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BANKRUPTCY PREDICTION MODELS: A COMPARATIVE ANALYSIS WITH POLISH DATA

Master Thesis

INTERNATIONAL BUSINESS ADMINISTRATION, finance

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Tallinn 2021

I hereby declare that I have compiled the thesis independently and all works, important standpoints and data by other authors have been properly referenced and the same paper has not been previously presented for grading.

The document length is 16338 words from the introduction to the end of conclusion.

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TABLE OF CONTENTS

TABLE OF CONTENTS

ABSTRACT

Companies should periodically analyse their financial situations in detail to ensure their continuity and to take precautions against future uncertainties and to perform crisis management effectively. While financial and economic analysis is diverse, one of the most important is the analysis of financial failure. In the literature, there are many financial failure models. It is possible to divide these models into one-dimensional and multi-dimensional models. While some of the researchers and practitioners mainly use multi-dimensional models, others prefer to use one-dimensional models. On the other hand, there is no common thought about which type of models have better performance to predict the failure of companies. Therefore, with this thesis, it is aimed to answer the question of which type of model has better performance to predict the failure of companies.

Selected models were classified as one-dimensional models and multi-dimensional models. For measuring the performance of the models, the Polish companies dataset which has 5-year financial statement datas of bankrupted companies is used. For evaluation of performance, all bankrupted companies' financials are calculated as selected models, and model results are compared regarding their accuracy ratio.
This study finds that multi-dimensional models are much more advantageous than one-dimensional models and predict bankruptcy earlier, especially compared to one-dimensional models.

In the literature, there are few comparisons of financial failure study but none of them analyse these models in the same study. Therefore, it is thought that this study will contribute to related literature and the result of this study answers the researchers' or practitioners' question of which type of model can have better prediction performance than others.

Key Words: Financial failure, bankruptcy, one-dimensional model, multi-dimensional models

INTRODUCTION

Globalization and rapid developments in technology force businesses to operate in an intensely competitive environment. For this reason, the determination of business-specific risks and effective risk management have become essential elements for long-term success. What is meant by effective risk management is the identification, assessment, and prioritization of risks or uncertainties followed up by minimizing, monitoring, and controlling the impact of risk realities. In this context, predicting financial failure and determining the factors affecting financial failure is becoming increasingly important for businesses (Miller, 2009). The fact that businesses have been in an intensely competitive environment in recent years makes it difficult for businesses to operate worldwide. The slight risk of financial failure, which occurs as businesses losses and/or experience liquidity problems, may become even more severe and go up to bankruptcy and the liquidation of the business if no measures are taken (Nguyen and Faff, 2010).

Significant contributions can be made in decision-making by predicting the future financial situations of the businesses. Thanks to financial failure prediction models, investors can switch different investment preferences, as well as business managers, can observe the signals of a failure in advance and take measures with early warning models. However, lenders are currently the group most concerned with estimating the risk of financial failure. They try to predict whether their loans will be repaid or not by using many models, especially the Altman Z score test (Shin and Lee, 2002).

Companies should be considered as living organisms. They can get ill throughout their life cycle, and for them, the most terrible illness is financial trouble. The best way to treat this disease is to identify symptoms and take remedial measures. When these financial troubles begin, at least one symptom indicates the presence of a threat or opportunity. These symptoms are also very significant for the prevention of financial failures. The goal of prediction models that many researchers are working on is to re-evaluate organizational strategies by establishing an early warning system.

The subject of this study, which is “financial failure”, has been the subject of intense research and discussion by economists, bankers, creditors, shareholders, accountants, marketing and management professionals, etc. The devastating and social effects of failure, can affect shareholders, creditors, government, etc. It obliges a corporate enterprise to continuously monitor its activities to prevent a possible failure. At this point, there is an important question: How can companies measure the possibility of financial failure? The basic answer to this question is “bankruptcy prediction models”.

Many researchers have developed models that predict this failure by studying financial failure for many years. These include Altman (1968, 1980), Marais (1979), Taffler (1982, 1984), Koh and Killough (1990), and Shirata (1998). Beaver (1966) was one of the first attempts to anticipate institutional failure. Beaver's "univariate" approach was to evaluate each ratio in terms of how it could be used alone to predict failure without considering other rates. Beaver's univariate analysis also led to a multivariate analysis by Edward Altman, who used multiple discrimination analyses in his effort to find a bankruptcy prediction model (Yap et al., 2011). This pioneering approach has also been the focus of this study. Financial failure will be predicted thanks to the various models to be made with the data of Polish companies.

While there are many financial failure prediction models in the literature, it is not clear which financial failure model predicts better than others in terms of the dimensional structure of models. Considering the importance of financial failure prediction in terms of companies, it is very critical to predicting the failure with high accuracy. When the related literature is analysed, few studies compare popular failure prediction models. Furthermore, the models are compared according to their types, multi-dimensional, or one-dimensional inside, but there is not faced any comparison between different types of models. This is the motivation of this thesis.

In literature; most studies focus on one-dimensional and multi-dimensional models separately or just compare Beaver and Altman due to popularity. With this study, comparing one-dimensional and multi-dimensional models will be accepted as a contribution.

This study aims to analyse the performance of one variable and multivariable bankruptcy prediction models and investigate the best model which predicts bankrupted companies with the highest accuracy score. With this study, the author aims to answer the questions below:

1) Are multivariable models better than one variable models while predicting bankruptcy of companies?
2) Which bankruptcy model is best fitted among others within this study?

Models' performance, which is the cornerstone of this study, will be measured with a dataset that belongs to Polish companies that operate between 2000-2012. The dataset which is used in this study is taken from the study "Ensemble Boosted Trees with Synthetic Features Generation in Application to Bankruptcy Prediction". The data was collected from the Emerging Markets Information Service database and the dataset includes 64 financial rates and corresponding class label that indicates bankruptcy of Polish manufacturing companies. Furthermore, in this dataset, periods can be classified as the bankruptcy period which is between 2007-2013, and the operating period which is between 2000 and 2012 (Ziebwa et all, 2016).

In the first part of this study, it will be provided to distinguish financial failure by explaining what the concept of failure is for businesses. The types and causes of financial failure will also be deepened with examples presented from the literature. In the second part of the study, various models that can predict financial failure will be examined under univariate and multivariate models. In the last part, where the empirical part of the study, the models' outputs will be calculated with Polish companies' dataset and outputs of the models will be compared with others in terms of which model is best fitted to predict a company's bankruptcy.

It is expected that multi-dimensional models predict the failure of companies better than one-dimensional models. It is considered that the results of this study will lead researchers and practitioners in terms of choosing which type of financial failure prediction model in their works.

1. CONCEPTUAL FRAMEWORK

Financial failure means simply that a company cannot meet its debt requirements. In other words, it is the event that the company is subjected to bankruptcy, liquidation, and other asset capture and distribution (Sun et.al., 2014). In this part of the study, the definition of financial failure will be expressed along with its scope.

1.1. Failure Descriptions and Types of Failures for Companies

Businesses basically aim to continuously increase their financial and brand value and profit from their main activities. While achieving these goals, companies should consider the benefit of the society they serve. However, while achieving these goals, businesses fail due to the 3 basic problems they face. Among these reasons, uncertainty, and risks in financial markets, global and local economic crises and managerial problems in business management can be shown. Failure is basically the state of not being able to conclude a task as expected (Altman, 1983).

A failure is an event that any business can encounter, regardless of the size of the business and the conditions of the country in which it is located. When we look at the concept of failure in business, it is seen that it has more than one definition. Among the definitions, many definitions are used to describe the failure, from the failure of a subsidiary of the business to the failure of the business with itself and its subsidiaries, from paying its debts longer than its due date, and losing its credibility to the bankruptcy of the company (Ross et al., 2002: 29).

There are many reasons behind the question of “Why a business fails?”. These include the inability to adapt to rapidly developing technology, faulty physical investments (place of establishment, office supplies, etc.), organizational and/or managerial errors, and finally financial reasons. However, if the financial reasons are to be detailed, excess debt burden, capital insufficiency, and faulty financial investments can be cited as examples (Park and Hancer, 2012: 313). When the concept of failure is considered from the perspective of businesses, it can be said that there are two types of failure. These are economic failure and financial failure.

1.1.1. Economic Failure

Economic failure can be defined as the inability to meet the costs of the business with the income obtained by a business (Brigham and Daves, 2007: 867). From this point of view, a company whose income is higher than its cost can be defined as successful. When we look at the causes of economic failure, incorrectly planned operating capacity, wrong pricing strategies, cash management failures and unsuccessful investments outside of the core business can be cited as examples.

1.1.2. Financial Failure

Financial failure is often confused with business bankruptcy but is different from economic failure and the concept of bankruptcy. Financial failure can basically be defined as a business losing its ability to pay its debts. Purnanandam (2008) defined the concept of financial failure as the value of the assets owned by the company is less than the debts it owns.

Financial failure occurs due to various reasons, and when it occurs, it causes disruptions in business activities (Mellahi and Wilkinson, 2004). The disruption in the activities causes a decrease in the activities of the business with its business partners (suppliers, buyers, etc.) and consequently a decrease in the rate of profit from its main activity. This event causes the cash management not to be managed effectively and the business, therefore, loses its ability to meet its liabilities. Businesses in this situation can borrow money from the financial sector to meet their liabilities. However, the debt obligations of businesses that follow this path are entering an increasing trend. As a result, this situation causes a vicious circle in businesses and brings about the process of bankruptcy and liquidation. From this point of view, all situations such as the struggle of businesses with financial difficulties, liquidation, and bankruptcy can be defined as a financial failure (Mellahi and Wilkinson, 2004:22-23).

According to Uzun (2005:160), financial failure is measured by comparing the registered debts of the business with the registered net assets. If a business's registered debts are more than its registered assets, the business loses its ability to pay its debts. Although this is a progressive form of technical liquidity loss, it is the last stage that can be reached during financial failure.

Beaver (1966:71-72) takes the concept of financial failure more simply than others. According to Beaver, financial failure is a decrease in the ability of businesses to fulfil their obligations on time. Subramanyam (2014) defined insolvency as a technical failure. According to the author, technical failure is the lack of cash required to fulfil current liabilities other than the assets owned by the enterprise.

Kolb (1983:704) examined the causes of financial failure. According to Kolb, financial failure can be analysed under three subheadings; insufficient liquidity, financial insufficiency, and bankruptcy.

When the definitions of technical failure and bankruptcy, which are the two main parts of financial failure, are examined, it can be seen that although the concept of bankruptcy can be clearly defined, some of the definitions of the concept of technical failure, or in other words, insolvency, resemble or exactly match the definition of bankruptcy. Moreover, it is a generally accepted result that financial failure is a process that starts with technical failure and ends with bankruptcy. The first part of this process can occur for any reason during the operation of the business. However, financial problems starting with this problem disrupt the cash flow of the operator and move to the second stage as the problem prolongs. If it does not take successful steps to solve these problems, the bankruptcy phase begins and finally, the liquidation process begins with bankruptcy (Ross et al., 2002).

Based on general economic theory, Lizal (2002) identifies three reasons or patterns that can detect the deterioration of the financial health of the company:

i. The neoclassical model accepts bankruptcy as a positive event in this situation. Because they view bankruptcy as the release of assets that are not efficiently allocated. In this case, the market basically has an ameliorative effect as inefficient businesses also consume input, which is economically undesirable as assets are allocated for unsuitable business activities.
ii. The financial model that works with the idea of the weighted average cost of capital is not minimal, where assets are properly allocated but the asset structure covering resources is poorly adjusted, ie the idea of the weighted average cost of capital. In other words, the capital structure is not optimal.

iii. The corporate governance model, which is based on the premise that both the assets and liabilities of the company described in the previous two models are used effectively, can lead to bankruptcy in ineffective problem management.

The concept of financial failure is sometimes used as bankruptcy in the literature, and the reason for this is stated. This situation is converted to a schematic in Table 1. variables that help distinguish bankruptcy from financial failure are discussed. According to this study of Platt and Platt (2006), cash flow / net sales are common variables in the model of both definitions; it is inversely proportional in both definitions.

Table 1. Definition of Bankruptcy/Failure

Author	Term Used	Definition
Altman	Bankruptcy	It is defined as having filed legally for bankruptcy and appointed a trustee or granted the right to reorganize under the provisions of national bankruptcy law.
Beaver	Failure	Financial failure; is not being able to pay financial liabilities that are due.
Blum	Failure	Not being able to pay the debts due, entering the bankruptcy process, making demands on the reduction of debts with creditors.
Booth	Failure	He did not make a general definition. Firms that have been suspended in the Australian stock market have been described as unsuccessful in financial analysis.
Deakin	Failure	Companies that are bankrupt or liquidated at the request of creditors.
Edminister	Failure	Used Beaver and Blum's definitions.
El Hennawy & Morris	Bankruptcy	If the company is being liquidated, it is a financial success.
Libby	Failure	Used Deakin's definition.
Taffler	Failure	Failure is defined as liquidation. Liquidation is grouped in two ways. Liquidation upon the request of the creditors, termination of the activity by the court decision.
Tamari	Failure	It is not defined.

Source: (Gordon and Prakash, 1987:576)

As can be inferred from Table 1, different researchers have used different definitions and terms in different time periods that are essentially similar but differ in terms of technical fine details. In the opinion of the author of this thesis, although there is no consensus among researchers on the use of the term, approaches to technical analysis of the financial situation have been similar.

1.2. Types of Financial Failure

Under this title, types of financial failure accepted in the literature will be examined. These are insufficient liquidity, financial insufficiency, and bankruptcy.

1.2.1. Liquidity Shortage

Liquidity is the ability to convert any assets owned by the business into cash (Ross et al., 2002:29). Two different liquidities can be mentioned; real liquidity and technical liquidity. While real liquidity is defined as the ability of the company to fulfil its current liabilities while it is in the liquidation process, technical liquidity can be expressed as the ability to pay the debts that are due (Subramanyam, 2014: 229).

According to Martin et al. (1993:825), insufficiency of liquidity can be defined as a company not having enough cash to pay its debts even though its assets are more than the value of its current liabilities. Businesses in this situation face financial failure. Another definition of illiquidity is defined by Ross et al. (2002: 832) as the inability of cash flows to meet operating liabilities. In cases where the business falls short of liquidity, it can be prevented from entering the bankruptcy process by selling some of the assets and turning them into cash (Altman, 1983: 17).

1.2.2. Financial Shortage

Financial shortage (insufficiency) can be defined as the book value of the debts belonging to the enterprise is higher than the market value of the assets of the enterprise. Financial insufficiency is seen as a more serious situation compared to insufficient liquidity. This is because the business has signs of economic failure and faces a situation of legally entering the bankruptcy process (Brigham and Gapenski, 1997:1035).

Ross et al. (2002) defined a negative business net worth as financial insufficiency because the net value of the assets owned by the business is less than the value of its liabilities. Faced with financial insufficiency, a business does not always mean that it is in economic failure. This is because, in the case of financial insufficiency, the net worth of the equity of the business is negative, while in the case of economic failure, the profitability of the business is not sufficient to continue its operations (Schall and Waley, 1980:741).

1.2.3. Bankruptcy

When the literature is scanned, it is seen that financial failure and bankruptcy are used synonymously in some studies. Bankruptcy, in its most basic definition, is the failure of the debtor business to repay its debts. In a bankrupt business, it is first observed that the assets are less than the debts. Therefore, the equity of the business is negatively valued (Altman, 1968:591).

Brealey et al. (2010: 448 - 449) emphasize in their study that the concept of bankruptcy is a legal process, and also, especially bankruptcy is the result of the decrease in the value of the business. According to the author, the condition for talking about bankruptcy is the transfer of the business to the creditors within the framework of a legal process. The company cannot fulfil its debt obligations should be legally transferred to creditors.

1.3. Causes of Financial Failure

In general, the term "financial failure" is used in a negative connotation to describe the financial health of an enterprise facing a temporary shortage of liquidity and facing difficulties that fail to fully fulfil its financial obligations within payment terms (Kliesti and Majerova, 2009); (Wroblowska, 2016).

A financial failure is an event that affects not only businesses but also the national economy, depending on the size of the business. For this reason, it is of great importance to correctly identify the causes of financial failure. If financial failure can be accurately predicted before it happens, it can be prevented by management before bankruptcy and liquidation processes begin. In this way, it can be prevented from experiencing bad scenarios at both macro and micro levels.

Mitroff (2001) explained eight main reasons for the deterioration of the financial health of businesses as follows:

- *Economic reasons:* Strikes, labor riots, market failure, a decline in basic earnings, and sharp changes in market prices.
- *Informational reasons:* Inaccurate information, loss of protected and confidential information, computer data processing, loss of sensitive data about customers, suppliers, and other stakeholders.
- *Physical causes:* Loss, destruction, or damage of important assets - raw materials, machinery and equipment, transport vehicles.
- *Reasons arising from human resources:* Departure, loss of key experts or managers, lack of qualified workforce in the labor market.
- *Reputation:* Slander, spreading false or worrying news about the company, harming the good name of the business, theft of intellectual property, imitation of the business logo.
- *Criminal causes:* Hostile capture, terrorism, workplace violence.
- *Natural disasters:* Earthquakes, fires, floods, hurricanes, hurricanes, volcano eruptions, etc.

Altman and Hotchkiss (2006) mention other causes of deterioration in the financial health of businesses that most of them cannot affect. These external factors are as follows:

- Economically problematic sectors (e.g. agriculture, textile industry, etc.)
- Liberalization of key sectors (e.g. airlines, financial services, health, energy),
- High real interest rates,
- International competition,
- Overcapacity across sectors.

The next cause of companies' failure, new technology is identified by Norton (2000) as an environmental factor that destroys the demand for legacy products or services. He also mentions government policies in this area as the cause of business financial health deterioration. However, he also stated that some businesses will survive under the same conditions, while others will fail. Charan and Useem (2002) summarize the main reasons for job failure as follows:

- Administrative errors,

- Passing to a different phase and collapse after the success achieved
- The behavior of competitors,
- Underestimating negative messages, feedback, and trends.

Another important issue to consider when evaluating the financial health of companies is the relationship between the age of the firm and the probability of failure. Dun and Bradstreet (1980) showed in their research that more than 50% of all failures occur in "older" businesses between the ages of two and five. After five years of existence, businesses tend to be more stable and experienced. As a result, they have easier access to capital, whether in the form of loans or by issuing stocks or bonds. In particular, financial reasons for corporate failure are:

- *Industrial sectors:* Some industries tend to be chronically "unhealthy". Businesses operating in these sectors are likely to fail soon.
- *Interest rates:* As a result of high-interest rates, some businesses will find themselves unable to repay their obligations to the bank in the form of interest or principal repayments.
- *Competition:* International division of labour and competition greatly increase business spending.
- *Equity Ratio of Debt:* Especially businesses in the USA increased the volume of foreign resources. Financial leverage has increased, but businesses have become more vulnerable. This fact is particularly important in a recession.
- *Deregulation:* The deregulation of key sectors leads to a competitive environment that reduces the value of monopoly rent.
- *Growth Rate:* The high speed of new job creation will cause higher job failure rates. New businesses are characterized by a higher probability of failure than established businesses.

G. W. Newton (2009), who bases his studies on both Dun and Bradstreet studies, lists the reasons for business failure as follows:

- Inability to manage cash flow,
- Starting a business with a low level of equity,
- Having a good business plan,
- Determining unreal and insufficient targets,

- Extreme optimism
- Anticipating the weaknesses of the company,
- Inadequate marketing and inexperienced management,
- Anticipating competition,
- Insufficient or incorrect transfer of decision-making powers,
- Recruiting unsuitable managers,
- Excessive dependence on a customer.

According to Brigham and Gapenski (1996), the causes of financial difficulties are often the result of a series of errors, bad judgment, and interdependent weaknesses and signs of a particular business or its management that can be directly or indirectly allocated to management.

Arnold (2013), on the other hand, identified some of the causes of business financial health deterioration that affect the risk of exposure to financial stress costs. This definition arises in terms of financial stress costs. He states that the reasons or factors are different and specific to each business:

- *Increased sensitivity of operating revenues to the macroeconomic situation:* If institutional foundations are sensitive to the volatility of the economy, shareholders and creditors may perceive a greater risk of financial stress and therefore demand higher returns rather than exposure to this higher risk than businesses less susceptible to economic events.
- *Inappropriate share of fixed and variable costs:* A business with high activity, capital intensive, that is, working with high operating expenses, cannot meet the need for capital with its own resources and therefore increases the share of foreign capital that can have fatal consequences.
- *Liquidity and unsuitability of company assets:* Some businesses invest in asset types that can be sold easily and quickly and allocate their funds to assets with high liquidity. The opposite can be the cause of financial health problems in a business.
- *The inability of the company to keep enough money:* Some businesses generate regular and sufficient cash flow; On the other hand, companies with delay and insufficient cash revenues may have problems in the future.

Czech authors Synek et al. (2007) highlighted the impact of the external environment on the business and identified these factors as follows:

- Political,
- Economic,
- Financial,
- Monetary,
- Legal and tax factors,
- Social factors,
- Factors stemming from the nature of the industry.

Zopounidis and Dimitras (1998) identified potential causes of financial failure in businesses in two groups. These are financial and investment reasons and non-financial reasons. According to this classification, reasons related to finance and investment are as follows:

- *The inappropriate proportion of the company's own resources and borrowed resources*- In many cases, improper dependence on borrowed resources results in higher profits, but also increases the risk of financial stress.
- *Insufficient creation of financial reserves*- During the period of economic growth, business owners prefer higher profits and therefore companies are exposed to financial stress risk in the long run.
- *Excessive long-term debt collection conditions*
- *Under-capitalization of a business* - If it means that long-term assets are covered only by long-term debt, it is a situation where the golden balance rule is not followed. The remainings are covered by short term debts.
- *Flexibility in cost reduction* — Represents one of the prerequisites or steps necessary to prevent company failure. In particular, reducing fixed and fee costs is problematic.
- *Errors regarding the company's own capital costs* - Some businesses, especially in the economic conditions of transition countries, often pretend the type of capital they borrow is free, but the opposite is true.
- *Wrong price calculation* - As a result, fair selling price is determined unfairly.

Non-financial reasons are summarized as follows in the statement of Zopounidis and Dimitras (1998):

- Lack of business strategy or bad strategy and bad management,
- Lack of information and wrong approach of management,
- Unwillingness and fear of taking vigorous actions,
- The inadequate competitive power of company products,
- Inappropriate product portfolio and bad marketing campaign,
- Low labour productivity,
- Late recognition of the first signs of institutional failure,
- Incorrect or no response to signs of corporate failure

Above, the reasons for financial failure, which were stated by more than one researcher, were sometimes discussed as a whole and sometimes examined with various cause groups. Each of these studies gained different perspectives with the scope it covers, and it was useful for companies to use it as an early warning signal before experiencing financial failure. The most common distinction in the literature is the one used by Slatter and Lovett (1999). They divide the causes of the financial health deterioration of the world into internal and external ones and investigate these causes in more detail. They also state that external factors can affect companies only minimally, but the company cannot be separated from the dynamically developing environment. Actions that cause failure due to what the business does are called internal causes, and the reasons that make the business financially unsuccessful, independent of the business, are called external causes.

Readers who want to get more detailed and comprehensive information about reasons for financial failure can take a look at the Appendix 2 section.

1.4. Evaluating the Causes of Financial Failure

The reasons for failure that can be generalized with the headings of administrative inefficiency, socio-cultural factors, economic instability, and public policy can be summarized as follows:

- *Administrative Inefficiency:* This is the most obvious source of failure. The first is that there is no well-stated corporate strategic plan. Derivatives of this may consist of over-expansion, ineffective sales force, high production cost, inappropriate cost strategies, low productivity, poor financial management strategy, poor risk assessment strategy (Bhattacharjee et al., 2002).
- *Overexpansion:* A company undertaking the expansion is likely to immobilize short-term funds, thereby creating a pathway for failure. Therefore, institutional expansion should be done to strictly follow the corporate strategic plan (Mbat, 2001).
- *Ineffective Sales Force:* The result of production is to sell the product. If the sales force is not properly trained and developed, the company may have difficulty selling its product, especially if the product is sold in a highly differentiated competitive market. This situation will create a cash flow problem and therefore a solvency problem (Gilman, 2001).
- *High Production Costs:* This is a situation where the production cost of a firm causes its product not to compete favorably with other different products in the market. This may be due to the over-employment of human and material resources or technical inefficiency in the production process (Bowen et al., 2009).
- *Poor Financial Management:* A firm whose financial manager cannot make effective financial management decisions has to experience an acute liquidity problem. These decisions include investment, financing, and dividend policy decisions (Richard and Steward, 1986); (Preston and Post, 1975).
- *Risk Assessment Strategy:* The risk associated with the investment decision should be appropriately assessed. This is because asset investments constitute the most important source of corporate earnings. Therefore, if the risk assessment is not done properly, company revenue will be spoiled (Mbat, 2001).
- *Improper Trade Policy:* Policies that affect sales, especially credit sales, should be carefully considered, as this can lead to debt accumulation and consequently liquidity crises (Alo, 2003).
- *Lack of a Manpower Training and Development Policy:* A firm that does not have a labor training and development policy cannot benefit from well-trained and expert personnel who can help achieve corporate goals. Evaluation of strategic business units will show the average underperformance of personnel occupying critical positions in the organization (Bedelan, 1987).

The above factors constitute the inefficiency and inefficiency of management. They are crucial to observation as an organization moves along the line of achieving its goals and objectives.

- *Capital Insufficiency:* A firm with low capital will fail sooner or later. This is because the firm does not have enough capital to purchase the relevant fixed assets, to invest in sufficient income-generating assets or sufficient working capital. Often, such firms experience an inadequate use of capacity. Also, the capital structure can create a problem that ultimately results in institutional failure. For example, if the capital structure has high gear instead of shifting to low gear, it can create revenue sharing problems (Caballero and Krishnamurthy, 1999).
- *Socio-Cultural Factors:* A company that produces products that are not absorbed by the immediate environment will have a difficult time selling its products. It will force the firm to seek distant markets that will result in higher marketing costs and an inability to sell their products (Hopenhayn, 1992).
- *Income Instability:* Environmental economic instability can lead to institutional failure. This is because any downturn in the economy can create some kind of financial trouble due to the inability of a firm to sell its products (Caballero and Hammour, 1994).
- *Public Policy:* It is a crucial external source of financial failure. When government policy goes against a firm's interests in the short term, the firm can go bankrupt. For instance; if the government imposes a ban on the import of a firm's inputs, production will not be possible when existing stock inputs are exhausted (Robson, 1996).

1.5. Previous Studies

Numerous studies have been conducted to determine the financial failure situation of businesses. In the studies, models that estimate the financial situation of the companies have been developed by using both different methods and different variables. There are two main steps in the creation of models: The first step is to classify businesses operating in the same or different business line according to their observed financial status. The next step is to create estimation models using independent variables and one or more methods. The models obtained are models that allow the companies to determine their future financial status. However, the prediction powers of all models created according to previous studies were found to be different. The reasons for this can be counted as the variables and methods used, the sample size, or the type chosen.

Leading authors in the financial failure literature are Beaver (1966, 1968), Altman (1968), Meyer and Pifer (1970), Deakin (1972), Sinkey (1979), Ohlson (1980), and Taffler (1983). These are explained together with the theories in the previous part of the study. In more recent studies in the literature, both these theories have been used and new approaches have been tried to be developed.

Andreev (2005) chose five financial ratios to develop a model that would predict the financial failure of companies in Spain. These rates are listed as Short-Term Debts / Total Debts, Working Capital / Total Assets, Sales / Cash, Profit Before Interest and Tax / Sales, and Total Debts / Equity. He used these ratios as independent variables and applied logistic regression and discriminant analysis. As a result of the analysis, he found that the logistic regression analysis predicted successful companies at a rate of 95.3% and stated that the overall prediction accuracy of the model was 74.2%. In the study, where he emphasized that the predictive power of unsuccessful enterprises with logistic regression analysis was very low, he stated that this ratio was found to be higher with discriminant analysis. He also emphasized the importance of the return on sales, in other words, the operating profit margin in distinguishing successful and bankrupt companies.

Xiaosi et al. (2011) used the data of a total of 304 companies, 152 successful and 152 unsuccessful in their study, in which they aimed to compare the capabilities of logistic regression analysis, artificial neural networks, and support vector machines in financial failure prediction. First, they determined 15 financial ratios and they reduced this number to 5 by applying principal component analysis. In the continuation of the study, they found the average, maximum value, minimum value, and variance of the financial ratios of the two groups that were successful and unsuccessful, and they stated that these values were different for the two groups. Therefore, they emphasized that the classification capability of 5 financial ratios is high. As a result of the analysis, they stated that the best model is the one obtained as a result of support vector machines. At the same time, they concluded that the model obtained as a result of logistic regression analysis is the worst model.

Diakomihalis (2012) chose 146 hotels, consisting of two, three, four, and five-star hotels in Greece, as a sample in his study, which aims to predict financial failure for hotel businesses. Using the data of these hotels, he calculated the Z1 (Z Score Model), Z2 (Z´), and Z3 (Z´´) values developed by Altman and compared these values. In this study where a prediction was made for 1 year ago, it was determined that the Z1 value gave the most successful result with a rate of 88.24%. For Z2 and Z3, these rates were found to be 83.33% and 80%, respectively. In addition, it has been determined that approximately 40% of hotel establishments according to Z1 value, 44.5% according to Z2 value, and 36.3% according to Z3 value are located in the bankruptcy zone.

Korol (2013) examined 60 companies in Latin America and 185 companies in Central Europe to develop a prediction model for the bankruptcy risk of companies. In this study, 14 independent variables are determined, consisting of financial ratios and ratios that show the change of these ratios. He used discriminant analysis, decision tree, and artificial neural networks methods in his study, which dealt with 135 active and 50 bankrupt companies in Central Europe and 30 active and 30 bankrupt companies in Latin America. With the help of these methods, it was determined that the most successful method was the decision tree analysis in the study, where the efficiency of 12 models, 3 models for 1 year and 2 years ago, was compared separately for companies in Latin America and Central Europe. While the correct classification rates of the prediction models for 1 year and 2 years ago developed for companies in Latin America were 96.66% and 95%, respectively, it was observed that these rates were 96.23% and 88.68% for companies in Central Europe.

Brédart (2014) aimed to predict financial failure by handling financially successful and unsuccessful companies in the USA and using financial rates. For this purpose, it has determined three easy-to-use financial ratios with low correlation among themselves: Net Profit / Total Assets, current ratio, and Total Equity / Total Assets. In this study, which deals with the period of 2000-2012, he stated that, according to the results of the descriptive statistics, the said ratio of successful companies is higher. The prediction accuracy of the logit analysis performed was found to be 83.82%.
Xu et al. (2014) used principal component analysis, soft set theory, and coarse set theory, which are among the dimension reduction methods. They calculated 66 financial ratios

belonging to 240 companies and applied size-reduction analysis using these financial ratios. In the continuation of the study, they supported these analyses with support vector machines, artificial neural networks, and logistic regression analysis. As a result of the applied analysis, it was determined that the best dimension reduction method was the soft set theory and it was seen that the number of financial ratios from 66 decreased to 9. On the other hand, it was emphasized that among these 9 ratios, four ratios, namely Net Profit / Sales, Management Fee / Total Cost, asset turnover rate, and leverage ratio, are the most useful ratios for financial failure prediction.

Geng et al. (2015) calculated the 31 financial indicators they determined in their study by using the data of the sample they chose from companies operating in China. In this study, they aimed to determine which method has the best performance in predicting financial failure, how early the financial failure of companies in the sample can be predicted, and which financial indicators have a more important role in determining financial failure. They emphasized that artificial neural networks are a better method than decision tree analysis and support vector machines. Firstly, they applied ANOVA for 31 financial indicators and reduced this number to 10.

Unlike other financial failure studies, Liang et al. (2016) used both financial ratios and corporate governance indicators as variables. In this comprehensive study, in which 190 variables including 95 financial ratios in seven different categories and 95 corporate governance indicators in five different categories, they analysed the data of 478 companies, 239 of which were successful and 239 of which were unsuccessful, for the period 1999-2009. As a result of the analysis, they determined that the performance of the model developed using financial ratios and corporate governance indicators were higher than the performance of the model developed using only financial ratios. At the same time, according to the analysis results, they concluded that the solvency and profitability ratios within the financial ratio categories and the indicators of the board structure and ownership structure within the categories of corporate governance indicators are the most important indicators in financial failure prediction.

Khan (2016) aimed to develop a model for financial failure prediction in the financial sector in Pakistan. For this purpose, he used a logit model and discriminant analysis. In addition, it also benefited from Altman's Z Score and Ohlson's O Score models. In this study, in which he examined 20 successful and 20 unsuccessful companies, he found that the correct classification power of discriminant analysis was 81.5% and that the logit model has a higher classification power than discriminant analysis with 85.5%. Khan stated that there are six financial ratios in the model developed with discriminant analysis and three financial ratios in the logit model, and stated that the variables in the stronger logit model are Undistributed Profits / Total Assets, EBIT / Total Assets, and Short-Term Liabilities / Total Assets.

In some studies, more than one method was applied and the estimation performance of the models resulting from these methods was compared. These studies are summarized below.

Low, Nor, and Yatim (2001) created a model for predicting financial failure with the help of logistic regression analysis in their study. In total, 11 variables were used. These 9 financial ratios are the size of businesses (total assets) and the rate of change in net profit used in Ohlson's (1980) study. The first classification is based on the ability to pay the debt. Businesses that fail to pay off debts were considered unsuccessful. In the data set of the study, the data of 26 unsuccessful companies and 42 successful companies were entered, and the predictive power of the model was tested with a control group consisting of 10 companies (5 unsuccessful and 5 successful companies). The correct classification rates of the model were 82.4% in the study group and 90% in the control group (Low et al., 2001: 49-61).

Liou and Smith (2006), added six macroeconomic variables and the size of the enterprises (sales) to the Taffler (1983)'s model, investigating whether the separation performance of the model increased. The most desirable result was determined as the reduction of the second type of error in the model. As a result of the analysis, the final version of the model included only two variables. These; they are financial ratio and macroeconomic magnitude (industrial production index). The correct classification rate of the model was found to be 69.10%. As a result, after adding macroeconomic variables and the size of the enterprises (sales) to the Taffler model, neither the second type of error nor the total separation performance of the model increased (Liou and Smith, 2006: 1-37).

Salehi and Abedini (2009: 398-409) conducted a similar study to the multivariate model created by Altman (1968) in 2009. As in Altman's study, the variables considered are financial ratios and these were obtained from the data of 60 companies traded in the Tehran Stock Exchange. The data set of the study was created to match 30 unsuccessful (those who do not continue to be traded in the stock exchange) and 30 successful companies (those who continue to be traded in the stock exchange). As a result of the research, the correct classification rate of the model one year before financial failure (t-1) was found to be 95%. The first type of error and the second type of error were seen as 7% and 3%, respectively. The correct classification rates of the model found for other t periods (t-2 and t-3) are respectively 83.50% (1st type error is seen as 23%, 2nd type error is seen as 10%), 90% (1st type error is seen as 7%, 2nd type error is seen as 13%).

Suntraruk (2014) tried to create a model with a high rate of correct classification. Hence, it used three main variables. These; four financial ratios, four macroeconomic magnitudes, and three variables related to corporate governance. The model created as a result of stepwise logistic regression analysis was found to have a 95.6% correct classification rate. However, it was seen that the only variable group that was not found significant in the model was macroeconomic variables (Suntraruk, 2014: 1-24).

Boisselier and Dufour (2011) aimed to evaluate the performance score and financial failure risk of enterprises with the backward stepwise logistic regression method. A matched data set was created by taking 450 companies that failed and 450 companies that were in good condition, which were classified according to the Diane Database. In this data set, financial ratios were entered as quantitative variables, and scores given by Banque de France (French Central Bank) to companies according to their financial status were entered as qualitative variables. The correct classification rate of the created model was found to be 73.36%, and the first type of error in the model (correct classification rate in the failed group) was 14.75%, and the second type error (correct classification rate in the successful group) was 38.54% (Boisselier and Dufour, 2011: 1-18).

Alifiah (2013) created a model that is subjected to logistic regression by using financial ratios and macroeconomic values. The financial ratios used belong to four main groups (liquidity, financial structure, turnover rates, and profitability) and were obtained from five-year data of 20 companies (10 failed and 10 successful). Therefore, the data set was created in the form of a crossover design. As a result of the analysis, it was found that five variables (four financial rates and interest rates) for financial failure prediction were statistically significant between 5% and 1%. While there is a positive correlation between interest rates and the superiority rate of the dependent variable, it has been determined that there is a negative relationship between financial rates and the superiority of the dependent variable. This means that when interest rates rise, the risk of financial failure in businesses increases. However, when the four significant financial ratios increase, the risk of financial failure in businesses decreases. The accurate classification rate of the model was 85%, first type error 14%, second type error 16% (Alifiah, 2013: 90-98).

Tinoco and Wilson (2013) firstly created models by using the logistic regression (panel logit) method with five combinations of three main variables (financial ratios, macroeconomic sizes, and market data). Afterwards, the prediction powers of the models (5 models) created within the same time intervals were compared using tools such as ROC (Receiver Operating Characteristics) curves (ROC Curves) and AUC (Area Under the ROC Curve). Finally, the models created by the logistic regression method were compared with both artificial neural network's models and Altman's (1968) Z-score original model according to their prediction power. The enterprises examined in the study are those listed on the London Stock Exchange, and businesses whose funds consisting of depreciation interest and earnings before tax are less than their financing costs, and businesses whose market value growth rates are negative for two consecutive years are classified. As a result, models with the highest predictive power are classified as models that include all variables (Tinoco and Wilson, 2013: 394-419).

Bozkurt (2014) aimed to identify the model that best explains the increase in systematic risks. In his work for this purpose; the author analysed the bankruptcy probabilities of 168 businesses traded on BIST by using eight different models including the Altman-Z Score model. In line with the results of the study; Altman-Z stated that the Ohlson-O and Springate-S insolvency models better explain the change in systematic risks in the BIST index.

Karadeniz and Ocek (2018), measured the risk of the financial failure of lodging companies that are traded on exchanges in both Turkey and Europe. They measured financial risk by bankruptcy models which included Altman Z Score, Altman Z' score, Springat to, Ohlson score, Fulmer , and CA-Score models. In addition, the dataset of the study consists of 5-year data of 75 lodging companies in 21 countries between 2012 - 2016. As a result of the study, when the number of businesses with financial failure risk indicated by the models for all years included in the analysis are compared, it is stated that the number of enterprises that show financial failure risk in Altman Z, Altman Z', Ohlson models, Springate and Fulmer models are close to each other. In addition, it has been concluded that the maximum risk of financial failure for companies between the years of 2012-2016 in Turkey and Europe are determined by Fulmer's bankruptcy model and Springat models.

Altman-Z and Springate models were applied to 166 companies from 7 different sectors by Kurklu and Turk (2017). As a result of this application, it has been revealed that both models are similar in predicting financial failure. According to this analysis, the Altman Z model states that 69% of the firms are successful, and Springate suggests that 57% of the firms are successful.

Another study measuring the accuracy of models related to financial failure was conducted by Edi and May (2018) for consumer goods companies listed on the Indonesian Stock Exchange. In this study, in which Altman, Springate, Zmijewski, and Grover models were compared, the model with the highest accuracy is the Springate model with approximately 70%. This model is followed by Grover, Altman, and Zmijewski, respectively.

The financial statement combinations of 14 companies included in a BIST Trade index made by Dizgil (2018) between 2012 and 2017 were examined according to the Springate financial failure prediction method and the S score calculated according to the Springate model is on average 0.99. According to this result, most of the companies are financially successful and the risk of bankruptcy is low. However, according to the Springate model, it has been determined as a result of the analysis in companies with bankruptcy and financial failure risk. However, it was observed that the bankruptcy and financial failure predictions regarding these companies did not come true. However, failure to predict bankruptcy or financial failure does not mean that companies are not at risk. In the next part of the study, the effect of the variables determined according to the Springate model and used in the calculation of the S score on the S score was examined with the help of various econometric analyses. As a result of the analysis, it is revealed that the Springate model gives useful results in terms of financial performance evaluation. According to the results, the Springate model does not predict a definite result in predicting bankruptcy.

All in all, failure concepts for businesses can be categorized as economic failure and financial failure. Although they are seen to be the same concepts, these two categories are different from each other. In this study, the author of this thesis aims to focus on the financial failure of companies that experience the problem of inability to pay debts. There are three classifications of financial failure. With the aim of the thesis, financial failure will be taken into account according to the bankruptcy definition.

Previous studies show that the financial failure concept was researched many times by researchers. While some of the researchers aimed to find the best ratios to predict bankruptcy, others worked on direct bankruptcy models. In the latter group, researchers generally focus on the accuracy of Altman Z score and its derivatives. Altman Z-Score worked on different samples of data. Some of the researchers compared the accuracy of different prediction models of financial bankruptcy. When their work is analyzed, it can be seen that these researchers focus on one type of the models: two dimensional or one dimensional. Furthermore, research group that focused on one-dimensional group can be gathered by adding the researchers that worked on financial ratios, directly. All in all, it is not faced with research on working both types of models. Therefore, the author of this study aims to analyze both models and compare the results with each other as a contribution to literature and practitioners.

2. MODELS FOR PREDICTION OF FINANCIAL FAILURE OF COMPANIES

Over the past years, researchers have developed models to assess the likelihood of financial failure. These studies usually try to create a model by using publicly available information from financial statements to estimate the probability of these businesses going bankrupt at some point by comparing the matching samples of non-bankrupt and insolvent firms (Wu et al., 2010).

When we look at the previous studies, it is seen that statistical methods are the leading methods used for financial failure prediction. Some of the models used in these studies are univariate, while some are multivariate. Therefore, it is possible to divide the models used for the prediction of financial failure into two groups as univariate and multivariate. When the literature is examined, it is seen that the methods used for predicting financial failure differ in parallel with the digitalizing world. In some studies, it is seen that methods such as genetic algorithms (Holland, 1975) and artificial neural networks (Odom and Sharda, 1990) are used in addition to statistical methods that we can call traditional.

The investigation of financial failure with a genetic algorithm was first carried out by John Holland in the literature. In his work named "Adaption in Natural and Artificial Systems", which Holland published in 1975, it is seen that machine learning method was used for the prediction of financial failure.

In the literature, predicting financial failure with artificial neural networks was first used in the study published by Odom and Sharda in 1990. This study was created from 129 businesses, 65 of which failed; While creating an artificial neural network model on this sample, five financial ratios in Altman-Z score were chosen as independent variables. While obtaining the financial ratios, the tables of the years in which the financially unsuccessful firms were successful were taken into consideration.

2.1. One-Dimensional Models

The purpose of one-variable models is to try to predict the financial failure of a business with the help of a single argument (Beaver, 1966; Weibel, 1973). In studies conducted with these models, it is generally tried to determine the most reliable variable that can explain the current financial situation of the enterprise.

During the use of univariate models, financial variables are handled separately while grouping the analysed businesses as successful and unsuccessful; The relationship between financial variables is not evaluated. Another means of this is that the analysis is performed by assuming that the financial variable under consideration has a normal distribution. This is the weak point of univariate models. If a non-linear relationship of some rates of the company with financial failure is taken into account during the application, this assumption is considered invalid and the accuracy of the results obtained as doubtful (Beaver, 1967).

Univariate prediction models are seen to be simpler when compared to multivariate analysis. This is because the firms included in the analysis can be classified as successful or unsuccessful only according to financial ratios, without any need for statistical information (Beaver, 1967).

The most common method used by businesses to measure their financial success is ratio analysis. Ratio analysis is performed by proportioning the two values in the financial statement. With this analysis, the financial statements of the business are measured in a more meaningful way with fewer variables by summarizing the financial variables. As it can be understood from here, while ratio analysis measures the financial success of the companies, these model's ratio some values to each other with the help of the financial statements of the company, and thus, more refined information is obtained with this method.

2.1.1. Beaver Model

In literature, one of the first studies using the ratio analysis method to predict financial failure belongs to William H. Beaver. His study, "Financial Ratios as Predictors of Failure", is published in 1966: Beaver examined the financial ratios of 158 companies, 79 of which were financially unsuccessful, as a sample between 1954-1964. In this model, firms that are considered to be financially unsuccessful are not only based on bankruptcy but are included in the comparison in financially troubled and troubled firms. The enterprises in the data set operate in 38 different sectors in total, and they are close to each other in terms of firm size. The criteria used in Beaver's study to identify financially unsuccessful companies (Beaver, 1966):

- Bankruptcy,
- Delay in paying interest on the business bond,
- The deposit accounts of the business have a negative value,
- Not paying dividends per share.

Besides, Beaver included some rates in the analysis in his study and proved that these rates are early warning signs that the business will experience financial failure 5 years ago. These proportions are:

- Total Liabilities / Total Assets
- Current Assets / Short Term Liabilities,
- Net Profit / Total Assets
- Cash Flow / Total Debts
- Net Working Capital / Total Assets
- Net Working Capital / Operating Expenses

At the end of his study, Beaver has determined that the most successful rate in predicting bankruptcy among these ratios is the Cash Flow / Total Debt ratio. Beaver's work was based on Patrick's (1932) earlier research work on the usefulness of rates. The result of Patrick's work has indeed shown that ratios and associated analytical methods can be used as powerful assessment tools. The aim of the study is not only to create a model for failure prediction but also to examine the value of the ratios and accounting data used in their calculations. At the end of the study, it is suggested that further research can be done using multi-radio analysis using multiple ratios to determine the bankruptcy potential in companies. It can be said that this proposal paved the way for Edward Altman to develop the bankruptcy prediction model.

According to Deakin (1972), although the predictive ability of the Beaver model's results is indisputable, the later Altman model has greater sensor uses and popularity.

He made the second study of Beaver on this subject in 1968; While carrying out this study, he was inspired by the effective capital market theory. In this study, Beaver tried to predict the failure of businesses with changes in the value of stock prices in financial markets. As a result of the study carried out, it has been proven that stock data are not effective in predicting financial failure (Beaver, 196: pp.71 - 111).

2.1.2. Sinkey Model

One of the early studies on financial failure belongs to J.F. Sinkey. He discussed the financial failures of banks in his study titled “A Multivariate Statistical Analysis of the Characteristics of Problem Banks” published in 1975. Sinkey concluded in his study that credit quality is statistically significant in predicting banks' financial failures. The credit quality of banks can be measured empirically by the financial ratios listed below (Sinkey,1975):

- Non-Performing Loans / Total Loans or Total Assets
- Problematic Credit Reserve / Total Assets
- Provisions for loan losses / Total Loans

Loans are the riskiest asset for most financial institutions. Thus, empirical evidence on asset quality indicates that the allowance for loan losses differs significantly between troubled and non-troubled banks (Sinkey, 1975).

In another study (1975) conducted by Sinkey with Walker in the same year, he aimed to model the problematic banks in the list of FDIC. 62 banks within the scope of the study were divided into two groups as problematic and uneventful, and then tried to predict the activities and financial behavior of banks by comparing the financial information of the banks included in the data set (Sinkey and Walker, 1975).

2.1.3. Weibel Model

In a study conducted in 1973, Weibel examined a total of 72 customers in the small business segment of a bank in Switzerland, 36 of which were in financial difficulties. The rates he takes into account in the analysis (Weibel,1973):

- Current Assets / Short Term Liabilities
- Cash Flow / Short Term Liabilities

- Stock Turnover Speed
- Foreign Resources / Equity
- Working Capital / (Operating Expenses-Depreciation)

2.2. Multi-Dimensional Models

Working with one-variable models will have questionable results. This is because these models consider a single variable for financial failure and ignore the correlation with other variables. Altman (1968) and Tamari (1966) also argue that it is not correct to work with a single variable in predicting financial failure because when working with a single variable, it is not correct to not study other variables that may be important. However, an analyst trying to analyse financial failure with financial ratios also needs to examine each ratio. Because the analysis is performed using only one ratio or the rates belonging to a certain group, the accuracy of the results obtained will be doubtful. Because while certain ratios follow a positive trend, some ratios may have a negative trend. For an analyst to reach the correct conclusion in his study on financial failure, he must consider the effects and impact aspects between financial ratios. For these reasons, multivariate models have been developed for predicting financial failure.

2.2.1. Tamari Model

Meir Tamari (1966) argued that multivariate models should be used instead of traditional one-variable models in predicting financial failure. Tamari developed a "Risk Index"; In this index, it is recommended to use multiple variables instead of using a single variable when evaluating the current risks of businesses (Tamari, 1966:15-21). Tamari completed his study by considering 6 variables that are accepted as generally valid. These variables and coefficients are given in Table 2 below.

Table 2. Tamari Model

Variable	Coefficient
Net Income/Sales	25%
Sales/Short Term Receivables	10%
Production Value/Stocks	10%

Production Value/Net Working Capital	10%
Current Assets/Short Term Liabilities	20%
Shareholders Equity/Total Liabilities	25%

Source: (Tamari,1966)

2.2.2. Meyer and Pifer Model

The creation of a multivariate model to predict the financial failure of banks was first performed by Meyer and Pifer in their work titled "Prediction of Bank Failures" published in 1970. Meyer and Pifer (1970) analysed 39 banks considered as financially unsuccessful in this study and evaluated their results by comparing failed banks with successful banks using the logistic regression method. At the end of the study, the model was determined to be 80% unsuccessful. This means that while 80% of the 39 banks included in the model could be classified into two groups as unsuccessful or successful, a correct grouping could not be reached for the remaining 20%.

2.2.3. Altman Z Model

Edward Altman published a study in 1968 in which he tried to predict financial failure with a multivariate model different from the traditional univariate model. Edward Altman (1968) is the name of the method he used to perform the analysis in this study, which is Multivariate Discriminant Analysis. The grouping of companies included in the data set during Multivariate Discriminant Analysis is based on bankruptcy. In the analysis, companies are divided into two groups as bankrupt and non-bankrupt. After this separation process, using the discriminant analysis method, the financial ratios that can distinguish these two groups are tried to be determined.

In Altman's study (1968), 33 of them went bankrupt and the other 33 were compared to enterprises that did not go bankrupt or were financially successful. Altman used the following 5 categories to classify the financial ratios used in the analysis:

- Liquidity
- Lever
- Profitability
- Affordability
- Activity

In the study, 22 financial ratios belonging to these groups were used and 5 financial ratios that were predicted as the highest predictive power were selected and formed the following multivariate discriminant function:

$$Z = .012X_1 + .014X_2 + .033X_3 + .006X_4 + .999X_5 \quad (1)$$

The meanings of the X variables in the function are included in Table 3.

Table 3. Descriptions of X Variables in the Altman Z Model

Variables	Descriptions
X_1	Net Working Capital / Total Assets
X_2	Undistributed Profits / Total Assets
X_3	Profit Before Interest and Tax / Total Assets
X_4	Total Market Value of Stocks / Book Value of Total Debt
X_5	Sales / Total Assets

Source: (Altman,1968)

As a result of the study, Altman reached 2 values for the estimation of the financial failures of the enterprises and created 3 separate areas when classifying the enterprises. If the Z score calculated for the business is lower than 1.81, the probability of this business to go bankrupt is seen as very high; On the contrary, if the Z score of the business is higher than 2.99, the probability of the business to go bankrupt is seen. In addition to these, businesses with an in-between Z score are in the grey area according to Altman. This means that businesses with this score cannot be considered financially successful or financially unsuccessful, and the bankruptcy of such businesses cannot be easily predicted. The explanations of the values and the areas they belong to can be seen in Table 4.

Table 4. Altman (1968) Classification of the Z Score

Z Score	Descriptions
<181	High probability of bankruptcy
1.81 – 2.99	Bankruptcy is not predictable
>2.99	No probability of bankruptcy

Source: (Altman,1968)

Altman (1983) conducted a new study by revising the X_4 variable at a different rate. In his study published in 1968, he changed the "Total Market Value of Stocks / Book Value of Total Debt" ratio to "Equity Book Value / Total Book Value of Debt" and re-established the model. The purpose of doing this is to include the bankruptcy risk of the businesses listed on the stock exchange to the model. In this study, Altman examined the enterprises operating in the manufacturing sector. The results are as follows:

$$Z' = .071X_1 + .847X_2 + 3.10X_3 + .42X_4 + .998X_5 \quad (2)$$

The new Z score classifications introduced for the revised model are shown in Table 6.

Table 5. Altman (1983) Classification of the Z Score

Z Score	Descriptions
<1.23	High probability of bankruptcy
1.23 – 2.90	Bankruptcy is not predictable
>2.90	No probability of bankruptcy

Source: (Altman,1983)

Altman used the discriminant analysis method in his study in 1993, this time produced a function that can be used by businesses outside the manufacturing sector. Altman (1993) reduced the function variables to 4. The function obtained as a result of the analysis is as follows:

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \quad (3)$$

Z score classification for the new function is shown in Table 6.

Table 6. Altman (1993) Classification of Z Score

Z Score	Descriptions
<1.10	High probability of bankruptcy
1.10 – 2.60	Bankruptcy is not predictable
>2.60	No probability of bankruptcy

Source: (Altman,1993)

2.2.4. Springate Model

It was developed in 1978 by Gordon L.V Springate. It is similar to the Altman model. It is a multi-stage and multi-variable model. Springate (1978) used the multivariate discrimination analysis method in this study. Developed a model to identify successful and unsuccessful businesses on 4 basic ratios and calculated an ‘S’ value. Processes with an ‘S’ value less than 0.862 are considered unsuccessful. The author tested the model on 40 businesses selected by random sampling. As a result of the research, the accuracy of the model was found to be 92.5%. The S score value in the Springate model is calculated as follows (Pakdaman, 2018):

$$S = 1.03X_1 + 3.07X_2 + 0.66X_3 + 0.4X_4 \quad (4)$$

The ratios in this formula are as follows (Pakdaman, 2018):

X_1: Working capital / total assets

X_2: Profit before interest tax / total assets

X_3: Profit before interest tax / short term debt

X_4: Sales / total assets

2.2.5. Grover Model

Jeffrey S. Grover reached this model as a result of his studies on 13 financial ratios. In this study, the Altman-Z score model was revised by using 35 companies that went bankrupt between 1982-1996 and 35 companies that did not. In this model, Altman added a ROA (Return on Asset) to the variables X_1 (Net working capital / Total Assets) and X_3 (Profit Before Interest and Tax / Total Assets) in the Z score model. The G-Score in the Grove model is calculated as follows (Grover and Lavin, 2001):

$$G = 1.650X_1 + 3.404X_2 - 0.016ROA + 0.0507 \tag{5}$$

The formulas in the model are as follows:

X_1 = Net working capital / Total Assets

X_2 = Profit Before Interest and Tax (EBIT) / Total Assets

ROA = Net Income / Total Asset

In this model;

If G-Score $\geq$ 0.01, the firm is successful,

If the G-Score $\leq$ -0.02, the firm is considered unsuccessful. Companies scoring points between the upper and lower limits are in the grey area.

2.2.6. Other Models

Apart from the above models, some researchers are important in terms of being the first of their period.

Ohlson (1980) created a logit (logistic regression) model for the first time in predicting financial failure. In fact, the author "used logit analysis to avoid the limitations arising from the assumptions of discriminant analysis". As a result of this study conducted in the USA, it was found that the financial ratios used one year before and two years before bankruptcy had predictive power. However, it was observed that the correct classification rate of the model one year before the bankruptcy was higher (Salehi and Abedini, 2009: 402).

Taffler (1983) created a model based on discriminant analysis for the manufacturing industry in the UK. However, the author "made a change in the discriminant method and calculated the performance score (Z-score) for the companies". As a result, 4 financial ratios were found to be significant for calculating performance scores (Liou and Smith, 2006: 5-6).

In this study by Fulmer (1984), it was tried to predict financial failure using multivariate separation analysis such as Altman and Springate. In Fulmer's model, 30 successful 30 unsuccessful businesses with an average asset size of $ 455 million were identified and used their data. An equation giving the H value is obtained. It found that firms with an H score of less than zero have a high level of financial problems and bankruptcy costs. He stated that firms with an H score greater than zero are financially successful.

In conclusion, while one-dimensional models are focusing on only one financial ratio, multi-dimensional models focus on sets of financial ratios. Independent from the types of models, models focused on working capital, sales, and ratio about the cash flow of a company. On the other hand, one-dimensional models do not offer comparable thresholds like multi-dimensional models. Therefore, it can be considered that one-dimensional models can be more subjective than multi-dimensional models. In the next section, the models will be run on the same data and results will be compared in terms of accuracy of models.

3. COMPARATIVE ANALYSIS OF FINANCIAL FAILURE PREDICTION MODELS

3.1. Aim of the Research

This study is mainly aimed to investigate the accuracy performance of financial failure models. In this context, research has been conducted to clarify and answer the following three research questions:

1) Which financial ratio is better than others in the scope of models that takes into account in the empirical part of this research?
2) Are multi-dimensional models better than one-dimensional models
3) Which bankruptcy prediction model is best fitted among others which are in the context of this research?

When related literature is analysed, there is some research on the comparison of financial bankruptcy models with limited sample sizes. On the other hand, it was not faced with a research on the comparison of well-known financial failure models with an empirical dataset. So, this research is also aimed to contribute to researchers who research about financial failure of companies on their future work in terms of empirical evidence of accuracies of well-known bankruptcy models.

3.2. Research Methodology

This research design adopts a quantitative and descriptive approach. In order to achieve its stated objectives the author of the thesis calculated the accuracy of the models using secondary data (3.3) provided by a previous study on the field.

According to bankrupted firms' financial ratio was calculated by each model and then counted how many firms can be detected as bankrupted among these firms. After this process, the accuracy ratio of models calculated as;

$$Accuracy\ Ratio\ of\ Model\ = \frac{Number\ of\ Bankrupted\ Companies\ Detected\ by\ Model}{Total\ Number\ of\ Bankrupted\ Companies}$$

The accuracy ratio of models was evaluated in accordance with the closeness of 100 percent. If the ratio is as much as close to 100% the model was evaluated as better performance than other bankruptcy models. Furthermore, the accuracy ratio will be evaluated by the time variable. The models' accuracy ratio was also compared by which accuracy ratio of the model is highest among years before the bankruptcy.

The financial bankruptcy model was selected regarding being able to calculate financial ratios that are parts of models. Therefore, the models that are selected by the author are;

1) Beaver Model
2) Weibel Model
3) Altman Model
4) Springer Model
5) Grover Model

Beaver and Weibel's models are selected because they are both one-dimensional models. For multi-dimensional models, Altman, Springer, and Grover were selected. Altman's model and Springer's model is highly used in bankruptcy prediction literature. On the other hand, Grover's model is not as popular as the other multi-dimensional models. Therefore, Grover's model was added to the research's context. Meyer and Pifer and Sinkey models cannot be selected. The reason for this is that they are the models that can be applied to only the banking sector.

Followed process for analysing data as described below;

1) Extracting each financial indicator that is available from the dataset
2) Calculating financial ratios related to each model
3) Calculating model's scores associated with each model
4) Classifying each model's scores as bankruptcy or non-bankruptcy by each model and prediction time before bankruptcy. The companies that are detected in the grey area are also evaluated as predicted non-bankrupted companies.
5) Calculating the accuracy of each model

3.3. Data

The bankruptcy dataset that is used in this research consists of the financial condition of Polish companies. The dataset is provided by Ziebva, Tomczak, and Tomczak (2016) that was used in the "Ensemble Boosted Trees with Synthetic Features Generation in Application to Bankruptcy Prediction" research paper. In this research, the researchers aim to find the best financial ratios that predict the failure of companies with the Extreme Gradient Boosting method which is one of the machine learning algorithms for classification. As a result, the model which is created by the authors has the best predictor for financial failure among other classification algorithms.

The donated data which is publicly available at UC Irvine Machine Learning Repository (UCI)[1] was taken from the Emerging Markets Information System (EMIS)[2] that includes information about all emerging markets data around the world. Data is compiled from financial statements of Polish companies.

The sampled companies were bankrupted between 2007-2013 and operated between 2000-2012. For the context of this research, 2000 observation points which are labelled as bankrupted manufacturing companies were taken into account. Dataset also includes information of after how many years companies were bankrupted. Dataset can be divided in terms of five classification cases in terms of year:

1) First-year financial rates of bankrupted after 5 years
2) Second-year financial rates of bankrupted after 4 years
3) Third-year financial rates of bankrupted after 3 years
4) Fourth-year financial rates of bankrupted after 2 years
5) Fifth-year financial rates of bankrupted after 1 year

Dataset is consisting of 64 independent variables and one binary dependent variable (bankrupted/nonbankrupt) which indicates the financial failure status of the company. All attributes list is described in Appendix 1.

[1] https://archive.ics.uci.edu/ml/datasets/Polish+companies+bankruptcy+data
[2] https://www.emis.com/

3.4. Definition of Variables

Among the models that are used and compared in this study, the ratios to be used and the criteria to be evaluated are given in Appendix 3.

3.5. Findings

3.5.1. Findings for One-Dimensional Models

The Beaver Model and Weibel Model is analysed with our dataset. The descriptive statistics, methodology, and findings are below.

Findings for Beaver Model:

Cash Flow / Total Debt that gives the most accurate results out of the 6 ratios used in the Beaver model. It is stated in the literature that this ratio is a good criterion for companies. However, a threshold has not been determined for this ratio. Therefore, firstly, it was decided to use the median by looking at the kurtosis and skewness values of the Cash Flow / Total Debt ratios of 10503 instances .

The median value of this ratio was determined as 0.03. Therefore, firms with equal and higher ratios than this value are predicted to be successful and smaller ones as unsuccessful (near to fail).

The descriptive part of each classification based on the Beaver Model is below:

Table 7. Descriptive Statistics Table for Beaver Model

Beaver – Success	N	Mean	Min	Max	Standard Deviation
Cash Flow / Total Debt	1034	0.46	0.03	66.33	2.36

Beaver – Fail	N	Mean	Min	Max	Standard Deviation
Cash Flow / Total Debt	966	-0.58	-224.78	0.02	7.36

Source: author’s calculation.

According to Table 7, the ability of companies that are not expected to experience financial failure is about half of their ability to pay their cash and total debts. In other words, the cash of these companies is almost half of their debts. This situation puts the firm in the need to generate cash in the medium and long term. If they fail to generate cash, they will be more likely to experience financial failure. Looking at the values of 996 data points classified as unsuccessful in Table 7, it was observed that most of them could not generate cash to pay their total debts.

When the firms whose ratios are determined are examined with a threshold of 0.03 based on the Beaver model, it is observed that the probability of financial failure of 1036 data points is lower. However, considering that 2000 observations in this data set were also labelled bankrupt, the accuracy of the model varies based on time period. Accordingly, the Beaver model correctly predicted 31% of these companies 5 years before they went bankrupt, while it predicted with 65% accuracy just before going bankrupt (1 year ago) (Table 8).

Table 8. Beaver Model Performance

	Beaver Model		
Bankruptcy	Predict Bankruptcy	Not Predict Bankruptcy	Accuracy
Before 5 Year	83	182	31.32%
Before 4 Year	148	235	38.64%
Before 3 Year	231	247	48.33%
Before 2 Year	251	234	51.75%
Before 1 Year	253	136	65.04%

Source: author's calculation.

The most successful forecast period of the model seems to be the one-year financial period before bankruptcy. Although previous research result by Beaver (1966) was reported as 90 percent success our calculated results have shown a lower prediction accuracy which leads us to question whether the model is too sensitive to the shape of the data. For more than two-years and longer periods, the accuracy rate is below 50% which signals that the model is ineffective to predict bankruptcy and illustrates that maturity of prediction power is not capable to help managers for financial planning.

Findings for Weibel Model:

Cash Flow / Short Term Liability that gives the most accurate results out of the ratios used in the Weibel model. For a successful company, the ratio of cash generated from operations to short-term liabilities is required to be 0.40 or higher (Schmidgall and Defranco, 2004: 4). The descriptive statistics table for 2000 observations for this model are listed below.

According to Table 9, the ability of companies that are not expected to experience financial failure is about 271 out of 2000 observations. These companies almost pay 2 times of their short-term liabilities in their current cash. Considering the failed firms' ratio average, they have no cash to pay short-term liabilities or any other operation.

Table 9. Descriptive Statistics Table for Weibel Model

Weibel – Success	N	Mean	Min	Max	Standard Deviation
Cash Flow / Short Term Liabilities	271	1.81	0.40	66.33	5.01

Weibel – Fail	N	Mean	Min	Max	Standard Deviation
Cash Flow / Short Term Liabilities	1729	-0.34	-224.78	0.29	5.60

Source: author’s calculation.

When the firms whose ratios are determined are examined with a threshold of 0.40 based on the Weibel model, it is observed that the probability of financial failure of 1729 samples is lower. However, considering that 2000 observations in this data set were also bankrupt, the accuracy of the model varies based on time period. Accordingly, the Weibel model correctly predicted 82% of these companies 5 years before they went bankrupt, while it predicted with nearly 90% accuracy just before going bankrupt (1 year ago) (Table 10).

Table 10. Weibel Model Performance

	Weibel Model		
Bankruptcy	Predict Bankruptcy	Not Predict Bankruptcy	Accuracy
Before 5 Year	218	47	82.26%
Before 4 Year	316	67	82.51%
Before 3 Year	424	54	88.70%
Before 2 Year	422	63	87.01%
Before 1 Year	349	40	89,72%

Source: author's calculation.

As observed from the accuracy table (Table 10) the accuracy metric of the Weibel Model has a promising performance in both long and short term forecast window. The power of the model in long term (5 years before bankruptcy) accurate prediction can be an efficient tool for managers to eliminate negative risks by taking early precautions.

3.5.2. Findings for Multi-Dimensional Models

In this section; Altman, Springate, and Grover Models are analysed with our dataset. The descriptive statistics, methodology, and findings are below.

Findings for Altman Model:

Altman Z Score Model eliminates the criticisms that the financial ratios used in the ratio analysis management are evaluated separately, resulting in contradictory results. Unlike financial ratios, in the Altman Z Score Model, financial ratios are used in interaction and combining with each other. Therefore, while analysing this model, multivariate discriminant analysis was used in his study. The 5 financial ratios determined by Altman were calculated over the data set and the model was developed with the weights Altman assigned for the Z-score. In addition, the fact that the companies in Altman's data set are manufacturing companies like the companies in our study is also important in terms of its results. The descriptive part of this model is as follows:

Table 11. Descriptive Statistics Table for Altman Model

Altman – Fail	N	Mean	Min	Max	Standard Deviation
Working Capital / Total Assets	1448	0.12	-22.16	73.12	4.35
Retained Earnings / Total Assets	1448	-0.02	-18.94	30.70	2.13
EBIT / Total Assets	1448	0.02	-13.15	29.60	1.74
Book value of equity / Total Liabilities	1448	5.73	-3.73	629.58	102.35
Sales / Total Assets	1448	5.49	0.00	353.60	20.15
Z-Score	1448	1.00	-1.94	1.23	0.38

Altman - Success	N	Mean	Min	Max	Standard Deviation
Working Capital / Total Assets	622	0.03	-5.74	4.53	0.53
Retained Earnings / Total Assets	622	-0.08	-3.12	0.49	0.33
EBIT / Total Assets	622	0.02	-4.45	2.40	0.27
Book value of equity / Total Liabilities	622	4.10	-0.98	476.16	30.51
Sales / Total Assets	622	2.55	0.00	41.18	5.09
Z -Score	622	3.73	1.22	95.95	4.75

Source: author's calculation.

While Altman evaluated the Z-Score in three groups in his model, this study reduced the results to two groups since we will compare this model with other models. Therefore, if the Z-Score is greater than or equal to 2.99, the firm is considered successful, if the Z-Score is less than 1.23 it is considered unsuccessful. In short, the uncertain area in the model is included in the safe area.

According to Table 11, the fact that the Z value is below 1.23 indicates that the financial situation of the enterprise is under great risk and it is located in the red zone because of its financial failure (1378 firm). In other words, serious efforts should be made to minimize or eliminate the possibility of bankruptcy in order to make the business financially successful. Z value between 1.23and 2.99 indicates that the business is located in an uncertain area in terms of bankruptcy status and is likely to go bankrupt within two years. This situation is a warning for businesses and indicates that the necessary measures should be taken by the enterprises. If the Z value is above 2.99, it shows that the business is financially successful and does not have a risk in terms of bankruptcy. However, businesses should be vigilant against systematic risks and unexpected situations.

The important point in Table 11, the ratio of Retained Earnings to Total Assets are negative values on average for successful companies. This point proves that Altman model predictions are quite strong when considered in our data set structure (It involves totally bankrupt firms). Another important point is that sales to total assets ratio might be effective to call a successful company. However, the reality of the dataset structure proves to us that sales revenue is not effective by itself. The crucial thing might be generating profit from cash.

Table 12. Altman Model Performance

	Altman Model		
Bankruptcy	Predict Bankruptcy	Not Predict Bankruptcy	Accuracy
Before 5 Year	250	38	86,81%
Before 4 Year	332	55	85,79%
Before 3 Year	400	60	86,96%
Before 2 Year	407	63	86,60%
Before 1 Year	339	50	87,15%

Source: author’s calculation.

When the firms whose ratios are determined are examined with a threshold of Altman Z-Score, it is observed that the probability of financial failure of 266 samples is lower. However, considering that 2000 observations in this data set were also bankrupt, the accuracy of the model varies based on time period. Accordingly, the Altman model correctly predicted 86% of these companies 5 years before they went bankrupt, while it predicted with 87% accuracy just before going bankrupt (1 year ago). In addition, Altman

Model makes the best prediction before 3 years from bankruptcy based on our data set (Table 17).

Findings for Springate Model:

Springate Model is accepted as an improved version of the Altman Z Score model. The Springate Model used four ratios of the Altman model and changed weights to find S-score. Firstly, these four ratios were calculated from the relevant data set of this study. At the end, the S Score value was calculated as the model said. The descriptive part of this model is observed in Table 13.

Table 13. Descriptive Statistics Table for Springate Model

Springate – Fail	N	Mean	Min	Max	Standard Deviation
Working Capital / Total Assets	1097	0.69	0.00	22.16	1.75
EBIT / Total Assets	1097	-0.26	-13.15	2.06	0.95
EBIT / Short Term Liabilities	1097	-0.67	-231.85	0.29	7.25
Sales / Total Assets	1097	1.16	0.00	14.84	0.90
S-Score	1097	-0.23	-160.50	0.86	5.23

Springate – Success	N	Mean	Min	Max	Standard Deviation
Working Capital / Total Assets	903	1.08	0.00	73.12	4.87
EBIT / Total Assets	903	0.36	-1.65	29.60	1.83
EBIT / Short Term Liabilities	903	0.57	-1.95	67.32	2.84
Sales / Total Assets	903	2.71	0.00	96.06	4.13
S-Score	903	2.22	0.86	46.97	2.72

Source: author’s calculation.

According to this model, if the S-Score is below 0.862, the business is considered close to bankruptcy or financially unsuccessful. Therefore; 1097 samples are close to bankruptcy. In other words, serious efforts should be made to minimize or eliminate the possibility of bankruptcy in order to make the business financially successful. If the S value is above 0.862, it shows that the business is financially successful and does not have a risk in terms of bankruptcy. According to Table 13, 903 samples are considered as successful based on their financials.

The interesting point is that the sales amount is not enough to fail. Therefore, other ratios will affect the income level. Both models (Altman and Springate) consider whole ratios at the same time. This side of the model might be close to accurate predictions.

Table 14. Springate Model Performance

	Springate Model		
Bankruptcy	Predict Bankruptcy	Not Predict Bankruptcy	Accuracy
Before 5 Year	117	148	44.15%
Before 4 Year	182	201	47.52%
Before 3 Year	261	217	54.60%
Before 2 Year	286	199	58.97%
Before 1 Year	251	138	64.52%

Source: author’s calculation.

Table 14 demonstrates the accuracy percentage of Springate predictions based on this study’s data set. When the firms whose ratios are determined are examined with a threshold of S-Score, it is observed that the probability of financial failure of 903 samples is lower. However, considering that 2000 observations in this data set were also bankrupt, the accuracy of the model varies based on time period. Accordingly, the Springate model correctly predicted 44% of these companies 5 years before they went bankrupt, while it predicted with 64% accuracy just before going bankrupt (1 year ago). Considering that the Springate Model is an improved version of Altman and one ratio is eliminated, the accuracy level affected more. The weight of the missing ratio is so low in Z-Score, the effect of missing part on S-Score and re-weighed ratios on S-Score created approximately a %20 decrease in accuracy level.

Findings for Grover Model:

Grover Model predicts financial failure with G-Score. This score involves three ratios which are observed in Table 15. Firstly, all ratios are gathered from our dataset, and G-Score is calculated based on Equation 5.

In this model; if G-Score ≥ 0.01, the firm is successful, and if G-Score ≤ -0.02, the firm is considered unsuccessful. Companies scoring points between the upper and lower limits are in the grey area. In the descriptive part, the grey area is included to successful companies to compare easily. However, this grey area is not involved to accuracy level in line with the literature

Table 15. Descriptive Statistics Table for Grover Model

Grover – Success	N	Mean	Min	Max	Standard Deviation
Working Capital / Total Assets	1584	0.98	0.00	73.12	3.91
Net Profit / Total Assets	1584	0.00	-32.05	2.35	0.83
EBIT / Total Assets	1584	0.01	-32.09	2.35	0.83
G-Score	1584	0.77	-0.02	20.29	1.05

Grover – Fail	N	Mean	Min	Max	Standard Deviation
Working Capital / Total Assets	416	0.43	0.00	10.50	1.12
Net Profit / Total Assets	416	-0.37	-6.82	0.00	0.57
EBIT / Total Assets	416	-0.37	-6.82	-0.03	0.57
G-Score	416	-0.71	-16.00	-0.02	1.32

Source: author’s calculation.

Table 15 shows us the descriptive statistics of the G-score and its dimensions for failed and successful companies. G-Score assumes that 416 samples are very close to financial failure. The interesting point is that the ratios under this model are not quite strong for successful companies as well. The main reason is that the whole dataset is fully bankrupt in the end. Therefore; the companies which have moderate G-score also consider their profitability and liquidity not to face failure.

Table 16. Grover Model Performance

	Grover Model		
Bankruptcy	Predict Bankruptcy	Not Predict Bankruptcy	Accuracy
Before 5 Year	29	234	11.03%
Before 4 Year	54	327	14.17%
Before 3 Year	82	391	17.34%
Before 2 Year	124	354	25.94%
Before 1 Year	127	253	33.42%

Source: author’s calculation.

Table 16 demonstrates the accuracy percentage of Grover predictions based on this study’s dataset. When the firms whose ratios are determined are examined with a threshold of G-Score, it is observed that the probability of financial failure of 1559 samples is lower. However, considering that 2000 observations in this data set were also bankrupt, the accuracy of the model varies based on time period. Accordingly, the Grover model correctly predicted 11% of these companies 5 years before they went bankrupt, while it predicted with 33% accuracy just before going bankrupt (1 year ago). This low accuracy makes this model not preferable to predict the bankruptcy especially for manufacturing firms when the size of firms are diverse.

3.5.3. Comparison of Models

The whole result of accuracy level based on one-dimensional and multi-dimensional models is shown as a table which is below to compare the performance of accuracy level for each model. In order to see more clearly how the predictive power of the model changes when there is less time left for bankruptcy, the time period to bankruptcy is listed as distant year to near year.

Table 17. Comparison of Models

	One-Dimensional Models		Multi-Dimensional Models		
Bankruptcy	Beaver Model	Weibel Model	Altman Model	Springate Model	Grover Model
Before 5 Year	31.32%	82.26%	86,81%	44.15%	11.03%
Before 4 Year	38.64%	82.51%	85,79%	47.52%	14.17%
Before 3 Year	48.33%	88.70%	86,96%	54.60%	17.34%
Before 2 Year	51.75%	87.01%	86,60%	58.97%	25.94%
Before 1 Year	65.04%	89.72%	87,15%	64.52%	33.42%

Source: author's calculation.

The points based on Table 17 are evaluated as follows:

- All models' predictions are gradually increasing except Weibel and Altman Models. Weibel's predictions are quite strong before 3 years from bankruptcy, Altman's accuracy level has the highest level before 4 years from bankruptcy.
- Before 1 year; the Weibel model's predictions were quite strong among one-dimensional models. The Altman Model also predicts more accurately comparing multi-dimensional models. All in all, the Weibel model's accuracy level is so high before 1 year from bankruptcy.
- Before 2 years from bankruptcy; Weibel Model's accuracy is still high compared with not only multi-dimensional but also all models. The Altman Model also predicts more accurately comparing multi-dimensional models.
- Before 3 years from bankruptcy; the same situation exists.
- Before 4 and 5 years from bankruptcy; Altman Model's accuracy is high compared with not only multi-dimensional but also all models. Therefore, multi-dimensional models' early prediction power is stronger than one-dimensional models.
- The lowest score for all prediction periods was obtained from the Grover model. Considering that it has obtained better results in previous studies, it seems that the reason is that the data used in these studies mostly consist of large-scale

companies. Since the turnovers of the companies used in this study are more diverse, it is observed that the generalization capability of the model is exceeded.

- The results of the Altman Model are in line with the results of previous studies. The difference between the prediction score of 5 years before bankruptcy 86.81% and 1 year before bankruptcy 87.15% is 0.34%. The model has once again proved its adequacy and robustness according to the results of this study.
- The best-fitting model in one-dimensional models is Weibel's model and the winner model in multi-dimensional models is Altman's model. If we consider the winners as representatives of each group:
    - The average accuracy of multi-dimensional model is greater than one-dimensional (86.66% > 86.04%)
    - The range of accuracy ratio in 5 years period before the bankruptcy of multi-dimensional is less than one-dimensional (0.34% < 7.46%) which leads us to conclude that multi-dimensional is more robust than one-dimensional.
    - The highest score in predicting 1 year before bankruptcy belongs to the one-dimensional model (89.72%). It proves that this model is more successful in explaining when bankruptcy is inevitable.
    - The highest scores 4 and 5 years before the bankruptcy is multi-dimensional (85.79% and 86.81%). This implies that the multi-dimensional model is more suitable for early warning than one-dimensional.

CONCLUSION

In recent years, the competition, which has been constantly worsening with the globalization of the world economy, the protectionist policies applied in international trade, the economic conditions that are getting harder day by day with the trade and exchange wars make it difficult for businesses to survive and achieve their goals. Economic problems in countries and problems arising from factors beyond the control of enterprises can cause financial failures and even bankruptcy processes for states and businesses, regardless of the development level of the countries. In a financial context, businesses need to be able to control their investment and operating costs, reduce their financing costs, and focus on the right asset and resource management in order to continue their operations under these severe and unexpected economic conditions.

In this study, a comparison is made to see which of the well-known bankruptcy prediction models in the literature can better predict companies experiencing financial failure.
Financial ratios, which take place as explanatory variables in the models, are also important in terms of the creditworthiness of businesses and to determine the future performance of the companies. For this reason, the fact that the ratios used in this model belong to manufacturing companies may be effective in decision-making processes for this industry for banks and financial institutions. For instance; as we have seen in most models analysis, manufacturing firms went bankrupt because they had high indebtedness or could not generate cash from sales, although they were selling.
The comparing models are crucial not only to find the best prediction but also see different perspectives through the model. Although these models are used for comparison in the literature, credit rating agencies also care and use these models.

In this analysis, 2000 bankrupt manufacturing companies' financial ratios samples are used to compare one-dimensional and multi-dimensional models' performance. In the final table (Table 17), the one-dimensional model's average accuracy is seen as higher than multi-dimensional models. This point is so critical due to the lack of threshold in the

Beaver Model. We assumed a threshold based on data and literature for the Beaver Model so this one might affect the accuracy level of the model at an insignificant level. Besides, the Grover Model prediction performance was weak in this study and this decreased the average value of multi-dimensional models. Also; Grover Model has not been studied more in previous comparative analysis, this study included this model for contribution to literature. However, it once again became clear with the results of this study why the literature did not prefer the Grover model. From an overall perspective; Weibel, Altman, and Springate models are so strong to predict failure.

In this study, the author of this study applied various statistical analysis methods to determine the relationship between model components. As a result of the correlation analysis, it was determined that there is a positive correlation between both model results. This study made significant contributions to the literature in terms of showing the advantages and disadvantages of both types of models in terms of comparing univariate and multivariate models. Since the data set in the study belongs to a single industry sector, the accuracy of the best univariate model is not much lower than the best multivariate model. However multivariate models are better at predicting bankruptcy at earlier periods than univariate models.

The advantage of predicting financial failure with univariate models is the ease of application of these models and the interpretation of the results of the models. On the other hand, the findings obtained with the help of univariate models have also been criticized for being misleading. That is to say, while the performance of the company was evaluated in terms of the selected financial ratio and it was determined that the business was successful, it was seen as a contradiction that the same business was determined as unsuccessful with a different ratio aspect. In addition, the fact that a variable that increases the explanatory power of the model, when included in a multivariate model, gives meaningless results in univariate models, was also among the criticisms. As a matter of fact, univariate financial failure prediction models ceased to be used after multivariate models began to be used in failure prediction. Univariate models maintain their importance as they are the oldest and fundamental studies in the development of financial failure prediction literature, despite the criticisms raised later.

As a result of this study, it can be said that the predictions of Springate and Altman are better, similar to the literature. Again, research on the Grover model, which is not used much in the literature, is included in this study. The accuracy level of the Grover model is quite low.

Although each method has its own strengths and weaknesses, it has been observed that the related methods have advantages to help companies especially in terms of determining the cash requirements of the companies and their ability to fulfil their financial obligations.

To sum up, according to the results, as we consider each group's winner as representative of the group, multi-dimensional models have better prediction performance with high accuracy than one-dimensional models. This result is important as a comparison of financial failure models in terms of their methodologies. In terms of the methodology, this study shows how models' success can be measured and which type of model is more successful regarding their accuracy. From this point of view, this thesis contributes to theory and practice while comparing various bankruptcy prediction models with secondary data that have not been studied before in this kind of comparative analysis.

LIST OF REFERENCES

Alifiah, M. N. (2013). Prediction of Financial Distress Companies in the Trading and Services Sector in Malaysia Using Macroeconomic Variables. Procedia-Social and Behavioral Sciences, 129(15), pp.90-98.

Alo, O. (2003). Issues in corporate governance. An FITC Publication.

Altman, E. I. (1968). Financial Ratios, Discriminate Analysis and the Prediction of Corporate Bankruptcy. Journal of Finance, 23, pp.589-609.

Altman, E.I. (1983). Why Business Fail. Journal of Business Strategy, 3(4), pp.15-21.

Altman, E.I. (1993). Corporate Financial Distress and Bankruptcy. 2nd Edition, John Wiley & Sons, New York.

Altman, E.I. and Hotchkiss, E. (2006). Corporate Financial Distress and Bankruptcy, 3rd ed, New Jersey: Willey Publishing.

Andreev, Y.A. (2005). Determinants of the decision–taking process of the entry into insolvency, evolution of the procedure and earnings management: an economic perspective of Spanish distressed companies. Doctoral thesis, Universidad Autónoma de Barcelona, pp.1-169.

Arnold, G. (2013). Corporate financial management. 5th ed. Harlow: Pearson Higher Education Limited.

Beaver, W. (1966). Financial Ratios As Predictions Of Failure. Journal Of Accounting Research 4, pp.71-127.

Bedelan, A. G. (1987). Management. Japan: Dryden Press Ltd.

Bhattacharjee, A., Higson, C., Holly, S. and Kattuman, P. (2002). Macroeconomic instability and business exit: Determinants of failures and acquisitions of large UK firms. Journal of Economic Dynamics and Control 1(2), pp.18 – 33.

Boisselier, P. and Dufour, D. (2011). Scoring Et Anticipation De Défaillance Des Entreprises: Une Approche Par La Régression Logistique. Identification et maîtrise des risques : enjeux pour l'audit, la comptabilite et le contrôle de gestion, pp.1-20.

Bowen, M., Morara, M. and Mureithi, S. (2009). Management of small business challenges among small and micro enterprises in Nairobi – Kenya. KCA Journal of Business Management 2(1), pp.16 – 31.

Bozkurt, İ. (2014). İflas Olasılığı ile Sistematik Risk İlişkisinin İncelenmesi ve Etkin İflas Göstergesi Modellerinin Tespiti: BİST' de Ampirik Bir Uygulama, Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 19(4), pp.127-142.

Brealey, R. A., Myers, S. C. and Marcus, A. J. (2011). Principles of Corporate Finance. (10th Edition). McGraw-Hill/Irwin.

Brédart, X. (2014). Bankruptcy prediction model: the case of the United States. International Journal of Economics and Finance. 6 (3), pp.1–7.

Brigham, E. and Gapenski, L. (1996). Financial Management. Dallas: The Dryden Press.

Brigham, E. F., and Daves P. R. (2007). Intermediate Financial Management. Thomson South Western, USA.

Caballero, R. and Hammour, M. (1994). The cleansing effects of recessions. American Economic Review 84, pp.1350-1365.

Caballero, R. and Krishnamurthy, A. (1999). Emerging markets crisis – An assets markets perspective. IMF Working Paper 99/129. Washington: The International Monetary Fund.

Charan, R. and Useem, J. (2002). Why companies fail. Fortune, May 27, pp. 36- 44.

Chen, X., Yang, W. and Huang, D. (2010). Corporate Life Cycle and the Accrual Model: An Empirical Study Based on Chinese Listed Companies. Frontiers of Business Research in China, 4(3), pp.580–607

Crafts, N. and Fearon, P. (2010). Lessons from the 1930s great depression, Oxford Review of Economic Policy, 26(3), pp 285-317.

Deakin, E. B. (1972). A discriminant analysis of predictors of business failure. Journal of Accounting Research. 10(1), pp.167-179.

Diakomihalis M. (2012). The accuracy of Altman's models in predicting hotel bankruptcy. International Journal of Accounting and Financial Reporting. 2 (2), pp.96–113.

Dizgil, E . (2018). Bist Ticaret Endeksinde Yer Alan Şirketlerin Springate Finansal Başarısızlık Modeli İle İncelenmesi . Bilecik Şeyh Edebali Üniversitesi Sosyal Bilimler Dergisi , 3 (2) , pp.248-267.

Dun&Bradstreet Inc. (1980) Dun & Bradstreet reference book of corporate managements, New York : Dun & Bradstreet, Inc.

Edi, E. and May, T. (2018). Ketepatan Model Altman, Springate, Zmijewski, dan Grover dalam Memprediksi Financial Distress. Jurnal Reviu Akuntansi dan Keuangan, 8(1), pp.79-92.

Eljelly, A. M. A. (2004). Liquidity-Profitability Tradeoff: An Empirical Investigation in an Emerging Market. International Journal of Commerce and Management 14(2), pp.48-61.

Geng R., Bose I. and Chen X. (2015). Prediction of financial distress: an empirical study of listed Chinese companies using data mining. European Journal of Operational Research. 241 (1), pp.236–247.

Gilman, L. J. (2001). Principles of managerial finance (9th Edition). India: Addison Wesley Longman.

Gordon V.K. and Prakash, A. J. (1987). Multivariate Normality and Forecasting of Business Bankruptcy, Journal of Business Finance and Accounting, 14(4), p.576.

Grover, J. and Lavin, A. (2001). Financial Ratios, Discriminant Analysis and The Prediction of Corporate Bankruptcy: a Service Industry Extension of Altman's Z-Score Model of Bankruptcy Prediction. Working Paper. Southern Finance Assosiation Annual Meeting.

Holland, J. H. (1975). Adaptation in natural and artificial systems. University of Michigan Press, Ann Arbor.

Hopenhayn, H. A. (1992). Entry, exit and firm dynamics in long run equilibrium. Econometrica, 60, pp.1127-1150.

Jenkins, D. S., Kane, G. D. and Velury, U. (2004). The Impact of the Corporate Life-Cycle on the ValueRelevance of Disaggregated Earnings Components. Review of Accounting and Finance, 3 (4), pp. 5-20.

Karadeniz, E. and Öcek, C. (2018). Konaklama işletmelerinde finansal başarısızlık riskinin ölçümü: Türkiye ve Avrupa karşılaştırması. Finans Politik & Ekonomik Yorumlar, 55(645), pp.9-59.

Khan U.E. (2016). Bankruptcy prediction for financial sector of Pakistan: evaluation of logit and discriminant analysis approaches. 6 (2), pp.210–220.

Kliestik, T. and Majerova, J. (2015). Selected issues of selection of significant variables in the prediction models. Proceedings of 10th international scientific conference: Financial management of firms and financial institutions, part II, pp. 537-543.

Kolb, B. A. (1983). Principles of Financial Management. Business Publication Inc., Texas.

Korol T. (2013). Early warning models against bankruptcy risk for Central European and Latin American enterprises. Economic Modelling. 31, pp.22–30.

Kürklü, E. and Türk, Z. (2017). Fınancıal Faılure Estımate In Bıst Companıes Wıth Altman (Z-Score) And Sprıngate (S-Score) Models . Osmaniye Korkut Ata Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi , 1 (1), pp.1-14.

Liang D., Lu C.C., Tsai C.F. and Shih G.A. (2016). Financial ratios and corporate governance indicators in bankruptcy prediciton: a comprehensive study. European Journal of Operational Research. 252 (2), pp.561–572.

Liou, D. and Smith, M. (2006). Macroeconomic Variables In the Identification of Financial Distress. Social Science Research Network (SSRNW).

Lizal, L. (2002). Determinant sof Finanicial Distress: What Drives Bankruptcy in a Transition Economy?, Lizal, Lubomir, Determinants of Financial Distress: What Drives Bankruptcy in A Transition Economy? The Czech Republic Case, pp.1-59.

Low, S., Mat Nor, F. and Yatim, P. (2001). Predicting Corporate Financial Distress Using The Logit Model: The Case of Malaysia. Asian Academy of Management Journal, 6(1), pp.49-61.

Martin, J. D., Petty, J. W., Keown, A. J. and Scott, D. F. (1993). Basic Financial Management. Prenticehall, USA.

Mbat, D. O. (2001). Financial management. Uyo: DOMES Associate.

Mellahi, K. and Wilkinson, A. (2004). "Organizational Failure: A Critique Of Recent Research And A Proposed Integrative Framework", International Journal Of Management Review. 5(1), pp.21-41.

Meyer, P.A. and Pifer, H.W. (1970). Prediction oí Bank Failures, The Journal of Finance,25, pp.853-86.

Miller, D., Friesen, P.H. (1984). A longitudinal study of the corporate life cycle. Management Science 30(10), pp.1161-1183.

Miller, W. (2009). Comparing Models of Corporate Bankruptcy Prediction: Distance to Default vs. Z-Score, SSRN Working Paper, pp.1-41.

Mitroff, I.I. (2001). Managing crises before they happen: what every executive needs to know about crisis management, New York: Amacom.

Newton, G.W. (2009). Bankruptcy and Insolvency Accounting, Volume 1: Practice and Procedure, 7th ed., New Jersey: Wiley Publishing.

Nguyen, H. and Faff, R. (2010). Does The Type of Derivative Instrument Used by Companies Impact Firm Value?. Applied Economics Letters. No:17, pp.681-683.

Norton, E.C. (2000). Long-term care," in Handbook of Health Economics, vol. 1, part B, A. J. Culyer and J. P. Newhouse, Eds.Amsterdam: Elsevier, pp. 955-994.

Odom, M. and Sharda, R. (1990). A neural network model for bankruptcy prediction. Proceedings of the International Joint Conference on Neural networks, pp.163–168.

Ohlson, J.A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy Journal of Accounting Research, 18(1), pp.109-131.

Ooghe, H. and De Prijcker, S. (2008),."Failure processes and causes of company bankruptcy: a typology", Management Decision, 26(2), pp. 223-242.

Padachi, K. (2006). Trends in Working Capital Management and its Impact on Firms' Performance: An Analysis of Mauritian Small Manufacturing Firms. International Re-view of Business Research Papers 2(2), pp.45 – 58.

Pakdaman, H. (2018). Investigating the Ability of Altman and Springate and Zmijewski and Grover Bankruptcy Prediction Models in Tehran Stock Exchange. Revista ESPACIOS. 39(14), p.33.

Park, S. S. and Hancer, M. (2012). A Comparative Study of Logit and Artificial Neural Networks in Predicting Bankruptcy in the Hospitality Industry. Tourism Economics, 18(2), pp.311-338.

Patrick, P.J.F. (1932). A Comparison of Ratios of Successful Industrial Enterprises With Those of Failed Firms, Certified Public Accountant, pp.656-662.

Platt, H. D. and Platt, M. (2006). Understanding Difference Between Financial Distress and Bankrupcty. Review of Applied Economics, 2(2), pp.141-157.

Preston, L. E. and Post, J.E. (1975). Private management & public policy. London: Prentice Hall International.

Purnanandam, A. (2008). "Financial Distress and Corporate Risk Management: Theory & Evidence". Journal of Financial Economics, 87(3), pp.706-739.

Richard, B. and Steward, M. (1986). Principles of corporate finance. Singapore: McGraw Hill Book Company.

Robson, M. T. (1996). Macroeconomic factors in birth and death of UK firms: Evidence from quarterly VAT registrations. The Manchester School 64, pp.170-188. http://dx.doi.org/10.1111/j.1467-9957.1996.tb00479.x.

Ross, A. S., Westefield, W. R., and Jafee, J. (2002). Corporate Finance. McGraw Hill Companies, USA.

Salehi, M. and Abedini, B. (2009). Financial Distress Prediction In Emerging Market: Empirical Evidences From Iran. Business Intelligence Journal, 2(2), pp.398-409.

Schall, L. and Haley, C. W. (1983). Financial Management (3th ed.). McGraw-Hill Book Company, New York.

Schein, E.H. (1999). The Corporate Culture Survival Guide: Sense and Nonsense about Culture Change. Jossey-Bass: CA.

Schmidgall, R. S. and DeFranco, A. L. (2004). Ratio analysis: Financial benchmarks for the club industry. The Journal of Hospitality Financial Management, 12(1), pp.114.

Shin, K.S. and Lee, Y.J. (2002). A Genetic Algorithm Application in Bankruptcy Prediction Modeling, Expert Systems with Applications, 23(3), pp.321–328.

Sinkey, J. F. (1975). A Multivariate Statistical Analysis of the Characteristics of Problem Banks. Journal of Finance, 30(1), pp.21-36.

Sinkey, J. F. and Walker, D. A. (1975). Problem Banks: Identification and Characteristics. Federal Deposit Insurance Corporation, 74 (3), pp.8-24.

Slatter, S. and Lovett, D. (1999). Corporate Tournaround: Managing in Distress," Middlesex: Penguin Books, London.

Springate, G. L. V. (1978). Predicting the possibility of failure in a Canadian firm (Unpublished master's thesis). Simon Fraser University, Canada.

Subramanyam, K. R. (2014). Financial Statement Analysis. McGraw-Hill Education, USA.

Sull, D.N. (2003). Revival of the Fittest: Why Good Companies Go Gad and How Great Managers Remake Them. Harvard Business School Press: Boston.

Sun, J. Li, H., Huang, Q. and He, K. (2014). Predicting financial distress and corporate failure: A review from the state-of-the-art definitions, modeling, sampling, and featuring approaches, Knowledge-Based Systems, 57, pp.41–56.

Suntraruk, P. (2014). Predicting Financial Distress: Evidence from Thailand. Martin De Tours School Of Management, Assumption University.

Synek, M., Dvoracek, J, Dvorak, J., Kislingerova, E. and Tomek, G. (2007). Managerial Economics [Manažerská ekonomika] 4th ed., Praha : Grada Publishing.

Taffler, R.J. (1983). 'The assessment of company solvency and performance using a statistical model'. Accounting and Business Research, 15(52), pp.295-308.

Tamari, M. (1966). Financial Ratios As a Means of Forecasting Bankruptcy. Management International Review 6(4), pp.15-21.

Tinoco, M.H. and Wilson, N. (2013). Financial Distress And Bankruptcy Prediction Among Listed Companies Using Accounting, Market, And Macroeconomic Variables. International Review Of Financial Analysis, 30(2013), pp.394-419.

Tsagem, M. M., Aripin, N. and Ishak, R. (2014). Impact of Working Capital Management and Corporate Governance on the Profitability of Small and Medium-Sized Entities in Nigeria: A Proposed Model, International Journal of Science Commerce and Humanity, 5, pp.77-83.

Uzun E. (2005). İşletmelerde Finansal Başarısızlığın Teorik Olarak İrdelenmesi. Muhasebe Ve Finansman Dergisi. 27(1), pp.158-168.

Weibel, P.F. (1973). The value of criteria to judge credit worthiness in the lending of banks. Bern and Stuttgart. Wharton Financial Institutions Centre. U.S.

Wroblowska, Z. (2016). Requirements for Brand Managers and Product Managers Responsible for Competitiveness of Product and Brands. Journal of competitiveness, 8(3), pp. 5-21.

Wu, Y., Clive Gaunt, and Stephen F. Gray. (2010). A comparison of alternative bankruptcy prediction models. Journal of Contemporary Accounting and Economics, 6, pp.34–45.

Xiaosi X., Ying C. and Haitao Z. (2011). The comparison of enterprise bankruptcy forecasting method. Journal of Applied Statistics. 38(2), pp.301–308.

Xu W., Xiao Z., Dang X., Yang D. & Yang X. (2014). Financial ratio selection for business failure prediction using soft set theory. Knowledge Based–Systems. 63(1), pp.59–67.

Yap, B. C., Helmi, M. H., Munuswamy, S. and Yap, J.R. (2011). The preddictive abilities of financial ratios in predicting company failure in Malaysia using a classice univariate approach, Australian Journal of Basic and Applied Sciences, 5(8), pp.930-939.

Yazdanfar, D. and Salman, A. K. (2012). The Life Cycle of Growth Path Among Micro Firms: Swedish Data. International Business Research, 5 (10), p.107.

Zieba, M., Tomczak, S. K., & Tomczak, J. M. (2016). Ensemble Boosted Trees with Synthetic Features Generation in Application to Bankruptcy Prediction. Expert Systems with Applications, pp.1-26.

Zopounidis, C. and Dimitras, A.I. (1998). Multicriteria Decision Aid Methods for the Prediction of Business Failure . Kluwer Academıc Publıshers B.V., Dordrecht, pp.1-171.

APPENDICES

Appendix 1: Attributes of Dataset

X1	net profit / total assets
X2	total liabilities / total assets
X3	working capital / total assets
X4	current assets / short-term liabilities
X5	[(cash + short-term securities + receivables - short-term liabilities) / (operating expenses - depreciation)] * 365
X6	retained earnings / total assets
X7	EBIT / total assets
X8	book value of equity / total liabilities
X9	sales / total assets
X10	equity / total assets
X11	(gross profit + extraordinary items + financial expenses) / total assets
X12	gross profit / short-term liabilities
X13	(gross profit + depreciation) / sales
X14	(gross profit + interest) / total assets
X15	(total liabilities * 365) / (gross profit + depreciation)
X16	(gross profit + depreciation) / total liabilities
X17	total assets / total liabilities

X18	gross profit / total assets
X19	gross profit / sales
X20	(inventory * 365) / sales
X21	sales (n) / sales (n-1)
X22	profit on operating activities / total assets
X23	net profit / sales
X24	gross profit (in 3 years) / total assets
X25	(equity - share capital) / total assets
X26	(net profit + depreciation) / total liabilities
X27	profit on operating activities / financial expenses
X28	working capital / fixed assets
X29	logarithm of total assets
X30	(total liabilities - cash) / sales
X31	(gross profit + interest) / sales
X32	(current liabilities * 365) / cost of products sold
X33	operating expenses / short-term liabilities
X34	operating expenses / total liabilities
X35	profit on sales / total assets
X36	total sales / total assets
X37	(current assets - inventories) / long-term liabilities
X38	constant capital / total assets
X39	profit on sales / sales
X40	(current assets - inventory - receivables) / short-term liabilities
X41	total liabilities / ((profit on operating activities + depreciation) * (12/365))
X42	profit on operating activities / sales
X43	rotation receivables + inventory turnover in days
X44	(receivables * 365) / sales

X45	net profit / inventory
X46	(current assets - inventory) / short-term liabilities
X47	(inventory * 365) / cost of products sold
X48	EBITDA (profit on operating activities - depreciation) / total assets
X49	EBITDA (profit on operating activities - depreciation) / sales
X50	current assets / total liabilities
X51	short-term liabilities / total assets
X52	(short-term liabilities * 365) / cost of products sold)
X53	equity / fixed assets
X54	constant capital / fixed assets
X55	working capital
X56	(sales - cost of products sold) / sales
X57	(current assets - inventory - short-term liabilities) / (sales - gross profit - depreciation)
X58	total costs /total sales
X59	long-term liabilities / equity
X60	sales / inventory
X61	sales / receivables
X62	(short-term liabilities *365) / sales
X63	sales / short-term liabilities
X64	sales / fixed assets

Appendix 2: Reasons for Financial Failure in Detail

Internal Reasons

The reasons for financial failure within the business are the reasons arising from administrative problems in the broadest scope. Although these problems can be controlled, it can be seen that the causes of financial failure in businesses are generally caused by managerial problems. Slatter & Lovett (1999) classify internal factors as follows:

- Poor management and mistakes,
- Inadequate financial and financial control
- Poor management of working capital,
- High expenditure items
- Inadequate marketing strategies
- Participation in projects larger than the size of the business
- Excessive production volume compared to financing structure,
- Negative effects of mergers and acquisitions,
- The company's inappropriate financial policy,
- Wrong and uncertain internal policies that will harm human resources.

As a result; Common problems seen in businesses experiencing financial failure due to internal reasons include mismanagement, business life cycle, low liquidity level, and insufficient working capital.

Managerial Errors

The most important reason for financial failure due to internal problems is managerial errors. Managerial errors that fail businesses can be listed as follows (Ooghe and De Prijcker, 2008):

- Inadequate financial planning,
- Excessive borrowing and capital insufficiency as a result of the unstable growth of the business,
- Incomplete coordination between Production, Sales and Finance departments,
- Lack of innovation,

- Continuation of the business activities uniformly,
- Not following sectoral activities,
- Not diversifying the customer portfolio,
- Not taking quick action in management activities in the enterprise,
- Unbalanced distribution of senior management powers in the organization, gathering the management in one hand,
- Expanding credit sales transactions despite the lack of customer intelligence,
- Not paying necessary attention to market research activities,
- Fixed expenses are much higher than the burden that the business can handle,
- Lack of technical knowledge about the field of activity of the people in the management.

As can be observed in the articles, the most common causes of internal fault in companies on the way to financial failure are administrative problems. A business gives many signals on the road to financial failure. Early action can be taken to prevent financial failure with managers who will notice these signals.

Insufficiency in Liquidity Level

Firms need liquidity to meet their short-term obligations. This ratio is in studies on institutional problems. The ratio of net working capital to total assets, defined as a company's net current assets and expressed as a percentage of its total assets, refers to the difference between current assets and short-term liabilities. Generally, firms that experience consistent operating losses will reduce existing assets relative to total assets. Basically, it is the amount of net current assets that a company must cover current liabilities and benefit from purchase discounts and profitable short-term investments. The purchase discount is normally available for customers who pay within a short period, so companies with more money on hand will have an advantage. The liquidity ratio (Altman, 1968) is in principle the measure of net liquid assets relative to total capitalization. He thinks that this ratio is more important than the other two liquidity ratios, flow ratio, and fast ratio.

Insufficiency in Working Capital

Working capital management is one of the most vital segments of the firm's financing decisions as an important incentive to the firm's performance. The importance of working capital for the success of the firm has been accepted as a traditional concept that stands out in all standard corporate finance textbooks. Above all, the effective management of working capital is a fundamental part of the overall corporate strategy and has positive contributions to the creation of a firm's value (Padachi, 2006). Therefore, the importance of managing working capital efficiently cannot be denied at the best efficiency level for the successful operation of each component of working capital and is an aim for the growth and sustainability of the company due to its effects on profitability (Tsagem et al., 2014).

Corporate finance literature has traditionally focused on the study of long-term financial decisions, particularly investments, capital structure, dividends, and corporate valuation decisions. Recently, short-term assets and liabilities, which are considered as important components of total assets, are now gaining more attention. Accordingly, effective working capital management is also important in monitoring in a way that minimizes existing debt and potential debt and protects firms from spending too much on assets. In addition, efficient working capital management will enable firms to redistribute insufficient use of internal firm resources to high-value use that can improve firms' performance (Eljelly, 2004). As a result of insufficient working capital, the success and efficiency level of the decisions taken by the companies can be affected, causing financial failure to the firm.

Companies' Business Life Cycle

Businesses are in an evolving and changing structure determined by internal factors such as strategy, financial resources, management capacity, and external factors such as macroeconomic conjuncture and environmental conditions. Some decisions are taken within the framework of factors inside and outside the firm in this statement cause businesses to experience different phases. As stated in the literature, this process is the life cycle of businesses. (Chen et al., 2010).

Business life cycle phases vary between 3-10 in the literature. The reason for this difference is that the problems faced by businesses can lead to different directions and strategies. Since these problems also affect the managerial and financial decisions taken in companies, they also determine the transition between phases and the duration of stay in phases. However, in the logic of the product life cycle, growth is the phase that is under a curve that initially increases within the framework of profitability or productivity but decreases as the firm ages (Yazdanfar and Salman, 2012).

As companies progress in the stage of success/growth, they can benefit from superior financial performance compared to their competitors. However, they are faced with declining learning abilities. The sales profitability at this stage brings high financial performance to the companies. However, some successful companies may fail to grow and fail in financial understanding. Behind this are their deteriorating learning abilities. It is used to explain why the growth of some firms deteriorates (or turning point) after the success phase Sull (2003: 44-45). The best time to refresh organizational learning is at the end of the success phase. Before firms enter the decline phase, they will recognize the problem of worsening learning skills across the organization, but still benefit from stable sales. In fact, this is a good time for firms to rebuild their learning capabilities. If a firm can stimulate corporate learning before the end of the success phase, it will prevent it from declining (Jenkins et al., 2004).

Renewal firms always go through three processes of change: freezing, learning, and re-freezing. Evolutionary learning and change always go on. Businesses are dynamic systems that interact with constantly changing environments. For this reason, the process of change always starts with some kind of survival anxiety (Schein, 1999: 115-127). The decreasing competitive power at this stage posed a direct threat to the existence of a firm. This situation forces the company to learn new and effective organization by breaking the spell of the past success formula. Companies try to improve their learning abilities after learning something that has worked well in the past. They try to do the right things faster, better, and more productively than their competitors. At this stage, their corporate performance will be lower than those of their competitors and the declining competitive power continues. The final step in the renovation phase is to create a sustainable new direction. Miller and Friesen (1984:1177) argued that birth and revival periods were accompanied by a bold, innovative, organic orientation. Organizations must invent and internalize new concepts that lead to high-performance behavior before the transformative change process ends.

External Reasons

Businesses may also suffer financial failure as a result of their environment and interaction with this environment. Issues such as social, legal, political, economic, and natural environment may cause events that are beyond the control of the enterprises and that will directly affect the business. The unimaginable nature of businesses makes it necessary to consider external factors while investigating the financial failure of the businesses. Slatter and Lovett (1999) list the external factors as follows:

- Negative changes in market demand for the company's products,
- Competition,
- Negative course in commodity prices

Social Environment

Businesses build their assets on the expectations of the society they live in. Therefore, the opinion of the society, the consumption behaviors and returns, the wishes and expectations of the environment are the issues that the business should consider. If the necessary attention is not paid to these issues, the expected results include a decrease in market share, a decrease in profitability, and a shake of customer loyalty (Slatter and Lovett, 1999).

Legal and Political Environment

Each business needs an appropriate legal condition for the continuity of its activity and to be able to manage all kinds of relationships it enters throughout its activity. The absence of this mechanism or its erroneous functioning prevents businesses that run out of responsibility from being sanctioned, causing financial failure for other businesses. For example, a business that establishes a debt-receivable relationship will lose its reputation and experience financial failure if the debt is not paid with the assurance of the law (Slatter and Lovett, 1999).

Economic Environment

Businesses that are a part of the economic system are affected by both the capital market, market fluctuations, and the financial and economic policies followed. Economic environmental factors affecting the financial success and activities of businesses are diversified such as the structure of national income, inflationary and deflationary trends, the latest state of economic development, and economic policies and summarized as follows (Slatter and Lovett, 1999):

- Negativities in a country's GDP and indicators such as GDP per capita, an increase in national income can take a share in the failure of businesses.
- Since inflation, which is associated with the increase in prices, will also have an effect on purchasing power, businesses may experience financial failure on both the cost and the sales side.
- Different sectors react differently in four basic stages of the economy (depression, development, renewal, welfare) and some may experience financial changes.
- The fact that the decisions taken by the state can directly affect the strategic and financial decisions of the enterprises can lead some businesses to failure.

The course of the economy should be predicted by the business managers and the negativities that may cause failure should be eliminated with a good strategy.

Natural Environment

Natural resources such as soil, water, air, or climate that mainly affect the production factor are included in the scope of the natural environment of the enterprises. The change in the environment can affect businesses both positively and negatively. Among the main natural environmental factors that may cause failure in businesses are insufficiency of energy resources, environmental pollution, and depletion of natural resources. As such negativities cause disruption in business activities, they can affect production and cause a decrease in sales. As a result, the profitability of the business is expected to decrease. In addition to these, environmental problems can cause serious cost increase in enterprises. Businesses that do not comply with recycling standards cause financial loss as the damage to the environment reaches a level that can damage their reputation (Slatter and Lovett, 1999).

Appendix 3: Models, Variables, and Estimation Criteria for the Study

Model	Type of Model	Variables of Models	Estimation Criteria
Beaver	One Dimensional	Cash Flow/ Total Debt	It has been observed in the literature that there is no threshold for this rate and those with higher ratios are considered more successful than others. When we look at the related data, since kurtosis and skewness values are not between -1.5 and +1.5, the data does not show a normal distribution. Therefore, firms with a median value above the relevant data are considered successful.
Weibel	One Dimensional	Cash Flow/ Short Term Liabilities	For a successful company, the ratio of cash generated from operations to short-term liabilities is required to be 0.40 or higher (Schmidgall and Defranco, 2004: 4).
Altman	Multi-Dimensional	X_1: Net Working Capital / Total Assets X_2: Undistributed Profits / Total Assets X_3: Profit Before Interest and Tax / Total Assets X_4: Book value of equity / Total Liabilities X_5: Sales / Total Assets $Z = .012X_1 + .014X_2 +. 033X_3 + .006X_4 + .999X_5$	If Z <1.23; High probability of bankruptcy If 1.23 < Z <2.99; Bankruptcy is not predictable (uncertain area) If Z >2.99; No probability of bankruptcy (safe area) Remark: In this study, the uncertain area is included to safe area only descriptive statistics part. This uncertain area is not involved to safe area during accuracy level calculations.
Springate	Multi-Dimensional	X_1: Working capital / total assets X_2: Profit before interest tax / total assets X_3: Profit before interest tax / short term debt X_4: sales / total assets $S = 1.03X_1 + 3.07X_2 + 0.66X_3 + 0.4X_4$	If S-Score ≥ 0.862; the firm is successful If the G-Score < 0.862; the firm is failed
Grover	Multi-Dimensional	X_1: Net working capital / Total Assets X_2: Profit Before Interest and Tax (EBIT) / Total Assets $G = 1.650\ X_1 + 3.404\ X_2 - 0.016ROA + 0.0507$	If G-Score ≥ 0.01; the firm is successful If the G-Score ≤ -0.02; the firm is failed

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