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Article

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Slovak Academy of Sciences, Bratislava

Reference: Vuković, Bojana/Milutinović, Sunčica et. al. (2020). Corporate bankruptcy prediction : evidence from wholesale companies in the Western European Countries. In: Ekonomický časopis 68 (5), S. 477 - 498.
<https://www.sav.sk/journals/uploads/0603142105%2020%20Vukovic%20a%20kol.%20+%20SR.pdf>.

This Version is available at:
<http://hdl.handle.net/11159/5303>

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Corporate Bankruptcy Prediction: Evidence from Wholesale Companies in the Western European Countries

Bojana VUKOVIĆ – Sunčica MILUTINOVIĆ – Nikola MILIĆEVIĆ –
Dejan JAKŠIĆ*

Abstract

The aim of this paper was to develop a model that can forecast the bankruptcy of the companies using logistic regression model. The sample consists of 23 bankrupts and 30 healthy companies selected from the initial sample of all large active companies (1740 companies). The companies operate in the trade industry, sector wholesale in Western Europe, in the time period from 2010 to 2018. The logit model was based on the choice between 23 financial indicators. The obtained results with high accuracy showed that the most important bankruptcy predictors were the following five indicators: return on equity, current assets/total assets, solvency, working capital turnover, stocks/current assets. The developed model provides an opportunity for all external stakeholders to easily identify companies that are facing the risk of bankruptcy. The possibility of the company's bankruptcy prediction, the assessment of risk and threatened circumstances to continue business is crucial information for making all future business decisions with the company.

Keyword: forecasting, bankruptcy, logistic regression, trade industry

JEL Classification: G33, M40

Introduction

One of the key principles of business operation is the principle of business continuity, i.e. going concern principle. The principle of business continuity implies that a company is established to operate with an unlimited duration of

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business. The two key problems that can endanger the going concern principle are financial and operational. Financial problems are reflected in the inability to settle mature obligations, while operational problems are reflected in the inability to achieve the operating success of the company or operate with significant and serious losses. Endangered financial and operational performance in the long run can lead the company into bankruptcy. Among them, there are other factors that may lead to bankruptcy such as high interest rates, business in a recession, heavy debts, government regulation, the nature of operations, inadequate management, and specifics of industry in which the company operates (Charitou, Neophytou and Charalambous, 2004). In this direction, it should be developed a methodological approach in order to make a difference between companies characterized by high probability of business failure and healthy companies.

Contemporary business conditions in which today's companies operate require companies to be able to fulfill their obligations in order not to be eliminated by the competition. The inability to settle liabilities may be due to a lack of funds or the weaknesses of the management in the use of these funds. The inability to settle the liabilities leads to the financial distress of the company. Financial distress in the long run leads to bankruptcy. According to Knox et al. (2009), bankruptcy happens in the case when the net worth of the company is negative or the liabilities value overcomes the assets value. From the external stakeholder's perspectives (customers, suppliers, creditors, investors, regulatory agencies, auditors, banks and the whole community), it is very important to anticipate the circumstances leading to the bankruptcy of the company, the risks of getting bankrupt, and the outcome after filing an application for bankruptcy. This is because the company's financial failure can lead to significant losses for all external stakeholders. The prediction of bankruptcy of a company is also significant from the aspect of the assessment of security of loan, measurement risk of collection of receivables, audit estimates of the threat of the principle of business continuity, and the valuation of the risk of non-payment of securities (Hensher and Jones, 2007).

The role of the model for the prediction of bankruptcy is reflected in providing warning signs to companies that bankruptcy may occur and to investors in assessing potential investment opportunities. The development of the prediction model of bankruptcy reduces the risk of doing business. Many well-known researchers have used financial indicators in order to predict the bankruptcy of businesses (Beaver, 1966). The most commonly used prediction tool for the bankruptcy of the company was discriminant analysis (DA). DA was used in research conducted by Altman (1968), Dambolena and Khoury (1980), Altman, Haldeman and Narayanan (1977), Altman, Giancarlo and Franco (1994), Lam

and Moy (2002), Gu (2002). On the other hand, Ohlson (1980), Lennox (1999), Laitinen and Laitinen (2000), Darayseh, Waples and Tsoukalas (2003), Kumar and Ravi (2007), Hermanto and Gunawidjaja (2010), Ahmadi et al. (2012) used logistic regression model. The research carried out by Ugurlu and Aksoy (2006) showed that the logistic regression model is more convenient and had greater predictive accuracy, especially in the first year before the bankruptcy process. The model of artificial neural networks, as a third prediction tool, was used in research conducted by Wilson and Sharda (1994), Nasir et al. (2000), Charalambous, Charitou and Kaourou (2000), Perez (2006), Brédart (2014), Salehi and Pour (2016). Inam et al. (2018) used all three techniques (DA, LR, ANN) to predict bankruptcy.

The analysis of the prediction of bankruptcy is significant from the aspect of the financial stability of the company. Analysis of the bankruptcy prediction can be of a quantitative and qualitative character. Quantitative methods of bankruptcy prediction are based on the use of financial indicators. The company's bankruptcy assessment usually starts with a group of financial indicators. The aim of the use of financial indicators of bankrupt or non-bankrupt companies was to determine whether these indicators can be used in the prediction of a bankruptcy of the companies. Financial indicators were used in order to compare the company's data at different times and with other companies. Inappropriate financial ratios of the company comparable to the industry average and the values in previous periods can be the first sign of financial difficulty. Comparing the values of financial indicators of failed and non-failed companies, we could draw conclusions about the financial health of the company.

In this paper, the logit regression model was used in order to predict corporate bankruptcy of all companies operate in the wholesale trade, except for motor vehicles and motorcycles. The sample was taken from the countries of Western Europe, because in the observed period, there was a larger number of companies that had bankrupted in relation to the countries of the Western Balkans. In the Western Balkans only nineteen companies were bankrupted (Bureau van Dijk, A Moody's Analytics Company, 2018). Along with, this topic has not been comprehensively researched in the Western Europe countries, especially having in mind the companies in the wholesale trade. Because of difficulties in maintaining liquidity and indebtedness within acceptable limits and high financial risk in the operations of these companies, this sector is very interesting for prediction. Problems from the aspect of liquidity can be extended deadlines for the collection of receivables, difficulties in collecting receivables and an increase in the volume of suspicious and controversial receivables. Indebtedness of companies in the wholesale trade is the result of high-interest rates and other unfavorable

borrowing costs. In addition, there is also a slowing inventory turnover of wholesale companies that can lead to inefficient management of working capital. In this direction, it is necessary to reassess the size of the order with the monitoring of market trends and the costs of keeping inventories. We analyzed the effects of twenty three financial indicators of bankrupt and non-bankrupt companies in twelve countries. We have chosen financial ratios in the model that had the greatest popularity and importance in previous research in the field of the company's bankruptcy. The company's data was picked out one year before the bankruptcy. According to size, both failed and selected non-failed companies in the sample are classified as large companies.

The structure of the paper is following. We are starting from Theoretical background. Further, we analyze the Data and the methodology and then the Results and discussion. In the last part of the paper are presented the Conclusion with limitations and guidelines for future research.

Theoretical Background

Generally, most companies that ran into bankruptcy had experienced financial distress, which usually has some symptoms indicated by financial ratios (Ahmadi et al., 2012). Financial ratios are often employed to provide a clue to many questions concerning the financial health of the company i.e. to indicate its financial strength (Sulaiman, Jili and Sanda, 2001). There is no theoretical approach in selecting variables for financial distress prediction models. According to Amendola et al. (2011), we have chosen variables to be included in the analysis based on a few varied criteria: they have a relevant financial meaning in a failure context; they have been commonly used in failure predictions literature; and finally, the information needed to calculate these ratios is available. Thus, like Ong, Yap and Khong (2011), we have selected the independent variables based on the significance and recognition of financial ratios in earlier research. In that direction, we have chosen financial indicators that provide information about profitability, liquidity, leverage and activity of the company. Profitability ratios show the earning capacity of the company, i.e the power of earning investment. Leverage ratios show the extent to which a company finances investments using other sources of financing. Liquidity ratios show whether the company has enough liquid assets to settle the maturing liabilities. Activity (efficiency) ratios show the efficiency of the turnover of the assets and the extent to which a company uses resources to make a revenue. Research conducted by Brédart (2014) showed that the key predictors of bankruptcy were the ratio of profitability, liquidity and solvency of the company.

A. Profitability Ratios

Profitability ratios help to provide a clue to the companies' ability to generate profit per each unit of sales, and higher profitability ratios are distinctive to non-bankrupt companies (Sulaiman, Jili and Sanda, 2001). Profitability ratios are expected to be negatively related to financial distress (Hussain et al., 2005). *Return on Assets* (ROA), as an indicator of profitability, represents the after-tax return relative to the total assets (Kim and Gu, 2006). It has a negative coefficient (Hussain et al., 2005). Profitability measured by ROA is the most critical issue of the failure of companies. The next, very similar indicator of profitability was *Return on Equity* (ROE). It also measures the earning capacity of the company, i.e the degree of return on the invested capital of the company. ROE has a negative coefficient. As this variable decreases, the probability of failure increases (Ugurlu and Aksoy, 2006). *EBITDATA* (EBITDA/Total Assets) is the most important predictor. The mean of this variable is significantly higher for the non-bankrupt companies and its coefficient has a negative sign. As EBITDATA decreases, the probability of facing financial distress increases (Ugurlu and Aksoy, 2006). *Gross profit margin* is the ratio of gross profit to total revenue. It represents the share of gross income in the total sales of companies. *Net profit margin* is the ratio of net income to total revenue. It is the most accurate indicator of the final effects, which indicates the percentage of income that is allocated in the form of profits which company can freely dispose of. The higher value of realized net profit margins is in favour of companies. Kim and Gu (2006) find that the negative net profit margin of the bankrupt group of companies implies that they were operating below breakeven prior to covering their financing costs. Due to the negative relationship between profitability and bankruptcy, the firm's bankruptcy probability decreases as the firm's profitability increases (Yazdanfar, 2011).

The interest cost ratio in the total revenue is a profitability indicator that analyzes a company's ability to cover interest expense on borrowing. This indicator is important for investors and creditors to gauge how risky a company is relative to its current or future borrowing volume. The share of the interest cost ratio in the total revenue serves to assess the company's ability to cover the costs arising from the use of borrowed capital. The ability of the company to settle interest obligations is an important indicator from a shareholder's perspective that serves to assess the financial position in the short term. A lower interest coverage ratio indicates greater company debt and potential for bankruptcy. A company that has a high value of this indicator has a better position in terms of meeting its annual interest expense. The higher value of this indicator shows that the company is more reliable in terms of debt settlement. Sulaiman, Jili and Sanda (2001) and Ahmadi et al. (2012) found that time interest earned ratio has a significant ability to predict failure.

B. Liquidity Ratios

Liquidity ratios give an indication of whether or not the company has sufficient cash to pay its obligations when they are due, and higher liquidity ratios are distinctive to non-bankrupt companies (Sulaiman, Jili and Sanda, 2001). *Current Liquidity* is used to check if the company is able to pay its debts and to continue doing his business. In other words, this ratio ascertains whether a company has the ability to pay back its short-term liabilities with its short-term assets over the next one year (Cultrera and Brédart, 2016). Brédart (2014) assumed that higher levels of liquidity will have a positive influence on the survival of businesses. Therefore, low liquidity generates higher risk of failure of companies. This ratio is negatively related to financial distress (Hussain et al., 2005). *Current Assets/Total Assets* ratio is the indicator of business activity, bearing in mind that the growth in share of current assets in total assets implies the growth of business activity. The high share of current assets is typical for manufacturing companies which are engaged in the production of products and provision of services and because of that companies often try to maintain a satisfactory current assets level in order to create a profit. The growth of current assets level in total assets of the company means that there was implemented a more conservative policy in the management of the company's current assets. A low level of current assets in total assets implies an aggressive policy of working capital management. *Stocks/Assets* and *Stocks/Current Assets* should show the extent to which stocks are in current and total assets of the company considering that stocks are very important to businesses in the wholesale trade sector. Adequate inventory management policy in the wholesale trade sector involves adjusting procurement time and quantity to avoid cash capture.

The next indicator that represented the long-term liquidity of a company is the *Solvency*. Solvency represents the unconditional ability of the company to settle the matured obligations or the ability of the company to settle its obligations at any time, even from liquidation or bankruptcy. Higher the solvency ratio, better is the ability of the company to meet key term obligations and lower will be the probability of default (Bandyopadhyay, 2006). *Quick ratio* measures the relative liquidity of the company. Companies that have enough liquid assets are in better liquidity position, since only liquid assets can generate cash immediately and are more capable in meeting their short-term obligations to creditors (Hussain et al., 2005). The funding rule 1:1 or *Acid test 1:1* assumes that the short-term financial equilibrium exists if the short-term assets are equal to short-term sources of funds. Acid test ratio indicates the company's ability to meet currently maturing obligations (Hussain et al., 2005). Thus, these two ratios are negatively related to financial distress. *Current Liabilities to Total Assets* ratio

represents the financial policy of working capital management. More aggressive management of current liabilities entails the use of a larger volume of current liabilities and therefore leads to rise in a liquidity risk. Current Liabilities to Total Assets is the most significant explanatory variable in determining the odds ratio or outcomes of financial distress (Hussain et al., 2005). A company is more likely to suffer financial distress if it had higher (positive) current liabilities to total assets ratio (Hussain et al., 2005). *Working Capital Ratio/Total Assets* is a measure of the net liquid assets of the company relative to the total capitalization. Working capital is the difference between current assets and current liabilities (Bandyopadhyay, 2006).

C. Leverage Ratios

Leverage ratios provide information concerning the extent to which the company finances its investments using funds from sources other than the company's owners, and lower leverage ratios are distinctive to non-bankrupt companies (Sulaiman, Jili and Sanda, 2001). Failing companies are expected to have higher financial leverage than healthy ones, since inability to meet high fixed debt service obligations is frequently a precipitating factor in a company's demise (Hussain et al., 2005). Leverage ratios are positively related to the probability of bankruptcy (Charitou, Neophytou and Charalambous, 2004). Charitou, Neophytou and Charalambous (2004) find that financial leverage variables possess a strong discriminatory power, consistent with the argument that one of the major reasons for company failure is their inability to meet their heavy debt burdens.

Debt ratio was the first indicator that measures a company's indebtedness. Kim and Gu (2006) kept only two variables for predicting bankruptcy in the logit model – total debts to total assets was one of them. A higher total debt to total assets ratio indicates that a company relies heavily on debt capital to finance its assets. Thus, the higher is the probability of a company falling into financial distress (Ong, Yap and Khong, 2011). The negative sign of the total debts to total assets suggests a higher probability of bankruptcy (Kim and Gu, 2006; Hussain et al., 2005). Ahmadi et al. (2012) find that an increase in net profit to total assets ratio, the ratio of retained earnings to total assets and debt ratio concurrent decreases the probability of bankruptcy. Sulaiman, Jili and Sanda (2001) find that the debt ratio has significant discriminating power in the logit model. Debt ratio was the most significant, among three, predictor variables that Charitou, Neophytou and Charalambous (2004) have included in their final multivariate model. Consistent with mentioned, the debt ratio is positively associated with the probability of bankruptcy.

Total Equity/Total Assets, as the next indicator of solvency, represents the ability of a company to repay its debts. This variable determines the repayment capacity of a company (Brédart, 2014). This ratio measures the proportion of the total outstanding debt payable in the current year or in the next accounting period against the total assets of the company. Laitinen and Laitinen (2000) find that the most important variable in the bankruptcy prediction in the third year before bankruptcy is the equity to total assets ratio, but not in a linear form. When this ratio increases, the company's financing is generally less dependent on borrowed capital (Cultrera and Brédart, 2016). *Debts/Equity* indicator represents the possibility of borrowing that measures the risk of investing in a company. This indicator is called the financial leverage coefficient as a synonym for indebtedness. The company should try to make it as lower as possible. It shows how many monetary units of debt are deposited in one monetary unit of capital. On the other hand, through the indicator *Equity/Debts* it is examined to what extent it is possible to reduce the equity of the company, but so that the total debts are not greater than the equity and that the companies become indebtedness and insolvent. Due to the positive relationship between leverage and bankruptcy, the firm's bankruptcy probability decreases as the firm's leverage decreases (Yazdanfar, 2011).

D. Activity Ratios

Efficiency (activity) ratios indicate how effectively the company is using its resources to generate sales revenue (Hussain et al., 2005). Higher efficiency ratios (except fixed asset turnover) are distinctive to non-bankrupt companies (Sulaiman, Jili and Sanda, 2001). *Fixed Asset turnover* measures the efficiency of using fixed assets to generate sales (Kim and Gu, 2006). *Total Asset turnover* is the best predictor of bankruptcy in the logistic regression model (Inam et al., 2018). It indicates the efficiency of using assets to generate revenue (Kim and Gu, 2006).

Sulaiman, Jili and Sanda (2001) find that total asset turnover has significant discriminating power in the logit model, and that non-bankrupt companies generate higher sales per total assets in comparison with bankrupt companies. Therefore, this ratio is negatively related to financial distress (Hussain et al., 2005; Ong, Yap and Khong, 2011; Bandyopadhyay, 2006). *Current Asset turnover* represents the company's ability to contribute to the creation of a company's sale through the use of different current assets such as inventory, cash, and accounts receivables. The non-failed firms have higher current asset turnover than failed firms but the difference is not significant (Ugurlu and Aksoy, 2006). The higher asset turnover ratio means the lower probability of a company going into financial distress (Ong, Yap and Khong, 2011). *Working Capital turnover* (Sales/Working

Capital) is negatively related to financial distress (Nam and Jinn, 2000), although Ugurlu and Aksoy (2006) found that the coefficient of the ratio is positive. The increase in net working capital turnover may result from insufficient net working capital levels and documents a positive relationship with the likelihood of company's failure.

Data and Methodology

In this paper, we analyzed financial indicators in the context of the company's bankruptcy prediction. The observed twelve countries of Western Europe were: Austria, Belgium, France, Germany, Ireland, Denmark, Luxembourg, Netherlands, Italy, United Kingdom, Portugal, and Spain. We focused on the wholesale trade sector. Hereby, we started from the initial sample of 1740 companies or all active large companies that operate in the wholesale trade in the time period from 2010 to 2018 in selected Western European countries. Our analysis included 23 companies that went bankrupt. So, for the purpose of this research, we have selected 30 leading companies, according to the value of the net income during the observed period. The source of data was the values of positions of the balance sheet and the company's income statement in the TP Catalyst database with all information on public and private companies (Bureau van Dijk, A Moody's Analytics Company, 2018).

In this research, the binary logistic regression was used in order to forecast the relationship between independent variables and the binary dependent variable. Bankruptcy was considered as a dependent variable, with value 1 if the company faces bankruptcy and value 0 in the case of a healthy company. Following the similar studies (Laitinen and Laitinen, 2000; Nam and Jinn, 2000; Charitou, Neophytou and Charalambous, 2004; Hussain et al., 2005; Pompe and Bilderbeek, 2005; Ugurlu and Aksoy, 2006; Hensher and Jones, 2007; Yazdanfar, 2011; Amendola et al., 2011; Ahmadi et al., 2012; Brédart, 2014; Aruldoss, Travis and Venkatesan, 2015; Salehi and Pour, 2016; Inam et al., 2018), for independent variables we have chosen the key financial indicators of profitability, liquidity, leverage and activity. All financial indicators used in this research were presented in Table 1.

After testing the multicollinearity and eliminating "problematic" variables, we applied the stepwise method. In this way, the obtained logistic regression model consisted of independent variables with statistically significant coefficients. Their relations with bankruptcy, as a binary dependent variable, would be presented through the equation, proposed by Kim and Gu (2006):

$$\text{Log} [P(x)/(1 - P(x))] = \beta_0 + \beta_1 X_{i1} + \dots + \beta_n X_{in}$$

where

- $P(x_i)$ – determines the probability of bankruptcy in the i th company,
- $1 - P(x_i)$ – determines the probability of non-bankruptcy in the i th company,
- β_0 – determines an intercept,
- $X_1 - X_n$ – determines the financial ratios,
- $\beta_1 - \beta_n$ – determines the coefficients of the n th financial ratios,
- $X_1 - X_{in}$ – determines n th financial ratio of the i th company.

In addition, for deeper analysis of predicted probability, we implemented the concept of marginal effects for each independent variable in final model. All data were processed by the use of statistical program Stata 13.

Table 1

Indicators and Method of Calculation

| Indicators | Method of calculation | Expected relationship with financial distress |
|---|---|---|
| Profitability Ratios | | |
| Return on Asset (ROA)- X_1 | Net Income/Total Assets | Negative (–) |
| Return on Equity (ROE)- X_2 | Net Income/Equity | Negative (–) |
| EBITDATA- X_3 | EBITDA/Total Assets | Negative (–) |
| Gross profit margin- X_4 | EBITDA/Total Revenue | Negative (–) |
| Net profit margin- X_5 | Net Income/Total Revenue | Negative (–) |
| Liquidity Ratios | | |
| Current liquidity- X_6 | Current Assets/Current Liabilities | Negative (–) |
| CATA- X_7 | Current Assets/Total Assets | Negative (–) |
| Solvency- X_8 | Total Assets/Total Liabilities | Negative (–) |
| Quick ratio- X_9 | Liquid Assets/Current Liabilities | Negative (–) |
| Acid test- X_{10} | Short-term Assets/Short-term sources of Funds | Negative (–) |
| CLTA- X_{11} | Current Liabilities/Total Assets | Positive (+) |
| WCRTA- X_{12} | Working Capital Ratio/Total Assets | Negative (–) |
| Leverage Ratios | | |
| TLTA- X_{13} | Total Liabilities/Total Assets | Positive (+) |
| TETA- X_{14} | Total Equity/Total Assets | Positive (+) |
| LE- X_{15} | Liabilities/Equity | Positive (+) |
| EL- X_{16} | Equity/Liabilities | Negative (–) |
| Activity Ratios | | |
| Fixed Asset turnover- X_{17} | Sales/Net fixed Assets | Negative (–) |
| Total Asset turnover- X_{18} | Sales/Total Assets | Negative (–) |
| Current Asset turnover- X_{19} | Sales/Current Assets | Negative (–) |
| Working capital turnover- X_{20} | Sales/Working capital | Negative (–) |
| ICR/TR- X_{21} | Interest Cost Ratio/Total Revenue | Negative (–) |
| The share of Stocks in Total Assets- X_{22} | Stocks/Total Assets | Negative (–) |
| The share of Stocks in Current Assets- X_{23} | Stocks/Current Assets | Negative (–) |

Source: Our own construction.

Results and Discussion

As mentioned earlier, we have started our research with twenty three different independent variables. However, bearing in mind the similarities between them, we needed to resolve the problem of multicollinearity. For this purpose, the correlation

analysis was used, whereby some variables with correlation coefficients larger than 0.5, were eliminated. As a result, from starting twenty three variables, twelve variables remained. Their VIF (variance impact factor) values, presented in Table 2, were lower than 5, and thus, there was no multicollinearity among independent variables.

Table 2
Variance Impact Factors of Variables (VIF)

| Variable | VIF | 1/VIF |
|-----------------|------|----------|
| X ₈ | 3.13 | 0.319174 |
| X ₆ | 3.03 | 0.329977 |
| X ₁₅ | 2.33 | 0.430077 |
| X ₂₀ | 1.91 | 0.522732 |
| X ₂ | 1.88 | 0.531441 |
| X ₁₃ | 1.65 | 0.606929 |
| X ₇ | 1.58 | 0.631373 |
| X ₁₇ | 1.32 | 0.754994 |
| X ₂₃ | 1.26 | 0.792137 |
| X ₁ | 1.18 | 0.845154 |
| X ₄ | 1.17 | 0.857977 |
| X ₂₁ | 1.04 | 0.964240 |

Source: Our own construction.

Afterwards, the stepwise method of logistic regression was applied, including selected twelve variables. The result of a forward elimination technique was a model that consisted of five independent variables, where each of them had a statistically significant coefficient with p lower than 0.1. In addition, the whole model was statistically significant with p lower than 0.01. The overall goodness of fit was also confirmed by the results of Hosmer-Lemeshow test, which p value was larger than 0.05.

Moreover, the results of link test (where p value for $\hat{\alpha}$ was lower than 0.05, while for $\hat{\alpha}^2$, it was higher than 0.05), suggested good model adequacy (Bio-stats, 2017).

Table 3
Stepwise Selection Procedure – Forward Elimination Technique

| Bankruptcy | Coef. | Std. Err. | z | P> z | [95% Conf.Interval] | |
|---|------------|-----------|-------|-------|---------------------|------------|
| X ₈ | -0.0676184 | 0.0247831 | -2.73 | 0.006 | -0.1161924 | -0.0190444 |
| X ₂ | -9.369579 | 3.810622 | -2.46 | 0.014 | -16.83826 | -1.900897 |
| X ₂₃ | -7.110392 | 3.011025 | -2.36 | 0.018 | -13.01189 | -1.208892 |
| X ₂₀ | -0.0598896 | 0.0254766 | -2.35 | 0.019 | -0.1098227 | -0.0099564 |
| X ₇ | 3.998006 | 2.196662 | 1.82 | 0.069 | -0.3073722 | 8.303383 |
| _cons | 2.195857 | 1.964763 | 1.12 | 0.264 | -1.655008 | 6.046722 |
| Log likelihood = -17.018239, LR chi2(5) = 38.51, Prob > chi2 = 0.0000, Pseudo R2 = 0.5308 | | | | | | |

Source: Our own construction.

As presented in Table 3, the final model included four variables with negative (Solvency, ROE, Stocks/Current Assets and Working Capital Turnover) and one variable (Current Assets/Total Assets) with positive effects on bankruptcy. It can be presented through the following equation:

$$\text{Log}[P(x)/(1 - P(x))] = 2.195857 - 9.369579 * X_2 + 3.998006 * X_7 - 0.0676184 * X_8 - 0.0598896 * X_{20} - 7.110392 * X_{23}$$

According to the presented results in Table 4, the average rate of profitability (X_2) was 15% which implied that the selected companies operated with a positive result and realized the return on equity. It was not observed a high level of dispersion of ROE, from -2.38007 to 0.6035016 . The average value of the next ratio, current assets/total assets (X_7), showed the value of 0.7643396 , with small value dispersion from 0.19 to 1 . The third ratio was solvency with average value of 30.77887 which shows that the assets of selected wholesale companies were more than sufficient to cover the debts in the observed period. However, this indicator showed a very high dispersion of value, from -43.232 to 80.978 . The negative average value of Working Capital Turnover ratio -8.294078 indicated that companies were not effectively using its working capital to support a certain level of sales. This indicator had a high level of dispersion, from -289.2 to 62.88443 . The last ratio, the ratio of Stocks to Current Assets, had the average value of 0.254717 which shows that stocks account for 25% of total current assets of companies in the wholesale sector, with a high dispersion of value, from 0 to 0.65 .

Table 4
Descriptive Statistics

| Variable | Mean | Std. Dev. | Min | Max |
|----------|-------------|-----------|-------------|-----------|
| X_2 | 0.1511743 | 0.3998884 | -2.380073 | 0.6035016 |
| X_7 | 0.7643396 | 0.2501577 | 0.19 | 1 |
| X_8 | 30.77887 | 27.17844 | -43.232 | 80.978 |
| X_{20} | -8.294078 | 55.38565 | -289.2 | 62.88443 |
| X_{23} | 0.254717 | 0.1961221 | 0 | 0.65 |

Source: Our own construction.

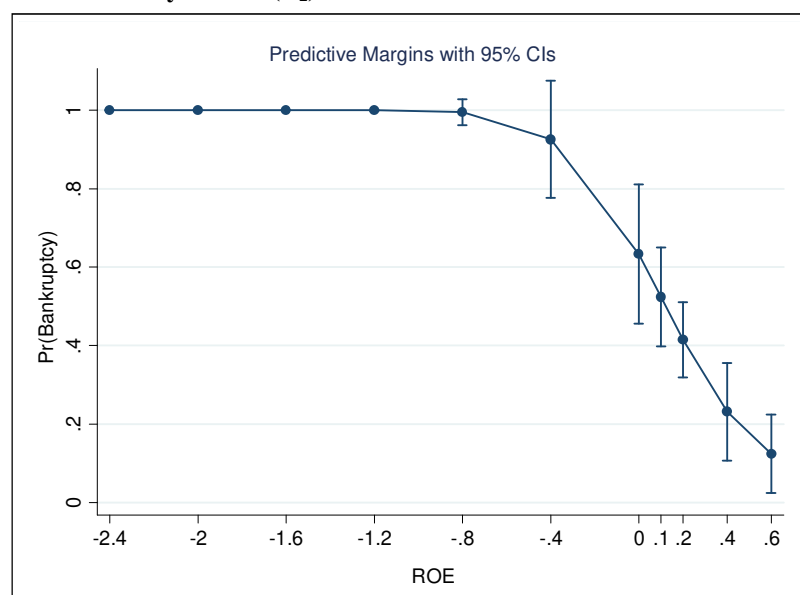
In further analysis, for evaluating the average predicted probability of bankruptcy in relation to independent variables, we applied the concept of marginal effects. As all regressors were continuous, predicted probabilities of bankruptcy were calculated for ranges of their different levels (Tables were presented in Annexes).

In the case of ROE (X_2), the average probability of bankruptcy decreases with the increase of this variable (Figure 1). Thus, for its positive values, the average probability of bankruptcy falls below 64. When ROE has the highest value of

0.6, this probability is around 12. The higher value of ROE means a stronger yield position of wholesale companies or the ability of the company's engaged equity to result in yield. This variable confirmed as one of the most important bankruptcy predictors in the research conducted by Ugurlu and Aksoy (2006); Inam et al. (2018); Amendola et al. (2011); Fedorova, Gilenko and Dovzhenko (2013); Sandin and Porporato (2007); and Smith and Liou (2007).

Figure 1

Predicted Probability – ROE (X_2)



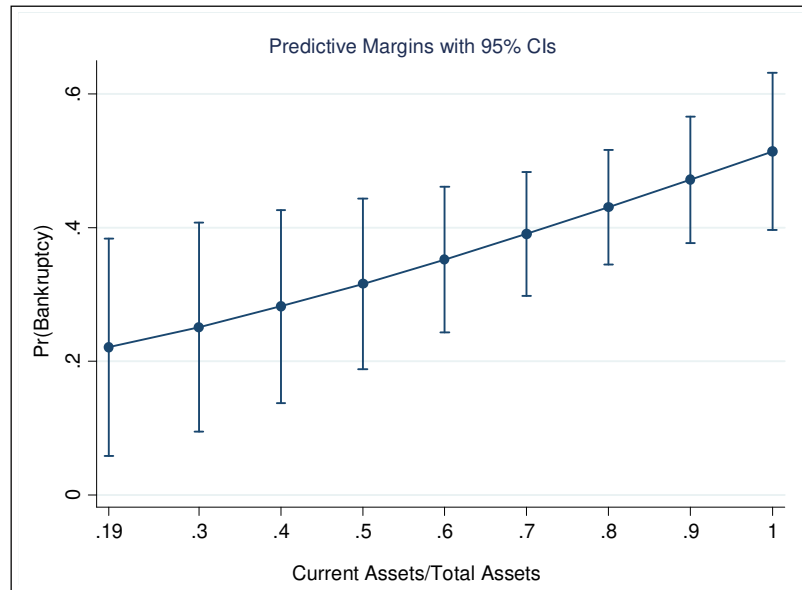
Source: Our own construction in statistical program Stata 13.

The average probability of bankruptcy is positively related to Current Assets/ Total Assets indicator (X_7). For its values higher than 0.19, the average probability of bankruptcy exceeds 22, where at value higher than 0.6, it is over 35 (Figure 3). So, as the share of current assets in total assets increases, the possibility for company's bankruptcy will also increase. This indicator shows the extent to which current assets are involved in working capital formation and affect liquidity growth. The structure of current assets of observed wholesale companies showed that stocks and cash were not widely represented in current assets. So, the high share of current assets in total assets that has a positive effect on the likelihood of bankruptcy can be the result of large volume of risky and uncollectible receivables. Since uncollectible receivables are most often the subject of litigation and write-offs, they greatly burden the operating costs of companies in the wholesale sector. Selling to insolvent buyers leads to write-offs, a matter costing the company

and negatively affecting its solvency. Endangered solvency in the long run leads to bankruptcy. The research conducted by Inam et al. (2018) confirmed that this indicator has an important role in predicting failure of the company.

Figure 2

Predicted Probability – Current Assets/Total Assets (X_7)

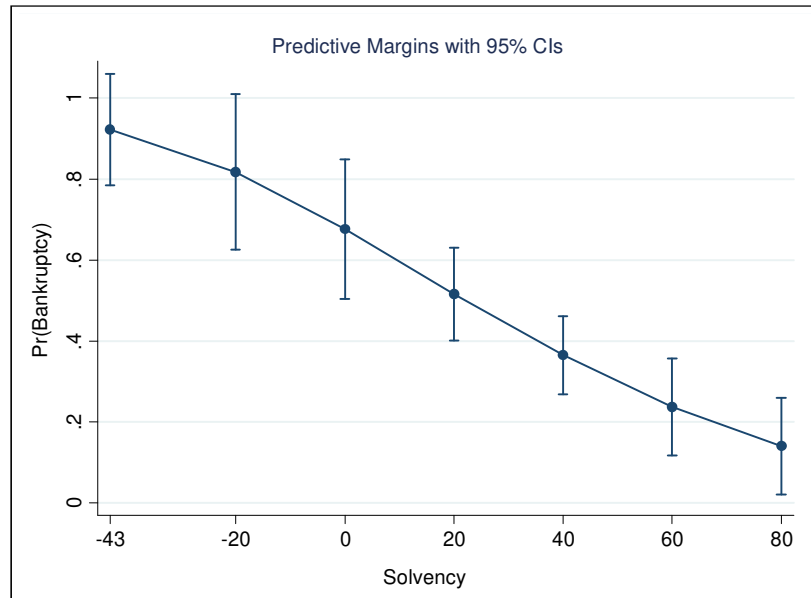


Source: Our own construction in statistical program Stata 13.

When it comes to solvency ratio (X_8), its increase positively reflects on the decrease of the average probability of bankruptcy (Figure 3). For its positive values, the average probability of bankruptcy falls below 68. For its values higher than 40, the average probability is under 37. When solvency has the highest value of 80, the average probability is around 14. Inam et al. (2018); Partington et al. (2001); Ong, Yap and Khong (2011); Bandyopadhyay (2006); and Sandin and Porporato (2007) confirmed that the solvency is among most significant indicators of the bankruptcy predictors.

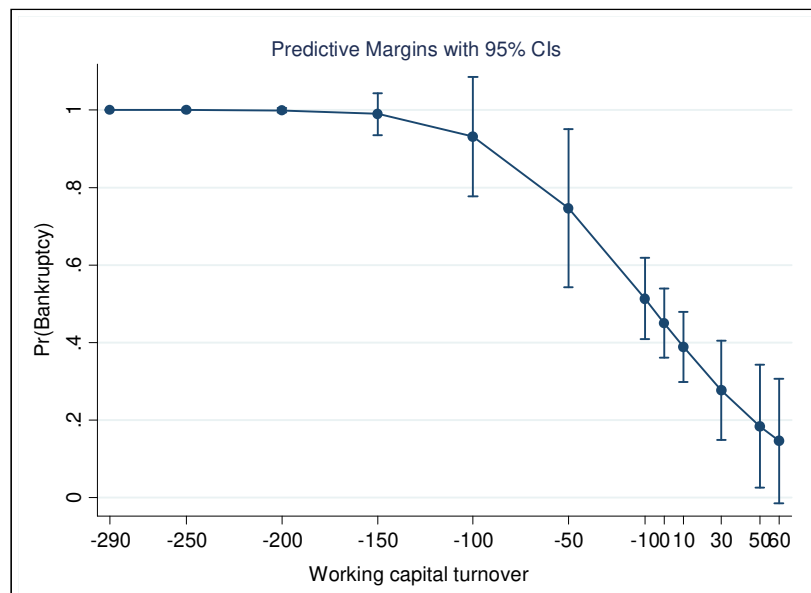
Negative relation with the average probability of bankruptcy is recorded in the case of the working capital turnover (X_{20}) variable, as well (Figure 4). Hereby, for positive values of this indicator, the average probability of bankruptcy is about 45. Only when Working capital turnover variable is 30, the average probability is lower than 29. When this variable has the highest value of 60, the average probability is under 16. The research conducted by Ugurlu and Aksoy (2006) and Nam and Jinn (2000) confirmed that working capital turnover variable has an important role in predicting failure of the company.

Figure 3
Predicted Probability – Solvency (X_8)



Source: Our own construction in statistical program Stata 13.

Figure 4
Predicted Probability – Working Capital Turnover (X_{20})

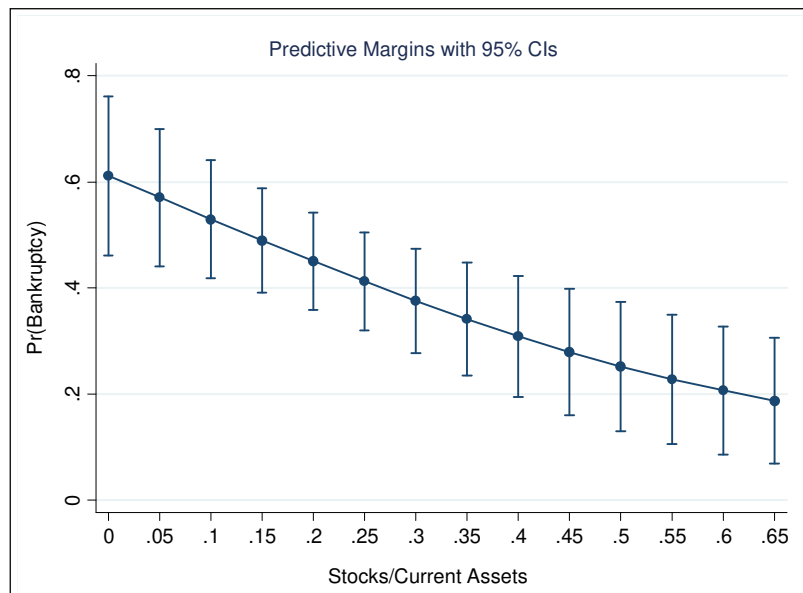


Source: Our own construction in statistical program Stata 13.

When it comes to Stocks/Current Assets (X_{23}), its increase is related to the decrease of the average probability of bankruptcy (Figure 5). When this indicator equals 0, the average probability of bankruptcy is about 61. On the other hand, when the value of Stocks/Current Assets is higher than 0.40, the average probability of bankruptcy is below 31. Stocks are necessary for the smooth running of business processes and the security of business in wholesale companies. The significant value of stocks is characteristic of the wholesale sector, which has the highest turnover of stocks and where adequate inventory management influences the efficient management of working capital.

Figure 5

Predicted Probability – Stocks/Current Assets (X_{23})



Source: Our own construction in statistical program Stata 13.

Conclusion

This paper attempted to develop a model that can predict the bankruptcy of the wholesale trade companies in the Western European countries. For that purpose we analysed twenty three key financial indicators of profitability, liquidity, leverage and activity using logistic regression model. The company's financial data were extracted from financial statements of the TP Catalyst database in the time period from 2010 to 2018 and processed by the use of statistical program Stata 13. From the initial sample of 1740 companies we have selected 30 leading

companies according to the value of the net income and 23 companies that went bankrupt during the observed period. The findings of this research indicate that five ratios are the major predictors of bankruptcy. The evidence with high accuracy reveals that Solvency, Return on Equity, Stocks/Current Assets, Working Capital Turnover have a negative effect on bankruptcy. Current Assets/Total Assets indicator has a positive relationship with the financial distress in wholesale companies.

Applying the concept of marginal effects for each independent variable in the final model in order to evaluate the average predicted probability of bankruptcy in relation to independent variables, we found in the case of ROE (X_2) that the average probability of bankruptcy decreases with the increase of this variable. This is understandable bearing in mind that higher earning capacity of the wholesale companies or the greater ability of the invested equity of wholesale companies to result in yield lead to less probability of bankruptcy. The average probability of bankruptcy is positively related to the Current Assets/Total Assets indicator (X_7). Bearing in mind that the largest share in the current assets of observed wholesale companies has uncollectible receivables, the increase in the volume of uncollectible receivables leads to the growth of current assets of the company. The policy of uncollectible receivables is not sustainable in the long run, which can endanger liquidity and lead to bankruptcy.

The increase in solvency (X_4) negatively reflects on the increase of the average probability of bankruptcy. High solvency is often the result of high business sustainability and lower risk of borrowing, meaning the attractiveness of the wholesale companies from the perspective of new investors and lenders. Wholesale companies are unlikely to make a loss of over 50% of their assets, so solvency is characterized as good. The average probability of bankruptcy decreases with the increase of the Working Capital Turnover (X_{20}) variable. Adequate policy for managing the working capital of companies in the wholesale sector is significant from the perspective of maximizing profitability and protecting the liquidity. On the other hand, a low value of working capital turnover ratio indicates that wholesale companies were not effectively using its working capital to support a certain level of sales. In circumstances when current liabilities are greater than current assets, companies have a problem with working capital turnover which calls into question the liquidity. Threatened liquidity in the long run increases the likelihood that the companies will go bankrupt. The average probability of bankruptcy decreases with the increase of Stocks/Current Assets variable (X_{23}). Given that stocks are one of the key determinants of wholesale business security and that this sector has the highest stock turnover, it is understandable that there is a negative relationship between the volume of stocks and the

likelihood of bankruptcy. Accelerating stock turnover in this sector is accomplished by determining the optimum amount of stocks to be ordered, by monitoring market movements and by controlling the cost of holding stocks.

The model can point to potential financial troubles over time and can help companies to avoid financial difficulties that lead to bankruptcy. In addition, this model provides information support for external stakeholders to recognize companies with disadvantaged circumstances to continue their business.

There are limitations to this research. Firstly, our study is geographically limited in the area of Western Europe. It is also limited to wholesale sector in the trade industry. Thirdly, we considered only financial data from financial statements. It would be advisable to include also organizational, operational and managerial factors, so that the behaviour of the dependent variable could be better described. Further research may also consider other factors that were not included in our model, and to conduct a comparative study that includes wholesale companies in different groups of countries in order to determine whether determinants of financial distress are the same in different business environments in other regions. Clearly, more research is needed on the bankruptcy of wholesale companies in the Western European countries in order to supplement the initial findings in this study. In addition, this sector is very interesting for prediction due to the problems of maintaining satisfactory liquidity and achieving a reasonable level of borrowing.

References

- AHMADI, A. P. S. – SOLEIMANI, B. – VAGHFI, S. H. – SALIMI, M. B. (2012): Corporate Bankruptcy Prediction Using a Logit Model: Evidence from Listed Companies of Iran. *World Applied Sciences Journal*, 17, No. 9, pp. 1143 – 1148.
- ALTMAN, E. I. (1968): Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance*, 23, No. 4, pp. 589 – 609.
- ALTMAN, E. I. – HALDEMAN, G. R. – NARAYANAN, P. (1977): ZETA TM analysis-A New Model to Identify Bankruptcy Risk of Corporations. *Journal of Banking and Finance*, 1, No. 1, pp. 29 – 54.
- ALTMAN, E. I. – GIANCARLO, M. – FRANCO, V. (1994): Corporate Distress Diagnosis: Comparisons Using Linear Discriminant Analysis and Neural Networks (the Italian Experience). *Journal of Banking and Finance*, 18, No. 3, pp. 505 – 529.
- AMENDOLA, A. – BISOGNO, M. – RESTAINO, M. – SENSINI, L. (2011): Forecasting Corporate Bankruptcy: Empirical Evidence on Italian Data. *EuroMed Journal of Business* Volume, 6, No. 3, pp. 294 – 312.
- ARULDOSS, M. – TRAVIS, M. L. – VENKATESAN, V. P. (2015): A Reference Model for Business Intelligence to Predict Bankruptcy. *Journal of Enterprise Information Management*, 28, No. 2, pp. 186 – 217.
- BANDYOPADHYAY, A. (2006): Predicting Probability of Default of Indian Corporate Bonds: Logistic and Z-score Model Approaches. *The Journal of Risk Finance*, 7, No. 3, pp. 255 – 272.

- BEAVER, W. H. (1966): Financial Ratios as Predictors of Failure. *Journal of Accounting Research*, 4, Empirical Research in Accounting: Selected Studies, pp. 71 – 111.
- BIOSTATS (2017): Stata for Logistic Regression. Available at: <https://people.umass.edu/biep640w/pdf/Stata%20for%20Logistic%20Regression.pdf>. [Accessed in February 2020.]
- BRÉDART, X. (2014): Bankruptcy Prediction Model: The Case of the United States. *International Journal of Economics and Finance*, 6, No. 3, pp. 1 – 7.
- BUREAU VAN DIJK, MOODY'S ANALYTICS COMPANY (2018): TP-Catalyst. Available at: <https://www.bvdinfo.com/en-apac/our-products/bvd-s-catalysts-solutions-by-task/catalysts-solutions-by-task/tp-catalyst>. [Accessed in February 2019.]
- CHARALAMBOUS, C. – CHARITOU, A. – KAOUROU, F. (2000): Comparative Analysis of Artificial Neural Network Models: Application in Bankruptcy Prediction. *Annals of Operations Research*, 99, No. 1, pp. 403 – 425.
- CHARITOU, A. – NEOPHYTOU, E. – CHARALAMBOUS, C. (2004): Predicting Corporate Failure: Empirical Evidence for the UK. *European Accounting Review*, 13, No. 3, pp. 465 – 497.
- CULTRERA, L. – BRÉDART, X. 2016. Bankruptcy Prediction: The Case of Belgian SMEs. *Review of Accounting and Finance*, 15, No. 1, pp. 101 – 119.
- DAMBOLENA, I. G. – KHOURY, S. J. (1980): Ratio Stability and Corporate Failure. *The Journal of Finance*, 35, No. 4, pp. 1017 – 1026.
- DARAYSEH, M. – WAPLES, E. – TSOUKALAS, D. (2003): Corporate Failure for Manufacturing Industries Using Firms Specifics and Economic Environment with Logit Analysis. *Managerial Finance*, 29, No. 8, pp. 23 – 36.
- FEDOROVA, E. – GILENKO, E. – DOVZHENKO, S. (2013): Bankruptcy Prediction for Russian Companies: Application of Combined Classifiers. *Expert Systems with Applications*, 40, pp. 7285 – 7293.
- GU, Z. (2002): Analyzing Bankruptcy in the Restaurant Industry: A Multiple Discriminant Model. *International Journal of Hospitality Management*, 21, No. 1, pp. 25 – 42.
- HENSHER, D. A. – JONES, S. (2007): Forecasting Corporate Bankruptcy: Optimizing the Performance of the Mixed Logit Model. *Abacus*, 43, No. 3, pp. 241 – 364.
- HERMANTO, B. – GUNAWIDJAJA, S. (2010): Default Prediction Model for SME's: Evidence from Indonesian Market Using Financial Ratios. [Graduate School of Management Research Paper, No. 13-04.] Depok: Universitas Indonesia. Available at: <http://dx.doi.org/10.2139/ssrn.1666703>.
- HUSSAIN, M. – NASSIR, A. – SHAMSHER, M. – HASSAN, T. (2005): Prediction of Corporate Financial Distress of PN4 Companies in Malaysia: a Logistic Model Approach. *Journal of Restructuring Finance*, 02, No. 02, pp. 143 – 155.
- INAM, F. – INAM, A. – MIAN, M. A. – SHEIKH, A. A. – AWAN, H. M. (2018): Forecasting Bankruptcy for Organizational Sustainability in Pakistan: Using Artificial Neural Networks, Logit Regression, and Discriminant Analysis. *Journal of Economic and Administrative Sciences*. Available at: <https://doi.org/10.1108/JEAS-05-2018-0063>.
- KIM, H. – GU, Z. (2006): Predicting Restaurant Bankruptcy: A Logit Model in Comparison with a Discriminant Model. *Journal of Hospitality and Tourism Research*, 30, No. 4, pp. 474 – 493.
- KNOX, K. – BLANKMEYER, E. – TRINIDAD, J. – STUTZMAN, J. (2009): Predicting Bankruptcy in the Texas Nursing Facility Industry. *The Quarterly Review of Economics and Finance*, 49, No. 3, pp. 1047 – 1064.
- KUMAR, P. R. – RAVI, V. (2007): Bankruptcy Prediction in Banks and Firms via Statistical and Intelligent Techniques – A Review. *European Journal of Operational Research*, 180, No. 1, pp. 1 – 28.
- LAITINEN, E. K. – LAITINEN, T. (2000): Bankruptcy Prediction Application of the Taylor's Expansion in Logistic Regression. *International Review of Financial Analysis*, 9, No. 4, pp. 327 – 349.

- LAM, K. F. – MOY, J. W. (2002): Combining Discriminant Methods in Solving Classification Problems in Two-group Discriminant Analysis. *European Journal of Operational Research*, 138, No. 2, pp. 294 – 301.
- LENNOX, C. (1999): Identifying Failing Companies: A Re-evaluation of the Logit, Probit and DA Approaches. *Journal of Economics and Business*, 51, No. 4, pp. 347 – 364.
- NAM, J. – JINN, T. (2000): Bankruptcy Prediction: Evidence from Korean Listed Companies during the IMF Crisis. *Journal of International Financial Management and Accounting*, 11, No. 3, pp. 178 – 197.
- NASIR, M. L. – JOHN, R. I. – BENNETT, S. C. – RUSSELL, D. M. – PATEL, A. (2000): Predicting Corporate Bankruptcy Using Artificial Neural Networks. *Journal of Applied Accounting Research*, 5, No. 3, pp. 30 – 52.
- OHLSON, J. A. (1980): Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, 18, No. 1, pp. 109 – 131.
- ONG, S. W. – YAP, V. C. – KHONG, R. W. (2011): Corporate Failure Prediction: A Study of Public Listed Companies in Malaysia. *Managerial Finance*, 37, No. 6, pp. 553 – 564.
- PARTINGTON, G. – RUSSEL, P. – STEVENSON, M. – TORBEY, V. (2001): Predicting Return Outcomes to Shareholders from Companies Entering Chapter 11 Bankruptcy. *Managerial Finance*, 27, No. 4, pp. 78 – 96.
- PEREZ, M. (2006): Artificial Neural Networks and Bankruptcy Forecasting: A State of the Art. *Neural Computing and Applications*, 15, No. 2, pp. 154 – 163.
- POMPE, P. – BILDERBEEK, J. (2005): The Prediction of Bankruptcy of Small- and Medium-sized Industrial Firms. *Journal of Business Venturing*, 20, No. 6, pp. 847 – 868.
- SALEHI, M. – POUR, M. D. (2016): Bankruptcy Prediction of Listed Companies on the Tehran Stock Exchange. *International Journal of Law and Management*, 58, No. 5, pp. 545 – 561.
- SANDIN, A. R. – PORPORATO, M. (2007): Corporate Bankruptcy Prediction Models Applied to Emerging Economies: Evidence from Argentina in the Years 1991 – 1998. *International Journal of Commerce and Management*, 17, No. 4, pp. 295 – 311.
- SMITH, M. – LIOU, D.-K. (2007): Industrial Sector and Financial Distress. *Managerial Auditing Journal*, 22, No. 4, pp. 376 – 391.
- SULAIMAN, M. – JILI, A. – SANDA, A. U. (2001): Predicting Corporate Failure in Malaysia: An Application of the Logit Model to Financial Ratio Analysis. *Asian Academy of Management Journal*, 6, No. 1, pp. 99 – 118.
- UGURLU, M. – AKSOY, H. (2006): Prediction of Corporate Financial Distress in an Emerging Market: The Case of Turkey. *Cross Cultural Management: An International Journal*, 13, No. 4, pp. 277 – 295.
- YAZDANFAR, D. (2011): Predicting Bankruptcy among SMEs: Evidence from Swedish Firm-level Data. *International Journal of Entrepreneurship and Small Business*, 14, No. 4, pp. 551 – 565.
- WILSON, R. L. – SHARDA, R. (1994): Bankruptcy Prediction Using Neural Networks. *Decision Support Systems*, 11, No. 5, pp. 545 – 557.

Annexes

Table 5

Predicted Probability – ROE (X_2)

| Pr (bankruptcy) predict | Margin | Delta-method Std. Err. | z | P> z | [95% Conf. Interval] | |
|----------------------------|-----------|---------------------------|----------|-------|----------------------|-----------|
| $X_2 = -2.4$ | 1 | 8.19e-08 | 1.2e+07 | 0.000 | 0.9999998 | 1 |
| $X_2 = -2$ | 0.9999999 | 5.94e-07 | 1.7e+06 | 0.000 | 0.9999988 | 1.000001 |
| $X_2 = -1.6$ | 0.9999968 | 0.0000196 | 5.1e+04 | 0.000 | 0.9999583 | 1.000035 |
| $X_2 = -1.2$ | 0.9998649 | 0.0006372 | 1 569.25 | 0.000 | 0.9986161 | 1.001114 |
| $X_2 = -0.8$ | 0.9946941 | 0.0165627 | 60.06 | 0.000 | 0.9622318 | 1.027156 |
| $X_2 = -0.4$ | 0.9254752 | 0.0760833 | 12.16 | 0.000 | 0.7763547 | 1.074596 |
| $X_2 = 0$ | 0.6331692 | 0.0904958 | 7.00 | 0.000 | 0.4558006 | 0.8105377 |
| $X_2 = 0.1$ | 0.5242352 | 0.0646354 | 8.11 | 0.000 | 0.3975520 | 0.6509183 |
| $X_2 = 0.2$ | 0.4150071 | 0.0489688 | 8.47 | 0.000 | 0.3190299 | 0.5109843 |
| $X_2 = 0.4$ | 0.2312857 | 0.0632974 | 3.65 | 0.000 | 0.1072251 | 0.3553463 |
| $X_2 = 0.6$ | 0.1241591 | 0.0513196 | 2.42 | 0.016 | 0.0235745 | 0.2247436 |

Source: Our own construction.

Table 6

Predicted Probability – Current Assets/Total Assets (X_7)

| Pr (bankruptcy) predict | Margin | Delta-method Std. Err. | z | P> z | [95% Conf. Interval] | |
|----------------------------|-----------|---------------------------|------|-------|----------------------|-----------|
| $X_7 = 0.19$ | 0.2206639 | 0.0829320 | 2.66 | 0.008 | 0.0581201 | 0.3832077 |
| $X_7 = 0.3$ | 0.2509841 | 0.0796899 | 3.15 | 0.002 | 0.0947947 | 0.4071735 |
| $X_7 = 0.4$ | 0.2818906 | 0.0736636 | 3.83 | 0.000 | 0.1375127 | 0.4262685 |
| $X_7 = 0.5$ | 0.3156932 | 0.0652053 | 4.84 | 0.000 | 0.1878933 | 0.4434932 |
| $X_7 = 0.6$ | 0.3519815 | 0.0555838 | 6.33 | 0.000 | 0.2430392 | 0.4609238 |
| $X_7 = 0.7$ | 0.3903003 | 0.0471968 | 8.27 | 0.000 | 0.2977963 | 0.4828043 |
| $X_7 = 0.8$ | 0.4302390 | 0.0437290 | 9.84 | 0.000 | 0.3445317 | 0.5159463 |
| $X_7 = 0.9$ | 0.4714626 | 0.0482226 | 9.78 | 0.000 | 0.3769481 | 0.5659770 |
| $X_7 = 1$ | 0.5136613 | 0.0598855 | 8.58 | 0.000 | 0.3962878 | 0.6310347 |

Source: Our own construction.

Table 7

Predicted Probability – Solvency (X_8)

| Pr (bankruptcy) predict | Margin | Delta-method Std. Err. | z | P> z | [95% Conf. Interval] | |
|----------------------------|-----------|---------------------------|-------|-------|----------------------|-----------|
| $X_8 = -43$ | 0.9226601 | 0.0700544 | 13.17 | 0.000 | 0.7853559 | 1.059964 |
| $X_8 = -20$ | 0.8179153 | 0.0979506 | 8.35 | 0.000 | 0.6259356 | 1.009895 |
| $X_8 = 0$ | 0.6763778 | 0.0878785 | 7.70 | 0.000 | 0.5041390 | 0.8486165 |
| $X_8 = 20$ | 0.5157695 | 0.0583360 | 8.84 | 0.000 | 0.4014332 | 0.6301059 |
| $X_8 = 40$ | 0.3645661 | 0.0489884 | 7.44 | 0.000 | 0.2685507 | 0.4605816 |
| $X_8 = 60$ | 0.2368574 | 0.0609520 | 3.89 | 0.000 | 0.1173938 | 0.3563211 |
| $X_8 = 80$ | 0.1399550 | 0.0611875 | 2.29 | 0.022 | 0.0200297 | .2598804 |

Source: Our own construction.

Table 8

Predicted Probability – Working capital turnover (X_{20})

| Pr (bankruptcy) predict | Margin | Delta-method Std. Err. | z | P> z | [95% Conf. Interval] | |
|----------------------------|-----------|---------------------------|---------|-------|----------------------|-----------|
| $X_{20} = .290$ | 0.9999972 | 0.0000186 | 5.4e+04 | 0.000 | 0.9999608 | 1.000034 |
| $X_{20} = .250$ | 0.9999691 | 0.0001737 | 5757.07 | 0.000 | 0.9996287 | 1.00031 |
| $X_{20} = .200$ | 0.9993897 | 0.0026844 | 372.29 | 0.000 | 0.9941283 | 1.004651 |
| $X_{20} = .150$ | 0.9899356 | 0.0277511 | 35.67 | 0.000 | 0.9355444 | 1.044327 |
| $X_{20} = .100$ | 0.9316962 | 0.0784923 | 11.87 | 0.000 | 0.7778541 | 1.085538 |
| $X_{20} = .50$ | 0.7466985 | 0.1038571 | 7.19 | 0.000 | 0.5431424 | 0.9502547 |
| $X_{20} = .10$ | 0.5133210 | 0.0535442 | 9.59 | 0.000 | 0.4083764 | 0.6182657 |
| $X_{20} = 0$ | 0.4503219 | 0.0452009 | 9.96 | 0.000 | 0.3617299 | 0.538914 |
| $X_{20} = 10$ | 0.3890493 | 0.0461837 | 8.42 | 0.000 | 0.2985309 | 0.4795678 |
| $X_{20} = 30$ | 0.2773956 | 0.0654097 | 4.24 | 0.000 | 0.1491948 | 0.4055963 |
| $X_{20} = 50$ | 0.1844734 | 0.0809351 | 2.28 | 0.023 | 0.0258435 | 0.3431033 |
| $X_{20} = 60$ | 0.1462070 | 0.0821593 | 1.78 | 0.075 | -0.0148223 | 0.3072363 |

Source: Our own construction.

Table 9

Predicted Probability – Stocks/Current Assets (X_{23})

| Pr (bankruptcy) predict | Margin | Delta-method Std. Err. | z | P> z | [95% Conf. Interval] | |
|----------------------------|-----------|---------------------------|------|-------|----------------------|-----------|
| $X_{23} = 0$ | 0.6119139 | 0.0765013 | 8.00 | 0.000 | 0.4619742 | 0.7618537 |
| $X_{23} = 0.05$ | 0.5706795 | 0.0661436 | 8.63 | 0.000 | 0.4410403 | 0.7003186 |
| $X_{23} = 0.1$ | 0.5297706 | 0.0569342 | 9.30 | 0.000 | 0.4181817 | 0.6413595 |
| $X_{23} = 0.15$ | 0.4895796 | 0.0501990 | 9.75 | 0.000 | 0.3911913 | 0.5879679 |
| $X_{23} = 0.20$ | 0.4503616 | 0.0469498 | 9.59 | 0.000 | 0.3583416 | 0.5423816 |
| $X_{23} = 0.25$ | 0.4123389 | 0.0473235 | 8.71 | 0.000 | 0.3195866 | 0.5050911 |
| $X_{23} = 0.30$ | 0.3757986 | 0.0503346 | 7.47 | 0.000 | 0.2771446 | 0.4744526 |
| $X_{23} = 0.35$ | 0.3411230 | 0.0544330 | 6.27 | 0.000 | 0.2344363 | 0.4478098 |
| $X_{23} = 0.40$ | 0.3087337 | 0.0582366 | 5.30 | 0.000 | 0.1945920 | 0.4228754 |
| $X_{23} = 0.45$ | 0.2789853 | 0.0608971 | 4.58 | 0.000 | 0.1596292 | 0.3983413 |
| $X_{23} = 0.50$ | 0.2520663 | 0.0621589 | 4.06 | 0.000 | 0.1302372 | 0.3738955 |
| $X_{23} = 0.55$ | 0.2279588 | 0.0622299 | 3.66 | 0.000 | 0.1059905 | 0.3499272 |
| $X_{23} = 0.60$ | 0.2064674 | 0.0615401 | 3.36 | 0.001 | 0.0858510 | 0.3270839 |
| $X_{23} = 0.65$ | 0.1872964 | 0.0604998 | 3.10 | 0.002 | 0.0687191 | 0.3058737 |

Source: Our own construction.