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COMPARISON OF BANKRUPTCY PREDICTION MODELS BASED ON ESTONIAN REAL ESTATE COMPANIES

Master's thesis

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ABSTRACT

The aim of this thesis is to identify the most suitable bankruptcy prediction model from the five-factor model of E. Altman for non-listed companies, the four-factor model of E. Altman for non-production companies, the Taffler and Tisshaw model, and the Springate model to predict possible bankruptcy for Estonian companies in the real estate sector. This master's thesis provides a literature review of the definition of bankruptcy and bankruptcy theories, a review of the history of bankruptcy law, and describes the bankruptcy process in Estonia and the existing and commonly used bankruptcy forecasting models. Additionally, it analyzes the statistics of bankrupt companies in Estonia for the period of 2009 to 2019 in the real estate sector and calculates the four selected models for bankrupt and non-bankrupt Estonian real estate companies. For this thesis, quantitative data were used, namely the annual reports of companies. At the end of the thesis, the results of the analyzed bankruptcy forecasting models for Estonian real estate companies are compared and evaluated.

According to the results revealed during the research, four models have the capabilities to predict the bankruptcy of a company in the Estonian real estate market. The most accurate of these is the four-factor model of E. Altman for non-production companies. Second is the five-factor model of E. Altman for non-listed companies. In third place is the Springate model, and in the fourth place is the Taffler and Tisshaw model. The accuracy distribution of the models is somewhat modest and is, respectively, as follows: 68.85%, 61.45%, 58.2%, and 55.75%. On the other hand, the accuracy control with the bankrupt company data presented outstanding results in using the five-factor model of E. Altman. Results showed 80.3% a year before bankruptcy and 56% three years before the bankruptcy.

In conclusion, the use of single bankruptcy prediction model is not justified for bankruptcy prediction due to a lack of sufficient level of accuracy.

Keywords: bankruptcy, multiple discriminant analysis, Altman’s Z-score, Springate model, Taffler and Tisshaw model

INTRODUCTION

No businesses are insured against bankruptcy, especially in the current economic climate, which was significantly affected by the pandemic. Additionally, according to statistics, many companies report bankruptcy annually in Estonia (Krediidiinfo AS… 2018, 28). The bankruptcy of an enterprise has a remarkable impact on creditors, suppliers, shareholders, and other people directly associated with the enterprise (Shi, Li 2019, 115). Bankruptcy prediction models for companies used across the world are also applicable to Estonia.

To examine model validity for the bankrupt companies, the author selected the field of real estate activities according to the EMTAK (Estonian Classification of Economic Activities) classified under section L. One of the reasons for this is the strong relationship between the real estate market and the economic situation in the country. There is an evident bond between rising real estate consumption with solid investment and economic growth. Growing housing prices are triggering this process, but the extreme house price appreciation process might deform capital allocation efficiency. As a result, long-term economic growth might lose its momentum because of crowding out investments in productive sectors. (Aizenman *et al*. 2019, 655) An equally important reason is that the author did not find any previous research written in Estonia on analyzing a model for predicting the bankruptcy of real estate companies. The research gap discovered by the author is the insufficiency of information on bankruptcy prediction models that are applicable to Estonian real estate companies.

The master's thesis will use quantitative data analysis from the annual reports of selected companies, namely multiple discriminant analysis. Annual reports were obtained from Äripäeva infopank. Each model applies different financial ratios to prevent the bankruptcy of an enterprise. The author will perform calculations and reveal the most accurate model. The accuracy of the model will be tested with the help of statistics. Data provided by the Center of Registers and Information Systems will be used in the master's thesis, which includes bankrupt companies from 2008 to 2019 in the field of real estate activities and 1,000 non-bankrupt randomly selected companies within the same field of activity from 2010 to 2019.

The aim of the thesis is to identify the most suitable bankruptcy prediction model from the five-factor model of E. Altman for non-listed companies, the four-factor model of E. Altman for non-production companies, the Taffler And Tisshaw model, and the Springate model to predict possible bankruptcy for Estonian companies in the real estate sector.

To achieve this aim, the author has set the following research tasks:

- Provide a literature overview of bankruptcy definition and theories of bankruptcy.
- Provide a literature review of the history of bankruptcy law and describe the bankruptcy process in Estonia.
- Describe existing and frequently used bankruptcy prediction models for companies.
- Provide and analyze the statistics of Estonian bankrupt companies for the period of 2009 to 2019 in the real estate sector.
- Analyze suitable companies for settlements and make an appropriate selection.
- Calculate the five-factor model of E. Altman for non-listed companies, the four-factor model of E. Altman for non-production companies, the Taffler and Tisshaw model, the Springate model for Estonian bankrupt and non-bankrupt real estate companies.
- Compare the results and evaluation of Estonian real estate companies analyzed bankruptcy prediction models.

The structure of the paper is as follows. The master's thesis will be divided into two main chapters. The first chapter is theoretical and will cover topics such as the concept of bankruptcy, an explanation of the process of the bankruptcy of an enterprise that takes place in Estonia, the history, and a description of models for preventing bankruptcy. The second chapter is empirical, and it covers an overview of the real estate sector in Estonia and the data analysis of bankrupt and non-bankrupt real estate companies. After processing the data, an analysis of existing models for preventing bankruptcy will be carried out using the data from Estonian real estate companies. The calculations will be performed for the following four models: the five-factor model of E. Altman for non-listed companies, the four-factor model of E. Altman for non-production companies, the Taffler and Tisshaw model, and the Springate model. Current research will determine the most appropriate models for preventing the bankruptcy of Estonian real estate companies.

1. LITERATURE REVIEW

This chapter will study the literature related to the bankruptcy process. The first sub-chapter will explain the meaning and concept of bankruptcy and the bankruptcy process. Furthermore, the filing for bankruptcy of companies in Estonia will be described. Since there will be an analysis of Estonian companies in the empirical part, it is important to understand the entire bankruptcy process. In the second sub-chapter, the bankruptcy prediction models and their history will be analyzed to specify the models that the author will use in the second chapter of this master's thesis. The most famous models, such as multiple discriminant analysis, as well as logit and probit analyses, will be considered separately.

1.1. The concept and history of bankruptcy

There are different theories of the origins of this word, and perhaps the word bankruptcy comes from the Italian words banca and rotta, which together mean broken bench (Quilter 1998, 49). There is also a theory that the word bankruptcy came from the Latin words bancus ruptus or the French words banque and route (Levinthal 1919, 2).

According to Altman's (1968) research, bankrupt companies are those that are experiencing operational and financial difficulties, as well as difficulties in meeting their fixed indebtedness obligations. The meaning of the process is described very accurately in the article Corporate and Personal Bankruptcy Law: "Bankruptcy is the legal process by which the debts of firms, individuals, and occasionally governments in financial distress are resolved. Debtors file for bankruptcy because they cannot pay their debts as they come due and/or because they have liabilities above their assets." (White 2011, 2)

According to Estonian Bankruptcy Act §1 the definitions of bankruptcy and debtor are the following: "Bankruptcy means the insolvency of a debtor declared by a court ruling" and "A debtor who is a legal person is insolvent also if the assets of the debtor are insufficient for covering the obligations thereof and, due to the debtor's financial situation, such insufficiency is not temporary.

Claims that have not fallen due are also regarded as obligations." (Bankruptcy Act 2004 §1) In other words, if a company cannot pay its debt to creditors, it can demand release from this debt or part of it, and this process is called declaring the process of bankruptcy. Bankruptcy can be formally expressed when an enterprise makes a declaration in a federal district court with a petition to liquidate its assets and participate in a company bankruptcy reorganization. It can be proceeding a reference to the net worth position of an enterprise. Altman and Hotchkiss (2006) have pointed out these two types of bankruptcy.

Various studies have been carried out to explain why enterprises go bankrupt. Five main reasons were identified that affect the fact that the enterprise can go bankrupt along with the interrelationships between them. The first is the general environment, including economics, technology, foreign countries, politics, social factors, and other external factors. These factors influence management's motivation and the relationship with investors or creditors. The second reason is the immediate environment, including customers, suppliers, banks, competitors, stockholders, and misadventure. In many companies, the influence of stockholders and customers is so significant that the changes can lead to irreversible consequences for the company and its success. The third is the management, which includes motivation, personnel characteristics, skills, and qualities. Most of all, this affects the motivation of employees and their ability to develop their skills, which is important for the successful development of the enterprise. The fourth is corporate policy, which includes strategy and investments, commercial, operational, personnel, finance and administration, and corporate governance. Undoubtedly, strategy and financial planning have a strong influence on the enterprise's success. If employees do not have sufficient knowledge or skills, this will affect the corporate policy. The fifth and final one is the company's characteristics. Of course, the company's size, industry, maturity, and flexibility have a strong impact on whether a business can handle crises. (Ooghe, Prijcker 2008, 224-226) For an enterprise to be successful, all these aspects must be taken into account. Even if the enterprise hangs on just one of these aspects, this can lead to failure. Even so, if a failure has occurred, it is necessary to know how the bankruptcy procedure takes place and what kind of laws are involved in this process.

Bankruptcy law has been widely adopted throughout history to cover both debt collection and the provision of new opportunities for debtors. It is very important to understand the true modern purpose of bankruptcy. Some believe that debtors could have used bankruptcy as a measure to fulfil their financial obligations, even if the debtors have the necessary funds to pay off the debts. Despite this, the very first goal of bankruptcy was still the goal of debt collection. Bankruptcy law now not only allows the possibility to collect debts but also helps debtors preserve some of their assets. (Currie 2009, 241) Bankruptcy law is essential for the protection of creditors and debtors. The origins of the bankruptcy law come from England.

The two concepts of bankruptcy and insolvency have been extensively studied in the literature. It is believed that the first bankruptcy law was implemented in England during the reign of Henry VIII in 1542. The bankruptcy law in England was only applied to traders until 1861, but, after that, it was used for all debtors. However, for debtors who could not pay off their debts and were not traders, Insolvency Acts were adopted in the early 19th century. This was necessary because non-traders could not go bankrupt. Firstly, the Insolvency Act freed debtors from imprisonment, and secondly, if the debtor paid off the creditor with all his property, he was released from the debt. In 1861, this law was abolished, and the bankruptcy court began to apply to all debtors, regardless of whether they were traders. In 1869, all Insolvency Acts in England were repealed. Interestingly, in 1867, the British North America Act was adopted in Canada. Based on the Constitution adopted in the United States in 1787, Congress began to pass laws. This led to serious debate because there were major differences between insolvency law and bankruptcy law. The debtor would use the insolvency laws, which would relieve him of the debt, and the creditor would use the bankruptcy laws. The debate continued until 1867. Until the British North America Act was passed, this same law gave the Parliament of Canada exclusive power precisely to prevent similar debates in Canada as were seen in the United States. (Honsberger 1972, 199-200) This describes the process of how the first bankruptcy laws were established. Currently, almost every country has its own individual bankruptcy laws, including Estonia.

1.2. Bankruptcy law and process of bankruptcy in Estonia

The first bankruptcy law in the history of Estonia was passed on June 10, 1992, and entered into force on September 1, 1992. The initial draft bankruptcy law was ready by the mid-1930s. Under Tsarist legislation, bankruptcy procedures were carried out until the 1940s, but they were not fully adopted into law. The most important basis for the current bankruptcy law was the Swedish bankruptcy law. When developing the current Estonian bankruptcy law, the laws of Germany, the USA, France, Finland, and other national laws were also taken into account as examples. (Varul 1993, 6-7) It is an ordinary practice to evaluate the experience of other neighboring countries as an example for drafting a law. Best practice experience provides the opportunity to make new regulations more refined and developed.

In Estonian law, the primary purpose of declaring bankruptcy is to sell the debtor's property at the highest possible price. It is also equally important to satisfy the claims of creditors at the expense of the money received from the sale of the debtor's property. The Bankruptcy Law sets out the consequences of declaring bankruptcy to maximize these goals. (Varul 1993, 30) Estonian bankruptcy law is considered to cover the interests of both parties, debtors and creditors.

The current Bankruptcy Act of Estonia was passed on January 22, 2003, and adopted on January 1, 2004. If the debtor cannot pay the creditor and their financial situation is not temporary, then the debtor is considered insolvent. During the bankruptcy procedure, the court organizes the collection of evidence and clarifies the reasons for the debtor's insolvency. County courts judge bankruptcy cases. (Bankruptcy Act 2004 §1-4)

The court, the general meeting of creditors, the bankruptcy committee, and the trustee are the bodies of bankruptcy proceedings. The bankruptcy committee performs the oversight function. The court and the general meeting of creditors decide the most critical issues, and the manager deals with the bankruptcy procedure. In Estonian law, the principle is fundamental that the burden on the court is minimal. Therefore, the most critical issues in bankruptcy proceedings are decided at the general meeting of creditors. Most importantly, in bankruptcy, power over the debtor's assets passes to the creditors. (Varul 1993, 52)

Bankruptcy law applies to most companies and individuals, but the state and local governments cannot go bankrupt. For certain types of debtors, such as credit institutions, general funds, and insurance companies, there are special insolvency rules in addition to the Bankruptcy Law. (Capital Market … 2017, 72)

Numerous company termination options are available. There is the compulsory liquidation and the voluntary termination of a company. Compulsory liquidation occurs by court order for companies that do not meet certain requirements. Voluntary termination of a company is decided by its owners. Liquidation can lead to the company's bankruptcy if the company does not have sufficient funds to pay off debts. The liquidation of an enterprise does not always mean its bankruptcy, just as bankruptcy does not always mean the termination of the enterprise. There is a possibility that the company will be reorganized and continue its business activities. (Ettevõtluse Arendamise Sihtasutus … 2017)

To declare bankruptcy companies in Estonia, it is necessary to go through the following stages (Riigi Infosüsteemi Amet … 2016):

1) Filing for a bankruptcy petition.
2) The court then decides to accept the bankruptcy petition and publishes a notice on the filing of the bankruptcy petition and the appointment of an interim trustee.
3) Conducting a preliminary court session in court.
4) Consideration of the bankruptcy petition in court.
5) The court makes a bankruptcy decision.
6) The court notifies the Commercial Register of the declaration of bankruptcy.

The bankruptcy petition should be submitted to the county court by the entrepreneur, their creditors, or other legally appointed persons. The application requires proof of insolvency and a list of debts. After deciding on the application, the court will appoint an interim trustee who protects the rights and interests of all creditors and the debtor, controls the debtor's economic activities, and manages the property. The application submitted by the debtor is considered within ten days, and the application submitted by the creditor is considered within 30 days. The court's decision is to either declare the enterprise bankrupt or not declare it. The court does not declare bankruptcy if the debtor has no property left to cover the creditors' debts. (*Ibid.,* 2016) The application process and the announcement of a bankrupt enterprise in Estonia are clear and understandable.

Bankruptcy proceedings' duration is at least three years and no more than seven years from the outset. A minimal period for the bankruptcy proceedings of three years is only possible with the court decision, which states that the company has sufficiently paid the creditors' debts. At the request of the debtor, starting from three to five years after the commencement of the proceedings on the case, the court may decide that the debtor will not be able to fulfil their obligations to creditors. Then the court releases them from fulfilling their obligations in the bankruptcy case. A maximum of seven years is imposed if the court considers that the exemption from default in a bankruptcy case is unreasonable. (Jurist Aitab 2021) Estonian bankruptcy law is equal to companies that work with real estate and other business areas and does not distinguish the process in any respect.

1.3. Bankruptcy prediction models

The interest of researchers in bankruptcy prediction has only grown over the past fifty years around the world. After Altman's revolutionary (1968) research, many academic studies were devoted to studying bankruptcy prediction models. Publications also increased after the 2008 global financial crisis, which indicates the importance of this topic. In the field of bankruptcy forecasting, the most commonly used models are logistic regression and neural networks. There are other innovative techniques, though, such as machine learning models. (Shi, Li 2019, 115)

There are many bankruptcy prediction studies, running from 1930 (Bellovary *et al.* 2007, 1). The bankruptcy prediction model has its origins in Beaver's (1966) scientific publications. He first wrote about using financial ratios as predictors of failure. Altman's (1968) research is considered the beginning of the use of financial ratios intended to prevent the bankruptcy of enterprises when multiple discriminant analysis was first applied. Altman (1968) has used the data of bankrupt enterprises and non-bankrupt ones for multiple discriminant analysis (Haber 2005, 87). In 1980, Ohlson became the first to apply logit regression analysis to estimate the probability of bankruptcy. In other words, he started to use the logit model. Later, in 1984, Zmijewski published a research paper that offered the first probit models for assessing the financial condition of an enterprise. Neural networks were founded by the end of the 1980s. It took roughly ten years to develop and establish itself as a primary method among the vast range of studies. (Bellovary *et al.* 2007, 1) Academic researchers have used various models to predict corporate bankruptcy, each with different assumptions and unique computational complexity. Traditional cross-sectional statistical methods are considered the most popular, such as univariate, risk index, MDA, and conditional probability models. A relatively large number of out-of-the-common models have already been developed. (Balcaen, Ooghe 2006, 6-7) Despite the newly developed models, Altman's (1968) research with 3461 citations remains the most commonly mentioned scientific article for the period of 1968 to 2017. Followed by Tam and Kiang (1992) with 595 citations (Shi, Li 2019, 120-121). It is visible in this research that the models created in the 1960s and the 1990s are still valuable in predicting the bankruptcy of enterprises compared to the models developed over the later decades.

A reasonably large number of bankruptcy prediction models have been created for enterprises in specific fields of activity (Table 1). There are 18 bankruptcy prediction models have been created for banks or savings and loan organizations, as well as 16 bankruptcy prediction models for manufacturing companies (Bellovary *et al*. 2007, 5). There are also other individual models created for specific fields of activity, which are indicated in Table 1. A trend for creating models with a specific field of activity is proposed, and more and more unfocused models are being created (Ibid., 5). Unfortunately, the author has not discovered a new global statistic on the bankruptcy prediction models developed for specific areas of business. The author presumes that the high number of models makes gathering statistics challenging.

Table 1. Global focused models for the period 1968-2007

Field of activity	Bankruptcy prediction models
Banks or savings and loan organizations	Meyer and Pifer (1970); Sinkey [1975]; Hanweck (1977); Martin (1977); Santomero and Vinso (1977); Pettway and Sinkey (1980); Rose and Kolari (1985); Lane et al. (1986); Pantalone and Platt (1987); Bell et al. [1990); Espahbodi (1991); Tam (1991); Salchenberger et al. (1992); Tam and Kiang (1992); Martin Del Brio and Serrano-Cinca (1995); Henebry (1996); Alam et al. (2000).
Manufacturing companies	Altman (1968); Taffler (1974, 1977); Diamond (1976); Tisshaw (1976); Mensah (1983); Appetiti (1984); Zavgren, (1985); Suominen (1988); Theodossiou (1991); Arkaradejdachachai (1993); Tsukuda and Baba (1994); Alici (1996); Sung et al. (1999); Zhang et al. (1999); Grover (2003)
Hospitality companies	Gao (1999)
Computer/software companies	Shah and Murtaza (2000)
Casinos	Patterson (2001)
Internet firms	Wang (2004)

Source: (Bellovary *et al*. 2007, 5)

Since 2006, theses related to enterprise bankruptcy prediction have been written in the two major Estonian universities: the University of Tartu and Tallinn University of Technology. A combination of new models and analyzing data on already created models has been used in the research. The most popular areas of activity are Manufacturing companies and Construction companies. The first numbers five written works on forecasting models, and the second four works. The rarest areas of thesis work related to forecasting models were Tourism, Information Technology, and Hospitality.

Table 2. Estonian academic papers related to industry-specific models for the period 2006-2021

Field of activity	Academic papers related to focused models
Manufacturing companies	Grünberg M. (2013); Gatski S. (2013); Pihlak K. (2014); Kelement, K. (2015); Vahter J. (2018)
Construction companies	Pedaste B. (2012); Holdt H. (2014); Salmistu M. (2017); Jack C. (2018)
Wholesale and retail trade	Lukason O. (2006); Paal M (2013)
Transportation	Onno A. (2015); Paal M. (2016)
Tourism	Vedernykova S. (2017)
Information technology	Kirt T. (2016)
Hospitality enterprises	Einstein M. (2021)

Source: compiled by the author

The author could not find any academic papers or studies related to predicting the bankruptcy of real estate companies in Estonia. Moreover, the author discovered only a few academic works related to the Asian market, such as the article by Treewichayapong, Chunhachinda, Padungsaksawasdi "Bankruptcy Prediction of Real Estate Firms in Thailand" (2011). Furthermore, equivalent studies have been carried out as "Comparative Analysis of Bankruption Prediction Models in Property and Real Estate Sector Companies Listed on the IDX 2017-2019" by Andriani and Sihombing (2021). However, a new model was not created and this was tested by Altman Z-Score, Springate S-Score, and Zmijewski X-Score models when predicting the bankruptcy of property and real estate companies. The absence of new bankruptcy prediction models led the author to identify the most suitable one among the most popular and accurate models from those available.

Bankruptcy prediction models are not so much divided by the areas of company activity as by different types of models. One of the classic statistical failure prediction models is the univariate failure prediction model. Univariate analysis implies that an optimal cut-off point for each measure or ratio is calculated. This procedure is carried out separately for each measure or ratio. Univariate analysis is elementary and based on a linear relationship between all indicators and the state of bankruptcy. (Balcaen, Ooghe 2006, 8-9)

The risk index model is a simple scoring system consisting of various coefficients, including ratios. Following the values of the coefficients of the company, a certain number of points is given from 0 to 100. The most important coefficients have a higher weight. High scores indicate that the company is in a good financial position. Weight distribution is subjective, though. (*Ibid.*, 10)

Two of the more classic statistical failure prediction models are **multiple discriminant analysis** and **conditional probability models**, the latter consisting of **logit** and **probit models** (*Ibid.*, 11-18). These models require special attention, since, firstly, the largest number of them has been created (Table 3), and, secondly, they are some of the most accurate (Bellovary *et al.* 2007, 6-9). The author will thus consider them in separate sub-chapters.

Table 3. The main methods for model development were used depending on the year

Year	Discriminant analysis	Logit analysis	Probit analysis	Neural Networks	Other
1960s	2	0	0	0	1
1970s	22	1	1	0	4
1980s	28	16	3	1	7
1990s	9	16	3	35	11
2000-2007	2	3	0	4	3
Overall	63	36	7	40	26

Source: (Bellovary *et al.* 2007, 6)

Based on the data from "An overview of bankruptcy prediction models for corporate firms: A systematic literature review" the study's research represents 312 international academic papers related to the research topic covering 1968 to 2017. The research shows a significant rise in publications starting from 2008. The reason for this was the economic crisis which prompted the researchers to look more closely at the possibility of business bankruptcy. However, as there is no information on the number of created models, the author has used previously created ones. In this study, 83.50% of the analyzed academic papers are publications written from 2008 to 2017. Logistic regression is the most popular model, mentioned in 123 out of 321 scientific papers, followed by Discriminant analysis, Multivariate Discriminant analysis & Z-score, and third Neural Network. (Shi, Li 2019, 123) There are many alternative methods to classic statistical failure prediction models, including survival analysis, decision trees, and neural networks.

Survival analysis is a tool used to analyze the time before a particular event, for example, the fact that a company will fail or become bankrupt. Several functions have been used for this analysis, two of which are the survival and risk functions. The survival function is the probability that an enterprise will not fail after a specific time. The risk function is the instantaneous failure rate at a specific time. In this method, data from previous years are used to calculate functions at each specific point in time. These functions do not need to be used to forecast the future but rather to analyze past failures. (Gepp, Kumar 2008, 15)

An important area of artificial intelligence and part of machine learning is considered to be **decision trees**. Decision trees are used to predict company bankruptcies using a recursive partitioning algorithm. (Chen 2011, 4515) One of the components of decision trees are branches that connect the tree's roots, i.e., the formula with the leaves, i.e., the result. Decision trees also consist of leaves, which are the possible results of the model. The last component is the nodes, which consist of tests for the correct selection of the branch. (Cielen *et al.* 2004, 529)

A neural network is a computerized concept where data are entered with problems and corresponding solutions. After analysis, training, and data processing, neural networks offer solutions to new similar problems than have been entered before. Neural networks consist of neurons, and neurons are elementary processors arranged in layers in a certain order and connected. After the data are entered into the input level, each neuron receives the information, adds the weights, and produces an output. These weights are adjusted in the process, and the strength of each output depends on them. Learning takes place so that the input and desired outputs are introduced to the input level. Then the data is processed and, based on the algorithm, compared with the desired output. Neurons bind weights that become stronger if the decision is correct and weaken if the decision is wrong. This process takes place until the relationship of the weights between the honest answer and the desired one is maximal. This will indicate that this answer can be used for forecasting. (Tucker 1996, 1-2)

Since there is no clear overview of the application of alternative methods in forecasting the bankruptcy of companies, further research into these methods is necessary (Balcaen, Ooghe 2006, 51). Since 2007, numerous machine learning technologies have been created and applied, including Adaboost, Case-based reasoning, Particle swarm optimization, K-nearest neighbor, Random Forest, and Naive Bayes classifier. These models are innovative and as popular as the established ones, and they are genuinely finding themselves useful in modern studies. (Shi, Li 2019, 123-124)

In light of the foregoing, the author has described the development of models over the past few decades and their classification in various fields of activity. Furthermore, works conducted in

Estonia were considered, and the fact that such works were not found in the field of real estate was highlighted. A deeper analysis of the models also showed their division into types. The following chapters will describe the most accurate and numerous models of Multiple discriminant analysis, Logit, and Probit analysis in more detail.

1.4. Multiple discriminant analysis

Multiple discriminant analysis (MDA) is a statistical technique used to classify and predict problems in which a dependent variable appears in qualitative forms, such as bankrupt or non-bankrupt. In MDA, it is essential to establish a group classification. There must be at least two groups. MDA obtains a linear combination of characteristics from discriminant coefficients. In the case of the definition of enterprises as bankrupt or non-bankrupt, these are financial coefficients. The advantage of the MDA method is that these characteristics are considered separately and in their interaction. (Altman 1968) The most popular MDA method is the linear combination of variables. (Balcaen, Ooghe 2006, 66)

The Linear MDA model's discriminant function is Z=V1X1+V2X2+…+VnXn, where Z is the discriminant score, V1, V2, and Vn are discriminant coefficients, and X1, X2, and Xn are independent variables. (Altman 1968, 592) The discriminant assessment can be either positive or negative. If it is low, it indicates that the company is in poor financial condition. (Balcaen, Ooghe 2006, 66)

Multiple discriminant analysis was applied by Altman for the first time in 1968. He used 66 manufacturing companies, half of them were bankrupt, and the other half, 33 companies, were non-bankrupt. The accuracy of this model is relatively high, with 72% accuracy in the prediction of bankrupt enterprises and 94% accuracy with non-bankrupt enterprises. The overall accuracy of this model is 83%. (Altman 1968, 599-600)

Altman's discriminant function was as follows (*Ibid.*, 594):

$$Z = 0.012\ X_1 + 0.014\ X_2 + 0.033\ X_3 + 0.006\ X_4 + 0.999\ X_5 \quad (1)$$

where

X_1 = Working capital/Total assets

X_2 = Retained earnings/Total assets

X_3 = Earnings before interest and taxes/Total assets

X_4= Market value equity/Book value of total debt

X_5 = Sales/Total assets

Z = Overall index

Result: Z above 2.99 – safe zone, 1.81≤Z ≤ 2.99 – gray zone, Z ≤ 1.81 – distress zone. The safe zone is a low bankruptcy risk area, the gray zone means uncertain results, and the distress zone means a high risk of bankruptcy. (*Ibid.*, 606)

Altman developed at least four MDA models. In 1977 the seven-factor ZETA model was developed. The ZETA model can predict the possible bankruptcy of a company within the next five years with an accuracy of 70%. This model has not been fully published, but it is known that there are seven financial ratios used in the model: return on assets, the stability of earnings, debt service, cumulative profitability, liquidity, capitalization, and size. (Altman *et al.* 1977, 42-50)

In 1983 Altman developed the five-factor model for non-listed companies. Since the 1968 model was only applicable to publicly traded companies, Altman modified the model using the same data but replaced the book value of equity with the market value. (Altman *et al.* 2016)

The result is the following Z-Score model (Altman 2006, 246):

$$Z = 0.717\ X_1 + 0.847\ X_2 + 3.107\ X_3 + 0.420\ X_4 + 0.998\ X_5 \tag{2}$$

where all values are the same as in Altman's (1968) discriminant function, except X_4 value:

X_4= Book value of equity/Book value of total liabilities

Result: Z above 2.99 – safe zone, 1.23≤Z ≤ 2.9 – gray zone, Z ≤ 1.23 – distress zone.

The Z-Score model (1968) has been adapted for nonmanufacturers and emerging markets. Therefore, in 1993 the four-factor model of Altman for non-production companies was established. If asset turnover is included, there will be a potential industry effect and, to minimize it, the industry-sensitive variable X_5 (Sales / Total assets) was excluded from the formula. (*Ibid.*, 247-248)

The result is the following Z-Score Model (*Ibid.*, 248):

$$Z = 3.25 + 6.56\ X_1 + 3.26\ X_2 + 6.72\ X_3 + 1.05\ X_4 \tag{3}$$

where values X_1, X_2, X_3 are the same, as in Altman's (1968) discriminant function, X_5 was removed and X_4 value is the following:

X_4= Book value of equity/Book value of total liabilities

Result: Z above 2.6 – safe zone, 1.10≤Z ≤ 2.6 – gray zone, Z ≤ 1.10 – distress zone (Abdulkareem 2015, 16).

Altman is not the only one who created MDA models. In 1983, in the United Kingdom, Taffler built an MDA model based on calculations for British fully listed industrial firms by using four ratios: profitability, working capital position, financial risk, and liquidity (Cimpoeru 2014, 219, 220). Altman's US model (1968) is potentially dangerous and wrong to apply in the UK or other market conditions than those in the United States. In 2007, a study was carried out on the application of the Taffler model 25 years after its creation and proved that the model has an actual failure prediction ability. For users and researchers of companies' financial reporting, this model is of great value since it demonstrates an excellent ability to predict the success of an enterprise in the future. (Agarwal, Taffler 2007, 21-22)

The Taffler function is the following (*Ibid*., 36-37):

$$Z = 3.2 + 12.18\,X_1 + 2.5\,X_2 - 10.68\,X_3 + 0.029\,X_4 \qquad (4)$$

where

X_1 = Profit before tax/Current liabilities

X_2 = Current assets/Total liabilities

X_3 = Current liabilities/Total assets

X_4 = (Quick assets – Current liabilities) / Daily operating expenses with the denominator proxied by (sales – profit before taxes – depreciation) / 365.

Result: Solvency threshold is zero, if Z score is positive then a company in a safe zone, but if Z is negative then a company in bankruptcy risk.

In 1977, the Taffler model was updated by Taffler And Tisshaw for enterprises not listed on the stock exchange and the following function was obtained (Machek 2014, 15):

$$Z = 0.53\,X_1 + 0.13\,X_2 + 0.18\,X_3 + 0.16\,X_4 \qquad (5)$$

where

X_1 = Profit before tax/Current liabilities

X_2 = Current assets/Total liabilities

X_3 = Current liabilities/Total assets

X_4 = Net sales/Total assets

Result: Z > 0.3 – the lower probability of bankruptcy, Z <0.2 – the higher probability of bankruptcy.

Gorgon L.V. Springate developed the MDA model in Canada in 1978. The Springate model was developed based on Altman's model, and, out of 19 financial ratios, four were selected. (Primasari 2017,29) Previously, models were developed for large companies and were not acceptable for small firms. Springate tested this model on 60 companies, 30 of which were bankrupt and 30 were not, and achieved an accuracy of 92.5%. (Huo 2006, 50)

The Springate model is the following (Oniga 2016, 21):

$$Z = 1.03\ X_1 + 3.07\ X_2 + 0.66\ X_3 + 0.4\ X_4 \quad (6)$$

where

X_1 = Working capital/Total Assets

X_2 = Earnings before interest and taxes /Total Assets

X_3 = Profit before taxes/Current Liabilities

X_4 = Sales/Total Assets

Result: $Z > 0.862$ – solvent, $Z < 0.2$ – insolvency danger.

One further MDA model for small companies was built by Fulmer in 1984 in the USA. The model was applied to 60 companies, 30 of them were bankrupt, and 30 others were non-bankrupt. Forty financial ratios were initially used in the model, but in the final version of the model, only nine remained. The accuracy of Fulmer's model is 98% in classifying the test companies one year prior to failure and by 81% if more than one year. (Venkataramana *et al.* 2012, 47)

The Fulmer's model function is the following (*Ibid*., 47):

$$H = 5.528\ X_1 + 0.212\ X_2 + 0.073\ X_3 + 1.27\ X_4 - 0.12\ X_5 + 2.235\ X_6 + 0.575\ X_7 + 1.083\ X_8 + 0.984\ X_9 - 6.075 \quad (7)$$

where

X_1 = Total assets/ retained earnings

X_2 = Total assets/sales

X_3 = Equity/profit before taxes

X_4 = Total assets/cash flow

X_5 = Total assets/liability

X_6 = Total assets/current liabilities

X_7 = Logarithm of total assets

X_8 = Total liabilities/working capital

X_9 = Interest/logarithm of profit before interest and taxes
Result: H <0 – the company is bankrupt.

Since there are a great deal of MDA models created all over the world, the author has considered only some of them. Altman's model was selected as the foremost bankruptcy prediction model created and, as a result, the most commonly cited and popular MDA model. Considering that Estonia is a significantly smaller country compared to the USA, Altman's model accuracy might be questioned on a smaller scale. The second model that the author decided to apply is the Taffler model. It was designed for use in the United Kingdom, and therefore much more suitable for the Estonian scale. The Taffler model will not use the data of companies listed on the stock exchange. The great advantage of the Gorgon L.V. Springate is that it is designed specifically for small businesses, and in Estonia, compared to the USA, businesses are small. The Fulmer model is unique because it uses nine financial ratios, making it slightly more accurate than other models. Based on the pros and cons of each model, the author will identify the most suitable for making calculations and identifying the most suitable bankruptcy prediction model for Estonian real estate companies.

1.5. Logit and Probit analysis

Logit analysis and probit analysis are more straightforward to calculate than analyses for MDA models, which have gained popularity. However, probit analysis is less popular because the calculations are more complicated than logit analysis. (Balcaen, Ooghe 2006, 64) The main difference is that the logit analysis needs the transform function, while the probit analysis uses the distribution function. (Hahn, Soyer 2005) If the relationship between variables and the probability is linear in MDA models, then the logistic distribution is used in the logit model. In the probit model, the cumulative normal distribution is used. The logit model is the most popular model for bankruptcy prevention. (Balcaen, Ooghe 2006, 68)

It is an accepted fact that logit analysis was invented in 1980 by Ohlson. In developing the Ohlson model, industrial enterprises from 1970 to 1976 were used, which were listed on the US exchange for at least three years, and he chose nine independent variables. For the model, 105 failed firms and 2000 non-bankrupt firms were used. Thus, Ohlson created three models: the first for predicting bankruptcy within one year and the second for predicting bankruptcy within 1 or 2 years. (Wang, Campbell 2010, 335) The overall accuracy of this model is 85% (Gerritsen 2015, 17).

The Ohlson model is the following (Ohlson 1980, 121):

$$O = -1.32 - 0.407 X_1 + 6.03 X_2 - 1.43 X_3 + 0.0757 X_4 - 2.37 X_5 - 1.83 X_6 + 0.285 X_7 - 1.72 X_8 - 0.512 X_9 \quad (8)$$

where

X_1 = Log (Total assets / GNP price-level index)

X_2 = Total liabilities / Total assets

X_3 = Working capital / Total assets

X_4 = Current liabilities / Current assets

X_5 = 1 If total liabilities > Total assets, 0 otherwise

X_6 = Net income / Total assets

X_7 = Funds provided by operations / Total liabilities

X_8 = 1 If net income is negative for last two years, 0 otherwise

X_9 = (NIt – NI t-1) / (INItI + INIt-1 I), where NIt = net income for recent period and t is the number of years.

A vast number of logit models have been created. They differ in the number of variables, the scope of the enterprises used to build the model, and predictive ability. Most of the model is not focused on a specific scope of activity of the enterprise, such as Azziz and Lawson (1989), it has ten variables/ratios, and its accuracy for тon-bankrupt firms ranges from 70.2% to 79.1%, and for bankrupt firms is about 53.9% to 92.3%. The model from Dambolena and Shulman (1988) is also relatively well-known, and it has 14 variables/ratios. Its accuracy for non-bankrupt firms is 68% to 86%, and for bankrupt firms from 84% to 98%, a popular field of enterprise activity for which logit models are created in manufacturing. (Janoškova 2016, 24) Using Finnish manufacturing firms, the Suominen model was created in 1988 using only three factors. Its accuracy for non-bankrupt firms is up to 95% and for bankrupt firms up to 70%. (Bellovary *et al*. 2007, 29) There are many logit models for manufacturing firms, such as Luoma and Laitinen (1991), Alici (1996), Zhang, Hu, Patuwo, Indro (1999), and other logit models have been created. In addition, logit models were created for more rare fields of activity, for oil and gas in 1995 by El-Temtamy, for banks, there are such models as those of Martin (1977), Platt and Pantalone (1987), for enterprises with the scope of the enterprises such as internet Wang (2004) and others. (Janoškova 2016, 24)

In 2007, Altman and Sabato built a logit model based on data from US enterprises. More than 2000 enterprises used the development of this model from 1994 to 2002. The model is designed for 1-year prediction, and the predictive ability of this model is 30% higher than that of the typical corporate model. (Altman, Sabato 2007)

The Altman-Sabato model function is the following (*Ibid.*):

$$\text{Log (PD/1-PD)} = 4.28 + 0.18\ X_1 - 0.01\ X_2 + 0.08\ X_3 + 0.02\ X_4 + 0.19\ X_5 \qquad (9)$$

where

X_1 = Ebitda/Total Assets

X_2 = Short Term Debt/Equity Book Value

X_3 = Retained Earnings/Total Assets

X_4 = Cash/Total Assets

X_5 = Ebitda/Interest Expenses

In relation to MDA and logit models (Table 3), the probit models are created much less frequently. Only seven logit models were developed in the period of 1960 to 2000 (Bellovary *et al*. 2007, 6). Zmijewski applied the first probit model for predicting the bankruptcy of companies in 1984 (Primasari 2017, 29). Zmijewski (1984) used three financial ratios that have been selected based on previous research. For the construction of the model, enterprises from the industrial sector were used for the period of 1972 to 1978, and a total of 40 bankrupts and 800 non-bankrupt enterprises were used. (Alali *et al.* 2018, 16)

The Zmijewski (1984) X-score model's function is the following (Zmijewski 1984, 69-72):

$$X = -\ 4.3 - 4.5\ X_1 + 5.7\ X_2 - 0.004\ X_3 \qquad (10)$$

where

X_1 = Net income / Total assets = ROA

X_2 = Total liabilities / Total Assets

X_3 = Current assets / Current liabilities = Current ratio

If the X-score turns out to be positive, then the company's financial indicators can lead to bankruptcy. If the X-score is negative, then the company is safe.

The logit and probit models the author has chosen to describe in the theoretical part of the thesis are the first of their kind, as well as the most popular and most explored. The author of the thesis references the Ohlson model as it is the first invented logit model. The Altman-Sabato model is demonstrated because the author uses other Altman models for calculations, and it was useful to describe one more of his models. Finally, the Zmijewski model is one of the first probit models. The author of the thesis will not carry out calculations in the empirical part using the logit and probit models in this thesis but will concentrate on MDA models. The number of created MDA models exceeds the created logit and probit models. Moreover, the MDA models were created earlier, which means they are more researched and tested. According to the author of the thesis, these are substantial reasons for using MDA models for calculations in the second chapter.

2. DATA ANALYSIS AND EMPIRICAL TESTING

This part of the thesis analyzes the accuracy of bankruptcy prediction models. In the first sub-chapter, the author provides an overview of the real estate sector in Estonia and an analysis of the statistical data of bankrupt companies for the period of 2009 to 2019 in Estonia in the field of real estate. Furthermore, the author will explain and provide an overview of the data in the quantitative research method to analyze the accuracy of models for predicting bankruptcy risk. Following this, the calculations will be performed for the following four models: the five-factor model of E. Altman for non-listed companies, the four-factor model of E. Altman for non-production companies, Taffler and Tisshaw model, and the Springate model. In the final subsection, a comparison of models will be made. The author will draw her conclusions and give recommendations for determining the most appropriate model for predicting the bankruptcy of Estonian real estate companies. Due to the sizeable data and large amount of calculations for this master's thesis, all the materials are reachable through Google drive with the source link in the list of references (Ivlijeva, 2022).

2.1. Overview of the real estate sector in Estonia

This thesis examines Estonian companies that, according to the EMTAK (the Estonian Classification of Economic Activities) classification, are classified as real estate activities under section L or under the number 68. Subsection L includes activities of real estate agencies, lessors, or brokers related to real estate. This activity can be either buying, selling, or renting real estate and providing services such as real estate appraisal. Real estate can be owned or rented, and the activities are carried out on a contract basis. The real estate activities section is divided into three main subsections. The first, which is numbered 681, is buying and selling of own real estate, the second, which is numbered 682, is rental and operating of own or leased real estate, and the third, starting with number 683, is real estate activities on a fee or contract basis. In addition, section L includes implementing construction projects, combined with acquiring property rights or leasing of the real estate. This section does not include the construction works themselves since general and specialized construction works are included in another section of the EMTAK classification, which is F - Construction. (Center of Registers and Informational Systems 2008)

The absolute number of operating real estate companies in Estonia for 2020 is 32,714 companies (Figure 1). The most significant number of companies, 55%, are private limited companies, which is explained by the fact that it is the private limited company that is the most popular legal form in Estonia. Apartment associations hold 33% of the operating real estate companies since the Apartment Association is automatically created to manage all apartment properties (Järve 2019, 4-12). All other legal forms have up to 4% of the total number of active real estate companies, the most numerous of which are non-profit organizations and commercial associations.

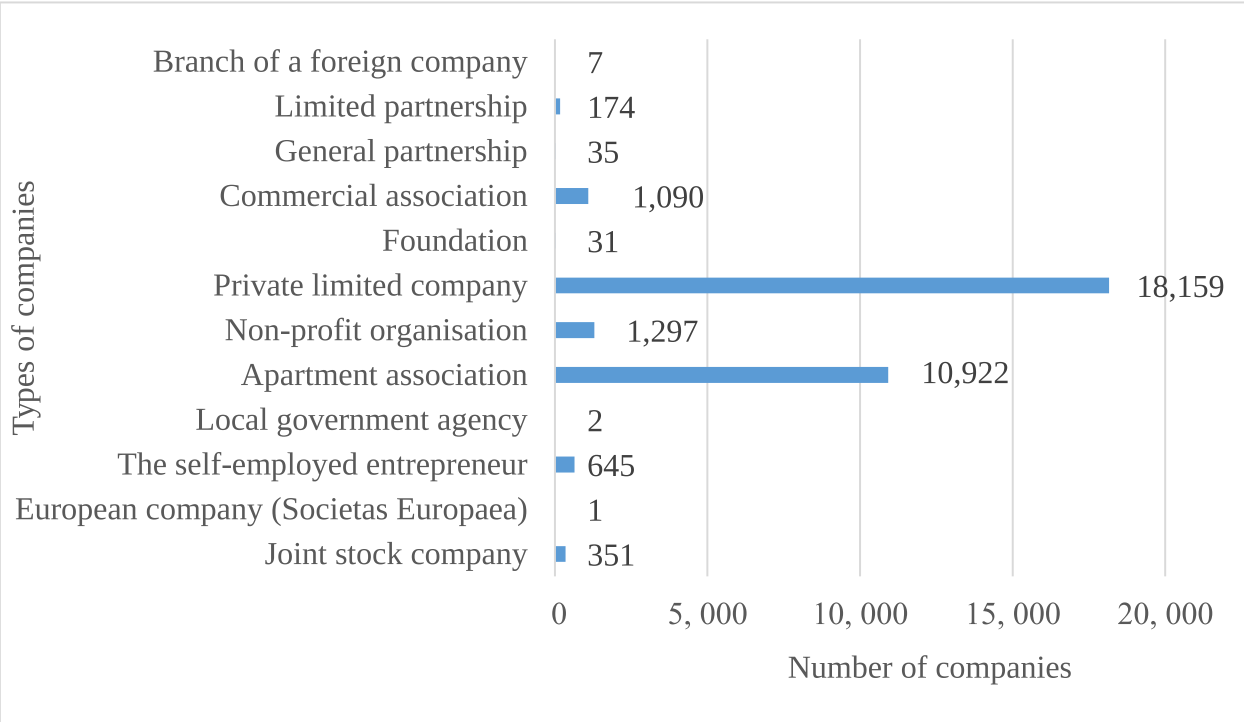

Figure 1. Operating real estate companies in Estonia for 2020, depending on their legal form
Source: Information provided by Center of Registers and Information Systems (2021), author's calculations

Based on the statistics of operating real estate companies in Estonia for the period of 2010 to 2020 (Figure 2), after the economic crisis of 2008, the number of operating companies increased and reached its peak in 2019. If in 2010 there were 21,577 registered companies in the sphere of real estate activity, then by 2019, there were already 33,617 of them. Since 2019, the situation with the coronavirus has affected the whole world, and by 2020 the number of operating companies has decreased. Based on the statistics, private limited companies are affected by crises, while other legal forms remain in a more or less stable state.

Figure 2. Operating real estate companies in Estonia for the period of 2010 to 2020, depending on their legal form
Source: Information provided by Center of Registers and Information Systems (2021), author's calculations

In total, during the period from 2008 to 2019, 248 companies went bankrupt in the real estate sector in Estonia, of which 212 were private limited companies, 26 joint-stock companies, along with others. The graph below (Figure 3) indicates that the peak of bankruptcy occurred in 2009 to 2011 after the economic crisis in 2008. The lowest number of companies that declared themselves bankrupt was in 2017, with only seven companies. In 2019, 12 real estate companies declared themselves bankrupt, all of which are private limited companies.

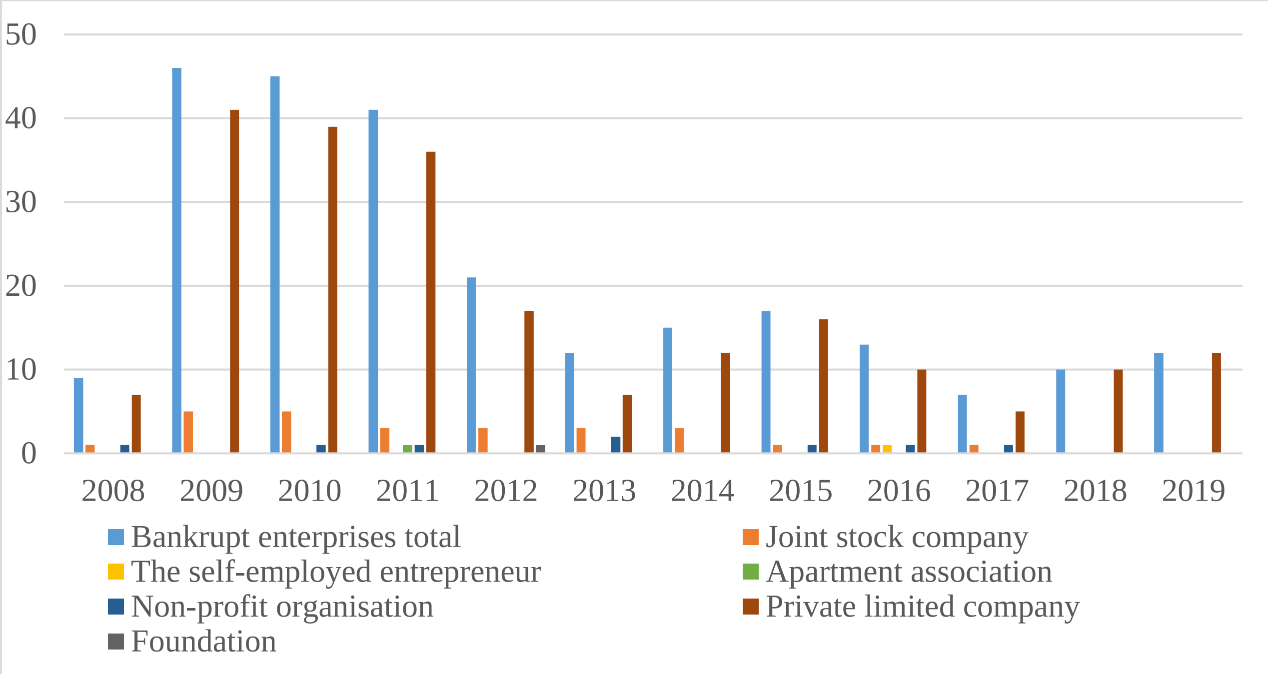

Figure 3. Bankrupt real estate companies in Estonia for the period of 2008 to 2019, depending on their legal form
Source: Information provided by Center of Registers and Information Systems (2021), author's calculations

In other spheres of activity, the percentage of declining companies per 1,000 operating is much higher. For example, in 2018, in accommodation and food service activities, this ratio was 3.78, and in the manufacturing field, 2.96 (Krediidiinfo AS … 2018, 11). In contrast, in real estate, it is only 0.31. This may be one of the reasons why it is in the real estate sphere of activity that the author has not found a single published study that allows the possibility to identify the best model for predicting the bankruptcy of Estonian companies in the future. That makes this master's thesis even more significant.

Based on the above statistical data, it concluded that companies become bankrupt even in the most stable years such as 2017 in the real estate industry. Additionally, this area of activity in Estonia is quite popular, and most of the companies are private limited companies.

2.2. Data requirements

The legal form of companies used in the analysis is private limited companies. In order to identify the most accurate bankruptcy prediction model for Estonian real estate companies, it was necessary to collect data from both bankrupt and operation companies. Following the Commercial Code § 4 item 5, every Estonian company is obliged to submit an annual report to the commercial register with the current field of activity of the company. In order to obtain the necessary data, the author contacted the Center of Registers and Information Systems, which also contains data on all companies that have declared themselves bankrupt. The author obtained data from all bankrupt companies in the Estonian real estate industry for 2008 to 2019 and general statistics of operating companies for 2010 to 2020. Only 1,000 randomly selected enterprise data could be provided to the author. The list of bankrupt companies includes companies declared bankrupt following the Estonian bankruptcy law. Companies are regarded as active if they submit an annual report.

The data for the analysis of the models have been acquired from the annual reports provided by the companies. Estonian companies must submit an annual report for the previous year by the end of June of the following year. Based on this, if the company went bankrupt from July to December, that is to say, in the second half of the year, the author used data from the previous year's annual report. And if the company went bankrupt from January to June, that is to say, in the first half of the year, then the author used the annual report data that preceded the last one. The sample excluded companies that did not provide annual reports under the conditions listed above and those that lacked some data. For example, those who did not have sales were excluded from both the sample of bankrupt and operating companies since they could be called non-operating companies. In addition, those companies were excluded in the annual reports from which there was already information about the further liquidation or bankruptcy of the company. Thus, of all the bankrupt Estonian real estate companies in 2008-2019, namely 248 companies, there were 61 companies suitable for further research. In addition, out of 1,000 of those companies that were provided to the author by the Center of Registers and Information Systems, 61 operating companies were randomly selected, which had all the data necessary for the calculations. An important criterion for the selection of operating as well as bankrupt companies was that they provided reports for at least the last three years in a row. Thus, the author received 122 companies with all the necessary data for analysis and calculations. Annual reports of companies were obtained from Äripäeva infopank.

2.3. Testing of bankruptcy prediction models

The author chose four bankruptcy prediction models for analysis based on the previously analyzed articles in the first part of the master's thesis. Next, the author calculated and analyzed two types of error for 122 companies within the selected four existing models: the five-factor model of E. Altman for non-listed companies, the four-factor model of E. Altman for non-production companies, the Taffler and Tisshaw model, the Springate model (an explanation of the choice of these particular models is written in sub-chapter 1.4 of this work). The two E. Altman models were chosen for their popularity and were among the first of their kind. The five-factor model of E. Altman for non-listed companies was chosen because only companies not listed on the stock market participate in the sample. The model of E. Altman for non-production companies is selected because the real estate industry includes companies that do not produce anything. The Springate model was chosen as the next model, as it is designed for small businesses, and in Estonia, most businesses are small businesses. Finally, the Taffler and Tisshaw model was developed in the United Kingdom, which is closer in economic terms (mentality, location, population, business) to Estonia than to the USA, as in the case of E. Altman models.

A Type I error means that a company that has declared itself bankrupt, based on the calculated data from the annual report prior to the bankruptcy, will continue to operate successfully. However, a Type II error indicates that at the moment (for the year 2021) the operating company, based on the annual report calculations for 2019, will go bankrupt.

All models used by the author consist of various financial ratios, the data for the use of which was taken from the balance sheet and company income statement. These were used in the calculations of financial ratio descriptions: Working Capital to Total Assets (Working capital/Total assets), Retained Earnings to Assets (Retained Earnings/Total assets), Return on Assets (ROA or Earnings before interest and taxes/total assets), Equity to Total Liabilities (Book value of equity/Book value of total liabilities), Assets Turnover (Sales/Total assets), Profit before taxes/Current liabilities (PBT/CL), Current assets/Total liabilities (CA/TL), Current liabilities/Total assets (CL/TA).

2.3.1. Five-factor model of E. Altman

The five-factor model of E. Altman for non-listed companies includes five financial ratios that show an enterprise's economic potential based on the annual report for the past year. In addition, the model includes such indicators as Working Capital to Total Assets, Retained Earnings to Assets, Return on Assets, Equity to Total Liabilities, Assets Turnover, each of which already indicates the financial condition of the company, and together in the function created by Altman are capable, in his opinion, of predicting whether the company will face financial difficulties. Descriptive statistics of data for bankrupt (the last year before bankruptcy) and successful companies are shown in Table 4.

Table 4. Descriptive statistics table of the five-factor model of E. Altman for non-listed companies

Bankrupt companies (1 year before)	Mean	Median	Min	Max	Standard Deviation
Working Capital to Total Assets	-2.81	-0.28	-124.58	0.99	15.97
Retained Earnings to Assets	-0.96	0.11	-71.96	5.23	9.29
Return on Assets	-1.67	-0.01	-54.73	0.48	7.33
Equity to Total Liabilities	1.01	0.07	-0.99	39.37	5.23
Assets Turnover	7.26	0.12	0.0001	403.45	51.59
Z-Score	-0.34	0.28	-52.91	81.89	13.83

Successful companies	Mean	Median	Min	Max	Standard Deviation
Working Capital to Total Assets	0.18	0.06	-0.88	2.07	0.47
Retained Earnings to Assets	0.52	0.57	-0.26	1.36	0.36
Return on Assets	0.07	0.04	-0.65	0.68	0.17
Equity to Total Liabilities	118.7	2.55	0.01	2245.36	401.53
Assets Turnover	0.36	0.11	0.002	2.68	0.57
Z-Score	50.98	2.36	-0.5	944.16	168.65

Source: compiled by the author

An interesting point shown in the Table 4 is that the average Assets Turnover in failing companies is significantly higher than the average in successful businesses. This result is possibly affected by an increase in Sales Turnover in the future bankrupt companies. For successful companies, it is an increase in Total Assets and a combination of these factors in both cases. However, the Assets Turnover ratio for real estate is generally lower than for other industries, as real estate businesses often have significant capital. Despite this, in combination with other financial ratios, which are mostly negative, the Z-Score median and the mean values as stated by the Table 4 are much lower than 1.23, indicating this model's effectiveness for bankrupt companies. The Equity to Total Liabilities ratio average in successful companies confirms that companies are more likely to be able to repay their liabilities. In contrast, in bankrupt companies, this ratio is much lower.

Table 5. Calculation results of the Five-factor model of E. Altman for non-listed companies

Bankrupt companies					
—	Total	Predicted as bankrupt	Gray zone	Predicted as successful	Accuracy
3 years before bankruptcy	50	28	10	12	—
%	—	56%	20%	24%	56%
2 years before bankruptcy	55	36	10	9	—
%	—	65.5%	18.1%	16.4%	65.5%
1 year before bankruptcy	61	49	6	6	—
%	—	80.3%	9.8%	9.8%	80.3%
Successful companies					
—	61	20	15	26	—
—	—	32.7%	24.6%	42.6%	42.6%
Total accuracy of the model (bankrupt companies 1 year before bankruptcy and successful companies)					61.45%

Source: compiled by the author

The best result of the five-factor model of E. Altman for non-listed companies based on Table 5 is bankruptcy prevention in short period effectiveness is 80.3%, while the Type I error is only 9.8%. The accuracy of this model for three years before the enterprise's bankruptcy is 56%, and the error of Type I increases to 24%. The number of companies with a dubious result also increases to 20%. While the effectiveness of successful companies was only 42.6%, the share of the Type II error was 32.7%. The overall accuracy of this model is 61.45%, but the model showed poor performance in predicting operating companies. The five-factor model of E. Altman for non-listed companies showed the best result of bankruptcy avoidance in the long term period, namely three years.

2.3.2. Four-factor model of E. Altman

Since the five-factor model was originally calculated for manufacturing companies and the value of Assets Turnover depends on the industry of the company, another additional model by E. Altman was created for non-production companies, in which the financial ratio of Assets Turnover was removed. To analyze the Z-Score result of the four-factor model of E. Altman for non-production companies, clarifying statistics provided in Table 6.

Table 6. Descriptive statistics table of the Four-factor model of E. Altman for non-production companies

Bankrupt companies (1 year before)	Mean	Median	Min	Max	Standard Deviation
Working Capital to Total Assets	-2.81	-0.28	-124.58	0.99	15.97
Retained Earnings to Assets	-0.96	0.11	-71.96	5.23	9.29
Return on Assets	-1.67	-0.01	-54.73	0.48	7.33
Equity to Total Liabilities	1.01	0.07	-0.99	39.37	5.23
Z-Score	-28.51	2.49	-1417.46	47.72	183.09

Successful companies	Mean	Median	Min	Max	Standard Deviation
Working Capital to Total Assets	0.18	0.06	-0.88	2.07	0.47
Retained Earnings to Assets	0.52	0.57	-0.26	1.37	0.36
Return on Assets	0.07	0.04	-0.65	0.69	0.17
Equity to Total Liabilities	118.7	2.55	0.01	2245.36	401.53
Z-Score	7.16	5.7	-91.04	72.03	18.23

Source: compiled by the author

An interesting fact on the report of Table 6 is that due to the change from the five-factor model to the four-factor model, the Z-Score for bankrupt companies has a large difference between the minimum and maximum values; thus, the dispersion of the data increased, the median Z-Score decreased to -28.51, and the mean increased to 2.49 (gray zone value). Whereas for operating companies, the dispersion of Z-Score data, on the contrary, decreased, mean 7.16 and median 5.7 are in the safe zone. Considering the data from Table 6, the mean of all financial ratios of bankrupt companies is negative, except for Equity to Total Liabilities ratio, and for operating companies, this particular financial ratio is very high. This means that companies can pay off long-term and short-term liabilities from the capital. The main reason for this is that the Equity to Total Liabilities ratio remains high because real estate companies' capital is usually higher than in other areas, mainly due to ownership and investments in real estate.

Table 7. Calculation results of Four-factor model of E. Altman for non-production companies

Bankrupt companies					
—	Total	Predicted as bankrupt	Gray zone	Predicted as successful	Accuracy
3 years before bankruptcy	50	11	5	34	—
%	—	22%	10%	68%	22%
2 years before bankruptcy	55	16	3	36	—
%	—	29.1%	5.5%	65.5%	29.1%
1 year before bankruptcy	61	28	6	27	—
%	—	45.9%	9.8%	44.3%	45.9%
Successful companies					
—	61	5	0	56	—
—	—	8.2%	0%	91.8%	91.8%
Total accuracy of the model (bankrupt companies 1 year before bankruptcy and successful companies)					68.85%

Source: compiled by the author

The probability of preventing company bankruptcy for the year by the four-factor model of E. Altman is very weak, only 45.9% with Type I error at 44.3%. Two and three years before the company goes bankrupt, the model's performance worsens and by three years is only 22%, while the effectiveness of determining a successful company in this model is very high, 91.8%, with a Type I error of only 8.2%. The overall performance of this model is 68.85%. Among all calculated models, the four-factor model of E. Altman for non-production companies showed the best result for identifying successful real estate companies in Estonia.

2.3.3. Springate model

The invention of the Springate model is based on the E. Altman model, created in 1968, and in the process of evaluating the model, the four best financial ratios were selected. A more detailed explanation is represented in the theoretical part of the thesis. A comparison of financial ratios of the E. Altman model from 1968 and the Springate model shows five financial ratios in the first and only four in the second. Both models combine three identical financial ratios. The difference is Retained Earnings to Assets and Equity to Total Liabilities in the Altman model, however, the Springate model uses Profit before taxes to the Current Liabilities financial ratio. To analyze the S-Score result of the Springate model, descriptive statistics provided in Table 8.

Table 8. Descriptive statistics table of Springate model

Bankrupt companies (1 year before)	Mean	Median	Min	Max	Standard Deviation
Working Capital to Total Assets	-2.81	-0.28	-124.58	0.99	15.97
Return on Total assets	-1.67	-0.019	-54.74	0.48	7.33
Profit before taxes/Current liabilities	-0.21	-0.12	-3.21	7.07	1.16
Assets Turnover	7.26	0.12	0.0001	403.45	51.59
S-Score	-5.25	-0.5	-135.27	4.92	19.36

Successful companies	Mean	Median	Min	Max	Standard Deviation
Working Capital to Total Assets	0.18	0.06	-0.88	2.07	0.47
Return on Total assets	0.07	0.04	-0.65	0.68	0.17
Profit before taxes/Current liabilities	1.56	0.42	-95.03	55.04	17.42
Assets Turnover	0.36	0.11	0.002	2.68	0.57
S-Score	1.56	0.68	-62.43	38.88	11.78

Source: compiled by the author

According to the Table 8, as a result, the mean and median of S-Score for bankrupt companies are negative, indicating this model's fairly high predictive ability. As in the five-factor model of E. Altman for non-listed companies, an interesting attribute is Assets Turnover. This is the only positive financial ratio among those calculated for bankrupt companies in this model and is fairly high. As mentioned before, factors that support the current result are a field of activity, an expansion in sales turnover, a decrease in total assets, and a combination of mentioned factors. Interestingly, the Springate model, like the five-factor model of E. Altman, uses the Assets Turnover financial ratio and the results of these models are better for bankrupt companies than the prediction result of the Four-factor model of E. Altman. Springate model S-Score must be greater than 0.862, which will indicate a successful company. In this case, according to the Table 8, the S-Score Mean is higher, but the Median is lower, which casts doubt on the identification of successful companies by the Springate model.

Table 9. Calculation results of Springate model

Bankrupt companies					
—	Total	Predicted as bankrupt	Gray zone	Predicted as successful	Accuracy
3 years before bankruptcy	50	17	13	20	—
%	—	34%	26%	40%	34%
2 years before bankruptcy	55	28	14	13	—
%	—	50.9%	25.5%	23.6%	50.9%
1 year before bankruptcy	61	44	11	6	—
%	—	72.1%	18%	9.8%	72.1%
Successful companies					
—	61	19	15	27	—
—	—	31.1%	24.6%	44.3%	44.3%
Total accuracy of the model (bankrupt companies 1 year before bankruptcy and successful companies)					58.2%

Source: compiled by the author

The Springate model showed a fairly good result for predicting bankrupt companies in a year. This model can predict with a probability of 72.1% that Estonian real estate companies will go bankrupt. Two years before the company went bankrupt, the probability fell to 50.9%, and the Type I error from 9.8% to 23.6%, when, as in three years, the probability of determining whether the company will go bankrupt in the future is very small, only 34%. Unfortunately, the result for determining successful companies was not encouraging, and it is only 44.3%, with a Type II error of 31.1%. The performance of the Springate model is 58.2% inaccuracy.

2.3.4. Taffler And Tisshaw model

Like the previously analyzed models, the Taffler And Tisshaw model was developed based on the Altman model. However, this model differs because it was developed for British companies, which are economically closer to Estonia than the USA. Descriptive statistics are provided in Table 10 to analyze the Z-Score result of the Taffler And Tisshaw model.

Table 10. Descriptive statistics table of Taffler And Tisshaw model

Bankrupt companies (1 year before)	Mean	Median	Min	Max	Standard Deviation
Profit before taxes/Current liabilities	-0.21	-0.12	-3.21	7.07	1.16
Current assets/Total liabilities	0.81	0.21	3.93	19.49	2.62
Current liabilities/Total assets	3.25	0.76	-0.01	125.58	16.04
Assets Turnover	7.26	0.12	0.0001	403.45	51.59
Z-Score	1.74	0.21	-1.12	86.93	11.11

Successful companies	Mean	Median	Min	Max	Standard Deviation
Profit before taxes/Current liabilities	1.56	0.42	-95.03	55.04	17.42
Current assets/Total liabilities	41.29	0.9	0.0003	782.97	141.33
Current liabilities/Total assets	0.2	0.08	0.0004	0.97	0.26
Assets Turnover	0.36	0.11	0.002	2.68	0.57
Z-Score	6.29	0.49	-14.46	89.16	18.52

Source: compiled by the author

In the Taffler And Tisshaw model Table 10 represents a Z-Score less than 0.2, which indicates a higher probability of failure. Interestingly, the indicator of the used financial ratio Assets Turnover does not indicate the probability of the analyzed bankrupt companies encountering financial problems, and this is confirmed by both median and mean of Z-Score. The Descriptive statistics analyses of Tables 4 and 8 have already described the reasons for the high values of Assets Turnover ratios. However, the mean of other financial ratios still indicates the financial problems of companies. Financial ratio Current Assets/Total Liabilities' mean is less than one, which indicates that companies will not be able to pay off current liabilities at the expense of working capital, which will lead to the use of other companies' assets. According to Table 10, in successful companies, Current Assets to Total Liabilities' mean is 41.29, which indicates the reverse situation. Moreover, for the financial ratio of Current Liabilities to Total Assets the mean showed an unsatisfactory result, which suggests that the company may have difficulties with payments on current liabilities, and this is one of the factors why the companies eventually went bankrupt, as is already known. While the same performance for operating companies leaves much to be desired, the average Z-Score demonstrates the effectiveness of this model for operating companies.

Table 11. Calculation results of Taffler And Tisshaw model

Bankrupt companies					
—	Total	Predicted as bankrupt	Gray zone	Predicted as successful	Accuracy
3 years before bankruptcy	50	17	6	27	—
%	—	34%	12%	54%	34%
2 years before bankruptcy	55	26	2	27	—
%	—	47.3%	3.6%	49.0%	47,3%
1 year before bankruptcy	61	30	9	22	—
%	—	49.2%	14.8%	36%	49,2%
Successful companies					
—	61	16	7	38	—
—	—	36.2%	11.5%	62.3%	62,3%
Total accuracy of the model (bankrupt companies 1 year before bankruptcy and successful companies)					55.75%

Source: compiled by the author

The accuracy of the Taffler And Tisshaw model for companies that went bankrupt the year before is a rather low 49.2%, and has become even lower. The accuracy three years earlier was 34%, with a Type I error of 54%. The accuracy of the same model for successful companies is higher and it is 62.3%, with a Type II error of 36.2%. The accuracy of the Taffler And Tisshaw model is 55.75% for Estonian real estate companies.

2.4. Comparison of models

The empirical analysis included calculations, descriptive statistics, and methodology for the following four models: the five-factor model of E. Altman, the four-factor model of E. Altman, the Springate model, and the Taffler And Tisshaw model. The data of 122 Real estate Estonian companies, 61 bankrupt companies for the period of 2008 to 2019, and 61 operating companies for 2010 to 2020 were used for calculations. The timespans prior to the bankruptcy of the companies analyzed in this table were one, two, and three years before the companies went bankrupt. Accuracy results for all models are provided in Table 12.

Table 12. Comparison of bankruptcy prediction models' results

Name of the model	Bankrupt companies			Successful companies		Total accuracy of the model
	Years before	Type I error	Accuracy	Type II error	Accuracy	
Five-factor model of E. Altman	3 years	24%	56%	32.7%	42.6%	61.45%
	2 years	16.4%	65.5%			
	1 year	9.8%	80.3%			
Four-factor model of E. Altman	3 years	68%	22%	8.2%	91.8%	68.85%
	2 years	65.5%	29.1%			
	1 year	44.3%	45.9%			
Springate model	3 years	40%	34%	31.1%	44.3%	58.2%
	2 years	23.6%	50.9%			
	1 year	9.8%	72.1%			
Taffler And Tisshaw model	3 years	54%	34%	36.2%	62.3%	55.75%
	2 years	49%	47.3%			
	1 year	36%	49.2%			

Source: compiled by the author

Based on Table 12 and a comparison of bankruptcy forecasting models, the following results are shown:

- Each model achieves an overall accuracy of over 55%.
- The best Total accuracy of the model in the four-factor model of E. Altman for non-production companies is 68.85%, but the accuracy of identifying a bankrupt company a year before bankruptcy is only 45.9%, Type I error 44.3%
- The best accuracy for identifying bankrupt companies a year before bankruptcy is the five-factor model of E. Altman for non-listed companies and is 80.3% with a Type I error of only 9.8%.
- The second place and a good result for identifying bankrupt companies a year before bankruptcy is the Springate model and is 72.1% with a Type I error of only 9.8%.
- The best accuracy for identifying existing businesses is the four-factor model of E. Altman for non-production companies with 91.8% accuracy. The second place is taken by Taffler And Tisshaw model with an accuracy of 62.3%.
- The most accurate model for determining the possible bankruptcy of a company over the long term is the five-factor model of E. Altman for non-listed companies, for three years the accuracy of determination is 56% c Type I error 24%, and for two years 65.5% c Type I error 16.4%.

To discuss the results, it is interesting that those models that show the best result for identifying bankrupt companies, such as the Springate model and the five-factor model of E. Altman, have the worst accuracy for operating companies. Conversely, those models that perform excellently in the accuracy of operating firms, such as the four-factor model of E. Altman and the above-average Taffler And Tisshaw model, perform worse than other models in accuracy for identifying bankrupt companies. When researching the accuracy of bankruptcy models, they must be tested in successful companies.

Recommendations from the author are that the five-factor model of E. Altman for non-listed companies will be useful for operating Estonian real estate companies, as it will allow the possibility to diagnose the financial data of the annual report and determining in time whether there are symptoms of a crisis. This bankruptcy model, among all the models calculated in this master's thesis, showed the best result for identifying bankrupt companies a one, two, and three years before the bankruptcy. Furthermore, the author considers the importance of the Type I error value of 24% three years prior to bankruptcy. Even if a company is in the gray zone after the bankruptcy prediction model calculations, it justifies further financial analysis. Bankruptcy is a situation where a company is not only unable to repay its debts from current assets but also from total ones. Accordingly, it is necessary to determine whether the company can repay its short-term obligations and whether the company has the resources for solvency. Based on this, some financial ratios, such as Return on Assets, Debt to Total Assets, Equity to Total Liabilities, and Retained Earnings to Assets, will give enough information about the state of the company. The author states that the calculation of a bankruptcy forecasting model for analyzing the financial situation of a company is not always necessary. Quite frequently, calculating financial ratios of the questionable areas in the annual report is sufficient. Therefore, the bankruptcy prediction model is rather a confirmation of the potential future financial situation of the company.

In conclusion, the use of only one model for diagnosing bankruptcy risk is not justified since none of the models could give a sufficient level of accuracy to guarantee the result of whether the company will succeed or fail.

CONCLUSION

In the current economic circumstances, an analysis of companies' financial condition is very relevant and is the basis for its further development and management decisions. No matter what area of activity the company operates and how big it is, its primary goal is to maximize profits, which requires the efficient use of capital. Therefore, analysis and evaluation of financial indicators are necessary for the owners of the company and investors. Consequently, it is crucial to determine the likelihood of financial complications for the company in the future.

In this master's thesis, real estate companies were analyzed according to the EMTAK (The Estonian Classification of Economic Activities) classification, classified as real estate activities under section L. This area was chosen because it is closely related to the country's economy. The author did not find any previous research written in Estonia on the analysis of models for predicting the bankruptcy of real estate companies. The research concentrated on private limited companies because during the years 2008-2019, 212 private limited companies went bankrupt in the real estate sector in Estonia, a total amount of 248 bankrupt companies. The total number of operating real estate companies in Estonia for 2020 is 32,714 companies, which confirms the relevance of this topic.

Statistical data and information on companies in the real estate sector in Estonia have been explicitly provided for this master's thesis by the Center of Registers and Information Systems. For the master's thesis, quantitative data were used, namely the annual reports of companies, which were obtained from Äripäeva infopank. Excluded from the sample were businesses that had not submitted an annual report for at least three years in a row prior to bankruptcy or until 2019 in the case of existing businesses and those that lacked some data. For example, those that did not have sales were excluded from both the sample of bankrupt and operating companies since they could be called non-operating companies. After the exclusion of companies not suitable for analysis, 61 bankrupt Estonian real estate companies remained in the database from the period of 2008 to 2019. In order to have the same number of active and failed companies in the sample, out of 1,000 operating companies provided by the Center of Registers and Information Systems, 61 operating companies were randomly selected, which had all the data necessary for the calculations. In the end, the database of this master's thesis includes 122 companies with all the necessary data for analysis and calculations.

Multiple discriminant analysis was chosen for the analysis, which is a classic statistical failure prediction model. The first choice fell on the five-factor model of E. Altman for non-listed companies since, firstly, the models of E. Altman are the most popular for preventing bankruptcy in companies and, secondly, only private limited companies, that is, those not listed on the stock exchange, participate in the sample. Real estate companies are not engaged in production, so the four-factor model of E. Altman for non-production companies was chosen as the second model. The Springate model was developed for small businesses, which are the majority in Estonia, so it is also involved. In terms of its mentality, location, and other factors, Estonia is closer to the United Kingdom than to the United States of America, so the last model for calculations was chosen by the Taffler And Tisshaw model.

The aim of the thesis was to identify the most suitable bankruptcy prediction model from the five-factor model of E. Altman for non-listed companies, the four-factor model of E. Altman for non-production companies, the Taffler And Tisshaw model, the Springate model to predict the possible bankruptcy for Estonian companies in the real estate sector. The research tasks to achieve this aim were to provide a literature overview of bankruptcy definition and theories of bankruptcy, as well as to provide a review of the history of bankruptcy law, to describe the bankruptcy process in Estonia and existing and frequently used bankruptcy prediction models. Additional tasks involved analyzing the statistics of bankrupt companies for the period of 2009 to 2019 in Estonia in the field of real estate and calculating four selected models for Estonian bankrupt and non-bankrupt real estate companies. The final task was to compare the results and evaluate them using the analyzed bankruptcy prediction models for Estonian real estate companies.

According to the study results, the most accurate model for detecting bankruptcy in real estate Estonian companies is the four-factor model of E. Altman for non-production companies – its accuracy is 68.85%. The second place is held by the five-factor model of E. Altman for non-listed companies with an accuracy of 61.45%, in third place is the Springate model with an accuracy of 58.2%, and in last place is the Taffler And Tisshaw model with an accuracy of 55.75%. At the same time, the best result in terms of accuracy of determining whether a company will go bankrupt in a year, two, or three years is the five-factor model of E. Altman for non-listed companies, whose accuracy is 80.3% a year before bankruptcy and 56% three years before. It is also noted that three years before bankruptcy in this model, Type I error is only 24%, which suggests that even if the company falls into the gray zone, this is a reason to analyze the situation at the company. Suppose the owners of the company get the result that, with a probability of 56%, the company will go bankrupt within the next three years. In that case, there is enough time to improve the company's financial condition and avoid bankruptcy. The Springate model showed a good result a year before the bankruptcy; the accuracy of bankruptcy was 72.1%, but, by the third year, it fell to 34%. To determine the success of a company, with an accuracy of 91.8%, the undisputed leader in the four-factor model of E. Altman for non-production companies. The author noted that those models that show the best result for identifying bankrupt firms show the worst option in the accuracy of identifying operating companies and vice versa. This is an important reason why it is always worth checking bankruptcy models for operating companies.

In conclusion, the year prior to bankruptcy will be predicted by more than 55% using any of the four prediction models. Using only one model for diagnosing bankruptcy risk is not justified since none of the models could give a sufficient level of accuracy to guarantee the result of whether the company will succeed or fail. The author recommends using the five-factor model of E. Altman for non-listed companies can be used for operating Estonian real estate companies, as it will allow the possibility to diagnose the financial data of the annual report and determine in due time whether there are symptoms of a crisis. Bankruptcy is a situation when a company is unable to repay its debts. Accordingly, it is necessary to determine whether the company can repay its obligations and whether the company has the resources for solvency. Based on this, some financial ratios will give sufficient information about the state of the companies.

This analysis can be expanded by the number of models used and their types and by expanding the sample of bankrupt companies from older to newer ones.

KOKKUVÕTE

PANKROTI PROGNOOSIMISE MUDELITE VÕRDLUS EESTI KINNISVARAETTEVÕTETE PÕHJAL

Anna Ivlijeva

Ettevõtte finantsseisundi analüüsimine on praegustes majandusoludes väga asjakohane ning loob aluse ettevõtte edasisele arengule ja juhtimisotsustele. Iga ettevõtte põhieesmärk, olenemata ettevõtte tegevusvaldkonnas ja suurusest, on maksimeerida kasumit, mis nõuab kapitali tõhusat kasutamist. Seega on finantsnäitajate analüüsimine ja hindamine ettevõtte omanikele ja investoritele hädavajalik. Sellest tulenevalt on ka oluline teada, milline on ettevõtte rahaliste raskuste tõenäosus tulevikus.

Selles magistritöös analüüsiti Eesti Majanduse Tegevusalade Klassifikaatori (EMTAK) 4. jao kohaselt kinnisvara alal tegutsevaid ettevõtteid. See valdkond valiti seetõttu, et see on riigi majandusega tihedalt seotud. Autor püüdis uurimistööga täita lünka Eesti kinnisvaraettevõtetele rakendatavate pankroti prognoosimise mudelite kohta saada olevas teabes. Uurimistöö keskendus osaühingutele, sest aastatel 2008–2019 läks Eesti kinnisvarasektoris pankrotti 212 osaühingut, kusjuures kokku pankrotistus 248 ettevõtet. 2020. aasta seisuga tegutses Eestis kokku 32 714 kinnisvaraettevõttet, mis kinnitab veelgi selle teema olulisust.

Statistilised andmed ja teave Eesti kinnisvarasektoris tegutsevate ettevõtete kohta on saadud spetsiaalselt selle magistritöö jaoks Registrite ja Infosüsteemide Keskuselt. Töö jaoks kasutati kvantitatiivseid andmeid, täpsemalt ettevõtete majandusaasta aruandeid, mis saadi Äripäeva infopangast. Valimist jäeti välja ettevõtted, kes ei olnud esitanud majandusaasta aruannet vähemalt kolm aastat järjest enne pankrotti või jätkuvalt tegutsevate ettevõtete puhul kuni 2019. aastani, samuti puudulike andmetega ettevõtted. Näiteks jäeti nii pankrotistunud kui ka tegutsevate ettevõtete valimist välja ettevõtted, kellel puudus müügitegevus, sest neis võis pidada mittetegutsevateks ettevõteteks. Analüüsimiseks mittesobivate ettevõtete väljaarvamise järel jäi

aastate 2008–2019 kohta andmebaasi 61 Eesti pankrotistunud kinnisvaraettevõtet. Selleks et valimis oleks tegutsevaid ja pankrotistunud ettevõtteid võrdsel määral, valiti Registrite ja Infosüsteemide Keskuse teatatud 1000 tegutsevast ettevõttest juhuslikkuse alusel välja 61 tegutsevat ettevõtet, kelle kohta olid olemas kõik arvutusteks vajalikud andmed. Lõpuks jäi niisiis magistritöö andmebaasi ettevõtteid, kelle kohta olid olemas kõik analüüsiks ja arvutusteks vajalikud andmed, kokku 122.

Magistritöö teoreetilises osas uuriti levinud pankrotiprognoosimismudeleid käsitlevaid kirjandusallikaid, mille alusel autor valis välja töös kasutatavad mudelid. Analüüsi jaoks rakendati mitmest diskriminantanalüüsi, mis on klassikaline statistiline ebaõnnestumise prognoosimise mudel. Esimeseks mudeliks valiti E. Altmani viie muutujaga mudel börsiväliste ettevõtete jaoks, kuna esiteks on E. Altmani mudelid kõige populaarsemad ettevõtte pankroti prognoosimise mudelid ning teiseks sisaldab valim ainult osaühinguid ehk börsil noteerimata ettevõtteid. Kuna kinnisvaraettevõtted ei tegele tootmisega, valiti teiseks mudeliks E. Altmani nelja muutujaga mudel mittetootmisettevõtete jaoks. Seejärel kaasati Springate'i mudel, sest see on välja töötatud väikeettevõtete jaoks, kes on Eestis enamuses. Ning viimaseks arvutuste tarvis kasutatavaks mudeliks valiti Taffleri ja Tisshaw' mudel, sest Eesti paigutub mõttemaailma, asukoha ja muude tegurite poolest Ühendkuningriigile lähemale kui Ameerika Ühendriikidele.

Lõputöö eesmärk oli selgitada välja, kas Eesti kinnisvarasektoris tegutsevate ettevõtete võimaliku pankroti prognoosimiseks sobib paremini E. Altmani viie muutujaga mudel (börsiväliste ettevõtete jaoks), E. Altmani nelja muutujaga mudel (mittetootmisettevõtete jaoks), Taffleri ja Tisshaw' mudel või Springate'i mudel. Selle eesmärgi saavutamiseks püstitati järgmised uurimisülesanded: anda kirjanduse põhjal ülevaade pankroti määratlusest ja pankrotiteooriatest, anda ülevaade pankrotiõiguse ajaloost, ning kirjeldada Eestis kehtivat pankrotimenetlust ning olemasolevaid ja sagedamini kasutatavaid pankroti prognoosimise mudeleid. Lisaülesannetena analüüsiti aastatel 2009–2019 Eestis kinnisvara valdkonnas pankrotistunud ettevõtete statistikat ning tehti valitud nelja mudeli põhjal arvutused Eesti pankrotistunud ja mittepankrotistunud kinnisvaraettevõtete kohta. Viimasena võrreldi tulemusi ja hinnati neid, kasutades Eesti kinnisvaraettevõtete jaoks analüüsitud pankroti prognoosimise mudeleid.

Uurimistöö tulemustest selgus, et Eesti kinnisvaraettevõtete pankroti prognoosimisel annab kõige täpsemaid tulemusi E. Altmani nelja muutujaga mudel börsiväliste ettevõtete jaoks: selle täpsus oli 68,85%. Teisele kohale jäi E. Altmani viie muutujaga mudel mittetootmisettevõtete jaoks (täpsus 61,45%), kolmandale kohale Springate'i mudel (täpsus 58,2%) ning viimasele kohale Taffleri ja Tisshaw' mudel (täpsus 55,75%). Kusjuures ühe, kahe või kolme aasta jooksul pankrotistumise prognoosimisel andis täpsuse poolest parimaid tulemusi E. Altmani viie muutujaga mudel mittetootmisettevõtete jaoks, mille täpsus üks aasta enne pankrotti oli 80,3% ja kolm aastat enne pankrotti 56%. Tähele tuleks panna ka seda, et kõnealuse mudeli puhul oli esimest tüüpi vea tõenäosus kolm aastat pankrotti kõigest 24%, mis tähendab, et isegi kui ettevõte jääb nii-öelda halli alasse, tasub ettevõtte olukorda analüüsida. Oletame, et ettevõtte omanikud saavad tulemuseks, et ettevõtte järgmise kolme aasta jooksul pankrotti minemise tõenäosus on 56%. Sellisel juhul on piisavalt aega ettevõtte finantsseisundi parandamiseks ja pankroti vältimiseks. Springate'i mudel andis häid tulemusi aasta enne pankrotti, mille korral pankroti õigesti prognoosimise täpsus oli 72,1%, kuid kolmandaks aastaks langes see 34% peale. Ettevõtte edu saavutamise hindamisel oli vaieldamatult parim, täpsusega 91,8%, E. Altmani nelja muutujaga mudel börsiväliste ettevõtete jaoks. Autor avastas, et mudelid, mis andsid ettevõtte pankrotistumise tuvastamisel parimaid tulemusi, olid ettevõtte tegevuse jätkumise tuvastamisel kõige ebatäpsemad ja vastupidi. Seega tasub tegutsevate ettevõtete puhul pankrotimudeleid alati kontrollida.

Kokkuvõtteks võib öelda, et aasta enne pankrotti on kõigi nelja käsitletud mudeli abil pankrotistumist võimalik prognoosida 55% täpsusega. Ainult ühe mudeli kasutamine pankrotiohu hindamiseks ei ole mõistlik, kuna ükski mudel polnud ettevõtte tegevuse jätkuvuse või mittejätkuvuse täielikult kindlaks määramiseks piisavalt täpne. Autor soovitab kasutada E. Altmani viie muutujaga mudelit mittetootmisettevõtete jaoks, mida saab rakendada Eestis kinnisvara valdkonnas tegutsevate ettevõtete puhul, sest see võimaldab hinnata majandusaasta aruandes sisalduvaid finantsandmeid ja teha aegsasti kindlaks, kas ettevõtte puhul esineb kriisi märke. Pankrot on olukord, kus ettevõte ei suuda oma võlgu tagasi maksta. Seega on tähtis kindlaks teha, kas ettevõte suudab oma võlgnevused kõrvaldada ja kas ettevõttel on maksevõime säilitamiseks piisavalt vahendeid. Seejuures on võimalik mõnedest finantsnäitajatest ettevõtte seisundi kohta piisavat teavet saada.

Seda analüüsi saab laiendada, kasutades rohkem eri liiki mudeleid ning laiendades pankrotistunud ettevõtete valimit vanematelt ettevõtetelt uuematele.

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