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Efficiency of Working Capital & Assets Management in the Function of SMEs Bankruptcy Prediction

DOI: 10.7595/management.fon.2023.0007

Abstract:

Research Question: This research has been conducted with the aim of determining whether it is possible to generate a model that can reliably predict bankruptcy of Serbian small and medium-sized enterprises (SMEs) using *Working Capital Management (WCM)* and *Asset Management (AM*) efficiency ratios**. Motivation:** Motive for this research is the fact there are not many business failure prediction models related to SMEs. In addition, existing models are not focused on efficiency of the two above mentioned categories. Also, previously developed models, especially traditional and ground-breaking ones, are not necessarily aligned with accounting procedures and economic environment of all countries, which indicates the need to develop a model that is adapted for Serbian territory. **Idea:** The idea is to develop a model that has the ability to predict whether an entity has a tendency to initiate bankruptcy proceedings in the next year. This is useful both for external stakeholders and for SMEs' owners themselves, as it allows them to better manage resources. **Data:** The research was conducted on a sample of 100 Serbian SMEs. Data for the calculation of ratio indicators is available on the Business Registers Agency webpage. **Tools:** The research was conducted as a combination of financial and statistical analysis instruments. Ratio indicators were used for financial analysis part, while statistical analysis was conducted in SPSS program v.26 and includes logistic (binary) regression. **Findings:** Results of the research indicate that AM efficiency indicators are suitable for SMEs bankruptcy prediction modelling, but also indicate that WCM ratios don't have great contribution in bankruptcy prediction for Serbian SMEs. A model that has a classification accuracy of 79% has been developed**. Contribution:** This research empirically tests how selected ratio indicators support SMEs bankruptcy prediction, and therefore can be beneficial for all SMEs stakeholders, but also other researches since the research methodology is explained in details.

Keywords: Financial distress, bankruptcy prediction, SMEs, financial ratios, logistic regression, business failure, statistical modelling

JEL Classification: G33, M40, M50

1. Introduction

Financial failure prediction is a critical matter that occupies the efforts of many researchers, since an inaccurate decision about the companies' financial status could cause costly financial losses (Aljawazneh et al., 2021). Virglerova and co-authors (2021) state that SMEs are more impacted by economic changes and they are more likely to experience financial crisis than bigger companies. According to Civelek et al. (2021) and Kljuncinkov et al. (2021) SMEs have a significant role in economy. Matenda and co-authors (2021) claim that private corporates, particularly small-to-medium enterprises (SMEs), are dominant legal forms of corporations in developing markets (p. 931). About 60% of all SMEs in the EU are family companies, producing 50% of all jobs. In Serbia, the SME sector generates about 30% of the total country's GDP (Arsic,

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2018, p.35). Micro, small, and medium-sized enterprises (MSMEs) are a vital component of the economy, as they contribute to the growth of income, job creation, total turnover, and export generation. In Serbia, this sector accounts for a vast majority of all active enterprises, representing up to 99.8% of them. Additionally, MSMEs are responsible for generating up to two-thirds of employment in the non-financial sector of the economy. These findings highlight the significant economic impact of MSMEs in Serbia and their critical role in driving economic growth and development (Minovic et al., 2016). Taking into account above stated, it is clear why the focus of this research is oriented towards SMEs sector.

The WCM plays important role to ensure the sustainability of the company in maintaining the business with an increase performance. Inefficient management of working capital could become a major cause of SME failure (Kasiran et al., 2016, p.302). The small firms are generally undercapitalized and hence dependent on owner financing, trade credit and short-term bank loans. Further, the size makes these firms more vulnerable to working capital fluctuations (Nobanee & Abraham, 2015, p.550). Effective working capital management has a direct impact on profitability and liquidity of the company (Vukovic & Jaksic, 2019, p.161). *Cash Conversion Cycle* (CCC) is used for WCM efficiency management. A closed cycle that starts from the process of procuring goods and materials, to shaping them into the final product or service that is sold with main aim to create added value is called CCC. Many authors have investigated the relationship between profitability and WCM using CCC and proved existence of positive relationship between mentioned indicators. Working capital turnover has been used in various models for prediction of business failure (Altman, 1968; Zenzerovic, 2011; Vukovic et al, 2020; Ohlson 1980; Pervan et al., 2011; Kovacova et al., 2019; Beslic Obradovic et al., 2018, etc.), while it is not the case with CCC. Considering the previous research related to CCC's impact on business success measured by ROA, it is expected that CCC will be of significant importance to predict failure of Serbian SMEs. Efficiency of asset management is calculated by comparing the achieved result (usually net result) and the value of the assets themselves, but it also includes asset structure ratios. Ratios related to asset management were previously included in various business prediction model, and it is expected that those will be of significant importance for bankruptcy prediction of Serbian SMEs.

The study is structured as follows: introduction, that is followed by theoretical background; next chapter presents materials and research methods, followed by results section where the bankruptcy prediction model is developed and tested. Last chapters are related to discussion, where the developed model is critiqued and compared to existing models, and concluding remarks.

2. Literature overview

Beginnings of bankruptcy predictions date from early '30s with the work of Fitzpatrick (1932) who analysed differences between unsuccessful and successful businesses. More precise and detailed bankruptcy prediction development started in mid '60s. Beaver (1966) proposed univariate data analysis based on entities financial statements data. His sample included 79 companies in time period 1954-1964. Altman (1968) developed model of 79% accuracy (hold-out sample) for manufacturing firms using multivariate technique - MDA. Sample that was in place for development of model included 33 bankrupted and 33 solvent companies. Out of 22 financial ratios, this author used only five as significant in the final model. Ohlson (1980) used logistic regression to generate bankruptcy prediction model. He did not balance the sample. His sample consisted of 2058 healthy, and 105 bankrupted companies. Classification accuracy of Ohlson's model was 96%. Generating business failure prediction models for SMEs is not widely present in the scientific community. The above stated is confirmed by the smaller share of such models in the total number of developed models. Starting from the ground-breaking SME bankruptcy prediction models, Keasey and Watson (1986) focused on small UK companies. They used judgemental method, but also MDA method with 5 factors. First model has predictive power of 62.8%-66.1% for failed companies and 66.7%-68.3% for non-failed companies. The second one has predictive power of about 75%. Peel and Peel (1987) analysed UK private companies. Authors developed bankruptcy prediction models using multilogit and multidiscriminant statistical methods. Predicting power of the models (for within-sample entities) was 78.8% for multilogit model, and 78.1% for multidiscriminant model. Furthermore, Laitinen (1991) analysed Finnish small & medium sized companies and using MDA technique. The author developed a model that has total accuracy of about 88.75% for the period one-year-before bankruptcy. Altman and Sebato (2007) generated logistic model that has 75% accuracy based on unlogged variables, and 87% based on logged variables. They also developed a MDA model, but it has lower accuracy of 60%. Ciampi and Gordini (2008) proposed discriminant and logistic regression analysis and made models for Italian SMEs based on sample of 1000 entities and 22 ratios. The first model has predictive power of 75.5%, while the second one has power of 80%. Cultrera and Bredart (2016) developed business failure prediction model for Belgian SMEs using logistic regression. The overall classification power is 79.23% (using training group). Svabova and co-authors (2020) generated bankruptcy prediction model for Slovak SMEs using logistic regression, but also discriminant analysis. One-year log regression prediction model for 2017 had 87,7% predictive power, while one-year and two-year log-regression models for 2018 had power of 90,9 and 89,7%. Discriminant analysis results were slightly better performance – higher than 90% both for one-year and two-year models.

Focusing on bankruptcy prediction models in the Balkans, it can be concluded that many articles are oriented towards testing the predictive power of existing, mostly traditional, models (Mizdrakovic & Bokic, 2017; Vlaovic-Begovic et al., 2021; Milic et al., 2021; etc). On the other hand, some powerful insolvency prediction models have been generated in the Balkan countries. For instance, Zenzerovic (2011) was focused on Croatian small, medium & big entities in his research. He divided the initial sample into two sub-samples. One for big entities, and the other for SMEs. Logistic regression model for SMEs has classification accuracy of 97%, while the one for big entities has accuracy of 92.5%. Working capital, ROA and liabilities to retained earnings (increased for depreciation) ratios were used in model for SMEs, and the same ratios without ROA were used in big entities bankruptcy prediction model. Pervan et al. (2011) developed two models for bankruptcy prediction in Croatia, using regression & discriminant analysis methods. Regression model showed better accuracy of 85.9%. Asset structure, leverage, liquidity and turnover (ROA) ratios were included, while WCM indicator was not significant in modelling. Stanisic et al. (2013) developed logistic regression bankruptcy prediction model for Serbian entities that has overall classification power of 75.4%. Debt ratio, and turnover ratios are included in the model, together with raw variables: EBITDA and employees number. The model was focused on big and medium-sized entities. Memic (2014) generated two bankruptcy prediction models for Bosnia and Herzegovina. This research is based on log regression and discriminant analysis. Model for bankruptcy prediction one year in advance performed with 84,96% and 81,45% overall correct classifications for discriminant and log regression model respectively. Activity, asset structure, debt, but also turnover (ROA, ROE) ratios are included in modelling. Beslic Obradovic and co-authors (2018) proposed insolvency log-regression prediction modelling for the Republic of Serbia, and developed model with total accuracy of 88.4%. It focuses small, medium & large manufacturing companies. Working capital, self-financing, and business effectiveness ratios are included in the final model. Vukovic and co-authors (2020) used non-proportional sample of 23 bankrupted and 30 healthy entities. Unlike other mentioned authors, they tested the model using marginal effects and concluded that possibility of bankruptcy decreases as ROE, share of stocks in current assets, solvency and working capital turnover increase, while possibility of bankruptcy and CATAR ratio are positively correlated. Papana and Spyridou (2020) developed various models for Greece companies. Their discriminant analysis model performed with accuracy of 63.3% and 78.3% for solvent and bankrupted companies respectively one year before bankruptcy occurred. Logit analysis performed worse than discriminant model with 61.67% and 70% of accurate classification for solvent and bankrupted companies respectively one year before bankruptcy. Models mostly included asset structure and profitability ratios.

3. Materials and research methods

The research sample counts 100 SMEs from Serbian territory, of which 50 companies in the sample are solvent, while the other 50 are bankrupt. Companies that initiated bankruptcy proceedings within one year are considered as bankrupt (*insolvent*) companies. All the entities that did not start any bankruptcy procedure are considered as solvent (*healthy*). Business years 2018-2021 and financial statements 2017-2020 were considered for the analysis, since the main goal is to predict bankruptcy one year before occurrence. Such modelling requires a well-structured sample. The sample is balanced by business activity, operating years, and also company size. Operating period median for bankrupted companies is 16 years, and 13 years for solvent companies. Average turnover of bankrupted companies is 363.533 KRSD[1], and 386.598 KRSD for solvent companies.

[1] KRSD – thousands of Serbian dinars

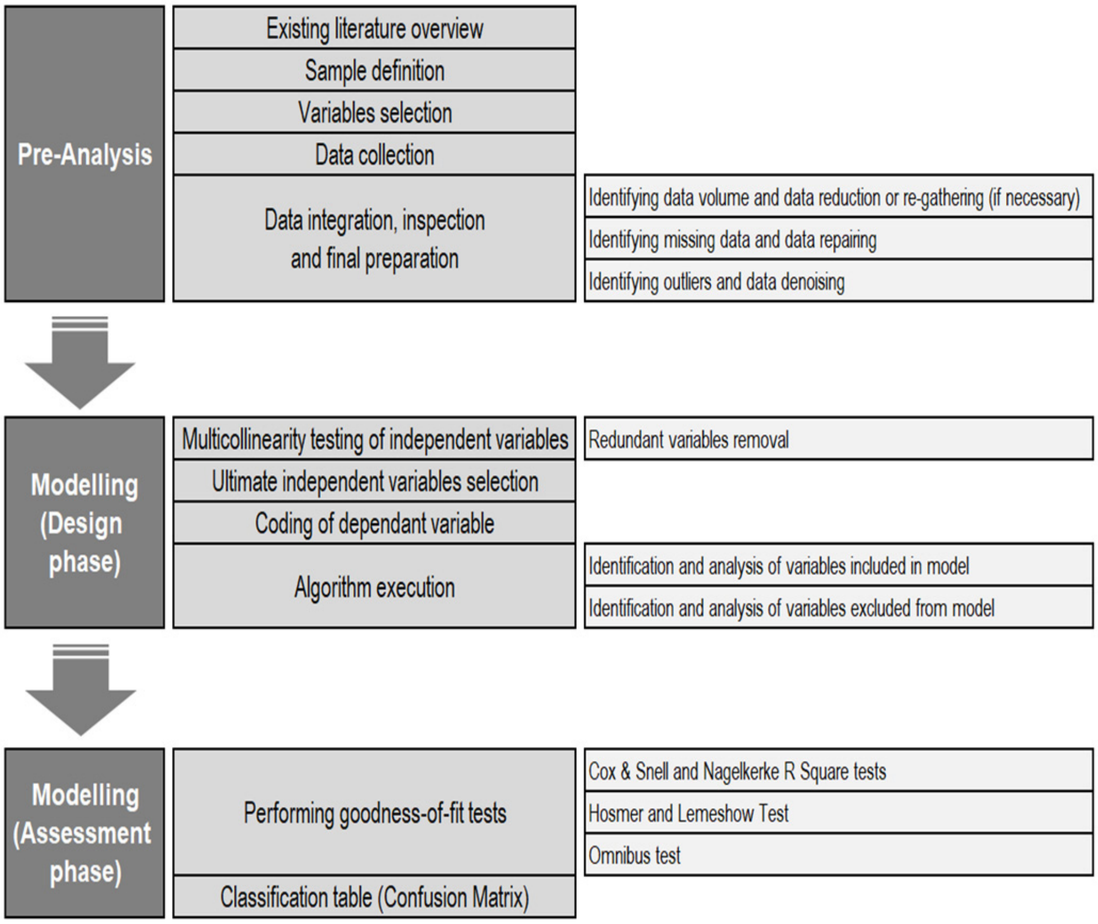

Figure 1: Research methodology overview
Source: Author

According to Masten and Masten (2012), a prevalent trait among bankruptcy prediction cases is the low proportion of firms that have gone bankrupt, which results in a limited proportion of the overall probability mass being attributed to such cases. Consequently, prediction models based on such data may accurately describe the characteristics of healthy firms but exhibit limited predictive power for identifying firms at risk of bankruptcy. As a remedy to this issue, many empirical studies seek to balance the estimation sample by including an equal proportion of healthy and bankrupt firms. This approach aims to improve the accuracy of bankruptcy prediction models and ensure that they are better equipped to identify firms that are at risk of financial distress. The sample of bankrupted companies is expanded with an equal number of healthy companies in this study. Balanced ratio of solvent and insolvent companies is included in a number of other traditional and ground-breaking business failure prediction models. (Altman, 1968; Fletcher & Gross, 1993, McKee, 1995, etc.)[2]. The whole research process is presented in Figure 1.

[2] Altman, 1968: 33 solvent VS 33 bankrupted; Fletcher & Gross, 1993: 18 solvent VS 18 bankrupted; McKee, 1995: 30 solvent VS 30 bankrupted.

Table 1: Independent variables overview

	#	Variable name	Symbol	Calculation method	Authors
Working Capital Management Ratios	1	**Cash Conversion Cycle**	**CCC**	IT+ART-APT (a)+(b)-(c)	None directly
	a)	Inventory turnover	IT (support for CCC calculation)	$\frac{365}{\frac{COGS}{\text{Average Inventories}}}$	
	b)	Accounts Receivable turnover	ART (support for CCC calculation)	$\frac{365}{\frac{\text{Operating income}}{\text{Average Sales Receivables}}}$	
	c)	Accounts Payable turnover	APT (support for CCC calculation)	$\frac{365}{\frac{COGS}{\text{Average Liabilities}}}$	
	2	**Working Capital Turnover**	**WCTA**	$\frac{\text{Working Capital}}{\text{Total Assets}}$	Altman (1968), Beslic Obradovic et al. (2018), Tserng et. al. (2014)
Assets Management Ratios	3	**Current Liquidity Ratio**	**CL**	$\frac{\text{Current Assets}}{\text{Current liabilities}}$	Ohlson (1980), Altman and Levallee (1980), Pervan, Pervan and Vukoja (2011), Beslic Obradovic et al. (2018), Vukovic et al. (2020), Sfakianakis, (2021), Svabova et al. (2020)
	4	**Return on Assets**	**ROA**	$\frac{\text{Net Result}}{\text{Total Assets}}$	Tserng et al. (2014), Zenzerovic (2011), Papana and Spyridou (2020)
	5	**Cash to Current Assets**	**CCA**	$\frac{\text{Cash}}{\text{Current Assets}}$	Bellovary, Giacomino and Akers (2007)
	6	**Current Assets to Total Assets Ratio**	**CATAR**	$\frac{\text{Current Assets}}{\text{Total Assets}}$	Vukovic et al. (2020)
	7	**Quick Ratio**	**QATA**	$\frac{\text{Quick Assets}}{\text{Total Assets}}$	Bellovary, Giacomino and Akers (2007)
	8	**Fixed Assets Turnover**	**FAT**	$\frac{365}{\frac{\text{Sales}}{\text{Average Fixed Assets}}}$	Vukovic et al. (2020)
	9	**Current Assets Turnover**	**CAT**	$\frac{365}{\frac{\text{Sales}}{\text{Average Current Assets}}}$	Altman and Levallee (1980), Beslic Obradovic et al. (2018)

Source: Author

As presented in Table 1, nine independent variables are chosen as inputs for regression modelling, with only one dependant variable present. Bankruptcy is dependant variable. Independent variables are calculated using entities' official financial statements available at *Business Registers Agency* webpage. Data for one year before bankruptcy is used for the variables calculation. The dependent variable is dichotomous. It means that dependant variable has only two possible values: "event occurred" or "event did not occur". Bankruptcy is considered as an "event occurred". Therefore, in this research paper there are only two possible outcomes for dependent variable: "entity went bankrupt" and "entity didn't go bankrupt". Due to the previously explained characteristics of the dependent variable, logistic regression will be in place to create business failure prediction model. When it comes to logistic regression (LR) methodology, "*Stepwise - Forward: LR*" method will be used to generate regression model. Model will be generated using SPSS *(Statistical Package for the Social Sciences*) v.26 software. As per Field's words (2009), when the forward method is employed, computer begins with a model that includes only a constant and then adds single predictors to the model based on specific criteria. The criteria is the value of score statistic: the variable with most significant score statistic is added to the model (Field, 2009, p.272). This method is useful when no previous research is available and it has been used by most of researchers that were developing bankruptcy prediction models.

Research hypothesis are defined as follows:

Hypothesis H1 – *Working Capital Management efficiency ratios can be a reliable basis for SMEs bankruptcy prediction modelling in Serbia*

Hypothesis H2 – *Asset Management efficiency ratios can be a reliable basis for SMEs bankruptcy prediction modelling in Serbia*

4. Results

4.1 Bankruptcy Prediction Model – Design Phase

High collinearity in regression model means that the analysis conclusions can be imprecise due to lack of estimations accuracy which is result of high estimator variances. Therefore, collinearity detection has to be initial phase in every econometric modelling (Salmeron et al., 2018). Collinearity assessment was done via VIF (Variance Inflation Factor) analysis.

Table 2: Multicollinearity test (VIF – Variance Inflation Factor)

Variables	Collinearity Statistics	
	Tolerance	VIF
CCC	0.941	1.062
CL	0.754	1.326
CATAR	0.922	1.084
CAT	0.935	1.069
ROA	0.904	1.106
CCA	0.797	1.255

Source: Author, SPSS output

VIF values (Table 2) demonstrate there is no multicollinearity present after removal of several variables. Multicollinearity is present when the VIF value is greater than 10 (Cohen et al., 2003; O'brien, 2007). In order to perform logistic regression, dependant variable has been encoded as follows in the Table 3.

Table 3: Coding of Dependant Variable

Dependent Variable Encoding	
Original Value	Internal Value
Bankrupt	0
Solvent	1

Source: Author, SPSS output

Stepwise logistic regression includes in the model only those variables that are important for predicting the outcome. By applying all the necessary statistical procedures, LR model was generated after two steps (iterations) and includes following indicators: (1*) Return on Assets* and (2) *Cash to Current Assets* as presented in the Table 4.

Table 4: Variables (ratio indicators) that are included in the bankruptcy prediction modelling

Variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	ROA	10.814	2.802	14.901	1	0.000	49730.400
	Constant	0.334	0.243	1.892	1	0.169	1.396
Step 2[b]	ROA	8.176	2.747	8.858	1	0.003	3555.157
	CCA	16.443	6.398	6.605	1	0.010	13841540.561
	Constant	-0.406	0.331	1.512	1	0.219	0.666
a. Variable entered on step 1: CAT							
b. Variable entered on step 2: CCC.							

Source: Author, SPSS output

The developed model that predicts bankruptcy of Serbian SMEs, looks more familiar in the following form:

$$P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 X_{1i} + b_2 X_{2i} + \cdots + b_n + X_{ni})}}$$

$$\boldsymbol{P(Y)} = \frac{\mathbf{1}}{\mathbf{1} + \boldsymbol{e}^{-(-\mathbf{0.406} + \mathbf{16.443}\ \boldsymbol{CCA} + \mathbf{8.176}\ \boldsymbol{ROA})}}$$

Table 5: Effects of potential removal of (included) variables from the model

Model if Term Removed					
Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	ROA	-69.315	37.880	1	0.000
Step 2	ROA	-57.110	26.032	1	0.000
	CCA	-50.375	12.561	1	0.000

Source: Author, SPSS output

Results in the Table 5 show the effect of variable removal from the model. Since “Sig. of the change” is lower than p value ($p < .01$) both for ROA and CCA in step 2, it can be concluded that removing these variables would affect significantly classification power of the developed model. In other words, exclusion of these two predictors from the model would be a mistake.

4.2 Bankruptcy Prediction Model – Assessment Phase

Once a logistic regression model has been fitted to a given set of data, the adequacy of the model is examined by overall goodness-of-fit tests. The purpose of any overall goodness-of-fit test is to determine whether the fitted model adequately describes the observed outcome experience in the data (Archer & Lemeshow, 2006, p.97). The assessment of developed bankruptcy prediction model includes several methods: *Classification table, Wald test, Cox & Snell R^2 test, Hosmer and Lemeshow test, Nagelkerke R^2 test,* and *Omnibus test.*

To begin with, values for Wald test are present in Table 4. The main aim of this test is to examine if an independent variable has a statistically significant effect on a dependent variable. As only CCA and ROA entered the final model, this test is done only for them. This also applies to other goodness-of-fit tests. When p-value (“Sig.”) of Wald test for a single independent variable is below confidence level α (5%), the independent variable has remarkable impact on the classification capacity of the model. Independent variables of the created bankruptcy prediction model have significant impact on the classification capabilities of the developed model, taking into account the p-values: 0.003 and 0.010 for ROA and CCA respectively.

Next performed tests are *Nagelkerke R^2* and *Cox & Snell $R^{2.}$* Results of these tests are available in the following table.

Table 6: Model Summary Statistics

Model Summary			
Step	**-2 Log likelihood**	**Cox & Snell R Square**	**Nagelkerke R Square**
1	100.749	0.315	0.420
2	88.189	0.396	0.528

Source: Author, SPSS output

According to Beslic Obradovic et al. (2018) the measures of pseudo R^2 range from the minimum of 0 to the maximum of approximately 1, where values greater than 0.4 indicate that the LR model is well-fitted. Ideally, if the R-squared is 1, it means that the predictors fully explain the dependent variable and in the future we can accurately determine the value of the dependent variable only on the basis of predictors (p.148). Values of 0.40 for Cox & Snell R^2 and 0.53 for Nagelkerke R^2 show that developed model is well-fitted and that it can explain variance of dependent variable (bankruptcy) in the range from 40% to 53%. That is an enviable percentage considering results in previous researches.

Table 7: Hosmer and Lemeshow (H&L) Test

Hosmer and Lemeshow Test			
Step	**Chi-square**	**df**	**Sig.**
1	10.689	8	0.220
2	9.913	8	0.271

Source: Author, SPSS output

The model is rated as well-fitted when the significance for *H&L* test exceeds 0.05 (Zenzerovic & Perusko, 2009, p. 362), and this is the case in the created model. This test is one of the most reliable for estimating the accuracy of a binary regression models.

Table 8: Omnibus test

Omnibus Tests of Model Coefficients				
		Chi-square	**df**	**Sig.**
Step 1	Step	37.880	1	0.000
	Block	37.880	1	0.000
	Model	37.880	1	0.000
Step 2	Step	12.561	1	0.000
	Block	50.441	2	0.000
	Model	50.441	2	0.000

Source: Author, SPSS output

Omnibus test is interpreted differently than *H&L test*. If significance is less than 0.05, model is adequate. Considering the fact that the created bankruptcy prediction model has chi-square of 50.441 with the probability that is lower than 0.05, generated model can be categorised as well-fitted.

Table 9: Classification table (Confusion Matrix)

<table>
<tr><th colspan="6">Classification Table a</th></tr>
<tr><td colspan="3" rowspan="3">Observed</td><td colspan="3">Predicted</td></tr>
<tr><td colspan="2">Went bankrupt?</td><td rowspan="2">Percentage Correct</td></tr>
<tr><td>Bankrupt (0)</td><td>Solvent (1)</td></tr>
<tr><td rowspan="3">Step 1</td><td rowspan="2">Went bankrupt?</td><td>Bankrupt (0)</td><td>32</td><td>18</td><td>64.0</td></tr>
<tr><td>Solvent (1)</td><td>7</td><td>43</td><td>86.0</td></tr>
<tr><td colspan="2">Overall Percentage</td><td colspan="3">75.0</td></tr>
<tr><td rowspan="3">Step 2</td><td rowspan="2">Went bankrupt?</td><td>Bankrupt (0)</td><td>39</td><td>11</td><td>78.0</td></tr>
<tr><td>Solvent (1)</td><td>10</td><td>40</td><td>80.0</td></tr>
<tr><td colspan="2">Overall Percentage</td><td colspan="3">79.0</td></tr>
<tr><td colspan="6">a. The cut value is .500</td></tr>
</table>

Source: Author, SPSS output

Classification table is the last step in accuracy assessment of the developed model. It shows the classification of each observation unit from the sample into a certain group. More precisely, it shows how correctly the model groups companies into two categories, in this case: bankrupt vs. solvent. The diagonal from upper-left to the lower-right shows the correct classifications, while the diagonal from lower-left to the upper-right indicates classification errors. Two types of error can occur: (1) Type I error, which is present when a company that initiated bankruptcy proceedings is classified as solvent, and (2) Type II error, which is present when a solvent company is classified as bankrupt.

In the first iteration, while only the asset management efficiency indicator (ROA) was included, the correct classification of bankrupt entities was 64%, while the correct classification of solvent entities was 86%. Type I error value is 18 entities, while Type II error value is 7 entities. The total predictive power was at the level of 75% of correctly classified companies for both outcomes. In the second iteration, after adding the CCA indicator, the predictive power of the model is raised, and the global level of misclassification is reduced. In the second iteration, 78% of companies that went bankrupt and 80% of those that have solvency status were correctly classified. Type I error is dropped to 11, while Type II error is raised to 10 entities. In the second iteration, the total predictive power is at the level of 79% measured by correctly classified companies for both outcomes.

5. Discussion

Bankruptcy prediction is worldwide phenomenon (Kovacova et al., 2019). Financial ratio indicators combined with statistical techniques have great contribution in insolvency prediction (Kuster, 2022). The truth is that all SMEs have to adopt their strategy and methodology of risk management, considering the fact they have lack of resources to resist internal and external threats (Olah et al., 2019). That being said, development of a model that could help in SMEs bankruptcy prediction is necessary. Every country has legal and accounting specific requirements, meaning that foreign developed models cannot always be reliable for bankruptcy prediction of local entities. Many models are developed as universal both for large and SME entities, and such models can sometimes be unreliable for predicting the bankruptcy of SMEs.

To the best of authors' knowledge, no previous research has been conducted to focus only the impact of asset and WCM on bankruptcy. CCC has never been linked to bankruptcy prediction, but only to profitability analysis, which is the added value of this research. Selection of several key variables for prediction is critical, in order to avoid overfitting of the model, which occurs when the model is too complex. Developed bankruptcy prediction model indicates that it is possible to predict insolvency one year in advance using financial ratios. Asset management ratios *Cash To Current Assets* and *Return on Assets* are included in the final model through stepwise linear regression. On the other hand *Cash Conversion Cycle* and *Working Capital Turnover* ratios were eliminated during model development as they did not have significant impact on bankruptcy prediction. Research hypothesis H_1 is rejected, considering the fact that stepwise log-regression modelling did not find working capital efficiency indicators as important factors for bankruptcy prediction of Serbian SMEs. On the other hand, research hypothesis H_2 is accepted, since two asset management ratios are included in the final developed model. In the final model, type I error was 11 firms, while type II error was 10 firms. Predictive power of the model is 79% correct classifications.

The predictors and their importance are different in models per country, meaning that application of a model to foreign firms can lead to wrong conclusions (Laitinen et al., 2022), which suggests the need to develop Serbian specific model, especially for SMEs. Most of researches in Serbia did testing of the existing traditional bankruptcy prediction models. On the other hand, developed models entities have significant classification power of 75% (Stanisic et al., 2013) and 88% (Beslic Obradovic et al., 2018), but are not focused specifically on SMEs segment that has its financial and business specificities, compared to big entities. Taking into account above-stated, the developed model is focused on SMEs, since bankruptcy prediction of that segment in Serbia is not covered enough with dedicated models.

In the Balkans, authors were focused at developing general bankruptcy prediction models for all-sizes entities, leaving plenty of space for SMEs bankruptcy prediction, which emphasizes the contribution of this research. Kliestik et al. (2018) revealed that *ROA* is probably the most common variable in bankruptcy prediction modelling. Durana et al. (2021) stated that declining operational ROA significantly increases the risk of bankruptcy. Many Balkan authors included ROA as important predictor for bankruptcy prediction (Zenzerovic, 2011, Pervan et al., 2011, Memic, 2014, Papana & Spyridou, 2020, etc.). The log-regression bankruptcy prediction model developed in this study also indicates the huge importance of ROA indicator, considering the fact it was the first one to be selected by stepwise LR algorithm. This demonstrates further that results of this research paper can be replicated in other Balkan countries.

Developed bankruptcy prediction model has better accuracy than following models: Altman (1968), Keasey and Watson (1986), Peel and Peel (1987), Altman and Sebato (2007) for model with unlogged variables, Ciampi and Gordini (2008) for MDA model, Stanisic et al. (2013), Papana and Spyridou (2020). The model has lower performance compared to following authors' models: Ohlson (1980), Laitinen (1991), Altman and Sebato (2007) for model with logged variables, Ciampi and Gordini (2008), Cultrera and Bredart (2016), Svabova and co-authors (2020), Zenzerovic (2011), Pervan et al. (2011), Memic (2014), and Beslic Obradovic et al. (2018).

Conclusion

Analysing financial distress is crucial considering its key role in every economy (Kuiziniene et al., 2022). SMEs are considered as crucial economic growth drivers, creating wealth, providing goods and services, and generating employment. However, they are commonly challenged by financial limitations and are at a greater risk of going bankrupt, regardless of their business environment or location (Yazdanfar & Ohman, 2020). The economy of Serbia has a substantial degree of unemployment and a high frequency of SMEs failure. Therefore, it is imperative to identify the key determinants influencing the business outcomes of SMEs. This will facilitate the development of an appropriate strategy aimed at mitigating the rate of SME failure, augmenting employment levels, and stimulating economic growth within the country (Nikolic et al., 2019). Improved analysis and more powerful models that can predict a financial crisis in advance are mandatory for failure prevention (Krulicky, 2021).

The issue of entity bankruptcy prediction is important both for the owners themselves and for external stakeholders. Based on bankruptcy prediction models, owners and managers can see if they are driving business towards success or failure. On the other hand, suppliers or banks can do analysis based on bankruptcy predictions models like this in order to conclude whether it is safe to cooperate with a specific entity. Logistic regression as a modelling method has a great advantage, considering that business owners and external stakeholders can easily do prediction by including values of their ratio indicators in the equation (model). A small number of studies are dedicated to SMEs, which emphasizes the importance of research results. Also, models that are present were in most cases created in foreign countries under some specific conditions and accounting standards that may not be the same as those in Serbia, and therefore those models may experience difficulties in predicting bankruptcy locally.

The research has several limitations. The first to mention is relatively small sample. This shortcoming is compensated by the use of advanced statistical software in the analysis. The first and basic assumption of the correctness of official financial statements can always be questioned. Achieving a suitable level of financial performance is vital for attaining success. Nevertheless, this outcome is not solely determined by the internal operations of a firm, but also heavily influenced by macroeconomic developments, which have a significant impact (Valaskova et al., 2021). Therefore, some macroeconomic and non-financial variables should be included in order to raise classification power of the model. Furthermore, research sample can be expanded to include SMEs from several countries having similar economic situation and reporting requirements or replicated on other countries to examine model applicability. To conclude with, generated model is focused on bankruptcy prediction one year before proceedings start. In some cases, prediction just a year before bankruptcy is too late for implementation of any healing measures. That being said, idea for the future research is to generate a model that would be able to detect potential business problems of SMEs 2 or even 3 years in advance. Business failure model with a total classification accuracy of 79% has been created in this iteration of research. It is focused only on small and medium entities. Taking into account other research and developed models, this predictive power can be considered as very good.

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Received: 2022-04-10
Revision requested: 2022-08-17
Revised: 2023-01-14 (3 revisions)
Accepted: 2023-05-03

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