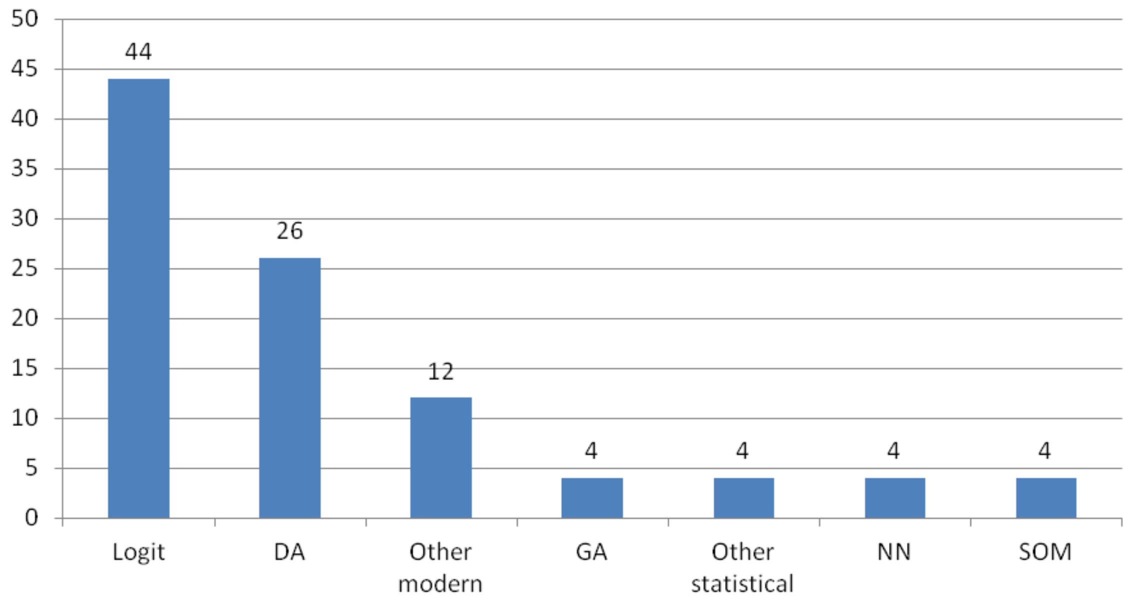

Figure 4: Number of the times the different techniques and methods applied

Abbreviation	*Type*	*Description*
Logit	Statistical	Logarithmic regression
DA	Statistical	Discriminant analysis
Other modern	Modern	Other modern AIES models including partial least squares, classification and regression tree, particle swarm optimization, learning vector quantization, rough sets, decision trees, support vector machine, and recursive partition algorithm
GA	Modern	Genetic algorithm
Other statistical	Statistical	Other traditional statistical models including univariate analysis, Probit regression and linear regression
NN	Modern	Neural network
SOM	Modern	Self-organizing map

Table 7: Bankruptcy prediction models

The overall prediction accuracy of the bankruptcy prediction models was reported in 29 of the reviewed 51 studies and it varied from about 69 % to 99 %. However, in about 40 % of the models, the overall prediction accuracy was over 90 % and in about 93 % of the models it was over 80 %, thus supporting the evidence of relatively good prediction ability of the bankruptcy prediction models developed in the studies as described earlier in the section 2.5.4.

3.4.3 Summary by predictor variables and variable categories

In total, 697 predictor variables were identified from the bankruptcy prediction studies and the prediction models developed and applied in the studies. The variables collected from the studies are such, which were included as independent variables into the final prediction model or models developed in each study. However, many of the reviewed studies included much larger set of initial variables from where the variables to be included into the final prediction model were selected. The initial set of variables was usually constructed based on the prior research and the researchers' professional judgment. The process for filtering predictor variables into the final prediction model is described in the figure 5.

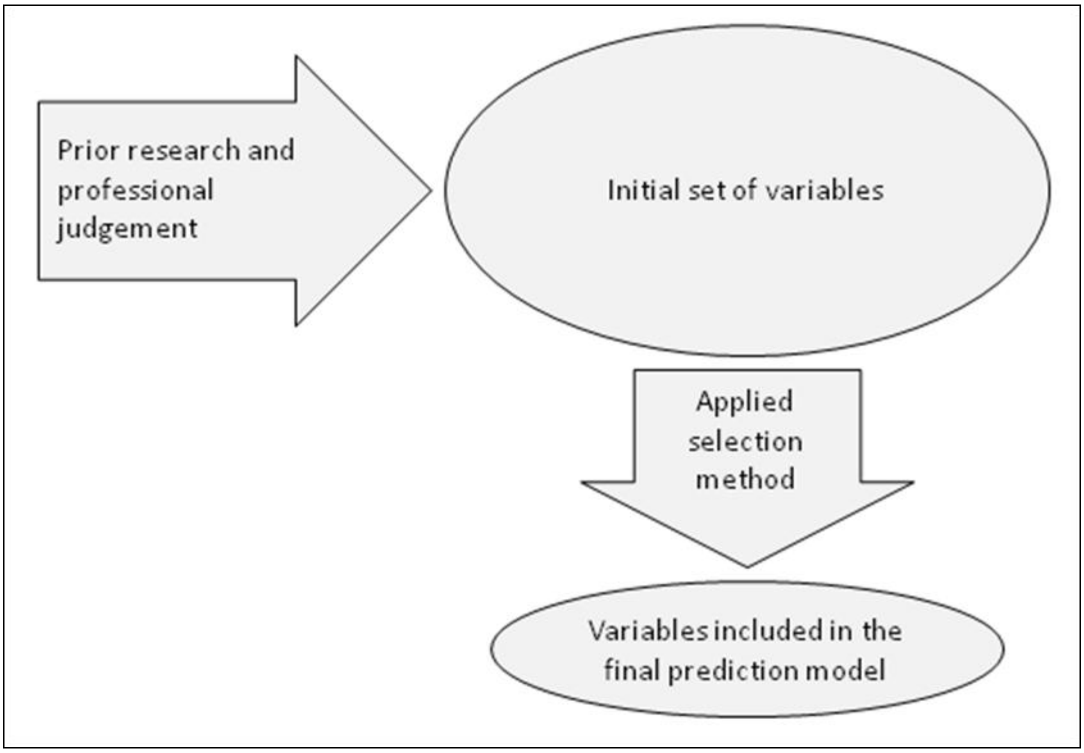

Figure 5: Process for filtering variables to the final bankruptcy prediction model

The selection methods applied into the selection process of the predictor variables from the initial set include such as prior research knowledge, professional judgment of the researcher, and statistical analysis. In addition, modern methods such as genetic algorithms were used in some of the studies to come up with the best possible set of predictor variables from the initial set, and many of the studies included a mix of these methods in the selection process.

The summary of the applied variable selection methods among the reviewed studies is described in the table 8 where statistical analysis includes such methods as step-wise discriminant and correlation analysis, factor analysis, and principal component analysis, and modern methods such as genetic algorithms, decision trees, and classification and regression trees. Together the reviewed studies included 89 different set of predictor variables that were included in to the final prediction model or models.

Variable selection method	*Times applied*
Statistical analysis	47
Expert opinion and statistical analysis	11
Prior research	8
Expert opinion	6
Prior research and statistical analysis	4
Based on theoretical framework	4
Modern method	4
Prior research and expert opinion	2
Expert opinion, theoretical bases and statistical analysis	2
Modern method and expert opinion	1

Table 8: Predictor variable selection methods

The predictor variables collected from the reviewed studies to this thesis work does not include the variables filtered out from the initial set of variables since they have no significance to the prediction model and in addition, many of the studies did not report a detailed list of what were the variables included in the initial set and left out of the final prediction model. The collected variables include also such that might be used in a similar model in other study as the variable selection methods also include the use of prior research. For example, Cram et al. (2004) included Altman's Z-score model (Altman 1968) and Ohlson's O-score model (Ohlson 1980) in their study. However, as the variables affecting the probability of the bankruptcy are sample specific (Becchetti & Sierra 2003), the coefficients and significances of the independent variables between same models in different studies more than likely end up being different.

The number of variables by functional categories described earlier in the section 3.3 is summarized in the table 9. The table contains both significant and insignificant predictor variables from the reviewed studies i.e. variables that were included in the final prediction model and were seen either significant or insignificant in the bankruptcy prediction.

Category	*Variable count*
Liquidity	233
Profitability	165
Financial leverage	117
Activity	81
Non-financial	43
Other financial	27
Size	25
Unidentified	6
Total	*697*

Table 9: Classification of predictor variables into categories

Even though the classification of each individual predictor variable into a category in the table 9 is based on the theoretical background presented earlier in the section 2, some judgement in some cases had to be done as it were noticed that there are discrepancies in the classification between financial ratios in the studies. For example, Taffler (1984) describes financial ratio cash flow to total liabilities as a measure of profitability. However Mills and Yamamura (1998) describe, that cash flow ratios such as financial ratio comparing cash flow to debt indicates the company's ability to carry its debt which relates the ratio more as a measure of liquidity. The classification of this variable in this thesis work is thus similar to what Mills and Yamamura (1998) describe.

In addition, there are some predictor variables that incorporate a more complex calculation than just a basic financial ratio thus making the determination of the category of the variable more ambiguous. For example, distance to default -variable is seen here as a measure of financial leverage, as it is described by Xu and Zhang (2008) to measure the distance between the current value of the assets and the debt amount of the company in terms of the volatility of the growth rate of the assets.

A summary of the number of the bankruptcy predictor variables by studies is provided in the appendix B, which contains the sum of both significant and insignificant predictor variables by functional categories from the bankruptcy prediction models applied in the reviewed studies. The number of predictor variables in the 89 different bankruptcy prediction models included in the reviewed studies varied from one to 30 variables per model. The distribution of models by their predictor variable count is shown in the figure 6. It can be seen from the figure that among the 89 bankruptcy prediction models identified from the reviewed studies, the bankruptcy prediction models with 1-10 predictor variables are by far the most popular.

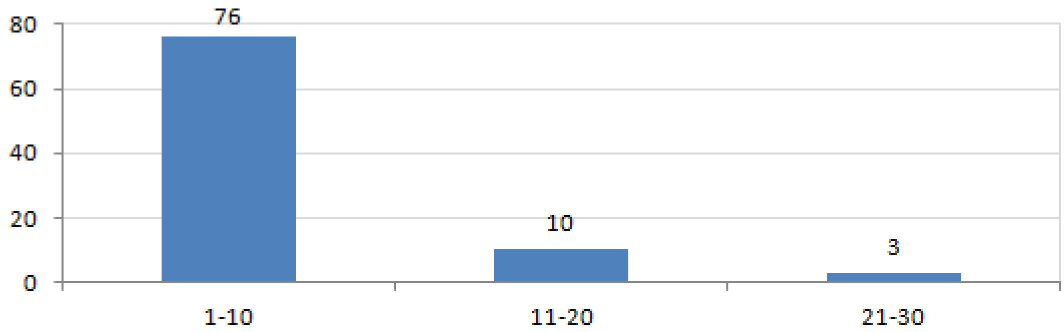

Figure 6: Number of predictor variables included in prediction models

The top 10 of the most popular individual predictor variables collected from the reviewed studies are listed in the table 10. The aggregate count of these 10 variables is 159 thus representing about 23 % of all of the 697 predictor variables collected from the reviewed studies.

Rank	*Variable*	*Category*	*Count*
1.	Net income / Total assets	Profitability	26
2.	Total liabilities / Total assets	Financial leverage	23
3.	Current ratio	Liquidity	19
4.	Cash flow / Total liabilities	Liquidity	16
5.	EBIT / Total assets	Profitability	16
6.	Working capital / Total assets	Liquidity	14
7.	Sales / Total assets	Activity	13
8.	Retained earnings / Total assets	Profitability	13
9.	Current assets / Total assets	Liquidity	11
10.	Net profit / Sales	Profitability	8

Table 10: Top 10 of the most popular predictor variables

4 Meta-analysis

4.1 Overview of meta-analysis

Meta-analysis is a statistical pooling of the findings of the studies included into the systematic literature review as it synthesizes and summarizes the results of several studies using a specific statistical technique (Petticrew & Roberts 2006, 37). Borkowski (1996) states that meta-analysis is widely used in the social sciences, but it has a very limited application in accounting and finance, as most of the empirical studies on that field of research lack of such a consistency across studies that they could be synthesized using sophisticated statistical meta-analysis methods. However, there are some research done in the field of accounting and finance using meta-analysis, such as the studies by Hite (1987) and Hay et al. (2006). But considering the requirements of meta-analysis mentioned inter alia by Borkowski (1996), these studies usually accompany a simpler statistical method than the recommended meta-analysis method.

Borenstein et al. (2009, 330) state that the most recommended meta-analysis method would require computing of the effect sizes of the variables. They continue that if the studies do not provide enough comprehensive statistical results to compute the effect sizes, then the second best option is to calculate a combined effect of p-values to measure the combined significance of the studies. However, Hunter and Schmidt (2004, 447-448) state, that the method of combining p-values to calculate overall p-value is such problematic and error-prone that the use of it should be avoided. And in addition, Ge and Whitmore (2009) have discovered discrepancies in the evaluation of the level of the significance of the research results when using p-values. They continue that the problems arise when assessing the goodness of statistical model based on logistic regression with binary response. This model happens to be by far one of the most used models in the bankruptcy prediction studies included into the literature review in this thesis work thus further limiting the use of p-values when analysing the collected data.

By considering these issues, the meta-analysis method chosen to be applied in this thesis work is a simple method where the occurrence of the significant variables is calculated to assess their popularity of use. Conducting a more sophisticated meta-analysis is difficult in the context of this work since there are various different bankruptcy prediction models and samples used in the included research studies i.e. the studies lack of the consistency required by sophisticated meta-analysis (Borenstein et al. 2009, 330). In addition, only some of the studies provide a research report with such a comprehensive independent variable specific statistics that allows enough statistical information to carry out a more complex meta-analysis. Thus the analysis in this work is conducted as a statistical summary where significantly positive independent variables measuring the same financial ratio or measure are summed up and the statistical significance of the analysis is assessed.

Borenstein et al. (2009, 3-7) describe that the meta-analysis is essentially used for analyzing the combined effect of the individual studies, rather than on the level of independent variables used in the studies, which is the actual purpose of the analysis in this thesis work. However, there are some studies where meta-analysis is used for analyzing the combined effect of independent variables. Hay et al. (2006) combine the effect of different independent variables affecting audit fee from prior research studies using meta-analysis to assess the combined effect of the p-values of the individual variables. And even though Abt et al. (2014) study is from a field of forestry industry, it shares a lot of methodological characteristics with this work as it evaluates the popularity of independent variables and variable groups used in prior studies where various statistical econometric models such as logistic regression were used for predicting the dependent variable. Abt et al. (2014) use a simple vote-counting based meta-analysis where each of the independent variable significances on the bankruptcy prediction model is assessed by the given p-values of the variables, and the significant variables are summed up to determine the popularity of their occurrence. Their approach is very similar to the meta-analysis method applied in this thesis work.

4.2 Assessing significance of predictor variables

The significance of the independent variables used in the prediction of the bankruptcy is assessed in the meta-analysis by using two methods. First, the significance of the variables is assessed directly by the significance reported in the reviewed study i.e. by variable specific p-value or level of significance given in the study report. In addition to the first method, the second method interprets individual variable's significance by the quality of the selection process of the variables to the final bankruptcy prediction model constructed in the study, as described earlier in the section 3.4.3.

The second method applies to research studies utilizing statistical step-wise selection where the study does not necessarily report the actual statistical significances of the independent variables, but expresses the selection method to be such that it ensures that the best variables are included into the bankruptcy prediction model. For example, Dambolema and Khoury (1980) state in their study that by applying a stepwise discriminant analysis into the selection of the predictor variables, they ensure that variables with maximum predictive power will be derived from a larger pool of variables serving as candidates for being a good predictor for bankruptcy. In addition to statistical step-wise selection, some of the modern methods used in the selection of the predictor variables, such as neural networks and genetic algorithms, can be assumed to produce such a set of predictor variables that has the best possible predictive power. This is because these novel methods are able to include a much more deeper and complex exploratory relationship in bankruptcy prediction between the selected independent variables than the traditional statistical techniques (Back et al. 1996; Chen et al. 2009).

Hence it is assumed that the variables selected to the final bankruptcy prediction model in the studies utilizing statistical step-wise selection or modern method such as neural network or decision trees are significant at conventional levels, thus representing as a valid proxy for bankruptcy prediction (Brezigar-Masten & Masten 2012; Back et al. 1996). The second method is carried out to obtain a wider view of the popularity of the financial variables, since the reviewed bankruptcy prediction studies included relatively large number of studies where the actual statistical significance of the independent variables were not directly reported, but the applied variable selection method was used as a justification to the assumption that the selected variables are the best predictors for bankruptcy.

4.3 Hypothesis development

The following hypotheses are constructed and tested as the theoretical justification and the bankruptcy research literature seem to suggest that the predictor variables that measure financial leverage, liquidity or profitability can be seen as good predictors for bankruptcy.

- H_1: *Liquidity predicts bankruptcy*

  Theory suggests that if a company fails to meet its short-term obligations because of a lack of liquidity, the risk for failure and bankruptcy is increased. The systematic literature review shows that the financial ratios and variables measuring liquidity were the most popularly applied bankruptcy predictors among the reviewed bankruptcy research literature.

- H_2: *Profitability predicts bankruptcy*

  Theory suggests that a company must have adequate profitability in order to keep the value of the company above the amount the company owes its creditors i.e. it must be enough profitable to be able to generate enough earnings to cover the financing costs of the investments, or the risk for failure and bankruptcy is increased. The systematic literature review shows that the financial ratios and variables measuring profitability were the second most popularly applied bankruptcy predictors among the reviewed bankruptcy research literature.

- H_3: *Financial leverage predicts bankruptcy*

  Theory suggests that if the real net worth of the company is negative i.e. company's total liabilities exceed its fair valuation of total assets, the risk for failure and bankruptcy increases thus including long-term solvency measured with financial leverage to the scrutiny. The systematic literature review shows that the financial ratios and variables measuring financial leverage were the third most popularly applied bankruptcy predictors among the reviewed bankruptcy research literature.

In addition, the hypotheses H_4, H_5 and H_6 are constructed to supplement the above hypotheses by including direction to the hypotheses. The theoretical justification for these hypotheses follow the above hypotheses, but these hypotheses H_4, H_5 and H_6 are refined by including the hypothesized direction of the change in the probability of bankruptcy by the change in the predictor variable's value, depending on which category the variable is included. The hypothesized effects of the changes in the values on the probability of bankruptcy are described in the table 11.

Category	*Change in value of the predictor variable included into the category*	*Expected effect on probability for bankruptcy*
Liquidity	Liquidity increases	Decreases
	Liquidity decreases	Increases
Profitability	Profitability increases	Decreases
	Profitability decreases	Increases
Financial leverage	Financial leverage increases	Increases
	Financial leverage decreases	Decreases

Table 11: Expected effects on probability for bankruptcy

By following the rules described in the table 11, the following hypotheses, H_4, H_5 and H_6 are constructed:

- H_4: *Lower liquidity increases the probability of bankruptcy*
- H_5: *Lower profitability increases the probability of bankruptcy*
- H_6: *Higher financial leverage increases the probability of bankruptcy*

The hypotheses $H_{4,}$ H_5 and H_6 are tested separately by using a sign test on a reduced dataset as the original dataset including all the predictor variables collected from the reviewed bankruptcy prediction studies contains a smaller amount of such studies in which the information of the coefficients or signs of the independent variables is included.

4.4 Statistical tests

Statistical tests were conducted using R-language which is a programming language and software environment for statistical computing, and is widely used among statisticians and data miners for developing data analysis (Andersen & Fox 2005). The software environment used in the analysis was R version 3.1.1 for 64-bit Microsoft Windows operating systems. An additional gmodels-package (version 2.15.4.1) was installed into the R software environment to include CrossTable-function necessary for the analysis. The CrossTable -function is the same function as statistical software SAS's Proc Freq -function and statistical software SPSS's Crosstabs -function.

4.4.1 Predictor variable category frequencies

The significance and the category of all of the 697 predictor variables collected from the reviewed studies were determined following the principles described earlier in section 4.2, and with the category of the variable as a list. The number of significant and insignificant variables by categories is summarized into the table 12. The frequencies of the categories are expressed in percentages in parenthesis in the table.

Category	*Total count*	*Significant*	*Insignificant*
Liquidity	233 (33,4 %)	159 (34,4 %)	74 (31,5 %)
Profitability	165 (23,7 %)	112 (24,2 %)	53 (22,6 %)
Financial leverage	117 (16,8 %)	85 (18,4 %)	32 (13,6 %)
Activity	81 (11,6 %)	36 (7,8 %)	45 (19,1 %)
Non-financial	43 (6,2 %)	27 (5,8 %)	16 (6,8 %)
Other financial	27 (3,9 %)	20 (4,3 %)	7 (3,0 %)
Size	25 (3,6 %)	19 (4,1 %)	6 (2,6 %)
Unidentified	6 (0,9 %)	4 (0,9 %)	2 (0,9 %)
Totals	*697*	*462*	*235*

Table 12: Number of significant and insignificant predictor variables by categories

A chi-squared test of independence was conducted to assess if there exists a statistical dependence between the different predictor variable categories and their significances, and to use the observed frequencies of the predictor variable categories to determine the expected frequencies of the categories. The chi-squared test of independence is seen suitable for the collected data since it consists of categorical variable where the observations are independent of each other (Carlson et al. 2007, 622-625). The category "Unidentified" was removed from the analysis since the category consists of predictor variables which function could have been not be reliably identified, and the observed frequency of the category in both significant and insignificant variables might violate the rule that the expected frequency of the group should be at least five to get reliable results with chi-squared approximations.

The data was imported into R from csv-file which included a row for each predictor variable with its category and significance. Significances were recorded to the csv-file by using binary variable which gave value 1 for significant and value 0 for insignificant variable. A contingency table was constructed in R from the imported predictor variable categories and their significances, and the Pearson's chi-squared test on the contingency table data was conducted. The expected frequencies for each category as a result from the chi-squared test are shown on the table 13.

Category	*Expected frequency* *Significant*	 *Insignificant*	 *% of totals*	*Significance (p-value)* *Chi-squared test*	 *Exact binomial test*
Liquidity	154,4	78,6	33,7 %	0,0001 ***	0,0001 ***
Profitability	109,4	55,6	23,9 %	0,0001 ***	0,0001 ***
Financial leverage	77,5	39,5	16,9 %	0,0001 ***	0,0001 ***
Activity	53,7	27,3	11,7 %	0,3173	0,3742
Non-financial	28,5	14,5	6,2 %	0,0935 *	0,1263
Other financial	17,9	9,1	3,9 %	0,0124 **	0,0192 **
Size	16,6	8,4	3,6 %	0,0093 ***	0,0146 **
Totals	*458*	*233*			

* Significant at the 10 % level
** Significant at the 5 % level
*** Significant at the 1 % level

Table 13: Results of significance of predictor variables by categories

The chi-squared test results in R reported a very small overall p-value of 0,0012 for statistics for all factors on the contingency table. This provides strong evidence to reject the null hypothesis of no association between the predictor variable categories and their significances thus it can be stated that the number of variables significantly differs between categories. The frequencies of the categories provide evidence that the most popular variables for bankruptcy prediction are in categories liquidity, profitability and financial leverage.

4.4.2 Predictor variable category significances

To assess the significance of the individual predictor variable categories, chi-squared tests were conducted for each category with R. The test was performed using the same contingency table data as in the test described in the previous section 4.4.1., which included the number of significant and insignificant variables for each category. In addition, exact binomial test on the individual predictor variable categories were conducted as the sample size might not be enough large to obtain absolutely reliable results by using the chi-squared test (Carlson et al. 2007, 623). The exact binomial test was also conducted using the same data described in the previous section 4.4.1.

Results from the both of these tests are shown on the table 13 where the p-values for each category from both, chi-squared test and exact binomial test are listed. A p-value of 0,0001 in the table 13 expresses the actual p-value reported in the test results being at the most 0,0001. The results shows that both, chi-squared test and exact binomial test produce similar results, and the results provide significant support for the hypotheses H_1, H_2 and H_3 as it is evident that the majority of the variables in the categories liquidity, profitability and financial leverage are significant and can be thus seen as a good predictors for bankruptcy.

4.4.3 Tests with divided datasets

By the systematic literature review it can be seen that the most of the bankruptcy research studies are U.S. based. To test the sensitivity of the study country being U.S. or non-U.S. to the results, an additional analysis was conducted on a divided datasets, from which the first included only studies that were originated in the U.S. and the second studies from the other countries than the U.S. In addition, the full dataset was divided into the other two datasets by the year of publication, so that the first dataset included studies published before year 2000 and the second studies published on year 2000 and after that. This division was performed to test the effect of the publication year, as it can be seen from the prior research literature that the utilization of the modern bankruptcy prediction models in the bankruptcy prediction emerged during the turn of the century, thus increasing the complexity of the bankruptcy prediction model development and probably affecting the popularity of the type of the financial variables utilized in the bankruptcy prediction.

The analyses on these divided datasets were conducted with R using Fisher's exact test of independence on the contingency tables constructed from each of the divided dataset, and exact binomial test on the individual predictor variable categories included into each of the divided dataset. These tests were used since the frequencies of some of the financial variable categories in the divided datasets were so small that using chi-squared tests would have generated unreliable chi-squared approximations.

Both of these analyses with the divided datasets show that the results are similar compared to the results obtained with the full dataset. The frequencies of the financial variable categories show that again, the financial variables measuring liquidity, profitability and financial leverage are the most popular ones. However, the results of these analyses were not as significant as for the full dataset. The results of the Fisher's exact test of independence for the divided datasets with the first containing U.S. based and the second containing non-U.S. based studies were significant only at 10 % level. For the other two datasets with the first including studies published before year 2000 and the second from that on, the results were significant at 5 % level. The tests by variable categories show that the number of significant variables in the categories liquidity, profitability and financial leverage was statistically as significant for the divided datasets as for the full dataset. However, for the dataset including predictor variables only from year 2000 and from that on, the result was significant only at 10 % level for the liquidity category though for the profitability and financial leverage categories in the dataset, the result was significant at least on a 5 % level. The results from these tests with the divided datasets indicates, that even though the statistical power decreases as the number of observations decrease, the results are rather consistent with the test results obtained with the full dataset.

4.4.4 Sign test by predictor variable categories

To test the hypotheses H_4, H_5 and H_6 a sign test was conducted. The test was carried out by using a dataset where the sign of each predictor variable were included in the data. However, only some of the research studies included into the systematic literature review reported information of the sign of the independent variables, so the dataset were first reduced to include only predictor variables with information of the sign of the variable. These variables were collected from studies where linear regression, logit or probit -model was applied as a bankruptcy prediction model, and the regression coefficients or signs of the independent variables were reported in detail.

The dataset were further reduced to include only variables which were seen significant by the study and which were from categories liquidity, profitability and financial leverage. In addition, there were also inconsistencies between individual variables' signs in some of the studies when the prediction model was applied to a different sample for example when predicting bankruptcy for different years, although each of the variables were seen significant (see for example Zavgren 1985; Becchetti & Sierra 2003; Hensher & Jones 2004). Thus predictor variables from these studies were also excluded from the reduced dataset because the sign of these variables could not have been unambiguously determined for the sign test.

In addition, the dataset were modified so that the sign reported for each predictor variable express its effect on bankruptcy probability so that a positive sign (+) was entered for the variable if the effect found in the study were positive i.e. the probability for bankruptcy decreases, and negative (-) if the probability for bankruptcy increases. The selecting of the sign for the predictor variables followed the principles shown earlier in the section 4.3 in the table 11. For some of the studies the original signs reported in the study were reversed because the dependent variable in the model constructed in the study was such that the higher value of the dependent variable indicated a lower bankruptcy probability (see for example Derwall & Verwijmeren 2010).

In total, the reduced dataset containing predictor variables with their category and sign included 131 significant variables. From these, 19 variables were such that the sign obtained from the study were in conflict with the expected sign determined by considering the theoretical aspects presented earlier in the section 2. For example, Graybeal et al. (1996) found out in their study that one of their variables measuring liquidity: current assets to total assets, is significant in predicting bankruptcy but the sign of the coefficient of the variable in their study was positive i.e. the increase in the value of the financial ratio measuring liquidity increases the probability for bankruptcy. However, the hypothesis H_4 suggests that the higher liquidity should decrease the risk for bankruptcy. And as the higher relative amount of current assets should increase liquidity, the variable could be associated with a negative expected sign which was used also for the sign test in this thesis work.

The results from the sign test using one-tailed exact binomial test conducted by R are shown in the table 14. Exact binomial test were used since the sample size of the reduced dataset was relatively small and the frequencies in some of the categories were low. A p-value of 0,0001 in the table 14 expresses the actual p-value reported in the test results being at the most 0,0001.

Category	*Number of negative variables*	*Number of positive variables*	*p-value*
Liquidity	5	38	0,0001 ***
Profitability	4	43	0,0001 ***
Financial leverage	10	31	0,0007 ***

*** Significant at the 1 % level

Table 14: Results from the sign test by categories

The results of the exact binomial test in the table 14 provide significant support for the hypotheses H_4, H_5 and H_6. By the results it is evident that the effects of the change of the value in the majority of the variables in the categories liquidity, profitability and financial leverage significantly follow the hypothesized direction. That is, a change in the predictor variable value causes a change in the expected direction in the probability of bankruptcy.

5 Discussion and conclusions

5.1 Discussion

The objective of this thesis work was to synthesize the prior research literature on bankruptcy prediction to find out which kind of variables are used as a proxy for financial distress, firm failure and bankruptcy. This study aggregated the number of different predictor variables included in the bankruptcy prediction models developed in the prior research literature, and classified the predictor variables by their financial function. The popularity of these classification categories was then assessed and theories on financial distress, firm failure and bankruptcy were studied to seek theoretical justification for the popularity of the categories.

The theories on firm failure and bankruptcy point out that there are a variety of factors from economy-wide macroeconomic factors to firm-specific factors that are affecting the bankruptcy risk of a firm. The systematic literature review was conducted in this thesis work to seek understanding on which kind of measures are used for assessing the effect of these factors to the bankruptcy risk and thus seem as suitable variables for predicting bankruptcy. This study provides significant evidence that financial ratios measuring firm specific financial information are the most popularly applied predictor variables in the bankruptcy prediction. Especially ratios measuring profitability, liquidity and financial leverage were found out to be significantly the most popular ones. The theoretical scrutiny of theories on firm failure and bankruptcy seems to give support for using of the bankruptcy predictor variables measuring functions in categories profitability, liquidity and financial leverage as there are elementary theories in which central are cash flow financing and its sufficiency on financial obligations, and the role of profitability as an operational precondition for all healthy business.

The refined analysis conducted in this study on the direction of the change in the bankruptcy risk by the change in the single financial measures in the categories profitability, liquidity and financial leverage provide additional support to the application of these financial ratios into the bankruptcy prediction. The results of the analysis show that the directions significantly follow the hypothesized directions constructed on the basis of the theoretical justification. However, there was some inconsistency between the studies in the directions of the effect of the single predictor variables on the bankruptcy risk. For example in five of the analyzed studies, some of the financial ratios measuring financial leverage by determining the relation between equity and debt, were found out to affect contrary to the hypothesized direction by which the increase in financial leverage should increase the risk for bankruptcy. The hypothesized direction is of course arguable, since for example a firm with a very poor business case might be unable to obtain debt financing to its investments because of the difficulties in convincing the lenders to take the risk, thus leading to situation where the firm has little or none debt at all. Hence it could be argued that in this case the lower financial leverage increases the risk for bankruptcy. However, in order to see the whole financial situation in relation to the bankruptcy risk, also other financial factors such as profitability should be observed. The research literature states that the use of financial ratios in bankruptcy prediction is seen less useful if they are not used together. This can be noticed from the reviewed studies as the prediction models developed in the studies are, excluding one univariate model by Beaver (1966), based on multiple various predictor variables measuring different financial functions thus observing the financial conditions of a firm with a wider view.

Many of the prior bankruptcy prediction studies have examined the use of various different predictor variables such as macroeconomic and non-financial variables. However it is questionable what is the contribution of these variables as they seem to be very often used in combination with the most popularly used financial ratios. The reasons for the unpopularity of using other than financial ratios is probably since the prior bankruptcy prediction research seems to be highly focused on the empirical bankruptcy prediction models where the predictor variable selection process is usually based on the popularity and predictive ability of the financial ratios in prior studies. As the seminal work on bankruptcy prediction was conducted by using statistical models with financial ratios as predictor variables, these variables were often inherited to the subsequent studies thus reducing the existence of other than financial ratios in the bankruptcy prediction research studies.

The use of macroeconomic variables were suggested by some researchers as for example global financial problems were seen to create the distinguishing between failing and non-failing firms more difficult. The lower popularity for using macroeconomic variables as a predictors of bankruptcy might be due to the fact that firm-specific factors such as financial ratios determined from accounting information were seen as the most important, as the theories on firm failure and bankruptcy sees that endogenous factors are the most critical ones causing financial distress. In that way a bankruptcy risk can be seen as an unsystematic risk. However, for example Lang and Stulz (1992) argue that the bankruptcy risk includes a systematic risk as they describe that a bankruptcy of a firm has a contagion effect to the other firms on the industry, but they state that a firm-specific financial leverage though has an import influence into the firm-specific bankruptcy risk.

When comparing the results of this study to similar work and their findings, Courtis (1978) also found out that in the prior research literature, among the single financial ratios, two financial ratios with other measuring liquidity and the other financial leverage, were mostly seen usable in the bankruptcy prediction. In addition, Courtis describes that financial ratios measuring profitability were also ranked high in compared to the rest of the categories. Dimitras et al. (1996) studied the bankruptcy prediction models and the popularity of the individual financial ratios included in the models from 47 prior research studies focused on developing bankruptcy prediction for manufacturing and retail firms. They found out that the five most frequently used financial ratios in bankruptcy prediction, when classified into the variable categories constructed in this study, were in order by popularity measuring liquidity, profitability and financial leverage which is identical to the findings in this thesis work. In addition, Dimitras et al. (1996) assessed the popularity of the different techniques and models applied into the bankruptcy prediction, and found out that the most frequently used by far were traditional statistical discriminant analysis and logit regression, which is similar to the findings in this work and corresponds also to the findings made by Aziz and Dar (2006) in their summary work on popularity and prediction accuracy of the different bankruptcy prediction techniques and models.

5.2 Conclusions

As a summary it could be concluded that even though there are various methods developed to the bankruptcy prediction, they still are mostly based on assessing accounting-based information using financial ratios. The lack of common theories on selecting the suitable financial ratios for the bankruptcy prediction seems to be compensated with the empirical findings from a vast pool of existing research literature that is commonly used as a starting point when developing new prediction models. This seems to be one of the main reasons why most of the studies end up utilizing quite similar variables measuring financial functions. These financial functions, mainly short-term and long-term solvency, and profitability, can be also recognized in common theories for firm failure and bankruptcy thus providing justification why measures of these functions are popularly applied into the bankruptcy prediction. However, the literature review revealed that the field of bankruptcy prediction research has still controversies of the models and predictor variables that are seen as the most suitable for bankruptcy prediction.

The question of how much the bankruptcy prediction accuracy would be improved by developing a robust, generally accepted theory to serve as a foundation for selecting the suitable predictor variables, or using a more sophisticated prediction model with more diversity in the predictor variables, is partly answered by findings from Akers et al. (2007) summary study on bankruptcy prediction studies from 1970 to 2000. Akers et al. found out that even though modern models utilizing sophisticated techniques such as genetic algorithms, has been recently applied into the bankruptcy prediction, the predictive accuracy of the prediction models is not significantly increased. It is arguable that if this is because the methodological foundation and the selection process of the predictor variables seem to be mostly derived from the prior studies. However, Akers et al. (2007) state that despite of the differences in the bankruptcy prediction models and predictor variables included in them, most of the models still show high predictive ability.

The rapid development of information technology, the evolution of business analytics, and dramatically increased amount of data collected and stored to computer systems will affect more and more the environment on which businesses operate. Novel and sophisticated technologies are developed to enable effective data mining and analytics from this rapidly expanding and vast information often referred as “Big Data” (Friess & Vermesan 2013). As this thesis work shows, these technologies have been already applied into the field of bankruptcy prediction for example in a form of using neural networks and genetic algorithms. There is no doubt that the evolution of the bankruptcy prediction will benefit and employ the rapid information technology development, and that in the future we will see a more real-time and accurate bankruptcy prediction and early-warning systems which incorporate use of a much more various and complex information, than only the financial ratios, in forecasting and preventing firm failures and bankruptcies.

5.3 Limitations of the study

From the systematic literature review conducted in this thesis work it can be noticed, that even though there are a vast number of bankruptcy prediction studies available, most of them are originated in U.S. and thus use U.S. companies as their sample for developing and testing the bankruptcy prediction models. In addition, many studies use publicly listed companies in their sample since the financial data for those are much easier to collect than for private and smaller companies. This might restrict the fact that how generalizeable the results are globally. Dimitras et al. (1996) study shows that there are some differences in the use of different predictor variables between the countries, but still the most popular ones were mostly all included in the prediction model regardless of the country.

The search for the studies included into the systematic literature review was conducted from well-recognized scientific journals. However, there is a possibility that some of the potential research studies are left out from the review since there might have been prior studies with some significant findings especially on the predictive ability of the individual predictor variables included into the bankruptcy prediction model, but due to the publication bias, the study was not published as its overall significance was not seen sufficient enough.

In this thesis work, the determination of the financial variable categories for classifying the predictor variables into categories by their financial function was constructed by considering the theoretical foundation related to the subject. However, establishing the categories and the classification of the variables in them include some subjective perception specific to this thesis work. To address this, the number and variety of categories were experimented by using a higher number of refined categories which were focusing on a narrower financial function. However, this analysis revealed that the category sizes with narrower focus would have been such small, that it would have impeded the comparative analysis of the data and the interpretation of the results. In addition, the classification of the variables into the financial function categories required some subjective discretion, but was always conducted by trying to justify the decision on the theoretical basis. Similar sensitivity analysis on the classification of the predictor variables to categories, as for the level of refinement of the categories, were made and the differences between the results were not seen to be significant as there were only few predictor variables which might have been allocated to a more than one category.

The meta-analysis on the systematic literature review findings in this thesis work was conducted with simple meta-analysis method by assessing only the number and significance of the predictor variables collected from the reviewed studies. In addition, a more detailed analysis using sign test was done on a reduced data sample restricted by the lack of detailed statistical data in some of the studies. It has been argued in the research literature focusing on meta-analysis methods that the analysis should be most preferable conducted by using such a sophisticated method that would consider the computing of the effect sizes of the results.

However, as described more in detail earlier in the section 4.1, the methodology differences in the prediction models of bankruptcy prediction studies and the limited reporting of statistical results prevented the use of a more sophisticated meta-analysis method in this thesis work.

6 References

Abt, R., Bardon, R., Coulston, J., Cubbage, F., Jeuck, J., McCarter, J., & Renkow, M. (2014). Assessing Independent Variables Used in Econometric Modeling Forest Land Use or Land Cover Change: A Meta-Analysis. Forests, Vol. 5 (2014), 1532-1564.

Agarwal, V, & Bauer, J. (2013). Are hazard models superior to traditional bankruptcy prediction approaches? A comprehensive test. Journal of Banking and Finance, Vol. 40 (2014), 432–442.

Agarwal, A., Barniv, R., & Leach, R. (2002). Predicting Bankruptcy Resolution. Journal of Business Finance and Accounting, Vol. 29, No. 3 & 4 (2002), 497-520.

Akers, M., Bellovary, J., & Giacomino, D. (2007). A Review of Bankruptcy Prediction Studies: 1930-Present. Journal of Financial Education, Vol. 33 (2007), 1-42.

Alfaro, E., Elizondo, D., Garcia, N., & Gamez, M. (2007). Bankruptcy forecasting: An empirical comparison of AdaBoost and neural networks. Decision Support Systems, Vol. 45 (2008), 110–122.

Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance, Vol. 23, No. 3 (1968), 589-609.

Altman, E. (1983). Why businesses fail. Journal of Business Strategy, Vol. 3, Issue 4 (1983), 15-21.

Altman, E. (1993). Corporate financial distress and bankruptcy: a complete guide to predicting & avoiding distress and profiting from bankruptcy. 2nd edition. USA, NJ: John Wiley & Sons, Inc.

Altman, E., Frydman, H., & Kao, D-L. (1985). Introducing Recursive Partitioning for Financial Classification: The Case of Financial Distress. Journal of Finance, Vol. 40, No. 1 (1985), 269-291.

Altman, E., Haldeman, R., & Narayanan, P. (1977). ZETA analysis: A new model to identify bankruptcy risk of corporations. Journal of Banking and Finance, Vol. 1 (1977), 29-54.

Andersen, R., & Fox, J. (2005). Using the R Statistical Computing Environment to Teach Social Statistics Courses. Department of Sociology, McMaster University. Available at: http://www.unt.edu/rss/Teaching-with-R.pdf [Read 25.2.2015].

Antes, G., Khan, K., Kleijnen, J., & Kunz, R. (2003). Five steps to conducting a systematic review. Journal of the Royal Society of Medicine. Vol. 96, No. 3 (2003), 118–121.

Argenti, J. (1976a). Corporate Planning and Corporate Collapse. Long Range Planning, Vol. 9, Issue 6 (1976), 12-17.

Argenti, J. (1976b). Corporate Collapse: The Causes and Symptoms. UK, London: McGraw-Hill Book Company Ltd.

Aziz, M., & Dar, H. (2006). Predicting corporate bankruptcy: where we stand? Corporate Governance: The international journal of business in society, Vol. 6, Issue 1 (2006), 18-33.

Aziz, A., Emanuel, D., & Lawson, G. (1988). Bankruptcy prediction - An investigation of cash flow based models. Journal of Management Studies, Vol. 25, No. 5 (1988), 419-437.

Back, P. (2001). Testing Liquidity Measures as Bankruptcy Prediction Variables. The Finnish Journal of Business Economics, Issue 3 (2001), 309-327.

Back, B., Laitinen, T., & Sere, K. (1996). Neural Networks and Genetic Algorithms for Bankruptcy Predictions. Expert Systems with Applications, Vol. 11, No. 4 (1996), 407-413.

Beaver, W. (1966). Financial ratios as predictors of failure. Journal of Accounting Research, Vol. 4, (1966), 71-111.

Beaver, W., Correia, M. & McNichols, M. (2012). Do differences in financial reporting attributes impair the predictive ability of financial ratios for bankruptcy? Review of Accounting Studies, Vol. 17 (2012), 969-1010.

Beaver, W., McNichols, M., & Rhie, J-W. (2005). Have Financial Statements Become Less Informative? Evidence from the Ability of Financial Ratios to Predict Bankruptcy. Review of Accounting Studies, Vol. 10 (2005), 93–122.

Becchetti, L., & Sierra, J. (2003). Bankruptcy risk and productive efficiency in manufacturing firms. Journal of Banking and Finance, Vol. 27 (2003), 2099-2120.

Bessler, D., Leatham, D., & Zhang, J. (2013) Aggregate business failures and macroeconomic conditions: A var look at the U.S. between 1980 and 2004. Journal of Applied Economics, Vol. 16, No. 1 (2013), 179-202.

Betts, J., & Belhuol, D. (1987). The effectiveness of incorporating stability measures in company failure models. Journal of Business Finance and Accounting, Vol. 14, No. 3 (1987), 323-334.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. Journal of Political Economy, Vol. 81, No. 3 (1973), 637–654.

Booth, P. (1983). Decomposition measures and the prediction of financial failure. Journal of Business Finance and Accounting, Vol. 10, No. 1 (1983), 67-82.

Borenstein, M., Hedges, L., & Higgins, J. (2009). Introduction to Meta-Analysis. USA, NJ: John Wiley & Sons, Inc.

Borkowski, S. (1996). An Analysis (Meta-and Otherwise) of Multinational Transfer Pricing Research. The International Journal of Accounting, Vol. 31, No. 1 (1996), 39-53.

Brezigar-Masten, A., & Masten, I. (2012). CART-based selection of bankruptcy predictors for the logit model. Expert Systems with Applications, Vol. 39 (2012), 10153-10159.

Campbell, J., Hilscher, J., & Szilagyi, J. (2008). In Search of Distress Risk. Journal of Finance, Vol. 63, No. 6 (2008), 2899-2939.

Carlson, W., Newbold, P., & Thorne, B. (2007). Statistics for Business and Economics, 6th edition. USA, NJ: Pearson Education, Inc.

Castanias, R. (1983). Bankruptcy Risk and Optimal Capital Structure. The Journal of Finance, Vol. 38, No. 5 (1983), 1617-1635.

Chen, H-J., Huang, S., & Lin, C-S. (2009). Alternative diagnosis of corporate bankruptcy: A neuro fuzzy approach. Expert Systems with Applications, Vol. 36 (2009), 7710–7720.

Chen, M-Y. (2011). Bankruptcy prediction in firms with statistical and intelligent techniques and a comparison of evolutionary computation approaches. Computers and Mathematics with Applications, 62 (2011), 4514-4524.

Chen, N., Ribeiro, B., Vieira, A., & Chen, A. (2013). Clustering and visualization of bankruptcy trajectory using self-organizing map. Expert Systems with Applications, Vol. 36 (2009), 7710–7720.

Cho, S., Hong, H., & Ha, B-C. (2010). A hybrid approach based on the combination of variable selection using decision trees and case-based reasoning using the Mahalanobis distance: For bankruptcy prediction. Expert Systems with Applications, Vol. 37 (2010), 3482–3488.

Choi, W., & Lee, S. (2013). A multi-industry bankruptcy prediction model using back-propagation neural network and multivariate discriminant analysis. Expert Systems with Applications, Vol. 40 (2014), 2941–2946.

Ciampi, F. (2014). Corporate governance characteristics and default prediction modeling for small enterprises. An empirical analysis of Italian firms. Journal of Business Research, Vol. 68, Issue 5 (2015), 1012–1025.

Courtis, J. (1978). Modelling a financial ratios categoric framework. Journal of Business Finance and Accounting, Vol. 5, No. 4 (1978), 371-386.

Cram, D., Hillegeist, S., Keating, E., & Lundstedt, K. (2004). Assessing the Probability of Bankruptcy. Review of Accounting Studies, Vol. 9 (2004), 5–34.

Dambolema, I., & Khoury, S. (1980). Ratio Stability and Corporate Failure. The Journal of Finance, Vol. 35, No. 4 (1980), 1017-1026.

Deakin, E. (1972). A Discriminant Analysis of Predictors of Business Failure. Journal of Accounting Research, Vol. 10, No. 1 (1972), 167-179.

Delen, D., Sharda, R., & Turban, E. (2011). Decision Support and Business Intelligence Systems. 9th edition. USA, NJ: Pearson Education, Inc.

Derwall, J., & Verwijmeren, P. (2010). Employee well-being, firm leverage, and bankruptcy risk. Journal of Banking and Finance, Vol. 34 (2010), 956-964.

Dichev, I. (1998). Is the Risk of Bankruptcy a Systematic Risk? The Journal of Finance, Vol. 53, No. 3 (1998), 1131-1147.

Dimitras, A., Zanakis, S., & Zopounidis, C. (1996). A survey of business failures with an emphasis on prediction methods and industrial applications. European Journal of Operational Research, Vol. 90 (1996), 487-513.

Dimitras, A., Slowinski, R., Susmaga, R., & Zopounidis, C. (1999). Business failure prediction using rough sets. European Journal of Operational Research, Vol. 114 (1999), 263-280.

Donoher, W. (2004) To File Or Not To File? Systemic Incentives, Corporate Control, and the Bankruptcy Decision. Journal of Management, Vol. 30, No. 2 (2004), 239–262.

du Jardin, P., & Severin, E. (2011). Predicting corporate bankruptcy using a self-organizing map: An empirical study to improve the forecasting horizon of a financial failure model. Decision Support Systems, Vol. 51 (2011), 701–711.

Edmister, R. (1972). An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction. The Journal of Financial and Quantitative Analysis, Vol. 7, No. 2 (1972), 1477-1493.

Fabozzi, F., Fabozzi, D., & Peterson, P. (2010) Basics of Finance: An Introduction to Financial Markets, Business Finance, and Portfolio Management. USA, NJ: John Wiley & Sons.

Friess, P., & Vermesan, O. (2013). Internet of Things: Converging Technologies for Smart Environments and Integrated Ecosystems. Denmark, Aalborg: River Publishers.

Ge, W., & Whitmore G. A. (2009) Binary response and logistic regression in recent accounting research publications: a methodological note. Review of Quantitative Finance and Accounting, Vol. 34, No. 1 (2010), 81-93.

Gordini, N. (2014). A genetic algorithm approach for SMEs bankruptcy prediction: Empirical evidence from Italy. Expert Systems with Applications, Vol. 41 (2014), 6433–6445.

Graybeal, P., Kane, G., & Richardson, F. (1996). Recession-Induced Stress and the Prediction of Corporate Failure. Contemporary Accounting Research, Vol. 13, No. 2 (1996), 631-650.

Gryglewicz, S. (2011). A theory of corporate financiald ecisions with liquidity and solvency concerns. Journal of Financial Economics, Vol. 99 (2011), 365–384.

Hall, G. (1994). Factors distinguishing survivors from failures amongst small firms in the UK construction sector. Journal of Management Studies, Vol. 31, No. 5 (1994), 737-760.

Hay, D., Knechel, W., & Wong, N. (2006). Audit Fees: A Meta-analysis of the Effect of Supply and Demand Attributes. Contemporary Accounting Research, Vol. 23, No. 1 (2006), 141-191.

Hensher, D. & Jones, S. (2004). Predicting Firm Financial Distress: A Mixed Logit Model. The Accounting Review, Vol. 79, No. 4 (2004), 1011-1038.

Hite, P. (1987). An Application of Meta-Analysis for Bankruptcy Prediction Studies. Organizational behavior and human decision processes, Vol. 39 (1987), 155-161.

Horrigan, J. (1968). A Short History of Financial Ratio Analysis. The Accounting Review. Vol. 43, Issue 2 1968, 284-294.

Hunter, J., & Schmidt, F. (2004). Methods of Meta-Analysis: Methods of Integrating Findings Across Studies and Related Software. USA, CA: SAGE Publications, Inc.

Jackson, R. H.G., & Wood, A. (2013). The performance of insolvency prediction and credit risk models in the UK: A comparative study. The British Accounting Review, Vol. 45 (2013), 183–202.

Ji, G., Yang, Z., & You, W. (2011). Using partial least squares and support vector machines for bankruptcy prediction. Expert Systems with Applications, Vol. 38 (2011), 8336–8342.

Jordan, B., Ross, S., & Westerfield, R. (2008). Corporate finance fundamentals: International student edition. 8th edition. USA, NY: The McGraw-Hill Companies, Inc.

Karels, G., & Prakash, A. (1987). Multivariate normality and forecasting of business bankruptcy. Journal of Business Finance and Accounting, Vol. 14, No. 4 (1987), 573-593.

Kim, H-J., Lee, T., & Shin, K-S. (2005). An application of support vector machines in bankruptcy prediction model. Expert Systems with Applications, Vol. 28 (2005), 127–135.

Konkurssilaki 120/2004. (2004). Finlex. Available at: http://www.finlex.fi/fi/laki/ajantasa/2004/20040120 [Read 3.4.2015].

Kurokawa, Y., & Takahashi, K. (1984). Corporate bankruptcy prediction in Japan. Journal of Banking and Finance, Vol. 8, Issue 2 (1984), 229-247.

Laakso, T., Laitinen, E., & Vento, H. (2010). Uhkaava maksukyvyttömyys ja onnistunut yrityssaneeraus. Helsinki: Talentum Media Oy.

Laitinen, E., & Laitinen, T. (1998). Cash management behavior and failure prediction. Journal of Business Finance and Accounting, Vol. 25. No. 7 & 8, 893-920.

Lang, H., & Stulz, R. (1992). Contagion and competitive intra-industry effects of bankruptcy announcements. Journal of Financial Economics, Vol. 32 (1992), 45-60.

Lee, Y-J., & Shin, K-S. (2002). A genetic algorithm application in bankruptcy prediction modeling. Expert Systems with Applications, Vol. 23, No. 3 (2002). 321-328.

Lincoln, M. (1984). An empirical study of the usefulness of accounting ratios to describe levels of insolvency risk. Journal of Banking and Finance, Vol. 8 (1984), 321-340.

Mensah, Y. (1983). The Differential Bankruptcy Predictive Ability of Specific Price Level Adjustments: Some Empirical Evidence. The Accounting Review, Vol. 58, No. 2 (1983), 228-246.

Mensah, Y. (1984). An Examination of the Stationarity of Multivariate Bankruptcy Prediction Models: A Methodological Study. Journal of Accounting Research, Vol. 22, No. 1 (1984), 380-395.

Merton, R. (1974). On the pricing of corporate debt: the risk structure of interest rates. Journal of Finance, Vol. 29, No. 2 (1974), 449–470.

Mills, J.,& Yamamura, J. (1998). The power of cash flow ratios. Journal of Accountancy, October (1998), 53-61.

MTV Uutiset - STT (2014). Vapaavuori: Valtio menettää Talvivaaran konkurssissa 200 miljoonaa. Published 6.11.2014. Available at: http://www.mtv.fi/uutiset/kotimaa/artikkeli/vapaavuori-valtio-ottaa-tilanteen-haltuun-valittomasti/4484238 [Read 16.1.2015].

Norton, C., & Smith, R. (1979). A Comparison of General Price Level and Historical Cost Financial Statements in the Prediction of Bankruptcy. The Accounting Review, Vol. 54, No. 1 (1979), 72-87.

Ohlson, J. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. Journal of Accounting Research, Vol. 18, No. 1 (1980), 109-131.

Opler, T., & Titman, S. (1994). Financial Distress and Corporate Performance. The Journal of Finance, Vol. 49, No. 3 (1994), 1015-1040.

Petersen, C., & Plenborg, T. (2012). Financial statement analysis: valuation, credit analysis and executive compensation. England: Pearson Education Limited.

Petticrew, M., & Roberts, H. (2006). Systematic reviews in the social sciences: a practical guide. USA, MA: Blackwell Publishing Ltd.

Platt, H., & Platt, M. (1990). Development of a class of stable predictive variables: the case of bankruptcy prediction. Journal of Business Finance and Accounting, Vol. 17, No. 1 (1990), 31-51.

Prihti, A. (1975). Konkurssin ennustaminen taseinformaation avulla. Helsinki: Painomies Oy.

Ravi, P., & Ravi, V. (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques – A review. European Journal of Operational Research, Vol. 180 (2007), 1-28.

Rushinek, A., & Rushinek, S. (1987). Using financial ratios to predict insolvency. Journal of Business Research, Vol. 15 (1987), 93-100.

Scott, J. (1981). The probability of bankruptcy: A comparison of empirical predictions and theoretical models. Journal of Banking and Finance, Vol. 5 (1981), 317-344.

Singhal, R, & Zhu, Y. (2013). Bankruptcy risk, costs and corporate diversification. Journal of Banking and Finance, Vol. 37 (2013), 1475–1489.

Taffler, R. (1984). Empirical models for the monitoring of UK corporations. Journal of Banking and Finance, Vol. 8 (1984), 199-227.

Theodossiou, P. (1991). Alternative models for assessing the financial condition of business in Greece. Journal of Business Finance and Accounting, Vol. 18, No. 5 (1991), 697-720.

Tilastokeskus (2014). Konkurssit 2013, joulukuu. Helsinki. Available at: http://tilastokeskus.fi/til/konk/2013/12/konk_2013_12_2014-01-29_tie_001_fi.html [Read 23.11.2014].

Tseng, F-M., & Hub, Y-C. (2010). Comparing four bankruptcy prediction models: Logit, quadratic interval logit, neural and fuzzy neural networks. Expert Systems with Applications, Vol. 37 (2010), 1846-1853.

Ward, T. (1994). An empirical study of the incremental predictive ability of beaver's naive operating flow measure using four state ordinal models of financial distress. Journal of Business Finance and Accounting, Vol. 21, No. 4 (1994), 547-561.

van der Wijst, N. & Westgaard, S. (2001). Default probabilities in a corporate bank portfolio: A logistic model approach. European Journal of Operational Research, Vol. 135 (2001), 338-349.

Wruck, K. (1990). Financial distress, reorganization, and organizational efficiency. Journal of Financial Economics, Vol. 27, Issue 2 (1990), 419-444.

Xu, M., & Zhang, C. (2008). Bankruptcy prediction: the case of Japanese listed companies. Review of Accounting Studies, Vol. 14 (2009), 534-558.

Zavgren, C. (1985). Assessing the vulnerability to failure of American industrial firms: a logistic analysis. Journal of Business Finance and Accounting, Vol. 12, No. 1 (1985), 19-45.

Appendix A

No.	*Authors*	*Study title*	*Journal*	*Journal issue*	*Country*	*Publ. year*	*Sample size*	*Sample country*	*Sample period*	*Industry*	*Size of companies*	*Prediction model(s)*
1	Agarwal & Bauer 2013	Are hazard models superior to traditional bankruptcy prediction approaches? A comprehensive test	Journal of Banking and Finance	Vol. 40 (2014)	UK and Germany	2013	2748	UK	1979-2009	mixed	public companies	DA and Logit
2	Agarwal et al. 2002	Predicting Bankruptcy Resolution	Journal of Business Finance and Accounting	Vol. 29, No. 3 & 4 (2002)	USA	2002	237	USA	1980-1995	N/A	public companies	Logit
3	Alfaro et al. 2007	Bankruptcy forecasting: An empirical comparison of AdaBoost and neural networks	Decision Support Systems	Vol. 45 (2008)	UK and Spain	2007	1180	Spain	2000-2003	N/A	mixed	NN and AI
4	Altman 1968	Financial ratios, discriminant analysis and the prediction of corporate bankruptcy	Journal of Finance	Vol. 23, No. 3 (1968)	USA	1968	66	USA	1946-1965	N/A	1-25 $M in total assets	DA
5	Altman et al. 1977	ZETA analysis: A new model to identify bankruptcy risk of corporations	Journal of Banking and Finance	Vol. 1 (1977)	USA	1977	111	USA	1964-1974	manufacturing and retail	public companies	DA
6	Altman et al. 1985	Introducing Recursive Partitioning for Financial Classification: The Case of Financial Distress	Journal of Finance	Vol. 40, No. 1 (1985)	USA	1985	200	USA	1971-1981	industrial and retail	mixed, public and private companies	DA and RPA
7	Aziz at al. 1988	Bankruptcy prediction - An investigation of cash flow based models	Journal of Management Studies	Vol. 25, No. 5 (1988)	USA and UK	1988	98	USA	1971-1982	mixed	public companies	DA and Logit
8	Back et al. 1996	Neural Networks and Genetic Algorithms for Bankruptcy Predictions	Expert Systems with Applications	Vol. 11, No. 4 (1996)	Finland	1996	74	Finland	1986-1989	mixed, mostly manufacturing	SMEs	DA, Logit, and GA
9	Beaver 1966	Financial Ratios As Predictors of Failure	Journal of Accounting Research	Vol. 4 (1966)	USA	1966	79	USA	1954-1964	mixed	0,6 - 45 $M in total assets	Univariate

No.	Authors	Study title	Journal	Journal issue	Country	Publ. year	Sample size	Sample country	Sample period	Industry	Size of companies	Prediction model(s)
10	Beaver et al. 2005	Have Financial Statements Become Less Informative? Evidence from the Ability of Financial Ratios to Predict Bankruptcy	Review of Accounting Studies	Vol. 10 (2005)	USA	2005	4781	USA	1962-2002	mixed	public companies	Logit
11	Beaver et al. 2012	Do differences in financial reporting attributes impair the predictive ability of financial ratios for bankruptcy?	Review of Accounting Studies	Vol. 17 (2012)	USA and UK	2012	14365	USA	1962-2002	mixed	public companies	Logit
12	Becchetti & Sierra 2003	Bankruptcy risk and productive efficiency in manufacturing firms	Journal of Banking and Finance	Vol. 27 (2003)	Italy	2003	over 4000	Italy	1989-1997	manufacturing	mixed	Logit
13	Betts & Belhuol 1987	The effectiveness of incorporating stability measures in company failure models	Journal of Business Finance and Accounting	Vol. 14, No. 3 (1987)	UK	1987	93	UK	1974-1978	N/A	N/A	DA
14	Booth 1983	Decomposition measures and the prediction of financial failure	Journal of Business Finance and Accounting	Vol. 10, No. 1 (1983)	Australia	1983	70	Australia	1964-1979	mixed	public companies	DA
15	Brezigar-Masten & Masten 2012	CART-based selection of bankruptcy predictors for the logit model	Expert Systems with Applications	Vol. 39 (2012)	Slovenia	2012	1184	Slovenia	1995-2001	mixed, mostly manufacturing	mixed, from very small to large	Logit and AI
16	Campbell et al. 2008	In Search of Distress Risk	Journal of Finance	Vol. 63, No. 6 (2008)	USA	2008	about 9000	USA	1963-2003	mixed	public companies	Logit
17	Castanias 1983	Bankruptcy Risk and Optimal Capital Structure	Journal of Finance	Vol. 38, No. 5 (1983)	USA	1983	18714	USA	1977	mixed	mixed, including many small firms	LR
18	Chen 2011	Bankruptcy prediction in firms with statistical and intelligent techniques and a comparison of evolutionary computation approaches	Computers and Mathematics with Applications	Vol. 62 (2011)	Taiwan	2011	200	Taiwan	2000-2010	N/A	public companies	DA, Logit, CART, SOM, GA, PSO and LVQ

No.	*Authors*	*Study title*	*Journal*	*Journal issue*	*Country*	*Publ. year*	*Sample size*	*Sample country*	*Sample period*	*Industry*	*Size of companies*	*Prediction model(s)*
19	Chen et al. 2009	Alternative diagnosis of corporate bankruptcy: A neuro fuzzy approach	Expert Systems with Applications	Vol. 36 (2009)	Taiwan	2009	200	USA	1998-2002	mixed	mixed	Logit and NN
20	Chen et al. 2013	Clustering and visualization of bankruptcy trajectory using self-organizing map	Expert Systems with Applications	Vol. 40 (2013)	Portugal and China	2013	1436	France	2003-2007	mixed	SMEs	SOM
21	Cho et al. 2010	A hybrid approach based on the combination of variable selection using decision trees and case-based reasoning using the Mahalanobis distance: For bankruptcy prediction	Expert Systems with Applications	Vol. 37 (2010)	Korea	2010	1000	Korea	2000-2002	manufacturing	asset size 1-7 M$ (USD)	Logit and Decision tree
22	Choi & Lee 2013	A multi-industry bankruptcy prediction model using back-propagation neural network and multivariate discriminant analysis	Expert Systems with Applications	Vol. 40 (2014)	Korea	2013	229	Korea	2000-2009	industrial	public companies	DA and NN
23	Ciampi 2014	Corporate governance characteristics and default prediction modeling for small enterprises. An empirical analysis of Italian firms	Journal of Business Research	(2014)	Italy	2014	3210	Italy	2008-2010	manufacturing, building and service sectors	turnover less than 5 M€	Logit
24	Cram et al. 2004	Assessing the Probability of Bankruptcy	Review of Accounting Studies	Vol. 9 (2004)	USA	2004	14303	USA	1980-2000	industrial	N/A	Logit
25	Dambolena & Khoury 1980	Ratio Stability and Corporate Failure	Journal of Finance	Vol. 35, No. 4 (1980)	USA	1980	68	USA	1969-1975	mixed	N/A	DA
26	Derwall & Verwijmeren 2010	Employee well-being, firm leverage, and bankruptcy risk	Journal of Banking and Finance	Vol. 34 (2010)	Australia and Nether-lands	2010	3210	N/A	2001-2005	mixed	very large companies	Logit

No.	*Authors*	*Study title*	*Journal*	*Journal issue*	*Country*	*Publ. year*	*Sample size*	*Sample country*	*Sample period*	*Industry*	*Size of companies*	*Prediction model(s)*
27	Dimitras et al. 1999	Business failure prediction using rough sets	European Journal of Operational Research	Vol. 114 (1999)	Greece	1999	80	Greece	1986-1990	mixed	N/A	Rough set
28	du Jardin & Severin 2011	Predicting corporate bankruptcy using a self-organizing map: An empirical study to improve the forecasting horizon of a financial failure model	Decision Support Systems	Vol. 51 (2011)	France	2011	500	France	2001-2002	retail	assets under 750 000 €	Hazard and SOM
29	Edmister 1972	An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction	The journal of financial and quantitative analysis	Vol. 7, No. 2 (1972)	UK	1972	42	USA	1954-1969	N/A	small companies	DA
30	Gordini 2014	A genetic algorithm approach for SMEs bankruptcy prediction: Empirical evidence from Italy	Expert Systems with Applications	Vol. 41 (2014)	Italy	2014	3100	Italy	2009-2012	manufacturing	small and medium-sized companies	Logit, SVM and GA
31	Graybeal et al. 1996	Recession-Induced Stress and the Prediction of Corporate Failure	Contemporary Accounting Research	Vol. 13, No. 2 (1996)	USA	1996	2122	USA	1968-1990	mixed	public companies	Logit
32	Hall 1994	Factors distinguishing survivors from failures amongst small firms in the UK construction sector	Journal of Management Studies	Vol. 31, No. 5 (1994)	UK	1994	58	UK	1989-1990	construction sector	small firms	Logit
33	Hensher & Jones 2004	Predicting Firm Financial Distress: A Mixed Logit Model	The Accounting Review	Vol. 79, No. 4 (2004)	Australia	2004	3032 firm years	Australia	1996-2000	mixed	public companies	Logit
34	Ji et al. 2011	Using partial least squares and support vector machines for bankruptcy prediction	Expert Systems with Applications	Vol. 38 (2011)	Canada and China	2011	120	Poland	N/A	N/A	N/A	SVM and PLS
35	Kurokawa & Takahashi 1984	Corporate bankruptcy prediction in Japan	Journal of Banking and Finance	Vol. 8, Issue 2 (1984)	Japan	1984	120	Japan	1961-1977	N/A	public companies	DA

No.	*Authors*	*Study title*	*Journal*	*Journal issue*	*Country*	*Publ. year*	*Sample size*	*Sample country*	*Sample period*	*Industry*	*Size of companies*	*Prediction model(s)*
36	Laitinen & Laitinen 1998	Cash management behavior and failure prediction	Journal of Business Finance and Accounting	Vol. 25, No. 7 & 8 (1998)	Finland	1998	82	Finland	N/A	N/A	middle sized	Logit
37	Lee & Shin 2002	A genetic algorithm application in bankruptcy prediction modeling	Expert Systems with Applications	Vol. 23, Issue 3 (2002)	Korea	2002	476	Korea	1995-1997	manufacturing	medium-sized companies	GA
38	Lincoln 1984	An empirical study of the usefulness of accounting ratios to describe levels of insolvency risk	Journal of Banking and Finance	Vol. 8 (1984)	Australia	1984	131	Australia	1969-1978	mixed	public companies	DA
39	Mensah 1983	The Differential Bankruptcy Predictive Ability of Specific Price Level Adjustments: Some Empirical Evidence	The Accounting Review	Vol. 58, No. 2 (1983)	USA	1983	106	USA	1975-1980	industrial	N/A	DA and Logit
40	Mensah 1984	An Examination of the Stationarity of Multivariate Bankruptcy Prediction Models: A Methodological Study	Journal of Accounting Research	Vol. 22, No. 1 (1984)	USA	1984	220	USA	1972-1980	industrial and retail	N/A	Logit
41	Norton & Smith 1979	A Comparison of General Price Level and Historical Cost Financial Statements in the Prediction of Bankruptcy	The Accounting Review	Vol. 54, No. 1 (1979)	USA	1979	60	USA	1971-1975	industrial	public companies	DA
42	Ohlson 1980	Financial Ratios and the Probabilistic Prediction of Bankruptcy	Journal of Accounting Research	Vol. 18, No. 1 (1980)	USA	1980	2163	USA	1970-1976	industrial	public companies	Logit
43	Platt & Platt 1990	Development of a class of stable predictive variables: the case of bankruptcy prediction	Journal of Business Finance and Accounting	Vol. 17, No. 1 (1990)	USA	1990	114	USA	1972-1986	mixed	public companies	Logit
44	Rushinek & Rushinek 1987	Using financial ratios to predict insolvency	Journal of Business Research	Vol. 15 (1987)	USA	1987	30	USA	N/A	mixed	mixed, including many small firms	DA

No.	*Authors*	*Study title*	*Journal*	*Journal issue*	*Country*	*Publ. year*	*Sample size*	*Sample country*	*Sample period*	*Industry*	*Size of companies*	*Prediction model(s)*
45	Singhal & Zhu 2013	Bankruptcy risk, costs and corporate diversification	Journal of Banking and Finance	Vol. 37 (2013)	USA	2013	769	USA	1991-2007	mixed	public companies	Logit
46	Taffler 1984	Empirical models for the monitoring of UK corporations	Journal of Banking and Finance	Vol. 8 (1984)	UK	1984	73	UK	1974-1978	manufacturing and retail	public companies	DA
47	Theodossiou 1991	Alternative models for assessing the financial condition of business in Greece	Journal of Business Finance and Accounting	Vol. 18, No. 5 (1991)	Greece	1991	363	Greece	1980-1983	manufacturing	at least 50 employees	LPM, Logit and Probit
48	van der Wijst & Westgaard 2001	Default probabilities in a corporate bank portfolio: A logistic model approach	European Journal of Operational Research	Vol. 135 (2001)	Norway	2001	35287	Norway	1995-1999	mixed	mixed (limited companies)	Logit
49	Ward 1994	An empirical study of the incremental predictive ability of beaver's naive operating flow measure using four state ordinal models of financial distress	Journal of Business Finance and Accounting	Vol. 21, No. 4 (1994)	USA	1994	227	USA	1984-1988	non-financial firms	N/A	Logit
50	Xu & Zhang 2008	Bankruptcy prediction: the case of Japanese listed companies	Review of Accounting Studies	Vol. 14 (2009)	Hong Kong	2008	3510	Japan	1992-2005	non-financial firms, mostly manufacturing	public companies	Logit
51	Zavgren 1985	Assessing the vulnerability to failure of American industrial firms: a logistic analysis	Journal of Business Finance and Accounting	Vol. 12, No. 1 (1985)	USA	1985	90	USA	1972-1988	mixed	public companies	Logit

Appendix B

No.	*Authors*	*Liquidity*	*Profitability*	*Financial leverage*	*Activity*	*Non-financial*	*Other financial*	*Size*	*Unidentified*	*Total*
1	Agarwal & Bauer 2013	5	4	2			3	3		17
2	Agarwal et al. 2002		1	2		5	1	1		10
3	Alfaro et al. 2007	21	6		9	4		3	3	46
4	Altman 1968	1	2	1	1					5
5	Altman et al. 1977	2	3				1	1		7
6	Altman et al. 1985	7	3	2				2		14
7	Aziz at al. 1988	10	1							11
8	Back et al. 1996	8	2	3	2					15
9	Beaver 1966	4	1	1						6
10	Beaver et al. 2005	1	2	1			1	1		6
11	Beaver et al. 2012	2	15	2			2	2		23
12	Becchetti & Sierra 2003	6	4	2	4	6	2	2	1	27
13	Betts & Belhuol 1987	17	4		2					23
14	Booth 1983						6			6
15	Brezigar-Masten & Masten 2012	5	4	3	3					15
16	Campbell et al. 2008	1	2	1			3	1		8
17	Castanias 1983	1	1	5				1		8
18	Chen 2011	2	3	2					1	8
19	Chen et al. 2009	5	3	4	2					14
20	Chen et al. 2013	6	8	2	12			1	1	30
21	Cho et al. 2010	12	6		3		1			22
22	Choi & Lee 2013	3	9		4					16
23	Ciampi 2014	1	2	1		5				9
24	Cram et al. 2004	3	6	3	1			1		14
25	Dambolena & Khoury 1980	12	15	18	12					57
26	Derwall & Verwijmeren 2010	1	3	1		2	2	1		10
27	Dimitras et al. 1999	5	4	3						12
28	du Jardin & Severin 2011	3	5	2						10
29	Edmister 1972	5	1		1					7
30	Gordini 2014	3	3	2						8
31	Graybeal et al. 1996	4	1	1				1		7
32	Hall 1994				1	4	1			6

No.	*Authors*	*Liquidity*	*Profitability*	*Financial leverage*	*Activity*	*Non-financial*	*Other financial*	*Size*	*Unidentified*	*Total*
33	Hensher & Jones 2004	5		3	2	6				16
34	Ji et al. 2011	9	6	3	3					21
35	Kurokawa & Takahashi 1984	2	4	2						8
36	Laitinen & Laitinen 1998	8		2						10
37	Lee & Shin 2002	4	4	1						9
38	Lincoln 1984	5	2	2						9
39	Mensah 1983	7	1	10	6					24
40	Mensah 1984	1		1	3					5
41	Norton & Smith 1979	4	1	3	2					10
42	Ohlson 1980	2	3	3				1		9
43	Platt & Platt 1990	4		2			1			7
44	Rushinek & Rushinek 1987	1	1	1						3
45	Singhal & Zhu 2013		2	2		4	2			10
46	Taffler 1984	8	2	2	1					13
47	Theodossiou 1991	3	6	6						15
48	van der Wijst & Westgaard 2001	3		1		5		1		10
49	Ward 1994	4	1	1	1		1	1		9
50	Xu & Zhang 2008	5	7	7	3	2		1		25
51	Zavgren 1985	2	1	1	3					7
	Totals	*233*	*165*	*117*	*81*	*43*	*27*	*25*	*6*	*697*