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BANKRUPTCY PREDICTION IN THE AGRICULTURE INDUSTRY OF UKRAINE

Bachelor's thesis

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I hereby declare that I have compiled the thesis independently
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ABSTRACT

Agriculture is one of the most crucial industries in Ukraine and the distinctive feature of this sector is a heightened threat of bankruptcy. The aim of this thesis is to determine whether bankruptcy prediction models are applicable in the agricultural industry of Ukraine. Besides that, the study indicates the accuracy of each model. Additionally, this research focuses on answering the question of what are the main factors that lead a firm to insolvency. The data of bankrupt and non-bankrupt agricultural firms are used to estimate the prediction ability. The financial statements for analysis are collected from the Orbis Europe database. The paired sample consists of 20 Ukrainian agricultural enterprises with similar peers. In order to evaluate the relevancy of using each model, the dichotomous classification test is applied. To predict insolvency, William H. Beaver's univariable, Edward I. Altman's Z-score and Davydova and Belikov's models are used. The companies are studied within five years before bankruptcy from the period of 2017-2018. The most accurate model is studied using the variance analysis.

The findings suggest that bankruptcy prediction models presented in this research are applicable in the Ukrainian agriculture industry. However, Altman's z – score results in lots of prediction uncertainties, and further investigation is needed to evaluate the true predictive accuracy of the model in the studied environment. Davydova and Belikov's model shows the highest prediction accuracy. The same model is examined with the variance analysis and the results indicate that the major failure factor for Ukrainian agricultural firms is low liquidity.

Keywords: bankruptcy prediction, agriculture in Ukraine, Z-score, univariate model

INTRODUCTION

Bankruptcy prediction is a crucial and widely discussed topic in finance and accounting. Insolvency means that a company is unable to repay its outstanding debts. Essentially, the disability to pay liability causes a loss of control of a firm's assets, which leads to the company's failure and the fact that it has become uncontrollable. The prediction of bankruptcy is an integral part of risk assessment and one of the major interests of creditors and investors. This topic remains relevant until today, especially during existing crises. The definition of failure is that company is unable to fulfill its obligations by the exercise time (Beaver 1966, 71).

The economy is cyclical and a possible recession could entail a wave of bankruptcies. The consequences have a negative impact on unemployment rates, creditor's financial position, tax revenues from companies, funding of social and cultural spheres, the credibility of management of failed firms and the brand itself. Moreover, the insolvency of manufacturing firms directly impacts the GDP, which will decline as soon as production volume decreases. After that, due to the low supply of the country, the import will increase. All the above are the factors that lead to unfavorable socioeconomic conditions.

The first remarkable model was created by William H. Beaver in 1966. Beaver implemented a paired-sample design to compensate for the industry effects and line up companies by asset size, but the most important is that he compared the financial ratios of bankrupt with non-bankrupt firms in order to evaluate their prediction capabilities and pick the most meaningful of them. The author studied each financial ratio separately and underlined its importance.

The next introduced model was based on previous studies and created in 1968 by Edward I. Altman. The author introduced his Z-score model where he performed a discriminant analysis using a multivariable equation to predict a company's failure. The model established itself as a versatile method of bankruptcy prediction. (Eidleman 1995) In addition, the Davydova's and Belikov's bankruptcy prediction model will be examined in this study. The function was developed based on the Altman's multivariable discriminant model by Russian researchers in 1999.

Agriculture in Ukraine is one of the most crucial areas of the country's economy. The contribution of this sector to the total GDP was 14.1% in 2017 (National… 2018, 3). Worldwide, the distinct specifics of agribusiness are seasonality and lasting cash conversion cycle. Agribusiness has a high sensitivity to the market. Thus, if there was fluctuation in demand, it would be impossible to satisfy it in a short-term perspective or vice versa; if there was a surplus of inventory, the products would expire quickly. It is extremely important to maintain stability in such valuable and unpredictable industry.

Agro-firms are subject to the high-risk default because of the soil fertility, global warming, small-scale production, etc. Defaults in the agriculture industry in Ukraine remain the same, and one of the reasons is that the deterioration of company's financial health remains undetected. The proposed models are not only able to save a company from huge losses, but they contribute to the economy by signalizing bankruptcy.

In this thesis, the traditional bankruptcy prediction models are applied to the Ukrainian agricultural firms to test the possibility of implementing them in such environment. Furthermore, bankruptcy prediction models not only provide forecast, but they assess the conditions of companies. By using variance analysis, this research generalizes the most common determinants that lead companies to default. Additionally, the obtained results are compared between companies that filed for bankruptcy and active firms. The study tries to answer the following questions:

Q1: Is it possible to use the traditional bankruptcy prediction model in the agricultural environment of Ukraine?
Q2: What are the main determinants, which lead agricultural firms to insolvency in Ukraine?
Q3: Which model is the most accurate for the agricultural firms of Ukraine?

The proposed models are used in this study to answer the research questions and fulfill the aim of this thesis. Both Beaver's and Altman's models are famous for their contribution to the bankruptcy prediction studies. Additionally, they are simple in use and can provide sufficient evidence to determine the major bankruptcy factors. The third model was chosen because of its connection to the researched environment, and it can show an interesting insights into failure prediction, using quartile reporting. For example, the usage of quarterly data improves financial ratios because of the possibility to make adjustments to the financial statements.

1. LITERATURE OVERVIEW

Debtors and lenders have always been around from ancient times until now. However, the interest in bankruptcy prediction occurred in the early 19th century when the first industrial revolution took place and supported the growth of manufacturing companies.

At that time, trends led the economy to be more capitalistic and finance-orientated, which increased the interest to research of the financial health of firms. Many major steps were taken in bankruptcy prediction research in the beginning of the 20th century. When the financial ratio analysis reached the academic level, the term "scientific ratio analysis" emerged. (Horrigan 1968, 284-294)

The Great Depression of the 1930s made another impetus for the development of financial ratios and appearance of early bankruptcy prediction studies. The tendency was driven by Winakor and Smith who started performing financial ratios analysis on the selection of firms that had been financially embarrassed (Horrigan 1968, 284-294).

The early studies concerning ratio analysis for bankruptcy prediction were univariate studies. These studies focused on individual ratios and sometimes compared ratios of failed companies with those of successful firms (Bellovary *et al.* 2007). Additionally, the problem of data collection at that point in time did not reach the capability to create a higher outcome.

The evolution of bankruptcy prediction models began with the publication of William H. Beaver's research where he excels by applying test on individual financial ratios with the aim to find the most important of them within a pair-matched sample. At the end of the article, he suggests using multi-ratio analysis. The second stage of the breakthrough was the work of Edward I. Altman where he used multiple discriminant analysis, which proved to be reliable and the most accurate model for that time.

After the publication of those articles, the development of the bankruptcy prediction models reached new levels: first, logistic analysis was published by Ohlson (1980), then, probit analysis by Zmijewski (1984), and finally the introduction of artificial intelligence (AI) and hybrid models. In general, they can be split into three groups: statistical models, artificial intelligence or machine learning models, and theoretical models. (Aziz, Dar 2006)

Statistical models use financial ratios, which have the highest prediction capabilities. The examples of statistical models are univariable analysis and multiple variable analysis. The machine learning models, which are used in bankruptcy prediction, are the subset of AI and which purpose is to not only use the same prediction variables but to "train" on its outcomes (Understanding AI… 2020). The theoretical models are rather focusing on the framework where companies are operating and investigates the environmental causes of credit risk (Crouhy, 2000).

The main causes of becoming insolvent could be divided into two groups: internal and external. The most high-risk factors that could lead companies to file for bankruptcy are external because they are uncontrollable from their perspective and complicated to predict. The external reasons are usually political, market and economic conditions. The internal difficulties are usually caused by inefficient management. Moreover, Franz T. Lohrke (2004) found that financial distress occurs more often due to poor corporate governance rather than by external pressure.

1.1. William H. Beaver's model

Willian H. Beaver was the first one to move forward after lengthy studies of using the univariable model of bankruptcy prediction. His contribution to the research on the topic was achieved by applying individual financial ratios to the sets of companies, which were classified as bankrupt and non-bankrupt. Beaver evaluated the forecasting ability of each financial ratio and picked the best of them according to their margin of error; the smaller the delusion is, the higher the predictive ability of the ratio. (Deakin 1972, 167-179)

The main goal of Beaver was to prove the forecasting abilities of financial statements using the financial ratios. The sub-goal of his research was to provide a starting point for the possible alternative failure prediction models and lay a foundation for future development. On his way to achieve the goal, Beaver compiled a sample of 158 companies in total. He designed it in the way that each non-failed firm had a failed match, which corresponded to the asset size and the industry they were operating in. This decision allowed him to get rid of possible disruption in the connection between ratios and bankruptcy. Beaver decided which ratios to use, relying on several measures. The first were the most frequent ratios, which had appeared in previous studies. As the second measure were the financial ratios which showed the best performance, and the third were cash-flow-orientated ratios. After this selection, he proceeded with 30 financial ratios.

To evaluate the connection between the ratios and bankruptcy, Beaver performed a profile analysis. He calculated the mean for each financial ratio of bankrupt and non-bankrupt firms and compared the results.

Furthermore, the Beaver describes four concept models of the theoretical ratio analysis. Beaver concludes that firms that are not meeting the concept criteria tend to be more exposed to file for bankruptcy. Also, he discovered that there is a difference in ratios of bankrupt and non-bankrupt companies. (Beaver 1966, 79-81)

Beaver tested whether his model can distinguish between failed and non-failed companies. The classification for the model was set based on whether the ratio is below or above critical value, and the outcome illustrated whether a company is bankrupt or not. Finally, he compared the predicted data with the actual one. As a result of his experiment, two different errors were generated. The Type I error classified a bankrupt company as non-bankrupt and Type II error showed exactly the opposite. The table below illustrates the percentage of misclassification of financial ratios.

Table 1. Percentage of firms misclassified

Ratios	Years before bankruptcy				
	1	2	3	4	5
Cash Flow to Total Debt	0.13	0.21	0.23	0.24	0.22
Net Income to Total Assets	0.13	0.20	0.23	0.29	0.28
Total Debt to Total Assets	0.19	0.25	0.34	0.27	0.28
Working Capital to Total Assets	0.24	0.34	0.33	0.45	0.41
Current Ratio	0.20	0.32	0.36	0.38	0.37

Source: Beaver (1966, 85)

It is seen from the table above that cash flow to total debt and net income to total assets have notable prediction ability for one year before bankruptcy. Cash flow to total debt has a slight increase in the number of misclassifications from year one to five. While net income to total assets has a substantial decrease in accuracy from year four to five. Also, gradual increase in the amount of errors might be observed for each ratio the more distant the bankruptcy is. It can be concluded that the size of the company is not that important as its cash flow and liquidity. (Beaver 1966, 86)

1.1.1. Limitations of the model

The model was still arguable because as all "traditional" bankruptcy prediction models it counted only on accounting data. Consequently, doubt was casted on using the model for decision-making process and translating possible strategies. (Johnson 1970, 1166 –1168). Furthermore, one of the most important issues related to the univariate analysis is that there is no single benchmark to compare the results of the ratios. (Morris, 1997) Usage of already calculated benchmarks, might create a possibility of random and incorrect predictions.

Also, Morris discussed in his book the nature of the accounting ratios. Meaning that there is a significant variance between ratios of companies operating in different industries, as well as in types of companies supporting similar activities. (Ibid.)

Another considerable fact is that there is a time lag in data collection, when the financial statements are being analyzed after the publication of the reports some time has already passed and the condition of the firm might have changed dramatically. (Ohlson 1980, 110)

Despite that, William Beaver's model provides an inspiration for the following research to create a multivariable model, which was a breakthrough in bankruptcy prediction.

1.2. Edward I. Altman's model

Edward I. Altman was the first to use the multivariate discriminant analysis and create a formula consisting of five factors for predicting bankruptcy (Bellovary *et al.* 2007, 4).

The study focused on 66 companies in total. In similar to William H. Beaver, Altman compiled his sample from two groups with failed and non-failed companies matching to each other by size and industry. Moreover, he eliminated small-size and large-size companies from the selection, and the reason for this was the fact that large companies rarely file for bankruptcy, and there was a lack of financial data of the small ones. (Altman 1968, 593)

Edward I. Altman composed a list of financial ratios relying on the performance of different variables discussed in previous studies. Also, he split them into five different classification categories: activity, leverage, liquidity, profitability, and solvency ratios. His final list was created by choosing the ratios, which were the most appropriate in correlation to each other. (Altman 1968, 594)

The Z-score formula, which was introduced by Edward I. Altman:

$$Z = 0{,}012X_1 + 0{,}014X_2 + 0{,}33X_3 + 0{,}006X_4 + 0{,}999X_5 \tag{1}$$

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 of Equity/ Total Liabilities
X_5– Sales/ Total Assets

X_1 (Working Capital to Total Assets) is a liquidity ratio, which measures net liquid assets to the total assets of a firm. X_2 (Retained Earnings to Total Assets) is a profitability ratio, which indicates a company's matureness and earning abilities. X_3 (Earnings Before Interest and Taxes to Total Assets) is an operating ratio that indicates return on total assets, therefore demonstrates a firm's true earning power. X_4 (Market Value of Equity to Total Liabilities) is a solvency ratio that shows the amount of equity, which might be decreased before the liabilities will exceed it. X_5 (Sales to Total Assets) is an efficiency ratio, which demonstrates how well a company manages its assets, therefore it does not directly indicate bankruptcy; however, Altman uses it because of its correlation to other ratios. (Altman 1968, 596)

Table 2. Predictive abilities of z – score

Years before bankruptcy	Correctly Classified	Incorrectly classified	Accuracy of the model (%)
1	31	2	95
2	23	9	72
3	14	15	48
4	8	20	29
5	9	16	36

Source: Altman (1968, 604)

It is seen from the Table 2 that the Altman's model reaches it's accuracy peak one year before bankruptcy. The number of correct classifications represents 95% of the Altman's sample. For the second year before bankruptcy z – score reaches 72%. The number of correct classifications decrease from second to fouth year before failiure. Also, it is seen that accuracy is sligtly higher for the fifth year then for fourth, but the result remains unreliable in terms of accuarcy. Altman outlined that the usefulness of the model emerges in two years before bankruptcy. (Ibid.)

The Altman's z – score was tested for the list of international firms and indicated to be applicable in such an environment (Altman *et al.* 2014). Also, the model gave an opportunity to measure the financial condition of Romanian agricultural firms. (Popescu, 2014)

1.2.1. Limitations of Altman z – score

Z – score, just like Beaver's univarite model has a considarable shortcoming - Altman's model relies on the accounting data while making the "prediction".

Altman has been criticized for not providing sufficient evidence to show the connection between financial ratios and bankruptcy (Johnson 1970). Charles Moyer also claimed that the model has low classification abilities of large firms. Moreover, the period studied by Altman was excessively long to produce a reliable result, because of the rapidly changing microenvironment (Al-Rawi *et al.* 2008). Beside that, Grice and Dugan (2001) found that the Z-score performed worse for more recent samples of companies.

Additionally, the usage of multivarite discriminat analysis itself was critisied by Joy and Tollefson (1975), Eisenbeis (1977), Moyer (1977), The listed studies focused on the incorrectness of the appication of the statictical method. (Jackson, Wood 2013)

1.3. Davydova and Belikov's model

Davydova Galina Vasilievna and Belikov Alexander Yuryevich were the one of the first Russian researchers who built a bankruptcy prediction model based on the Altman's multivariable discriminant analysis. The aim of their research was to create a risk assessment model of bankruptcy prediction that could be easily implemented. A distinctive feature of their study was an adaptation of the model to the post-Soviet environment.

The primary task was to apply the classical Altman's Z-score to the sample of 608 Russian companies, bankrupt and non-bankrupt, accordingly. The results indicated the low prediction abilities of the model. (Davydova, Belikov 1999, 13-20) In addition, the authors highlighted the difficulties regarding data collection because the vast majority of firms were private limited companies they did not have market value. Additionally, the researchers compared the means of individual ratios with American companies and found that there was a significant difference between liquidity ratios (Working Capital to Total Assets). The possible reason for that might be the superiority of current assets over total liabilities in the Eastern companies and the preference of Western firms to finance their assets by long-term debt. (Davydova, Belikov 1999, 13-20)

The selection of variables for the future model was based on preliminary polls of the management of different firms and previous studies. As a result, 13 ratios were chosen to put into use.

The final R formula was introduced:

$$R = 8{,}38 * K_1 + K_2 + 0{,}054 * K_3 + 0{,}63 * K_4 \quad (2)$$

where

K_1– Working Capital/ Total Assets

K_2– Net Income/ Total Equity

K_3– Sales/ Total Assets

K_4– Net Income/ Cost of goods sold

The results were interpreted in the following way: if the value of the R-model exceeded 0.42, it indicated that the company had less than 10% probability to fail. The lower the value, the higher the risk of filing bankruptcy 0.32–0.42 demonstrates low probability (15–20%), 0.32–0.18 medium probability (35–50%), 0.18–0 high probability (60–80%), and lower than 0 shows the maximum default probability (90–100%).

Altman's bankruptcy prediction model was created versatile, while Belikov differs by having a narrower focus and another approach to the selection of variables. Moreover, the usage of quartile data helped the author to make an adjustment to the statements in order to improve the accuracy of some ratios. The agribusiness is known for its seasonality, which means that financials of companies might vary significantly in a year. For instance, the process of cultivations assumes a large number of cash outflows before the harvest, which takes place in the middle of autumn, and is carried along with the following short-term cash inflows. The lasting production procedure might require the attraction of additional funds, which directly influence the financial condition of companies. These factors might increase the accuracy of forecast in the former Soviet countries. Therefore, it would be interesting to try it not only in Russia, but in Ukraine as well.

1.3.1. Limitations of the model

The model's limitations are similar to the Altman's z – score because both of them are based on the multivariable discriminant analysis. The model was criticized for an inability to asses the company's condition without apparent indicators of financials "illnesses". (Erimizina, Erimizina 2017)

2. SAMPLE SELECTION

The research population consists of two sets of companies. The first group includes financial statements of active companies, meaning that they continued to operate after 2018. The second group includes financial data of bankrupt companies, which have filed for bankruptcy at the end of 2017-2018. Additionally, the companies for the first group were selected by having similar peers to companies from the second group. They have been matched by asset-size, operating revenue, and the number of employees. The researched period is five years before the bankruptcy, and the financial statements of non-bankrupt companies are studied within the same timeframe.

It is also worth noting, that the large agricultural companies have not been considered for the research. The study focusses on the medium, small, and micro companies. Under the Ukrainian legislation №2164-VII (as of 1 January 2018), the size of the company is determined by their number of employees and operating revenue, meaning that companies that have less than ten employees and the maximum of two million euros of operating revenue are classified as micro firms, from ten to 50 employees and up to ten million of operating income as a small company, and from 50 to 250 employees and without exceeding 50 million of operating revenue the middle size company.

The financial data has been collected from the Orbis Europe database and the further analysis is performed in the Microsoft Excel program.

2.1. Review of Agriculture in Ukraine

The agriculture has been owned by the government when Ukraine was part of the Soviet Union. After the land reform in 1994, the land started to be transferred to the private entities and holdings. It should be noted that under Ukrainian law No. 2242-III (as of 1 January 2001) the land cannot be sold. It was adopted in order to prevent the unfavorable monopolization and fundamental ownership of land by wealth part of the population until economic stability is achieved. Despite the fact of recovery from the global financial crisis the moratorium has been prolonged and finally canceled only at 2020.

From 2000 to 2010 cultivation of wheat became the main production area of the Ukrainian agriculture industry. Moreover, Ukraine became a leader in the export of barely and the average share of the global sty market for this period reached approximately 14,1%. Although, after 2010 the production has decreased due to a decline in the amount of land utilized from 5 to 3,3 million hectares in the end of 2012. (Rozwadowski et al. 2018)

According to Ukrstat (2017), the number of agricultural firms reached 80,321 in 2010, and in the end of 2018, it declined to 76,328 resulting in a reduction of the working force involved in agro-industry by 23%. After 2010 agriculture in Ukraine was the number one sector by the number of bankruptcies. Moreover, it has a predominant amount of unprofitable enterprises than any other industry in Ukraine. (Frolova, Gonchar 2015, 109-113)

Economically, the agricultural industry produced 10.14% in 2018 of total gross domestic product, which is less by almost 4% compared to the previous year (The World Bank… 2019). The amount of utilized agriculture area reached 4,508 million hectares and the arable land amounted to 32,541 million in 2016. Noteworthy, that 70% of the total land of Ukraine was utilized for agricultural purposes. Agriculture is one of the top three the most influential industries in Ukraine by contribution to gross domestic product.

2.2. Characteristics of the industry

The main characteristic of the industry is that it is closely linked to the natural processes, which are not in human control (Ivasenko 2011). Also, the distinction of agriculture is that it has high seasonality meaning that the production period does not coincide with the actual working period and the costs appear much earlier than profits. Moreover, the production cycle requires a huge number of expenditures and initial investments.

Equally important is that the industry is known for creating positive externalities. The farmland is a nature reserve by itself. The agriculture multifunctionality contributes to food security, utilization of rural land. In some countries, it is increasing tourism rates. (Switzerland 2000)

2.3. Challenges of the agricultural industry

In terms of financials, the first challenge is coverage of operational costs, because of the lasting period before the cash is actually collected. So, the agribusiness assumes a high need in crediting and special capital budgeting structure. (Andriychuk 2002). The following problem is insufficient funding of small-medium enterprises and a lack of governmental support. Moreover, there is no land market and the only possibility to benefit from the land is a temporary rental agreement, which adds additional financial pressure on the farms. Another problem is the inability to satisfy the fluctuations in demand rapidly, because of the lasting production period the company might experience a shortage of surplus after the harvest.

Additionally, the agribusiness suffers from market risks such as fluctuations in input and output prices, inflation, instability in exchange rates. Also, there is a pollution threat, which decreases land fertility. (OECD 2011)

In conclusion, it can be said that agribusiness is a very sensitive type of activity, which implies high risks and unpredictable events. The factors like global tendency in fertility decline, poor legislation, high seasonality, etc… remains an important starting point in investor’s decision making. The development of agriculture in Ukraine requires additional funding and technology improvement for the most part.

3. APPLICATION OF THE PREDICTION MODELS

In this chapter, three models are presented: William H. Beaver's univariate model, Edward I. Altman's Z-score and Davydova and Belikov's R–score. The quantitative method is used to analyze each of them. At the end of this chapter, the variance analysis is executed on the most accurate model to examine the main bankruptcy determinants.

3.1. Application of William H. Beaver's model

The process of applying the model starts with the selection of financial ratios to put in use. As Beaver estimated the five ratios, which showed the highest performance in predicting the bankruptcy, they are used in this research as well. A mean of individual ratios for a year is calculated and the profile analysis is conducted. The values of financial ratios for one year of bankrupt firms are compared to the values of non-bankrupt in order to see the difference between them and the annual tendency.

Beaver separated his sample into two parts. For each group the critical values were calculated, and two tests were performed. To compile this research, two sets of Beaver's cut-off points were applied.

The prediction ability of the model is based on the fact that the less the result of a single ratio is in relation to the critical value, the higher is the probability of the failure occurring (Beaver 1966, 86). Additionally, the dispersion in this study is minimized in order to increase the accuracy of prediction. The most distant values from the central tendency were removed from the research population.

3.1.1. Profile analysis

Beaver conducted a profile analysis to identify the relation between the financial ratios of failed and non-failed firms. From the comparison of the averages, the general tendency of the condition of the firm might be concluded. Moreover, it is possible to determine the possible factors of firms going bankrupt.

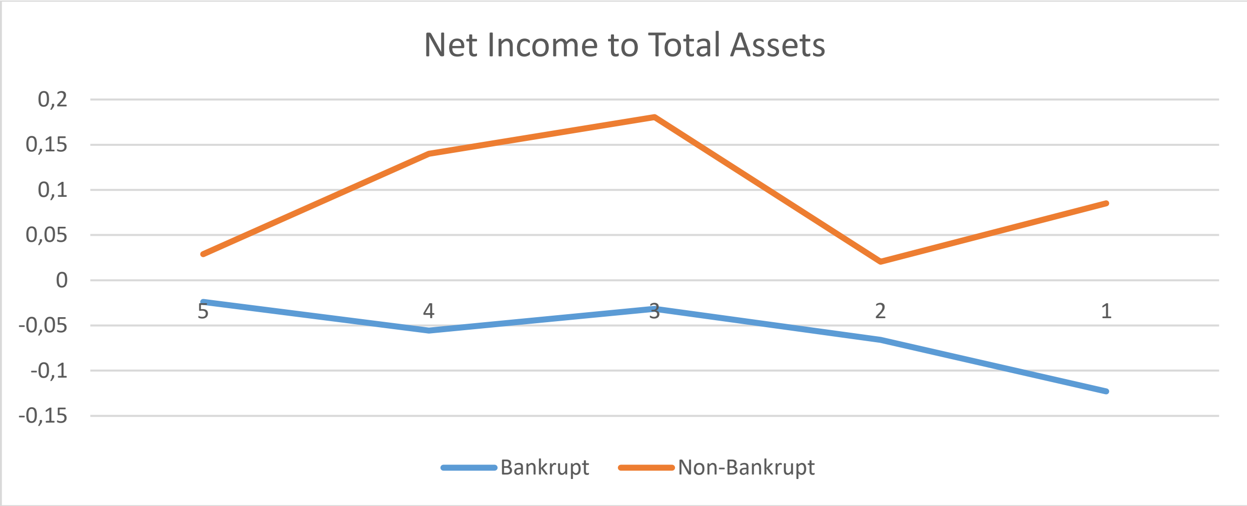

Figure 1. Means of net income to total assets from five year prior bankruptcy
Source: Author's results based on collected data

From the figure above, a significant difference between means of failed and non-failed companies is seen, especially for the fourth and third year before the bankruptcy. The graph illustrates that from the fourth year to the second similar tendency in ratios has remained, meaning that both bankrupt and non-bankrupt ratios are facing an upward trend and then downward within a two-year period. That is more likely caused by the economic condition at that time. Also, there is a substantial decline in the mean of non-bankrupt firms from the third to second year before bankruptcy. The reason for that might be the dramatic drop in net income. However, some corrective actions were taken to improve the ratio, for instance, more efficient cost management.

The same cannot be said about bankrupt companies where the average ratio has been in a declining trend. In summary, the return on assets shows how well the company is managed, and by indicating the distinctions between researched groups, it can be concluded that non-bankrupt firms have a higher ability to generate the profit in relation to their assets.

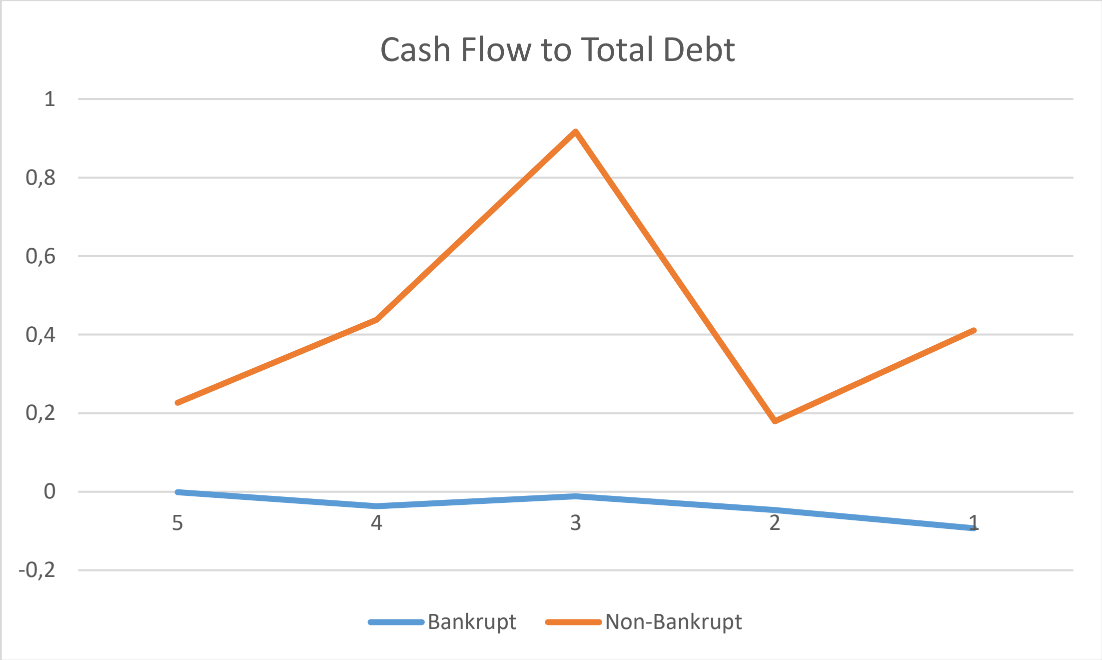

Figure 2. Means of cash flow to total debt from five year prior bankruptcy
Source: Author's results based on collected data

The figure above demonstrates the difference between the averages of ratios of bankrupt and non-bankrupt companies. From year to year, the ratios of bankrupt do not show a significant deviation from the central tendency, but it still represents the principle that the closer the company is to the bankruptcy, the lower the ratio. This might be observed as a continuous decrease in the value of ratios from year three to the bankruptcy. Also, the low value of the ratio might be explained by relatively low cash flow, according to the existed debt of the firms. The mean of non-bankrupt firms shows a rapid growth from the fifth to third year, and from the third to second year it goes down substantially. Similarly, to the net income to total assets ratio discussed previously in this thesis, the change in management strategy resulted in the improvement of the coverage ratio.

Also, the high cash flow to the total debt ratio in year three indicates an opportunity for a firm to attract additional funds, which might be another explanation for the ratio to decrease in the following year. To conclude, it can be said that non-bankrupt firms have a greater ability to meet their obligations and the possibility to take more debt.

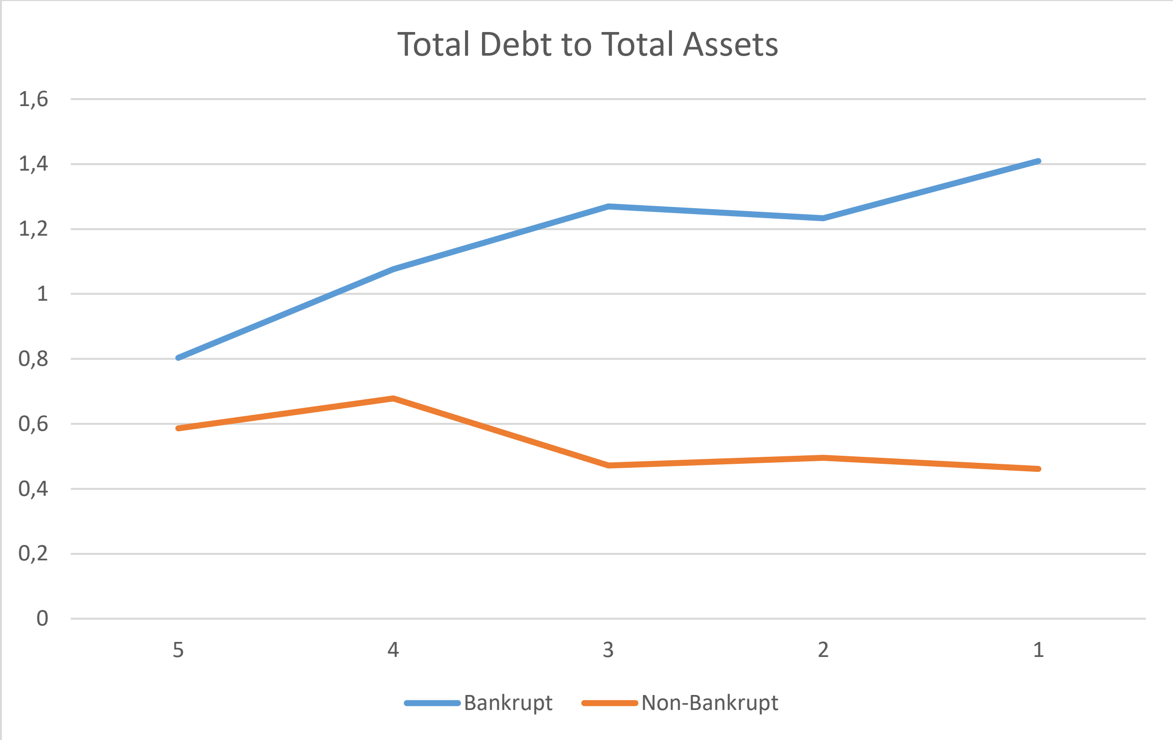

Figure 3. Means of total debt to total assets from five year prior bankruptcy
Source: Author's results based on collected data

Figure 3 demonstrates the difference between the averages of total debt to the ratios of total assets of bankrupt and non-bankrupt firms. By comparing two means, the amount of debt increases from year five to four, and then the difference between them starts to grow. It is important to highlight that for this ratio Beaver classified that the higher the value, the more financially embarrassed the company is. It can be seen from the graph that non-bankrupt firms have a decrease in the number of assets financed by debt from year four to three, and then the ratio maintains the same level. When the bankrupt firms have an upward tendency in the value of the ratio, the growth starts from year five until year three where it has a minimum decline, and from year two to one before bankruptcy continues to rise. To summarize, it can be said that financially "ill" companies tend to finance their assets predominantly by debt, and the more debt is taken, the riskier the position of the company is.

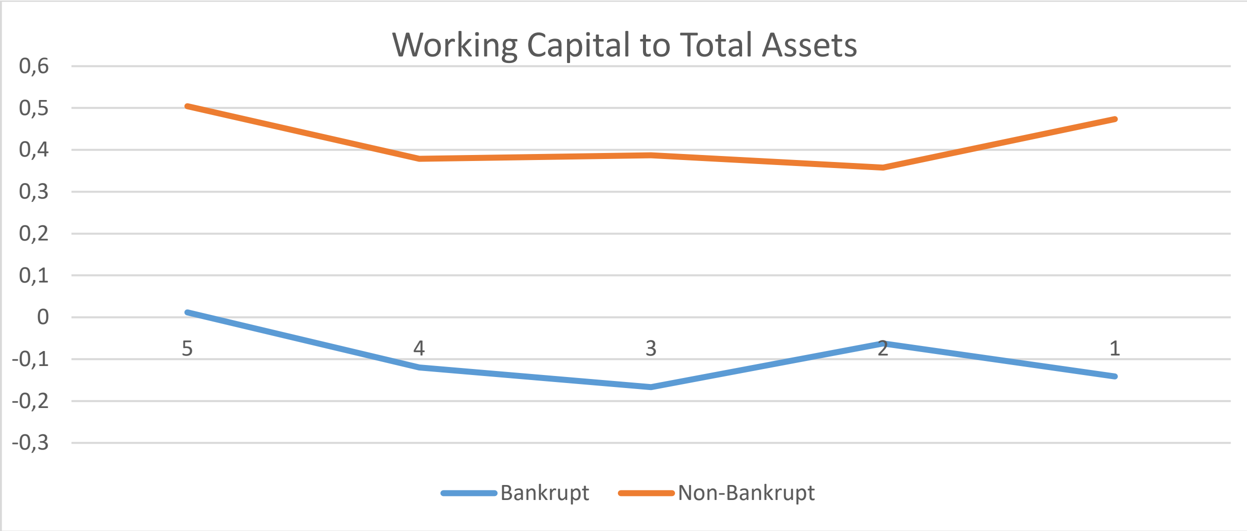

Figure 4. Means of working capital to total assets from five year prior bankruptcy
Source: Author's results based on collected data

Figure 4 represents the differences in averages for working capital to total assets ratio of bankrupt and non-bankrupt companies five years before bankruptcy. The liquidity ratio for non-bankrupt firms has a slight decline from year five to four, and then remain steady until the second year before bankruptcy. From the second to first year it climbs up, which is good for the financial condition of a firm. The bankrupt values are gradually declining from year five to three, followed by an increase up to year two, and declining from year two to one before bankruptcy. Additionally, when comparing with other ratios, the bottom line of the value occurs a year before the company stops to operate. In this case, it is seen that the lowest value appears in year three. Here, the working capital to total assets ratio is not a leading driver for bankruptcy, because industry specifications assumes the possibility of having low amount of current assets for some period.

So, in this case to predict the bankruptcy the overall tendency must be observed rather than a numerical value. From all the above, it can be concluded that bankrupt companies have a lower ability to pay back their short-term obligation by having fewer liquid assets.

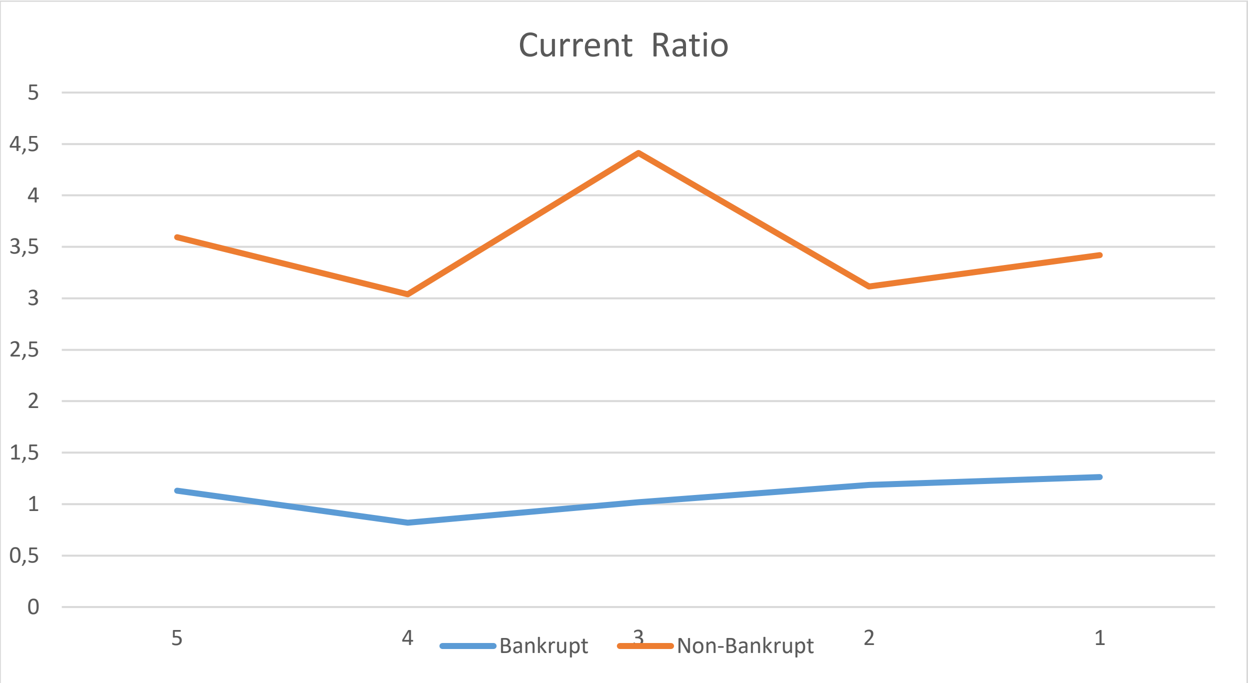

Figure 5. Means of current ratio from five year prior bankruptcy
Source: Author's results based on collected data

Figure 5 illustrates the differences in means for a current ratio of bankrupt and non-bankrupt companies five years before bankruptcy. The current ratio of the non-failed firms is quite high despite the rapid changes from the fifth to first year before bankruptcy. The value of bankrupt companies is considerably lower. The slight decrease in ratios might be seen from the fifth to fourth year. An interesting fact showing that the current ratio remains an upward tendency from year four until the bankruptcy. The failed companies are less liquid than the non-failed.

3.1.2. Application of the classification test

Beaver performed the classification test and identified two types of errors: Type I error and Type II error. The first type of error classified failed companies as non-failed and Type II error classified non-failed firms as failed, accordingly.

Table 3. The number of errors for each type.

Year	1		2		3		4		5		Total	
Error type	I	II	I	II	I	II	I	II	I	II	I	II
Cash Flow to Total Debt	1	3	2	4	3	3	1	3	0	4	7	17
Net Income to Total Assets	1	2	3	4	4	3	2	3	2	4	12	16
Total Debt to Total Assets	3	6	2	5	0	5	3	4	4	5	12	25
Working Capital to Total Assets	2	1	3	3	2	3	3	3	2	4	12	14
Current Ratio	2	2	3	5	1	3	0	5	1	5	7	20

Source: Author's results based on collected data

From the table above it is seen that the majority of errors were generated by Type II error, which means that the model is performing better in classifying the bankrupt firms correctly. However, classifying non-bankrupt companies wrong might have a negative effect on the decision-making process of active companies.

Also, by calculating the sum of errors of the separate financial ratios, it might be concluded that Cash Flow to Total Debt performs better than other ratios with the smallest amount of false classifications. The Total Debt to Total Assets has performed worse than all the others.

The prediction ability of the model is evaluated after the calculation of the amount of misclassifications for each year divided by the total number of companies. The higher the percentage, the lower the prediction capability of the ratio.

Table 4. The forecast power of the model

Ratios	Years before bankruptcy				
	1	2	3	4	5
Cash Flow to Total Debt	0.20	0.30	0.30	0.20	0.20
Net Income to Total Assets	0.15	0.35	0.35	0.25	0.30
Total Debt to Total Assets	0.45	0.35	0.25	0.35	0.45
Working Capital to Total Assets	0.15	0.30	0.25	0.30	0.30
Current Ratio	0.20	0.40	0.20	0.25	0.30

Source: Author's results based on collected data

Table 4 shows that Total Debt to Total Assets has the lowest predicting power. The possible reason for that might be the fact that the cut-off values for leverage ratio were derived from the Beaver's sample and the difference in the amount of debt between companies used in this study is significant. So, the critical value needs to be adjusted in order to improve the prediction capability of the ratio. The Working Capital to Total Assets showed the best performance. It has a 85% accuracy one year before the failure, and then the predicting capability of the ratio ranges around 70%. Net Income to Total Assets has a good predictive power as well, showing slightly higher percentage of error during the years.

The common observation for all the ratios presented, except the Working Capital to Total Assets, is that the predictive abilitity is high one year before the bankruptcy and then it loses its power. The univarite model shows lower predictive power than in the Beaver's study.

3.2. Application of the Edward I. Altman's model

In comparison to the Beaver's model, who concentrated on individual financial ratios, Edward I. Altman uses a five-factor linear formula to assess the financial condition of companies. Furthermore, he developed the model by applying distinct ratios from the Beaver's model.

It was noticed during this research that the original Altman formula is designed for the publicly held corporations. The absence of shares makes the calculations for a market capitalization of the company irrelevant. The best performance showed the modification for the original Z-score.

The revised Altman Z- score for private firms:

$$Z = 0,717X1 + 0,847X2 + 3,107X3 + 0,42X4 + 0,998X5 \quad (3)$$

where
X1 – Working Capital/ Total Assets

X2 – Retained Earning/ Total Assets

X3 – Earnings Before Tax and Interest/ Total Assets

X4 – Book Value of Equity/ Total Liabilities

X5 – Net Sales/ Total Assets

The discrimination zones are set in the way that if the company's Z–score is lower than 1.23, the company will be more likely to file for bankruptcy. The range between 1.23 and 2.9 is classified as a "grey zone", which indicates the uncertainty of the prediction. The scores above 2.9 represent a secure position of the firm.

Table 5. The classification ability of Altman's model for bankrupt firms

	1	2	3	4	5
Distress zone	7	7	7	7	7
"Grey zone"	2	1	1	3	2
Safe zone	1	2	2	0	1

Source: Author's results based on collected data

The unexpected result, which is presented in Table 5, is that the Z-score preserves the same level of accuracy for five years before bankruptcy takes place. Since Altman found that the more there is distance with the bankruptcy of the company the less prediction ability of the model has. This might be explained by the fact that the Ukrainian companies were very close to the liquidation exposure during the researched period, and they continued to operate, even though their financial condition was poor. There are very few incorrect predictions for failed companies; likewise for the number of uncertainties. It can be concluded that the Z-score performed well in classifying the companies which filed for bankruptcy.

Table 6. The classification ability of the Altman's model for non-bankrupt firms.

	1	2	3	4	5
Distress zone	1	3	2	3	2
"Grey zone"	6	3	4	2	3
Safe zone	3	4	4	5	5

Source: Author's results based on collected data

It can be observed from Table 6 that the model performed significantly worse for non-failed than failed companies. However, it is worth considering that the classification resulted in lots of uncertainties in the prediction. Also, it is seen that the majority of the "grey zone" classifications appeared in the one year before bankruptcy. The frequency of the "grey zone" might be explained in a way that as it was estimated in the financial ratios analysis for the Beaver's model, the Ukrainian agriculture companies experienced a recession in financials from year three to two and then maintained growth from year one. The above might be a possible reason for the companies to fall into the "zone of ignorance" in such quantities in the last year.

It is complicated to estimate the accuracy and prediction ability of this model because there are many uncertainties in the classification. However, the scores of non-bankrupt companies are relatively close to being placed into the safe zone, meaning that their financial condition is rather stable than distressed. To obtain more accurate information regarding the application of the Altman's Z-score for the Ukrainian agricultural firms, further research is needed. For instance, the calculation of critical values specifically for the data set of this research (see Appendix 1)

3.3. Application of Davydova and Belikov's model

The Davydova and Belikov's model is a linear formula based on the Altman's Z-score, but instead of using five variables, the model has only four. It is noteworthy that the second variable (Net Income/ Total Equity) does not have a coefficient unlike the other multivariate models. Additionally, the important distinction of the model is the usage of Net Profit to Cost of Goods Sold ratio, which demonstrates the cost-effectiveness of a company and is applicable only for manufacturing and merchandising firms. Moreover, the model provides four levels of risks.

The classification is set in the following way: the R-score that is lower than 0 indicates the maximum failure probability, scores between 0–0.18 implies high probability, 0.18–0.32 represents medium exposure, 0.32–0.42 demonstrates low, and more than 0.42 stands for minimum bankruptcy likelihood.

Table 7. The classification ability of the model for the bankrupt companies

Years before bankruptcy	1	2	3	4	5
Maximum	7	6	5	3	4
High	0	1	0	1	0
Medium	0	0	0	0	0
Low	0	0	0	0	0
Minimum	3	3	5	6	6

Source: Author's results based on collected data

The model performed well in correctly classifying seven out of ten companies one year before bankruptcy (Table 7). The level of accuracy might be considered the same during the second year because the failure possibility remained high and higher. However, there is a significant decrease in accuracy from the third to fifth year before bankruptcy where the level of classification ability barely reaches 50%.

Table 8. The classification ability of the model for the non-bankrupt companies

Years before bankruptcy	1	2	3	4	5
Maximum	0	0	0	0	0
High	0	0	0	0	0
Medium	0	0	0	0	0
Low	0	0	0	0	0
Minimum	10	10	10	10	10

Source: Author's results based on collected data

It can be seen that the Davydova and Belikov's model has outstanding classification capability for non-failed firms. The interesting fact is that the level of accuracy does not decline regardless of the bankruptcy year before. On the other hand, during this study it was found that the financial of companies vary markedly, and at some point, they could be close to the industry average and below it. That rises an important question: why the model does not show the accurate level of their financial condition? This could be an interesting topic to study in further research.

To calculate the model's prediction power, the number of misclassifications for each year were divided by the total amount of companies.

Table 9. Davydova and Belikov's model prediction ability five years before bankruptcy

Years before bankruptcy	1	2	3	4	5
Prediction accuracy (%)	85	85	75	70	70
Correct Classifications	17	17	15	14	14
Incorrect Classifications	3	3	5	6	6

Source: Author's results based on collected data

As shown in Table 9, the model has a good predictive ability. The peak of accuracy is achieved for the first two years before failure. From year two to five the precision of the model gradually starts to decrease up to 70%. It can be said that the model is a trustworthy method for bankruptcy prediction.

In comparison to the original research where the quartile data is used, the predictions in this study are made on the annual basis. The prediction ability in the Davydova and Belikov's study reached 81% of accuracy prior three quartiles before bankruptcy. It means that the model performed better within this dataset.

3.2.1. Variance analysis

To determine which financial factors lead Ukrainian agricultural companies to failure, the variance analysis is executed. Variance analysis shows which component of the score influences the total change the most among the others. In business, it is used to explore the shifts in a company's financial condition and discover the causes that different variables change over time.

Since the Davydova and Belikov's model showed the best predicting ability among tested, the components of it will be used in the variance analysis in order to discover the financial determinants of a company's failure. The R-scores from two years prior to bankruptcy will be examined because during these years the predictive capability is the highest and the changes in financials are easily identifiable. To perform this kind of analysis, the average R-score is computed for ten companies. Additionally, the ratios from the formula were separately computed for the firms, and the mean for a sample of each ratio was found. Also, it is worth to mention that the ratios retained coefficients, which were originally in the formula.

Table 10. The absolute changes and their contribution to total change

Years before bankruptcy	1	Absolute change	2	Total Contribution (%)
R	-2.24	-1.10	1.14	100
K1	-1.34	-0.73	-0.61	67
K2	-0.39	-0.51	0.12	47
K3	0.06	0.02	0.04	-1
K4	-0.56	0.13	-0.70	-12

Source: Author’s calculations based on collected data

It is seen from Table 10 that due to a decrease in K1 (Working Capital to Total Assets) by 0.73, which is 67% of the total change of the companies filed for bankruptcy. By analyzing the trend, it can be said that the main indicator of financial condition deterioration in this formula was the liquidity ratio. This means that before losing the status of an active firm, Ukrainian agricultural companies were losing the cash and inventory, which causes the inability to pay for their obligations. In agribusiness, it is crucial to maintain enough cash because the amount of current assets relies on the season and harvest.

Second, the most influential factor was K2 (Net Income to Total Equity). Due to a decrease in the second variable by 0.51, which is 47% of the total change the companies in this study failed in. The return on assets represents the ability to run the company. The substantial decline of the ratio might be explained by the loss in net income and a simultaneous decrease in equity through retained earnings. As it was previously noticed, some of the Ukrainian agricultural companies continued working even though having loss from period to period. Additionally, the ROE can be divided into three ratios to get a better understanding of the determinants of bankruptcy. However, it is complicated to achieve mathematically, so it could be examined in future research. The last two ratios are not taken into consideration because they have positive impact on the R-score and low contribution to the total change.

CONCLUSION

The aim of this research paper was to examine the possibility of applying the bankruptcy prediction models to the Ukrainian agricultural companies. Three models were tested in this study: William H. Beaver's univariate model, Edward I. Altman's Z-score and Davydova and Belikov's model for bankruptcy prediction. The paired sample consisted of ten failed and ten non-failed firms. The grouping of the companies was executed following the four main criteria: industry activity, asset size, operating revenue, and the number of employees. The data was gathered from financial statements of the selected companies with a necessity of having information prior five years before bankruptcy.

The first model tested showed that it can predict the failure. However, it is complicated to interpret the results and only four out of five ratios performed on the decent level. The important outcome of the model application was an illustrative difference between the values of ratios, meaning that the non-bankrupt companies are having their average values higher than bankrupt.

The second model applied resulted in many uncertainties in the predictions, which made it difficult to assess its accuracy, nevertheless it is certainly applicable to the Ukrainian agricultural firms. The evaluation of the predictive ability made no sense in that context because considering the companies that fell into "grey zone" as misclassifications would disrupt the result and make the prediction capability of the model to decline substantially. The adjustment of cut-off values is needed to provide a reliable answer about how accurate the model is.

The third model has shown the highest prediction accuracy for the Ukrainian agricultural firms. Even though it has an arguable classification ability as all non-bankrupt firms in the research's sample were assigned to the minimum risk category. Therefore, the risk assessment of the model could be a topic for future research. In addition, it must be noticed that the model has the strongest predictive power only two year before bankruptcy and then decreases to 70%.

Also, this study attempted to answer the question: what are the main determinants of leading the company to bankruptcy? The Beaver's profile analysis provides sufficient evidence of individual ratios to represent the major bankruptcy drivers by showing the connection between ratios and failure. Moreover, the variance analysis of R-score was performed to investigate the contribution to total change in value and underline the main influencers. It is important to notice that variance analysis focused on average trends, and to get more specific information each company must be studied separately.

In this study it was found that the Beaver's bankruptcy prediction model produces 65% of the total errors classified as Type II, which means that the model performed worse in correctly classifying non-bankrupt firms than bankrupt. The classification of the Altman's model produced the predominant amount of Type II errors as well. In contrary to the first model tested, the Davydova and Belikov's model showed a better result for non-bankrupt companies, meaning that Type I error surpassed the number of Type II errors in this case.

To further develop this study and increase the accuracy of results, it would be suggested to:

- expand the sample;
- derive the critical values from the researched population;
- test more recent models of bankruptcy prediction;
- apply deeper analysis of the components of ratios;
- perform a variance analysis for separate companies.

To conclude all the above, it could be stated that all three model are applicable for the Ukrainian agricultural firms.

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APPENDICES

Appendix 1. Z-scores of non-bankrupt firms

Years before bankruptcy	1	2	3	4	5
1	1.20	1.44	0.96	1.09	1.12
2	5.38	3.01	4.33	3.67	2.95
3	1.95	2.76	2.50	2.97	2.90
4	1.41	1.31	1.82	0.97	0.51
5	1.90	0.89	1.44	2.10	2.53
6	2.69	0.02	2.45	1.49	1.35
7	3.30	3.09	3.39	4.16	2.25
8	2.65	3.77	4.65	4.71	4.89
9	2.56	1.14	0.40	0.58	5.74
10	3.25	9.59	10.32	6.28	3.29

Source: author’s calculations

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