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Practical application of the CCB model in Czechia

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Abstract

This research aimed to present a new bankruptcy prediction model and apply this original prediction method in practice. The Come Clean Bankruptcy (or CCB) model uses relevant financial indicators and ratios to detect the signs of impending financial distress in time so that the management can take appropriate measures to avoid it. The model was applied to the data reported by 199 entities operating in the textile/clothing industry in the Czech Republic. Analyzing data reported for the previous seven years enabled us to predict which companies are more likely to end in a difficult financial situation. Afterward, comparing these predictions with the actual development of those companies in 2013-2020 serves to verify the efficacy and usability of the model to corporate reality. The research has shown that companies that went bankrupt in the analyzed period represented only a fraction of the data set (roughly 4.5%). Despite the small number of financial failures occurring during the analyzed period, the CCB model could detect impending bankruptcy in one-third of the cases.

Key words: *Bankruptcy model, predicting risks, financial distress, Czech Republic*

JEL classification: *M41*

1. Introduction

Nowadays, there is a wide range of available organizational and financial measures for *saving* companies that found themselves in financial distress, each corresponding to the specific circumstances in the company and the causes of the financial distress. Though the efficacy of those measures is ever increasing, there is little doubt that it is much more advantageous, both in terms of time and financial costs, to *prevent* the bankruptcy in the first place, rather than to solve it once it occurs.

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That is why financial analysis and its models - the main tools used for the early detection of a crisis – have been given much attention in scientific research over the last 50 years. The number of models and bankruptcy-detecting strategies is ever-increasing and the current tendency is to focus on testing the validity of those strategies/models with an empirical approach, which is the case of this paper, too. The quality of existing financial analysis systems is determined directly by their complexity. Although the elementary methods of processing the data do not have the necessary explanatory power, their application is frequent. Complex systems allow for a more detailed depiction of the situation in the company, yet they tend to be confusing for the users of financial analyses. The results pinpoint the problem that financial analysis users can understand less than three-quarters of such an analysis. Unlike many other creditworthy/bankruptcy models, this model provides a clear explanation of the obtained results.

Virtually all financial analyses require the use of data reported in financial statements. However, accounting data alone only reflects the past and not the prospects for the future. In other words, it defines the current values of strongly variable quantities (Kovanicova, 1999). These shortcomings can be eliminated by comparing the data with each other, expanding its explanatory power. That is why financial ratios are the fundamental methodological tool for financial analysis. Prediction models are often based on recommended values of indicators, which are nevertheless too broad. The CCB model, on the other hand, compares the individual ratios of a selected company with values of 198 competing entities operating in the same sector of the economy, which increases the explanatory power of data and accuracy of the analysis.

This paper deals with the hypothesis that the data of companies falling within the same industry should provide more accurate results when compared to the data of companies operating in various sectors. Even a single company sector hit by a major crisis affects the entire set of companies. Therefore, the data provided should not include outliers that make them suitable and reliable material for any financial analysis, including bankruptcy prediction. The paper opens up with an overview of relevant literature that has brought new perspectives on the issue of bankruptcy prediction models. The following chapters depict the methodological basis of the research, presenting the financial indicators and ratios used so that the reader can understand their role in the assessment of the financial health of companies. The paper aims at testing the validity of the selected bankruptcy prediction model dealt with in chapters 4 and 5 with the actual application of the model on the data sample and the explanation of provided results. The paper concludes with a discussion on the applicability of the model for practical use and further research.

2. Literature review

The first prediction models which appeared during the 1920s were rather simple in their structure. They usually included only one indicator to be analyzed, such as the FitzPatrik (FitzPatrik, 1932) or Smith and Winakor (1935) models. Since then, the domain of prediction models saw tremendous development. The number of examined ratios progressively increased throughout the following decades and along with it, the number of prediction models too. Bellovary et al. (2007) indicate that from 1968 till 2007, more than 165 models have been introduced in scientific publications. Recent prediction models and analyses are increasingly complex in their structure and methodology.

Mantziaris (2015) discussed the suitability of Edward Altman's prediction model, which appeared for the first time in 1968 and became universally accepted, for current times. More precisely, he applied the multi discriminant analysis (MDA) model on a set of 40 companies operating in Greece, out of which 50% went bankrupt due to the financial crisis of 2008. Mantziaris (2015) argues that the model is not suitable for times of great economic uncertainty and disturbances. Furthermore, it does not take into account new trends in corporate management, such as the use of higher debt to run a business. Therefore, the author concludes that Altman's model needs to be modified to stay relevant in the domain of financial predictions.

López-Gutiérrez et al. (2015) conducted an extensive empirical analysis focused on the possible effects of financial distress on investment activities in companies. The data obtained for 4029 companies operating in Germany, Canada, Spain, France, Italy, the UK, and the USA between 1996 and 2006 for this study has shown that financial distress is not the only factor influencing the investment. The propensity to underinvest additionally depends on the investment opportunities available to the company. López-Gutiéerrez et al. (2015) have used extensive data set for their research, yet the author of this paper thinks that reducing the number of companies and focusing on specific markets (such as Europe or the US) would maybe provide more solid results.

A similar study to the one presented herein in terms of number of analyzed companies was conducted in Lithuania. Šlefondorfas (2016) has proposed a new bankruptcy prediction model and applied it on the data of 145 companies (72 already bankrupt and 72 still operating). The author thinks that the best way to predict future development is to create a model that is specifically designed for a particular country, as the model in question was able to correctly classify 89% of the analyzed companies.

Standard Logistic and Bayesian modeling was used in the Shrivastava et al. (2018) study to predict distressed firms in the Indian corporate sector. The analysis is based on a sample of 628 companies over the 10-year time within the period 2006-2015.

According to the results, Bayesian methodology seems to perform consistently better in terms of predictive capabilities.

Klepac and Hampel (2017) predicted financial distress of agriculture companies operating in the European Union based on Logistic regression, the Support vector machines method with the RBF ANOVA kernel, the Decision Trees and the Adaptive Boosting based on the decision trees to acquire the best results. The authors' goal was to discover whether it is possible to predict financial distress 1-3 years ahead with solid accuracy. The chosen methodology performed well for one-year ahead predictions. However, for a long-spanned period before bankruptcy, the models are not efficient enough to predict bankruptcy.Recent models are increasingly based on linear and logistic regressions, survival analysis, linear and quadratic programming, multivariate adaptive regression splines, and multiple-criteria programming. Neural networks and their predictive capabilities have been studied in greater detail by Cleofas-Sánchez et al. (2016). Their work compared several different neural models (MLP, RBF, BN and VP) with the hybrid associative memory with translation (HACT). The results of their analysis (concerning over nine real-life financial databases) have shown that the HACT neural network predicts the default cases better than the remainder of the methods analyzed. Lee and Choi (2013) created a back-propagation neural network in order to carry out a multi-industry investigation of Korean companies.

The CCB Model, similarly to the models used in some of the research presented above, use relevant financial indicators to determine whether a company is or is not endangered by bankruptcy in the foreseeable future. The choice of indicators was based on data of companies that went bankrupt in the past as well as on generally accepted theoretical assumptions concerning the sustainable development of companies. These indicators reflect above all the trends in cash flows, optimal capital structure, and the company's liquidity, as it has been shown that these areas, including (under)investment, as shown in López-Gutiéerrez (2015), reveal essential information about the financial health of a company. The author of this paper agrees with the conclusion of Šlefondorfas (2016) that using data from companies operating in the same country is beneficial to the overall validity of the prediction as it increases its accuracy. The CCB model works in addition with companies that operate in the same market/industry, to obtain even more reliable results.

3. Methodology

Predicting bankruptcy with the use of the CCB Model consists of several steps (see Table 1). The selection of financial indicators and ratios, briefly mentioned above, represents the first and the crucial step in the whole process of an accurate prediction, then used for several other analysis methods, such as the Du Pont chart and determination of the break-even point, to obtain an idea about the optimal indebtedness of a company.

Steps n. 4, 5 and 6 consist of actual assessment of the values obtained for each company and comparing them with other entities operating in the same industry (in this case the textile industry).

Table 1: The CCB model methodology

Step in the CCB model		Reason	Goal
1	Financial ratios	Comparing companies according to absolute values is misleading.	Organizing input data in order to set up the Du Pont chart.
2	Du Pont chart	Global incorporation of examined variables.	Building financial leverage.
3	Monitoring of the break-even point and financial leverage	The value of the company is affected by financial leverage.	Defining the optimal indebtedness.
		Considering company's performance	Company's risks.
4	Incorporation of competing entities	Intercompany comparison.	External environment of the company.
5	Global analysis	Analysis of non-economic variables.	Company as a whole.
6	Bankruptcy intervals and decisions	Assigning the probability of bankruptcy over time.	Deciding on bankruptcy.

Source: Author's research

As mentioned above, the selection of proper ratios appears to be crucial for any bankruptcy prediction model. The following paragraphs therefore explain in detail what those indicators are and why they were chosen.

When a company borrows funds, it is expected to pay regular installments. Debt provides the basis for financial leverage since shareholders obtain the remaining amount once the creditors are paid off. Regarding the amount of debt, the extent of financial leverage seems to be a necessary monitoring variable.

There are many ways to look at financial leverage. In the CCB model, the value of liabilities is added to the ratio of long-term debt to total capital, because long-term liability agreements (lease) oblige the company to pay a series of fixed payments. The debt ratio can thus be defined as (1.1):

$$\frac{Long-term\ Debt + Lease\ Value}{Long-term\ Debt + Company\ value + Capital} \tag{1.1}$$

It should be noted that this ratio uses book values, not market values. The market value of a business determines whether the creditors will get their money back. Using the market value of the debt, therefore, seems more appropriate.

The above-defined debt ratio considers only long-term debt obligations. The current ratio defined as the difference between total liabilities and equity (debt capital) to total liabilities is not used by the CCB model. EBIT and depreciation-to-interest coverage ratio represent another measure of financial leverage.

Earnings to interests' ratio is defined by the relationship (1.2):

$$\frac{EBIT + Assets}{Interest} \tag{1.2}$$

Regular interest payments are an obstacle that a company has to deal with in time to avoid bankruptcy. The ratio constructed this way provides information on when the interest payments will no longer be covered by earnings. This value does not include fixed liabilities (regular repayments of existing debt, long-term lease payments).

If the volume of company loans increases, or if creditors provide their funds, the total coverage of the debt by assets is not absolutely decisive. This issue becomes serious in case the capital was provided to the company for a shorter time horizon. The CCB model is, however, a prediction model with standard five-year analysis.

The creditor/analyst must assess whether the company will have enough cash to repay the debt, despite the shorter time horizon. The focus should therefore be on liquid assets which have more reliable values. The weight of the liquidity ratio is insignificant in the model, as liquidity ratios are highly volatile. The ratio of net working capital to total assets is considered as the gross ratio of potential cash (1.3).

$$\frac{Current\ Assets - (Outstanding\ Debt + Payables + Other\ Liabilities)}{Total\ Assets} \tag{1.3}$$

The introduction of the current ratio (current assets to liabilities) that serves the same purpose, could be criticized. When a company borrows a large number of funds from a creditor and invests it in marketable securities, the net working capital does not change, but the current ratio does. For this reason, short-term investments/debts are not used to calculate the current ratio. Sales of selected assets can also be included in the process of monitoring financial distress.

The liquidity of assets also plays an important role. Cash, marketable securities, and outstanding receivables are a priority. The numerator of the ratio can be the net of receivables.

For bankruptcy purposes, the version without receivables seems like a more suitable option (1.4):

$$\frac{Cash + Marketable\ Securities}{Current\ Liabilities} \tag{1.4}$$

In the CCB model, the relationship (1.4) is again increased by receivables so that the numerator of the current quick ratio is not changed. The denominator contains current expenses. The ratio (1.4) transforms to an interval measure that uses the average daily operating expenses in the denominator.

$$\frac{Cash + Marketable\ Securities + Receivables}{Daily\ Operating\ Costs} \tag{1.5}$$

It follows from the nature of the relationship (1.3) that the analysis requires longer time span than just one calendar year. The denominator represents an average. The interval rate provides information on the number of days during which the amount of liquid assets will be sufficient, even if no other cash is available to the company.

The CCB model measures company's performance with the return on total assets. Income is defined as earnings before interest, but after tax. If only operating performance is to be measured, we need to add interest tax shields to the taxes. This allows to obtain taxes that the company would pay if it was fully funded by shares. Using the tax rate of 20%, the return on total assets will be determined by the relationship (1.6):

$$\frac{EBIT - (Tax + Shield)}{Average\ Total\ Assets} \tag{1.6}$$

The analyzed company has a return on total assets of 7.3%, while its EBIT in the amount of CZK 1,190k is adjusted for a/ taxes in the amount of CZK 399k and b/ interest tax shields. These shields are obtained by multiplication of the tax rate and net interest (that is 0.20 × 151k CZK). Rising assets in the denominator put pressure on lower returns. This measurement finds its application precisely in the framework of intercompany comparison of entities that may have a significantly different debt ratio.

All companies should achieve a higher return on assets, but their capabilities are limited by competition. If the expected return on assets is fixed by competition, the company must opt for a compromise between a/ the ratio of sales to assets and b/ the profit margin. The actual procedure will vary by industry. In the textile industry, the low ratio of sales to assets is offset by a higher margin, i.e. revenues relative to sales.

Based on the results of the market efficiency tests, described in the previous chapters, we can assign market value ratios to the analyzed ratios of the CCB model. Even though the payout ratio does not fit into this group, it is the only ratio characterizing the external dividend environment. Equation (1.7) provides information on how much of the earnings are paid out in the form of dividends. In the event of a stronger decline in corporate income, there is no reduction in dividends. However, if the income is variable, the company's management sets a low payout ratio. When the income drops unexpectedly, the payout ratio tends to temporarily increase.

Similarly, if management predicts a higher income in the future, it may pay higher dividends. Incomes not paid in dividends are again reactivated in business operations.

$$\frac{Dividents}{Earnings\ per\ Share} \tag{1.7}$$

$$1-\frac{Dividents}{Earnings\ per\ Share} \tag{1.8}$$

Multiplication of the relationship (1.8) by the return on capital allows to find out how fast the shareholders' investment is growing due to the activation of earnings. The following applies to the analyzed company (1.9):

$$\frac{Debt-Dividents}{Earnings\ per\ Share} \times \frac{Earnings\ per\ Share}{Capital} \tag{1.9}$$

The CCB model compares this value with yields from previous years. The way in which dividends (dividend policy) are determined has been sufficiently described and confirmed in the past (Lintner, 1956). Lintner's model explains dividend payments as follows. The dividends in the following year di_1 is equal to the constant share of earnings per share Es (1.10):

$$\text{I. } di_1 = target\ dividend = target\ ratio \times Es \tag{1.11}$$

The dividend change will be equal to (1.12):

$$di_1 - di_0 = changed\ target = target\ ratio \times Es - di_0 \tag{1.12}$$

Companies rely on shareholders preferring a steady rise in dividends. Therefore, even in conditions that seem to guarantee an increase in dividends, companies take a partial step towards their target payment. Dividend changes correspond to the model (1.13):

$$di_1 - di_0 = pace\ of\ adaptation \times target\ change = \\ = pace\ of\ adaptation \times (target\ ratio \times Es - di_0) \tag{1.13}$$

The more conservative the company is in terms of the capital structure, a/ the slower it moves towards the goal, and b/ the lower the pace of adaptation is going to be. The CCB model shows that dividends depend in part on a/ current results and b/ dividends in the previous year.

These depend on the dividends in the year prior. Therefore, dividends can be recorded as a weighted average of current/past earnings. When current earnings are growing, yet less than in the previous year, The probability of the increase in the amount of dividends is the greatest.

Another monitored group within the CCB model is the a/ market value ratios or b/ ratios combining the accounting / market aspect.

$$\frac{Share\ Price}{Earnings\ per\ Share} \tag{1.14}$$

The price to earnings ratio (1.14), or P/E, is a common evaluation benchmark used by investors. If the assumption of a steady growth of dividends is met, the current share price is as follows (1.15):

$$\frac{di_1}{r_i - g} \tag{1.15}$$

In this relationship, di_1 stands for the expected dividend in the next year, r is the return that investors demand for similar investments, and g is the expected rate of dividend growth. The P/E ratio can be identified by dividing by expected earnings per share. A high P/E ratio means that:

1) investors expect significant dividend growth or,
2) the stock is not particularly risky, meaning that investors are ready for lower return, or
3) the company expects a significant average growth, therefore it pays out a large share of earnings.

The last fundamental characteristic observed within the CCB model is the relationship between the share price and its book value (1.16):

$$\frac{Share\ Price}{Share\ Book\ Value} \tag{1.16}$$

This figure provides an external perspective on the bankruptcy prediction purposes, the overall property structure of the company is assessed. Revalued assets / liabilities seem to be an optimal choice within the CCB model.

The last characteristic (1.16) can be substituted/supplemented with Tobin's q. The starting point is the market value of the company's debt/equity to the market reproduction costs of replacing the company's assets. This ratio is similar to the market/book value ratio, except that the numerator q includes all debt + equity of the company, not just net equity. Similarly, the denominator covers all assets and not just net capital. These assets are reported in replacement costs, not acquisition costs. The effect of inflation could also be considered here.

The ratios analyzed above describe, yet do not explain, whether/how the debt, which is crucial for the prediction of financial distress, affects the company's earnings. Indebtedness increases the expected flow of earnings per share, but not the share price. This is because the expected flow of earnings is precisely offset by a change in the rate at which earnings are capitalized.

The expected return on assets of the company r_a is equal to the expected operating income divided by the total market value of securities:

$$\frac{\textit{Expected Operating Income}}{\textit{Market Value of all Secturities}} \tag{1.17}$$

In perfect capital markets, companies do not decide on borrowing funds based on the operating income or the total market value of its securities. Therefore, the expected return on assets r_a of the company is not affected by the decision to borrow funds. In the case of the analyzed company, it can be assumed that the investor controls the entire debt of the company, including shares. The investor has a natural right to operating income. Therefore, the expected return on the portfolio = r_a. Expected return on portfolio = weighted average of expected returns for individual holders. The expected return on the portfolio composed of all the company's securities is equal to the following structure. Expected return on assets = the sum of the debt ratio multiplied with expected return on debt (r_D) and the equity ratio multiplied with the expected return on capital (r_E). Relationship (1.18) can be noted as follows:

$$rA = \left(\frac{Debt}{Debt + Equity} \times rD\right) + \left(\frac{Equity}{Debt + Equity}\right) * rE \tag{1.18}$$

The equation can be adjusted to get the relationship for r_E- the expected return on equity of the indebted company. Expected return on capital = expected return on assets + debt-to-capital ratio multiplied with the difference between expected return on assets + expected return on debt. Relationship (1.18) is modified as follows (1.19):

$$rE = rA + \frac{Debt}{Equity}(rA - rD) \tag{1.19}$$

The expected rate of return on the debt of an indebted company is directly proportional to the debt-to-equity ratio (D/E), expressed in market values. The growth depends on the difference between r_A, the expected return on the company's portfolio of all securities, and r_D, the expected return on debt:

$$r_E = r_A \tag{1.20}$$

4. Empirical data and analysis

The financial indicators and subsequently financial ratios were obtained for a total of 199 companies. For the sake of brevity, the Table 2 as well as Tables 3 and 4 in the following chapter include only a sample of 31 companies so that the reader could get an idea of how exactly the data were processed.

Table 2: Analyzed entities

Number	Company	Registration n°
1.	2P SERVIS s.r.o	280 49 390
2.	5. AVENUE EXCLUSIVE s.r.o	284 34 501
3.	Actual spinning a.s	287 11 891
4.	Adient Strakonice s.r.o	280 85 272
5.	ALIJAN s.r.o	269 16 258
6.	ALLIGARD s.r.o	252 00 933
7.	ALONSO & co., s.r.o	264 04 991
8.	ALTREVA spol. s.r.o	607 07 879
9.	AMANN s.r.o	472 83 416
10.	ANE KONSULT spol. s r.o	648 25 477
...		
90.	KONTEST s.r.o	277 15 019
91.	KONYA - M s.r.o.	263 77 675
92.	KORDÁRNA Plus a.s	277 58 711
93.	Koutný spol. s r.o	607 50 197
94.	Kümpers Textil s.r.o.	632 17 961
95.	KUS PRÁCE s.r.o	283 40 361
96.	KVD CZ s.r.o	260 72 351
97.	L & L STUDIO PRAHA s.r.o	276 58 821
98.	LASY, s.r.o	262 43 814

Number	Company	Registration n°
99.	LEATHER TRADE s.r.o	288 90 001
100.	LEKA Grünau a.s	255 81 856
...		
190.	VŘÍDLO, výrobní družstvo	000 28 860
191.	VŠEZEP s.r.o	008 70 838
192.	VÚB a.s	455 34 420
193.	Výrobní družstvo VKUS Frýdek-Místek	000 31 330
194.	VÝVOJ, oděvní družstvo v Třešti	000 30 732
195.	W & P company s.r.o	263 84 701
196.	WLADITA Ltd, s.r.o	261 38 336
197.	X tašky s.r.o.	270 83 446
198.	YATE spol. s r.o	432 26 990
199.	ZITA studio s.r.o	279 86 365

Source: Business Register maintained by the Czech Statistical Office

A total of 14 financial variables (Table 3) is obtained for each company and then processed in several steps. First, the variables are used to define financial ratios (Table 4). Then the original value x_{ij} is transformed to standardized variable u_{ij}, in the case of an indicator with the character +1 (2.1) and in the case of an indicator with the character -1 (2.2):

$$u_{ij} = \frac{x_{ij} - x_{pj}}{s_{xj}} \tag{2.1}$$

$$u_{ij} = \frac{x_{pj} - x_{ij}}{s_{xj}} \tag{2.2}$$

where the value of x_{ij} is the value of the j-th indicator in the i-th company, x_{pj} is the arithmetic mean calculated from the values of the j-th indicator and s_{xj} is the standard deviation obtained from the values of the j-th indicator.

Then an arithmetic mean (2.3) and standard deviation (2.4) of the standardized values are calculated:

$$d_{np} = \frac{\sum_{j=1}^{m} u_{ij} \cdot p_j}{\sum_{j=1}^{m} p_j}, i = 1, 2, \dots , n \tag{2.3}$$

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{2.4}$$

Finally, the companies are ranked according to the arithmetic mean by the likelihood of bankruptcy, where the lower the mean value, the higher the probability of bankruptcy.

As mentioned in the previous chapters, the CCB model was applied to a set of 199 existing companies operating in the same domain of economy (textile industry) and in the same geographical area (the Czech Republic). The reason for this is obvious, as comparing companies operating in various industries and/or countries would result in misleading predictions.

In accordance with the methodology, the first step of analysis consisted of obtaining financial statements reported by companies and compiling selected financial indicators or variables. Data from current financial statements could not be used as it would require a certain waiting period in order to verify the prediction accuracy of the model. For this reason, the model works with the year 2013 as the starting point for prediction and a seven-year time span for predicting the onset of bankruptcy. For the sake of brevity, the data in Table 3 represent only one out of 7 years that were used for the prediction.

The variables in Table 3 then served as the basis for financial ratios (see Table 4) that are essential for the prediction. These include short-term receivables turnover rate, short-term payables turnover rate, other payables, immediate liquidity, quick ratio, current liquidity, return on investments, return on equity, return on operating capital, debt ratio, net working capital, financial coverage of debt capital, interest coverage and coverage of fixed assets with long-term capital. The reasoning behind the choice of these particular indicators was already discussed in the previous sections of this article.

The next step consisted of determining the arithmetic mean of the indicators (x_{pj}) and standardized variable (S_{xj}) for each of the analyzed ratios using the formulas (2.3) and (2.4). Standardized variables were defined for the monitored indicator and monitored entity. The sum column represents the simple sum of the standardized values. The average of the standardized values is obtained by dividing the sum by the number of monitored variables. The use of differentiated weights would lead to a distortion of the final ranking, as the selection of the monitored ratios was made while taking into account the goal of detecting impending bankruptcy. The calculation, therefore, considers unit weights that do not distort the final ranking.

Companies were finally arranged in Table 5 with those with the best prospects (lowest probability of bankruptcy) at the top of the table to those with the worst prospects (high probability of bankruptcy) at the bottom. The average value of CCB indicator ranges between 12.15 and -0.61. Companies were divided into three groups defined by two threshold values – lower 9% and 22%. The 15 companies thus represent entities that are at high risk of bankruptcy and the 34 companies is considered approaching bankruptcy. We can therefore conclude that the situation of a total of 49 textile/clothing companies from the reference package is considered problematic. The remainder of companies falls within the category for which bankruptcy cannot be predicted at the moment.

The final step lies in the comparison of prediction provided by the CCB Model and the actual development of analyzed companies during the years 2013-2020. Table 6 contains 9 companies that went bankrupt or became insolvent as well as information whether the CCB Model was able to anticipate that state.

Table 6: Actual development of companies

Company Serial No.	Company Name	Bankruptcy	Date	Predicted
16.	ATRON, s.r.o	YES	Nov. 1, 2019	No
33.	BRULEKO s.r.o	YES	Jan. 1, 2019	No
47.	DIVERSO KV s.r.o.	INSOLVENCY	Jan 16, 2017	No
49.	Durocas Czech s. r. o.	YES	Nov. 5, 2019	Yes
91.	KONYA – M s.r.o.	YES	Nov 9, 2018	No
139.	PRVNÍ CHRÁNĚNÁ DÍLNA s.r.o	INSOLVENCY	Jan. 23, 2020	Yes
144.	RESCUE s.r.o	YES	Nov. 21, 2019	No
185.	VIGA BEST s.r.o.	YES	Apr. 27, 2019	No
152.	Schwinn Tschechien s.r.o	LIQUIDATION	Apr. 1, 2020	Yes

Source: Business Register maintained by the Czech Statistical Office

The Table 6 contains information about the companies which, due to various factors and variables affecting the market, eventually declared bankruptcy, insolvency or liquidation. All failed companies were limited-liability companies, and the issues of bankruptcy, insolvency, and liquidation occurred between 2017 and 2020. The last column of the table is essential for assessing the model accuracy as it reveals whether the failure was predictable or unpredictable by the CCB model. Three of the failed companies, namely Durocas Czech s.r.o., PRVNÍ CHRÁNĚNÁ DÍLNA s.r.o, and Schwinn Tschechien s.r.o. were evaluated as approaching or being at high risk of bankruptcy. The rest of the companies belong to those companies for which bankruptcy is unpredictable. (yet not completely ruled out either).

5. Results and discussion

The CCB model used financial indicators from the last 7 years in order to calculate financial ratios relevant for bankruptcy prediction. These ratios were then used to determine the main CCB indicator (ranging from -0,61 to 12,15) where the following rule is applied – the lower the indicator, the higher the probability of financial distress. As shown in Table 5, a total of 49 companies was thus marked as approaching bankruptcy or being at high risk of bankruptcy. Three out of nine companies that actually went bankrupt during the analyzed period can be found in this group. In order to objectively assess the efficiency and accuracy of the CCB model, we first need to discuss what the ambitions of the model are.

The CCB model is primarily an auxiliary tool for management. It provides reasonably accurate estimates of a company's current situation and its evolution shortly. However, its outputs are not visible in binary terms. In other words, even if, a company according to the results obtained via the CCB model, is not threatened by bankruptcy, it should not suppose that there is absolutely no risk of getting into financial problems. Likewise, a company that finds itself in the lower end of Table 5 should not immediately opt for drastic measures to avoid bankruptcy. The company should rather obtain the information through the CCB model, primarily because the CCB model can help the company lead a more complex and in-depth analysis of its financial situation. Therefore, the model has mainly preventive functions and needs to be used as such. One of the greatest advantages of the model is the simplicity of its use. Despite the extensive data set, both in terms of the number of companies and the number of financial statements used as a base for the prediction, it remains easy to navigate, and the outputs are very straightforward so that there is no room for misinterpretations. One could argue that more advanced prediction methods, such as machine learning predictions, outperform the CCB model in terms of accuracy. There is no doubt that AI has seen increasing progress in recent years, and the accuracy of AI-based predictions is ever-increasing, too. These analyses, however, require a state-of-the-art software program and such data sets that will provide good results. Also, even though not a minor factor, it requires a person or a team who understands the complexity of machine learning, or else this service needs outsourcing.

All the above leads to higher costs of performing such an analysis. For small businesses, careful of every additional expense, advanced prediction methods, therefore, may be unattainable. That is where the CCB model could be perhaps most useful; in small businesses that want to obtain a reasonably accurate estimate of the company's situation without incurring excess costs.

6. Conclusions

Even though financial distress or bankruptcy may have a slightly different definition depending on the legislation applicable in a particular country or state, it has always been perceived as a situation that should be avoided. Prevention of bankruptcy is always more convenient and less expensive than resolving the bankruptcy that has already occurred. Due to the current pandemic resulting in uncertainty in the markets, we expect the interception of the potential risk of financial distress will move even higher in the list of management priorities.

The presented CCB model is an analysis instrument specifically designed for this purpose. The research has the main objective to detect the impending bankruptcy signs and has primarily been based on the selected indicators of the company's financial health. It includes sustainable development, optimal capital structure, and liquidity. Ensuring the applicability of the model in practice was one of the key objectives of the research. Its explanatory power was tested on the data of 199 companies operating in the textile/clothing industry in the Czech Republic. All the data necessary for the prediction were from standard financial statements. The comparison of predicted development and actual evolution of tested entities has shown that the CCB model was able to predict bankruptcy/insolvency proceedings in one-third of the cases, even though the number of companies that found themselves in this situation was rather small, considering the extent of the referential package (only 9 out of 199).

The CCB model leaves enough room for future research. The first and most obvious way of developing the model would be to apply it to a set of companies operating in a different sector and compare its accuracy to the analysis accuracy herein. Secondly, researchers could put focus on modifying the financial ratios used for the analysis by either adding new ratios to the mix or reducing the number of ratios. The results could then again be compared with the results of the current CCB model. According to the research hypothesis, as described in the introduction, the CCB model should provide quite reliable results, mainly because it uses data from companies operating in the same sector as well as the same country. Since failed companies represented a mere fraction of the referential package, the author believes that the accuracy of the prediction provided by the model has met the expectations. In addition, any assessment of the results must involve the crucial role of the model, which is *the preventive* role. Had the model been used in time by the companies that were eventually evaluated as "approaching the bankruptcy". In three cases the management might have taken necessary steps to deter the bankruptcy. That is quite a high number because the model in question does not require the use of complex software or algorithms, nor is it demanding in terms of financial costs, which is an important factor, especially for small to medium-sized companies.

The research results lead us to conclude that the described model represents a suitable and reliable tool for detecting financial distress in companies. Bankruptcy or insolvency is a legal situation arising under specifically-defined conditions that may differ by country. Therefore, the CCB model should be perceived merely as an auxiliary tool for the management, and the company's outputs should prompt a further analysis or expert opinion of its circumstances.

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Praktična primjena CCB modela u Češkoj

Vitezslav Halek[1]

Sažetak

Cilj ovog istraživanja bio je predstaviti novi model predviđanja stečaja i potom ovu originalnu metodu predviđanja primijeniti u praksi. Model Come Clean Bankruptcy (ili CCB) koristi relevantne financijske pokazatelje i omjere kako bi na vrijeme utvrdio znakove nadolazećih financijskih problema tako da ih uprava može izbjeći poduzimanjem odgovarajućih mjera. Model je korišten na podacima za 199 subjekata koji posluju u tekstilnoj/odjevnoj industriji u Češkoj. Analizom tih podataka za sedam prethodnih godina moguće je predvidjeti za koje je tvrtke vjerojatnije da upadnu u tešku financijsku situaciju. Ta se predviđanja zatim uspoređuju sa stvarnim razvojem tih tvrtki u razdoblju 2013. – 2020. godine kako bi se provjerila učinkovitost i upotrebljivost modela u korporativnoj stvarnosti. Istraživanje je pokazalo da su poduzeća koja su u analiziranom razdoblju stvarno otišla u stečaj predstavljala samo djelić skupa podataka (otprilike 4,5 %). Unatoč malom broju financijskih pogrešaka koje su se dogodile tijekom analiziranog razdoblja, model CCB-a je u trećini slučajeva uspio detektirati nadolazeći stečaj.

Ključne riječi: *Model stečaja, predviđanje rizika, financijski problemi, Češka Republika*

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Appendices

Table 3: Selected Financial Variables

Ref. No.	Company	Short-Term Receivables Turnover	Short-Term Payables Turnover	Other Payables	Immediate Liquidity	Quick Ratio	Current Liquidity	Return On Investments	Return On Equity	Return On Operating Capital	Debt Ratio	Net Working Capital	Financial Coverage Of Debt Capital	Interest Coverage	Fixed Assets Coverage With Long-Term Capital
1.	2P SERVIS s.r.o	0,0000	0,0000	0,6656	0,5216	1,1786	1,3604	0,8851	0,8851	0,1387	0,6656	0,2399	2,2492	0,0000	0,2814
2.	5. AVENUE EXCLUSIVE s.r.o	x	x	0,7019	0,5317	0,5357	1,4246	-0,8692	0,0000	x	0,7019	0,2981	-2,7097	0,0000	0,0000
3.	Actual spinning a.s	0,0000	53,9461	0,1683	0,0000	0,0093	0,0093	-0,2061	-0,2070	-0,1553	0,3067	-0,1511	-1,7557	0,0000	1,1786
4.	Adient Strakonice s.r.o	104,5218	111,4530	0,6384	0,1414	1,1574	2,1041	-0,0868	-0,3465	-0,1447	0,7924	0,1975	-11,1146	-0,2653	0,7437
5.	ALIJAN s.r.o	102,2878	106,2731	0,5467	0,3830	1,2021	1,8085	0,1893	0,6964	0,1439	0,8133	0,2533	6,2564	0,0000	0,5971
...															
90.	KONTEST s.r.o	0,0000	0,0000	0,8975	0,0995	0,9254	0,9640	0,5631	0,4656	0,0151	0,8975	-0,0322	14,7710	0,0000	1,0560
91.	KONYA - M s.r.o.	4,1216	41,3491	0,5044	0,1223	0,3938	2,2026	0,1077	0,2068	0,0126	0,8282	0,5389	13,9336	0,1738	0,0236
92.	KORDÁRNA Plus a.s	x	x	0,0073	1,4000	136,1333	136,1333	0,0266	0,0232	x	0,0073	0,9927	0,2778	0,0000	0,0000
93.	Koutný spol. s r.o	34,3594	20,2779	0,0417	3,0234	4,2321	7,5752	0,1233	0,0757	0,0646	0,1158	0,7612	1,0616	0,0000	0,1084
94.	Kümpers Textil s.r.o.	15,1742	25,1299	0,5871	0,0551	0,4942	0,6440	0,0831	0,1027	0,0277	0,6616	-0,0468	9,1622	0,5191	1,0230
95.	KUS PRÁCE s.r.o	x	x	0,0000	x	x	x	0,0000	0,0000	x	0,0000	1,0000	x	x	0,0000
...															
190.	VŘÍDLO, výrobní družstvo	35,6543	12,1675	0,0413	2,2848	4,0795	7,8470	-0,0223	-0,0223	-0,0216	0,0736	0,5041	-3,5658	0,0000	0,4500
191.	VŠEZEP s.r.o	53,4709	69,9363	0,5382	0,1504	1,0684	2,6063	0,0453	0,0629	0,0393	0,6478	0,2347	16,7312	0,4016	0,7211
192.	VÚB a.s	57,7528	10,0242	0,2753	1,4449	2,1170	2,5624	0,0808	0,0719	0,0653	0,2968	0,3329	4,6689	0,0229	0,6048
193.	Výrobní družstvo VKUS Frýdek-Místek	24,5168	18,4869	0,2272	0,3166	1,2447	2,4590	0,2133	0,2314	0,0529	0,3691	0,3515	2,2791	0,0983	0,5373
194.	VÝVOJ, oděvní družstvo v Třešti	30,7162	64,8016	0,1248	0,9657	1,5001	2,2161	0,1407	0,1208	0,0615	0,3537	0,3847	3,6760	0,0000	0,4395
195.	W & P company s.r.o	0,0000	0,0000	0,9744	0,0343	0,1175	0,9318	0,0860	0,7823	0,0084	0,9744	-0,0357	23,7872	0,4596	0,7702

Source: Author’s calculation

Table 4: Financial Ratios with Standardized Variable and Arithmetic Mean

Company Serial N°	Debt Ratio	Earnings Multiplied By Interests	Working Capital To Total Assets	Quick Ratio Net Of Re-ceivables	Operating Cost	Interest Tax Shields	Return On Capital	Price-Earn-ing Ratio	Expected Return On Debt	(Q) Value	Indebted Company	Sum Total	Average	Rank
X_{pj}	1,67	295,51	-0,05	0,92	19,12	0,16	0,09	11,72	0,21	2,27	3,04	×	×	×
S_{xj}	9,42	1681,02	3,14	6,15	224,43	1	1	44,98	1,05	3,85	46,99	×	×	×
1.	-0,16	-0,02	0,26	0,33	-0,06	0,07	0,1	-0,14	0,05	-0,25	-0,06	0,12	0,01	57.
2.	3,79	-0,17	0,76	-0,14	-0,08	2,11	2,15	0,88	-0,12	0,91	2,2	12,29	1,12	7.
3.	-0,11	0	0	-0,15	-0,07	0	0	0	0	-0,41	-0,06	-0,8	-0,07	122.
4.	-0,09	-0,18	0,05	-0,13	-0,06	-0,1	2,05	-0,24	-0,15	-0,29	2,26	3,12	0,28	16.
5.	-0,09	-0,18	0,05	-0,13	-0,07	-0,14	-0,26	1,53	-0,44	-0,26	-0,05	-0,04	0	60.
...														
90.	-0,12	-0,12	0,13	-0,05	-0,07	-0,09	-0,06	-0,08	-0,07	-0,27	0	-0,8	-0,07	122.
91.	-0,07	-0,15	0,09	-0,14	-0,08	-0,09	-0,13	-0,11	1,16	-0,1	0,02	0,4	0,04	50.
92.	-0,14	-0,16	0,11	-0,14	0,07	0,03	0,02	-0,09	-0,05	-0,22	-0,06	-0,63	-0,06	109.
93.	-0,17	3,19	0,27	0,56	-0,06	0,07	0,05	-0,09	-0,01	-0,28	-0,06	3,47	0,32	14.
94.	-0,1	-0,17	-0,15	-0,15	-0,08	-0,05	-0,08	0,37	-0,1	-0,33	-0,06	-0,9	-0,08	142.
95.	0,11	3,21	0,15	-0,14	-0,07	0,01	-0,05	-0,24	-0,06	-0,37	-0,04	2,51	0,23	19.
...														
190.	-0,17	-0,11	0,2	0,47	-0,06	-0,11	-0,08	0,11	-0,19	-0,36	-0,06	-0,36	-0,03	77.
191.	-0,11	-0,17	-0,13	-0,14	-0,07	-0,04	-0,07	0,63	-0,08	-0,5	0	-0,68	-0,06	109.
192.	-0,15	-0,13	0,09	-0,03	-0,06	-0,04	-0,04	0,13	-0,12	-0,41	-0,06	-0,82	-0,07	122.
193.	-0,08	-0,15	-0,25	-0,12	-0,08	-0,1	-0,17	0,76	-0,13	0,19	-0,05	-0,18	-0,02	68.
194.	-0,15	-0,1	0,13	0,05	-0,07	0	0	0,02	-0,06	-0,25	-0,06	-0,49	-0,04	89.
195.	-0,08	-0,17	-0,33	-0,14	-0,08	-0,13	-0,08	-0,2	-0,98	-0,27	-0,06	-2,52	-0,23	198.

Source: Author’s calculation

Table 5: Ranking of Companies based on Probability of Bankruptcy

	Rank	Average Value (According to Table 4)	Analyzed Company (Reference n.)
Bankruptcy cannot be Predicted	1.	12,15	74.
	2.	8,84	76.
	3.	2,89	140.
	4.	2,28	83.
	5.	2,03	134.
	6.	1,97	132.
	7.	1,12	2.
	8.	0,84	164.
	9.	0,54	165.
	10.	0,43	31.
	11.	0,40	156.
	12.	0,39	119.
	13.	0,37	154.
	14.	0,32	93.
	15.	0,31	163.
	16.	0,28	4.
	17.	0,25	145.
	18.	0,24	11.
	19.	0,23	95.
	19.	0,23	110.
	19.	0,23	118.
	22.	0,22	54.
	22.	0,22	182.
	22.	0,22	184.
	25.	0,20	63.
	26.	0,19	131.
	27.	0,18	42.
	27.	0,18	117.
	29.	0,15	39.
	29.	0,15	116.
	31.	0,14	16.
	31.	0,14	127.
	33.	0,13	10.
	34.	0,12	44.
	34.	0,12	169.
	36.	0,10	7.
	37.	0,08	12.
	37.	0,08	59.
	37.	0,08	112.
	40.	0,07	15.
	40.	0,07	33.
	40.	0,07	89.
	40.	0,07	121.

	Rank	Average Value (According to Table 4)	Analyzed Company (Reference n.)
Bankruptcy cannot be Predicted	44.	0,06	73.
	44.	0,06	137.
	44.	0,06	176.
	47.	0,05	32.
	47.	0,05	43.
	47.	0,05	114.
	50.	0,04	8.
	50.	0,04	91.
	52.	0,03	65.
	52.	0,03	120.
	52.	0,03	166.
	55.	0,02	85.
	55.	0,02	153.
	57.	0,01	1.
	57.	0,01	109.
	57.	0,01	146.
	60.	0,00	5.
	60.	0,00	48.
	60.	0,00	68.
	60.	0,00	148.
	60.	0,00	179.
	65.	-0,01	107.
	65.	-0,01	144.
	65.	-0,01	172.
	68.	-0,02	14.
	68.	-0,02	34.
	68.	-0,02	47.
	68.	-0,02	53.
	68.	-0,02	64.
	68.	-0,02	71.
	68.	-0,02	150.
	68.	-0,02	173.
	68.	-0,02	193.
	77.	-0,03	45.
	77.	-0,03	56.
	77.	-0,03	72.
	77.	-0,03	75.
	77.	-0,03	96.
	77.	-0,03	100.
	77.	-0,03	111.
	77.	-0,03	122.
	77.	-0,03	126.
	77.	-0,03	138.
	77.	-0,03	185.
	77.	-0,03	190.

	Rank	Average Value (According to Table 4)	Analyzed Company (Reference n.)
Bankruptcy cannot be Predicted	89.	-0,04	18.
	89.	-0,04	40.
	89.	-0,04	55.
	89.	-0,04	161.
	93.	-0,05	6.
	93.	-0,05	17.
	93.	-0,05	28.
	93.	-0,05	36.
	93.	-0,05	46.
	93.	-0,05	50.
	93.	-0,05	66.
	93.	-0,05	102.
	93.	-0,05	123.
	93.	-0,05	125.
	93.	-0,05	128.
	93.	-0,05	155.
	93.	-0,05	162.
	93.	-0,05	171.
	93.	-0,05	194.
	93.	-0,05	200.
	109.	-0,06	9.
	109.	-0,06	30.
	109.	-0,06	35.
	109.	-0,06	62.
	109.	-0,06	87.
	109.	-0,06	92.
	109.	-0,06	103.
	109.	-0,06	143.
	109.	-0,06	147.
	109.	-0,06	149.
	109.	-0,06	157.
	109.	-0,06	175.
	109.	-0,06	191.
	122.	-0,07	3.
	122.	-0,07	22.
	122.	-0,07	29.
	122.	-0,07	51.
	122.	-0,07	58.
	122.	-0,07	79.
	122.	-0,07	81.
	122.	-0,07	82.
	122.	-0,07	84.
	122.	-0,07	90.
	122.	-0,07	104.
	122.	-0,07	113.

	Rank	Average Value (According to Table 4)	Analyzed Company (Reference n.)
Bankruptcy cannot be Predicted	122.	-0,07	136.
	122.	-0,07	151.
	122.	-0,07	186.
	122.	-0,07	189.
	122.	-0,07	192.
	122.	-0,07	197.
	122.	-0,07	198.
	122.	-0,07	199.
	142.	-0,08	13.
	142.	-0,08	19.
	142.	-0,08	38.
	142.	-0,08	69.
	142.	-0,08	80.
	142.	-0,08	94.
	142.	-0,08	124.
	142.	-0,08	159.
	142.	-0,08	181.
Approaching Bankruptcy	151.	-0,09	20.
	151.	-0,09	26.
	151.	-0,09	37.
	151.	-0,09	52.
	151.	-0,09	88.
	151.	-0,09	98.
	151.	-0,09	115.
	151.	-0,09	130.
	151.	-0,09	135.
	151.	-0,09	152.
	151.	-0,09	174.
	151.	-0,09	188.
	163.	-0,10	57.
	163.	-0,10	77.
	163.	-0,10	86.
	163.	-0,10	196.
	167.	-0,11	60.
	167.	-0,11	78.
	167.	-0,11	97.
	167.	-0,11	129.
	167.	-0,11	133.
	167.	-0,11	168.
	167.	-0,11	170.
	174.	-0,12	21.
	174.	-0,12	25.
	174.	-0,12	49.
	174.	-0,12	67.
	174.	-0,12	105.

	Rank	Average Value (According to Table 4)	Analyzed Company (Reference n.)
Approaching Bankruptcy	174.	-0,12	180.
	174.	-0,12	183.
	181.	-0,13	23.
	181.	-0,13	24.
	181.	-0,13	27.
	181.	-0,13	106.
High Risk of Bankruptcy	186.	-0,14	41.
	186.	-0,14	61.
	186.	-0,14	108.
	186.	-0,14	142.
	186.	-0,14	158.
	186.	-0,14	167.
	186.	-0,14	177.
	186.	-0,14	187.
	194.	-0,16	178.
	195.	-0,17	139.
	196.	-0,18	160.
	197.	-0,19	99.
	198.	-0,20	70.
	199.	-0,23	195.
	200.	-0,61	101.

Source: Author’s research