“Assessment of bankruptcy risks in Czech companies using regression analysis”

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ARTICLE INFO	Muhammad Yousaf and Petr Bris (2021). Assessment of bankruptcy risks in Czech companies using regression analysis. *Problems and Perspectives in Management*, *19*(3), 46-55. doi:10.21511/ppm.19(3).2021.05
DOI	http://dx.doi.org/10.21511/ppm.19(3).2021.05
RELEASED ON	Tuesday, 27 July 2021
RECEIVED ON	Tuesday, 20 April 2021
ACCEPTED ON	Wednesday, 16 June 2021
LICENSE	This work is licensed under a Creative Commons Attribution 4.0 International License
JOURNAL	"Problems and Perspectives in Management"
ISSN PRINT	1727-7051
ISSN ONLINE	1810-5467
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

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ASSESSMENT OF BANKRUPTCY RISKS IN CZECH COMPANIES USING REGRESSION ANALYSIS

Abstract

Bankruptcy is an important topic in academic research and practice. It is a burning issue worldwide in the current COVID-19 situation. The aim of this study is to examine the financial risks of Czech companies. By employing the stepwise regression technique to estimate the financial risks, the p-values of all selected 15 financial ratios (explanatory variables) were calculated. If the p-value of the variable is more than the level of significance, the particular variable is removed from the model and another regression model is calculated. The findings from the stepwise regression revealed that return on capital, current ratio, net working capital turnover rate, and current assets turnover rate have a positive influence on company's financial health. On the contrary, return on capital employed, asset turnover rate, inventory turnover rate, fixed assets turnover rate, and debt to equity ratio negatively impact the company's financial health. The findings of this study will be fruitful for managers, policymakers, and investors of the companies to estimate and assess financial risks.

Received on: 20th of April, 2021
Accepted on: 16th of June, 2021
Published on: 27th of July, 2021

Keywords financial ratios, Cribis database, Czech firms, stepwise regression, COVID-19

JEL Classification G32, G33

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INTRODUCTION

The consequences of the COVID-19 pandemic could be seen and felt around the world. European countries, mainly Central European countries, are also being intensely affected by the pandemic. The pandemic is severely affecting different sectors of the economies, labor markets, and companies, becoming a cause of bankruptcy for several famous brands in many industries (Donthu & Gustafsson, 2020). However, some companies and businesses are struggling, and some are booming in this situation. According to the Cribis database statistics, around 16,111 companies were shut down in the Czech Republic in 2020, which was the highest number in Czech history in a year. About 1,336 companies in January 2021, 1,093 companies in February 2021, and 1,260 companies in March 2021 were shut down in the country. Therefore, bankruptcy has become a burning issue in the current situation.

Assessment of bankruptcy risks are important not only for investors that consider making investment decisions but also for managers and policymakers to make decisions on how to improve the financial performance of the companies. Kristóf and Virág (2020) argued that bankruptcy prediction has gone an important consideration in the last many decades, but the prediction in ex-socialist countries got substantial attention more than 20 years later compared to western countries. Therefore, Kristóf and Virág (2020), Durica et al. (2019), Kliestik et al. (2018), and Valaskova et al. (2018b) focused on Central European countries. However, a few studies focused on financial risks for Czech

Conflict of interest statement:
Author(s) reported no conflict of interest

http://dx.doi.org/10.21511/ppm.19(3).2021.05

companies. The uniqueness of the current study is that it uses the financial ratios that can be used in the prediction model for Czech enterprises. This study is highly relevant as it focuses on the assessment of bankruptcy risks of Czech companies using the financial ratios of multiple sectors simultaneously to a comprehensive overview. The main aim of this study is to examine the financial risks of Czech companies. Therefore, liquidity, activity, profitability, and indebtedness ratios were comprised as these ratios affect the financial health of the companies.

There are different methods and models used to estimate business failure over time such as Altman (1968), Springate (1978), Ohlson (1980), and Zmijewski (1984) models, etc. Bărbuță-Mișu and Madaleno (2020) claimed that these models use different statistical techniques and independent variables, and offer valuable information about the financial risks and financial performance of the companies. However, Valaskova et al. (2018a) and Valaskova et al. (2018b) mentioned and applied the decisive criteria at the Slovak companies to examine the financial risk of the Slovak companies. Slovakia and the Czech Republic are countries with similar history, political, economic, social, and legislative environments; therefore, it can be assumed that the same criteria can be used in Czech conditions. Therefore, the decisive criteria are employed to examine the bankruptcy risks in Czech companies. The criteria are that if a company's net income is negative, equity to debts ratio is less than 0.08, and current ratio is less than 1, then the company is in default or unhealthy. The outcomes were obtained of the selected explanatory variables by using the stepwise regression analysis.

1. LITERATURE REVIEW

Any risk is, in fact, the likelihood that adverse conditions will occur or that an adverse event will occur. Risks associated with financial activities are called financial risks. This term refers to the probability that the actual return will be less than predicted. Knowing the financial risk is very important for investors and stakeholders, especially when considering future decisions. Depending on the level of risk, investors decide how much of their free funds to invest in a given commodity. Risk-averse investors prefer the lowest possible risk, even at the cost of lower profits. The problem of predicting the financial risks of a company has become a crucial area of research. Therefore, scholars from all over the world are engaged in developing forecasting models to predict financial risks.

Mai et al. (2019) used textual disclosures to study the forecasting bankruptcy of the US firms by using a comprehensive bankruptcy database of 11,827 US publicly traded firms from 1994 to 2014 by deep learning models that produce superior prediction performance. The findings of the study showed the rate of bankrupt firms from 1994 to 2014, where the rate of bankruptcy was the highest during 2007–2009 due to the financial crises. Premachandra et al. (2009) used primary data set of 609 bankrupt US firms where the data was obtained from Altman's bankruptcy database that covers a period from 1991 to 2004. After employed data envelopment analysis (DEA) and logistic regression (LR), the outcomes revealed that the DEA model performs better than the LR model as the DEA model is correctly identifying 84 to 89% of cases of bankrupt firms whereas the LR model was showing the corresponding values from 16 to 64%.

Reizinger-Ducsai (2016), Bărbuță-Mișu and Madaleno (2020), Kliestik et al. (2020a), and Lin et al. (2019) provided methodological reviews of bankruptcy prediction. However, no proper empirical model was developed. Different scholars selected different sectors to predict bankruptcy. For example, Andrea (2014) focused on dairy firms, Belyaeva (2014) – on IT firms, Andrea and Pető (2015) – on meat processing firms, Fenyves et al. (2016) – on accommodation services, Dorgai et al. (2016) – on commercial enterprises, and Zoričák et al. (2020) focused on construction and manufacturing sectors. However, the data from eleven sectors are employed in the current study.

Premachandra et al. (2009) claimed that the research on bankruptcy evaluation could be divided into three types. Firstly, there is a focus on a specific model and evaluation of the bankruptcy by testing a particular model. Secondly, a set of variables is used and then a specific model is implemented. Thirdly, there is a focus on the bankruptcy evaluation process. The current study deals with the first type as some financial ratios are calculated and then a model is employed to evaluate the bankruptcy of the selected companies.

Ozturk and Karabulut (2020), Kliestik et al. (2020a), Hosaka (2019), Valaskova et al. (2018a), Ben Jabeur (2017), Karas and Režňáková (2012) used financial ratios to predict the bankruptcy of a firm. However, the number of financial ratios with different methodologies (and different topics) is reported differently. For instance, Bose (2006) reported 24 financial ratios, Wang and Chen (2006) used 11 ratios, Hua et al. (2007) included 22 ratios, Zaini and Mahmuddin (2019) employed 24 financial ratios, and Habibi and Iqbal (2021) used 47 financial ratios. According to Zaini and Mahmuddin (2019), there is no standard of the numbers of financial ratios. However, most of the financial ratios selected in the study are the same ones that were used before.

In recent years, Pavol et al. (2018), Valaskova et al. (2018b), Kliestik et al. (2018), Prusak (2018), Popescu and Dragota (2018), Nyitrai and Virag (2019), Durica et al. (2019), Nyitrai (2019), and Zoričák et al. (2020) focused on Visegrad Four (V4) countries. Different methodologies were used. For example, Nyitrai (2019) used the CHAID technique, Valaskova et al. (2018a) used stepwise regression, and Durica et al. (2019) employed a stepwise binary logistic regression approach. Most of the studies about the bankruptcy risks focused on two countries: Slovakia and Hungary. Kristóf and Virág (2020) claimed that *"Evaluating the most important features and results of Hungarian corporate bankruptcy prediction, it can be argued that the country can be proud of the rich set of empirical models and methodological development throughout the analyzed period"*. Various studies focused on V4 countries, particularly Hungary and Slovakia, but there is not much known about the bankruptcy risks of the Czech companies. Only Vochozka et al. (2020), Karas and Režňáková(2012), Knot and Vychodil (2006) focused on the Czech Republic. The Czech Republic was included with other countries in some studies such as Bărbuță-Mișu and Madaleno (2020), Kliestik et al. (2020b), etc. Therefore, the current study fills this gap about the Czech companies as firms from eleven sectors were included to study a comprehensive review of the bankruptcy risks in the companies.

2. DATA AND METHODOLOGY

The secondary data of the Czech companies was obtained from the CRIBIS database, where the data is classified according to CZ-NACE. CRIBIS is a part of the global CRIF group, which was founded in 1988. Cepel et al. (2020), Kotaskova et al. (2020), Jenčová et al. (2019), Štefko et al. (2017), and Holienka et al. (2016) had already used the secondary data from the CRIBIS database. The final sample contained 7,779 Czech companies from eleven sectors (the study period is 2019). The list of the sectors includes Sector 1: Accommodation and food service activities; Sector 2: Agriculture, forestry, and fishing; Sector 3: Construction; Sector 4: Education; Sector 5: Financial and insurance activities; Sector 6: Human health and social work activities; Sector 7: Information and communication; Sector 8: Manufacturing; Sector 9: Mining and quarrying; Sector 10: Transportation and storage; and Sector 11: Wholesale and retail trade; repair of motor vehicles and motorcycles.

In the first step, 15 financial ratios (independent variables) of the Czech companies in the selected sample were computed. The complete detail about the selected variables (ratios) and their measurement is given in Table 2. Based on the computed financial ratios, the companies were classified into two groups by the decisive criteria: healthy or non-default companies; and unhealthy or default companies. If a company has positive net income, the ratio (X6) is greater than 1, and the equity to debts ratio is more than 0.08, then the company is healthy or non-default (marked by the value 1). If these conditions are not met, the company is unhealthy or default (marked by the value 0). According to the calculation of the decisive criteria, Czech companies are classified into bankrupt and non-bankrupt firms. The sample consists of 7,779 Czech companies from 11 sectors, where around 13.1% of them experienced some financial risks or are unhealthy.

Table 1 provides information about the Czech companies by sector-wise data of total and unhealthy companies. Table 1 was prepared after em-

http://dx.doi.org/10.21511/ppm.19(3).2021.05

Table 1. Sector-wise data of Czech companies

Source: Authors' elaboration.

Sector	Information about total companies		Information about default (unhealthy) companies	
	Number of companies	Percentage	Number of default companies	Percentage
1	447	5.75	112	10.97
2	900	11.57	120	11.75
3	927	11.92	58	5.68
4	127	1.63	28	2.74
5	111	1.43	10	0.98
6	416	5.35	71	6.95
7	557	7.16	47	4.60
8	871	11.20	157	15.38
9	266	3.42	31	3.04
10	856	11.00	141	13.81
11	2301	29.58	246	24.09
Total	7779	100.00	1021	100.00

ploying the decisive criteria. Table 1 revealed that sector 5 has only 1.43% of total companies by comparing to other sectors, and the default percentage of sector 5 is 0.98%, which is the lowest percentage among default companies. On the other hand, sector 11 has 29.58% of companies in the current study, and the percentage of default companies is the highest than other sectors. However, the proportion of default companies is higher than the total number of companies in sectors 1, 4, and 8. Conversely, the proportion of default companies is lower than the total number of companies in sectors 3, 7, and 11.

According to Table 2, there are two types of variables in the regression analysis: independent variables (15 financial ratios) and dependent variables (financial health of the company). All the data of the financial ratios were treated in linear regression analysis. As the independent variable has 15 financial ratios, multiple regression has been employed to find out which financial ratio has an impact on the financial health of the company. The financial ratios such as profitability ratios, turnover ratios, activity ratios, liquidity ratios, and financial structure were calculated for the selected Czech companies.

Equation 1 is presented the linear regression model. The main objective of the regression analysis is to find the existing independence and to examine the relationship, which changes one variable dependence on others. As the number of explanatory variables is more than one, multiple regres-

Table 2. List of the selected ratios and their measurements

Source: Authors' elaboration.

Variables	Proxy	Measurements
Return on assets	X1	Net income/total assets
Return on equity	X2	Net income/equity
Return on capital employed	X3	EBIT/capital employed, where capital employed = total assets – current liabilities
Return on capital	X4	Earning after tax (EAT)/total liabilities
Current ratio	X5	Current assets/current liabilities
Quick ratio	X6	(Current assets – inventory)/current liabilities
Cash ratio	X7	Cash and cash equivalents/current liabilities
Interest coverage ratio	X8	EBIT (Earnings before interest and taxes)/interest expense
Receivable turnover rate	X9	Sales/accounts receivables
Inventory turnover rate	X10	Cost of sold goods/inventory
Asset turnover rate	X11	Sales/total assets
Net working capital turnover rate	X12	Sales/(current assets – current liabilities)
Fixed assets turnover rate	X13	Sales/fixed assets
Current assets turnover rate	X14	Sales/current assets
Debt to equity ratio	X15	Total liabilities/equity

sion is appropriate for equation 1 as suggested by Valaskova et al. (2018a) and Valaskova et al. (2018b).

$$y_i = \beta_0 + \sum_{i=1}^{k} \beta_j \cdot x_{ij} + u_i. \qquad (1)$$

In equation 1, y_i is a dependent variable, β_0 is intercept, β_j are unknown parameters, and x_i are independent variables that represent the values of financial ratios from X_1 to X_{15}. β represents the direction (slope) of the parameters and μ_i is a random variable.

3. RESULTS

The descriptive statistics of all the selected variables is presented in Table 3. All estimations were performed using STATA 16.0 software.

According to Table 3, the mean and standard deviation of the selected variables are slightly different from each other. The values of mean, standard deviation, minimum, and maximum of X_8 are different from all other variables. The reason is that the numerator (earnings before interest and taxes) of X_8 is much bigger than its denominator (interest expense). In Table 3, the values of kurtosis and skewness are computed to check the normality in the data. For the standard normal distribution, it is recommended that the value of kurtosis should be zero, which is unlikely for real-world data. For the normal distribution, Simon et al. (2017) suggested that the skewness and kurtosis should be within the range ± 3, and ± 10, respectively. According to Table 3, most of the values of skewness and kurtosis are showing that the data used in the study is normally distributed.

Table 4. Variance inflation factor (VIF)

Source: Authors' elaboration.

Variable	VIF	1/VIF
X_1	7.34	0.136
X_2	3.34	0.299
X_3	1.46	0.685
X_4	5.17	0.193
X_5	1.46	0.685
X_6	1.14	0.877
X_7	1.22	0.820
X_8	1.36	0.735
X_9	2.23	0.448
X_{10}	1.28	0.781
X_{11}	5.03	0.199
X_{12}	1.09	0.917
X_{13}	1.89	0.529
X_{14}	5.2	0.192
X_{15}	1.36	0.735

To check the multicollinearity in the data, the variance inflation factor (VIF) coefficient criteria was employed. VIF coefficient is the indicator that diagnoses the existence of multicollinearity between the independent variables (Sharma et al., 2020). Multicollinearity is not a serious problem if the value of the VIF coefficient of each explanatory

Table 3. Descriptive statistics of the selected variables

Source: Authors' elaboration.

Stats	Mean	Maximum	Minimum	S.D.	Kurtosis	Skewness	N
FH	0.354	0.807	0.000	0.241	1.999	0.337	7772
$_x1$	0.057	0.263	–0.086	0.086	3.160	0.757	7729
X_2	0.113	0.678	–0.447	0.243	3.854	0.209	7762
X_3	0.267	2.229	–0.299	0.576	8.102	2.388	7733
X_4	0.056	0.240	–0.067	0.076	3.248	0.865	7768
X_5	2.546	9.135	0.515	2.240	5.196	1.724	7619
X_6	0.227	6.979	–19.404	5.575	9.155	–2.507	7615
X_7	0.200	1.562	0.000	0.407	7.798	2.420	7704
X_8	65.946	650.063	–19.476	161.626	10.079	2.869	5798
X_9	4.573	17.612	0.000	4.754	4.104	1.295	7542
X_{10}	1.929	18.754	0.000	4.659	9.887	2.832	5476
X_{11}	1.019	3.738	0.000	1.100	3.181	1.091	7768
X_{12}	2.661	26.028	–17.132	8.746	4.852	0.533	7608
X_{13}	7.510	57.547	0.000	14.363	8.767	2.593	7608
X_{14}	1.839	6.217	0.000	1.847	2.848	0.917	7749
X_{15}	2.801	10.533	0.000	2.474	6.130	1.914	7762

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variable is less than 10 (Nachane, 2006). Table 4 is describing the values of the VIF coefficient and 1/VIF. All the values of VIF coefficients of the independent variables are less than 10, therefore, there is no multicollinearity issue in the data. The data can be processed for further analysis.

In the multiple regression analysis, the *p*-values of all 15 financial ratios (variables) were calculated to compare with the level of significance. If the *p*-value of a financial ratio is more than 0.05 (level of significance), then that particular financial ratio was removed from the model and another regression was calculated. Therefore, the stepwise regression was used to recognize the least significant financial ratio in the model to realize which factors are significant enough to manage financial risks and to forecast the default of the Czech companies. Table 5 shows the outcomes of the first regression model for all 15 financial ratios.

Table 5. Regression analysis of all selected financial ratios

Source: Authors' elaboration.

	Coef.	Std. Error	t	*p*-value
Intercept	0.319	0.006	56.250	0.000
X_1	–0.120	0.066	–1.820	0.068
X_2	0.042	0.016	2.710	0.007
X_3	–0.024	0.004	–5.940	0.000
X_4	0.311	0.061	5.120	0.000
X_5	0.056	0.001	48.000	0.000
X_6	0.000	0.000	–0.300	0.761
X_7	0.007	0.006	1.010	0.314
X_8	0.000	0.000	13.170	0.000
X_9	0.001	0.001	2.010	0.045
X_{10}	–0.001	0.000	–2.450	0.014
X_{11}	–0.051	0.004	–12.180	0.000
X_{12}	0.001	0.000	5.580	0.000
X_{13}	–0.001	0.000	–3.770	0.000
X_{14}	0.020	0.002	8.070	0.000
X_{15}	–0.040	0.001	–42.560	0.000
Prob > *F*	0.000			
R^2	0.684	Adj. R^2	0.683	

From Table 5, it is clear that the *p*-value of X_6 is the highest of other values. Therefore, X_6 is removed from the model and the regression is run again. Table 6 shows the results of the regression, as well as the *p*-value of all the financial ratios.

Table 6. Regression analysis of all selected financial ratios

Source: Authors' elaboration.

E2DRatio	Coef.	Std. Err.	t	*p*-value
X_1	–0.111	0.065	–1.7	0.089
X_2	0.041	0.016	2.64	0.008
X_3	–0.024	0.004	–6.04	0.000
X_4	0.305	0.060	5.05	0.000
X_5	0.056	0.001	50.94	0.000
X_8	0.000	0.000	13.29	0.000
X_9	0.001	0.001	1.88	0.06
X_{10}	–0.001	0.000	–2.35	0.019
X_{11}	–0.050	0.004	–12.09	0.000
X_{12}	0.001	0.000	5.54	0.000
X_{13}	–0.001	0.000	–3.96	0.000
X_{14}	0.019	0.002	7.97	0.000
X_{15}	–0.040	0.001	–42.78	0.000
_cons	0.320	0.006	57.3	0.000
Prob > *F*	0.000			
R^2	0.683	Adj. R^2	0.682	

According to Table 6, it is clear that the *p*-value of X_1 (return on assets) is the highest of other values. Therefore, X_1 is removed from the model and the regression is run again. Table 7 shows the results of the regression. The *p*-value of all the independent variables is less than the value of significance (0.05).

Table 7. Results of the stepwise regression analysis

Source: Authors' elaboration.

	Coef.	Std. Error	t	*p*-values
Intercept	0.319	0.005	58.320	0.000
X_3	–0.024	0.004	–6.030	0.000
X_4	0.295	0.029	10.270	0.000
X_5	0.057	0.001	52.430	0.000
X_8	0.000	0.000	13.070	0.000
X_{10}	–0.001	0.000	–2.410	0.016
X_{11}	–0.051	0.004	–12.470	0.000
X_{12}	0.001	0.000	5.790	0.000
X_{13}	–0.001	0.000	–3.900	0.000
X_{14}	0.022	0.002	11.040	0.000
X_{15}	–0.040	0.001	–45.030	0.000
Prob > *F*	0.000			
R^2	0.683	Adj. R^2	0.682	

After employing the stepwise regression, the results are presented in Table 7. All the selected variables (financial ratios) are statistically insignificant as the *p*-values of all the independent variables are less than 0.05.

4. DISCUSSION

From Table 7, it can be observed that the following ratios have significant impacts on the financial health of Czech companies. The significant financial ratios are: return on capital employed (X_3), return on capital (X_4), current ratio (X_5), interest coverage ratio (X_8), inventory turnover rate (X_{10}), asset turnover rate (X_{11}), net working capital turnover rate (X_{12}), fixed assets turnover rate (X_{13}), current assets turnover rate (X_{14}), and debt to equity ratio (X_{15}). Hence, the model can be presented like this in equation 2.

$$\begin{aligned} Y &= 0.319 - 0.024X_3 + 0.295X_4 + \\ &+ 0.057X_5 + 0.0001X_8 - 0.001X_{10} - \\ &- 0.051X_{11} + 0.001X_{12} - 0.001X_{13} + \\ &+ 0.022X_{14} - 0.040X_{15}. \end{aligned} \tag{2}$$

The findings from the stepwise regression in equation 2 revealed that return on capital employed (X_3), inventory turnover rate (X_{10}), asset turnover rate (X_{11}), fixed assets turnover rate (X_{13}), and debt to equity ratio (X_{15}) have a negative impact on the dependent variable. The Czech companies should decrease the values of these ratios to increase the financial health of their companies, holding all other variables constant. Increasing one unit in X_3, X_{10}, X_{11}, and X_{15} will raise the risk of the financial health of the Czech companies by 0.024, 0.001, 0.051, and 0.040 units, respectively. The magnitude of the coefficient of X_{10} (inventory turnover rate) is very small, conversely, the magnitude of X_{11} (asset turnover rate) is big among financial ratios that have a negative impact on the financial health of the Czech companies. On the other hand, return on capital (X_4), current ratio (X_5), interest coverage ratio (X_8), net working capital turnover rate (X_{12}), and current assets turnover rate (X_{14}) have a positive influence on the financial health of the companies. Therefore, the Czech companies should increase the values of return on capital employed, current ratio, net working capital turnover rate, and current assets turnover rate. In this way, the Czech companies will increase their financial health, holding all other variables constant. Increasing one unit in X_4, X_5, X_8, X_{12}, and X_{14} will increase the financial health of the Czech companies by 0.295, 0.057, 0.000, 0.001, and 0.022 units, respectively. The magnitude of the coefficient of X_4 (return on capital employed) is big, conversely, the magnitude of X_8 (interest coverage ratio) is very small among financial ratios that have a positive impact on the financial health of the Czech companies. R^2 is known as the coefficient of determination that indicates how close the data are to the fitted regression line. The value of R^2 is 68.3 % and adjusted R^2 is 68.2%. The value of Prob > F shows the significance of the model as the value is lower than the significance level (0.05). Hence, the formed regression model of the bankruptcy prediction of the Czech companies is statistically significant.

CONCLUSION

The assessment of bankruptcy risks is essential for investors that consider making investment decisions on bonds, equity, and creditors. The assessment of the bankruptcy risks is also significant for managers and policymakers as they make decisions to improve the financial performance of the companies. The current study provides a comprehensive review regarding the empirical research of bankruptcy prediction of Czech companies. The main aim of this study is to investigate the financial risks of Czech companies.

To explore the aim, the secondary data of the Czech companies was obtained from the CRIBIS database for the period of 2019. The final sample contained 7,779 Czech companies from eleven sectors. In the multiple regression analysis, p-values of the selected financial ratios were calculated to compare with the level of significance (0.05). If the p-value of a financial ratio is more than 0.05, then the financial ratio is removed from the model, and another regression model is estimated by using the stepwise regression technique. Finally, the statistically significant ratios that affect the future financial development of the company were estimated. The outcomes through multiple regression analysis exposed that return on capital employed, inventory turnover rate, asset turnover rate, fixed assets turnover rate, and debt to eq-

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uity ratio has a negative impact on the dependent variable. Therefore, the values of these financial ratios should be reduced because these ratios increase the risks of the financial health of the Czech companies. On the other hand, return on capital, current ratio, interest coverage ratio, net working capital turnover rate, and current assets turnover rate have a positive impact on the financial health of the companies. Hence, the values of the financial ratios should increase as the ratios rise the financial health of the Czech companies.

AUTHOR CONTRIBUTIONS

Conceptualization: Petr Bris.
Data curation: Muhammad Yousaf.
Formal analysis: Muhammad Yousaf.
Funding acquisition: Muhammad Yousaf.
Investigation: Petr Bris.
Methodology: Muhammad Yousaf.
Project administration: Petr Bris.
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Software: Muhammad Yousaf.
Supervision: Petr Bris.
Validation: Petr Bris.
Visualization: Petr Bris.
Writing – original draft: Muhammad Yousaf.
Writing – review & editing: Petr Bris.

ACKNOWLEDGMENTS

This study is supported by the Internal Grant Agency (IGA) in Tomas Bata University in Zlin, the Czech Republic, under the projects No IGA/FAME/2021/008 and IGA/FAME/2021/014.

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