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SECTORAL SPECIFICITIES OF APPLICATION OF BANKRUPTCY FORECASTING MODELS[1]

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ABSTRACT

The study had been undertaken to improve the methodology of bankruptcy forecasting by clarifying the normative values of the existing models considering industry allocation of companies and for the development of author's model of bankruptcy forecasting. First of all, the forecast accuracy for companies of 8 industries in current
standards of bankruptcy forecasting models had been evaluated. The application of the methodology of cART (classification And Regression Tree) allowed to specify the original normative values and offer new individual borders of estimation for each industry. The calculated values demonstrated a high forecasting ability and allowed to balance the indicators of prediction accuracy for bankrupt companies and the financially stable organizations. From a common set of financial indicators used in different models, the coefficients that has the most significance for prediction of bankruptcy were selected. We have developed a new model that demonstrates high accuracy of results within a given sample, and the standards of evaluation for companies in various industries. Practical application of the proposed developments will improve the efficiency and accuracy of prediction of bankruptcy, will allow to timely adjust the financial status of the companies threatened with bankruptcy.

KEY WORDS
BANKRUPTCY, FORECASTING OF BANKRUPTCY, FORECASTING MODELS, CLASSICAL MODEL, BANKRUPTCY BY INDUSTRY

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Trelevance of bankruptcy forecasting of economic entities resulted in large numbers of case studies. Among the main challenges of examining the issue we can single out the development of effective tools for evaluating the financial condition of the company, therefore many different models to determine the probability of bankruptcy have been developed.

Existing forecasting models represent some combination of the financial performance of the company that reasonably determines the probability of loss of financial stability, based on existing conditions. The accuracy of the forecast of a certain model impacts the timeliness of decision-making, directed to prevent financial insolvency.

Domestic and foreign authors propose a number of models that show fairly accurate results of forecasting and acquired the status of a classic. These include two-factor and five-factor model of E. Altman, models of D. Fulmer, model of R. J. Taffler and H. Tisshaw, G. Springate, R. S. and G. Saifullin and G. Kadykova, O. P. Zaitseva, etc. Classical models of bankruptcy forecasting were tested for many organizations and has demonstrated their accuracy and reliability, but testing on diverse samples have shown that the prediction results significantly differ depending on the size of the firm, its industry affiliation, legal organizational form, degree of state regulation, the government's presence among the shareholders and its share. The identified issue has been addressed with the new models, which turned out to be a lot of [LieuP. T., Linc. w., YuH. F., 2008; NamJ.H., JinnT., 2000; Bandyopadhyay A., 2006].

At the root of most bankruptcy forecasting models lies financial indicators (ratios) that characterize different aspects of the organization activity. Modern authors analyze a selection of the most representative indicators and the establishment of the correct standards of their evaluation.

Many foreign researchers have tried to compare the accuracy of predicting bankruptcy using accounting indicators and market data, to identify models and financial performance indicators that demonstrate the most accurate result [Li M.Y., Miu P., 2010; BauerJ., Agarwaal V., 2014; Tian S., Yu Y., Guo H., 2015;
L. chiaramonte, B. casu, 2017; F. Lin et al.,2014]. A major contribution to the development of this issue has been made by T. Korol, who systematized and explored 26 bankruptcy forecasting models using a sample of enterprises in Central Europe and Latin America. The models were divided into statistical models (logit and probit approaches, discriminant analysis models) and models based on "soft" computing (building artificial neural networks, genetic algorithm) [Korol T., 2013].

None of the considered models can't be called universal. Scientists seek to develop the most optimal model for bankruptcy predicting, but the large number of internal and external factors that determine the specifics of each company activity, does not allow to develop the perfect formula which can equally accurately predict the probability of bankruptcy for all organizations. That is why modern researches in the field of bankruptcy directed to the specification of the existing models, based on private characteristics of the companies under review, with the aim to improve the effectiveness of forecasting. In particular, the interpretation of assessment results of the financial condition of the organization is influenced by its industry affiliation.

In our study we made an attempt to improve the existing classical and modern models of bankruptcy forecasting by clarifying the values of the calculated indicators based on specificity of the industry of companies proposed by the authors.

First of all, 10 models of bankruptcy forecasting, both classic and modern, had been selected.

The performance of each model was tested at a sample of 5318 enterprises, which are divided into sub-groups by industry sector: manufacturing, agriculture, real estate, construction, hotels and catering, transport, science and trade. As a result, performance assessment boundaries calculated in the process of application of models, they were specified taking into account the industry specifics of the company.

The empirical basis of the study included the data of registers of accounting with the allocation of the company by industry:

- construction (716 enterprises, including 340 bankrupts);
- agriculture (727 enterprises, including 129 bankrupts);
- manufacturing industry (702 enterprises, including 339 bankrupts);
- construction (726 enterprises, including 349 bankrupts);
- hospitality and catering (380 companies, including 134 bankrupts);
- science (553 enterprises, including 263 of them that are bankrupts);
- trade (714 enterprises, including 334 bankrupts);
- transportation (800 enterprises, including 403 bankrupts).

We assumed that the belonging of the company to a certain industry has a significant impact on its activities. A similar idea had been repeatedly considered in the works of foreign and domestic authors [Sayari N.,c. S. Mugan, 2017; Ilysheva N. N., Kim N. V., 2007; Fedorova E. A., Dovzhenko S.E., F. Fedorov, F.Y., 2016]. When calculating most of the models use various financial ratios, normative values of which are recommended to be evaluated based on the average values of these indicators, logically to assume that the values calculated in the bankruptcy prediction models, should consider sectoral specificities of companies.

Of the huge number of models used to predict bankruptcy, we selected the most popular, variables of which best fit to formed sample of enterprises (table 1). Considered classical models such as the modified five-factor model of E. Altman, four-factor predictive model of R. J. Taffler and H. Tisshaw, G. Springate, four-factor model of R. Lis, model of R. S. Saifulina and G. Kadykova, have been repeatedly described and characterized in the economic literature. Their effectiveness has been tested and proven on a large sample of companies, so consideration of these models is still in the spotlight.

In conditions of significant growth of financial information volume and the diversity of challenges in forecasting the bankruptcy, the classical models are still widely used in practice, but their prognostic capability is not always high. Special attention should be paid to less studied models. Models of [GalvãoR. K. H., Becerra V. M., Abou-SeadaM., 2004; Šorins R., Voronova I., 1998; ZmijewskiM. E., 1984; Brîndescu-OlariuD., 2017] selected by the principle of compliance of the financial coefficients with the parameters available in
considered sample and the relative simplicity of calculation. However, we can still name many of similar models that have also demonstrated their effectiveness for certain companies. Let us consider the selected models in greater detail.

M. E. Zmijewski analyzed 17 models of bankruptcy forecasting, having assessed how the sample companies for testing the developed models has been formed. The limited empirical base used to test the model, does not allows us to speak about its universal applicability. Sam M. E. Zmijevski suggested a model on the basis of three financial ratios (returns on assets, the ratio of total liabilities to total assets, current liquidity ratio), by assuming that if the calculated index is greater than 0, the reporting company must be attributed to the number of bankrupts.

R. Šorins, I. Voronova united in their model the rate of return on assets by EBIT, turnover of total assets, the ratio of net working capital to total assets, the ratio of retained earnings to total assets, the ratio of book value of equity to total liabilities. Three of listed ratios focus on a comparison of individual characteristics of the company's activities with the value of its total assets, thus, the basis of assessment of financial stability is the assets of the economic subject. If calculated in accordance with this model index is less than 0 then the company should be attributed to the number of bankrupts.

[1] The Article is based on the results of researches carried out at the expense of budget funds and assigned by the state order of the Financial University 2017.

Model of D. D. Brîndescu-Olariu developed in conditions of the rapid increase in the number of insolvent companies in Romania. Under the influence of the economic crisis and accession to the European Union there is an urgent need to find a convenient and accessible tool that will allow us to assess the financial condition of a company. As a result, a logistic regression model that takes into account five ratios was built. As noted by the author, this model does not give an absolute prediction accuracy, however, ensures the correct grouping of companies with respect to their financial stability. The model was tested on a sample consisting of 53 thousand companies.

R. K. H. Galvão, V. M. Becerra, M. Abou-Seada was looking for the most accurate and effective coefficients for the purpose of forecasting of bankruptcy. After analyzing the existing models and technology of financial indicators selection to build them, the authors identified the advantages and disadvantages of different coefficients, built a model of bankruptcy forecasting using prior and genetic (artificial) selection. The final model synthesizes ratios of total assets turnover, ratio of the net working capital to total assets, the ratio of retained earnings to total assets, ratio of book value of equity to total liabilities. Thus, for this model, in part, the same criteria have been selected, as for the model of

R. Šorins, I. Voronova. Model of R. K. H. Galvão, V. M. Becerra,

M. Abou-Seada was tested on 70 companies in the UK and showed the result with an accuracy of 74%.

The analysis of predictive ability of models for enterprises of different industries have shown that the same standard normative values can show different degree of accuracy since companies, engaged in various activities, have many specific features. There are several models that demonstrate high prediction accuracy for companies of any sector (e.g., model of R. K. H. Galvão,)

V. M. Becerra, M. Abou-Seada, D. Brîndescu-Olariu) (table 2). At the same time, it is impossible to call some models consistently effective (e.g., model of R. J. Taffler, H. Tisshaw), because for some industries the prediction accuracy barely more than 50%.

Enterprises of some sectors (e.g. real estate) are generally difficult to predict the insolvency: the indicators of predictive capability are often low regardless of the model applied.

It is also necessary to pay attention to the obtained values of the predictive capability of models for bankrupt non-bankrupt companies compared to total predictive capability. The effectiveness of the model application usually estimated by a general indicator of predictive capability. Sometimes, however, a high indicator of the overall predictive capability can be obtained exclusively by accurate prediction of one of the components (bankrupts or non-bankrupts). The most striking example is the application of a modified five-factor model of E. I. Altman for enterprises in the field of science. The overall predictive ability of the model reached 47.6%. The model predicts the bankruptcy of the company with 100% accuracy, and conducts calculation for non-bankrupt enterprises with an accuracy of 0%. In the calculation for the given sample of organizations in the field of science the existing standard refers them to the category of insolvent organizations. Due to the 100% convergence of calculations for bankrupt companies overall predictive ability of the model shows average values.

In order to improve the prediction of bankruptcy for companies in various industries, we have specified standard values of the considered models: selected individual borders of estimation for each industry. Normative values calculated with application of classification methodology And Regression Tree (cART), which by means of building a binary decision tree allowed us to divide the set of financial indicators of the company (in this case these are the final coefficients resulting from the application of bankruptcy forecasting models) into two parts according to some threshold, which allows to assess the financial condition of the company. Thus, the cART methodology find out the optimal calculated value of the model through which companies can be divided into a financially stable and susceptible to bankruptcy. This methodology was also used in [Hung c., chen J. H., 2009; Korol T., 2013].

To review selected models, information about companies was taken in information systems "SPARK" and "Ruslana", data of Rosstat and the Central

Bank of the Russian Federation were used.

The results of the updated values of the estimated coef ficients calculated by the models presented in table 3. For each model the original value of the indicator, recommended by the author to distinguish the bankrupt companies, the values of the indicators for enterprises, calculated using the cART methodology. The table shows that it is impossible to identify a single tendency of values change in calculated indicators in comparison with the original ones. In fact, interpretation of values is necessary for each individual model based on industry affiliation of companies.

All calculated values of indicators for all sectors and models are distinctly different from the original values proposed by the authors. Often the results for separate industries are different. This suggests that industry affiliation of the company has a significant impact on its financial performance, and hence on the probability of bankruptcy, calculated through the listed models For manufacturing industries only the four-factor model demonstrated a slight deviation of calculated indicator from the original one. However, for other industries the model changes its threshold valuation. It can be said that the indicators used to determine bankruptcy in this model, have a lower specificity in the manufacturing industry. In the case of model D. chesser obtained values are slightly different in different industries. Consequently, the financial performance of mentioned models is close, despite industry affiliation.

Some models, like the model of S. R. Saifulin and G. Kadykov for agriculture, transport and hotel business, model of E. Altman for transport, give the values, which change their sign from positive to negative, i.e., in some cases companies can operate successfully even with negative value of the evaluation indicator. A similar situation is observed in the application of the model of R. Šorins, I. Voronova. Initially, all companies with a value of the calculated index below 0 were allocated to bankrupts. The values lower the border in the negative plane, and thus the companies are able to continue effective operation even with the negative value of required indicators To confirm the significance of the found values of the coefficients and their validation we calculated the number of organizations that may be bankrupt in accordance with these indicators. Further, the forecast was compared with a real financial condition, indicated by 1 if the company is bankrupt and 0 if the organization is financially stable. The results are presented in table 4, where percentage shows the degree of forecast accuracy, carried out with the use of

Table 1

The models of bankruptcy prediction, used for verification, and their contents

The author of the model	Ratio	Interpretation of results
Altman E.	$Z = 6{,}56 \times ALT_1 + 3{,}26 \times ALT_2 + 6{,}72 \times ALT_3 + 1{,}05 \times ALT_4$, where ALT_1 – is the ratio of net working capital to total assets; ALT_2 – ratio of net profit to total assets; ALT_3 – return EBIT; ALT_4 – the ratio of book value of equity	At $Z \leq 1{,}1$ – bankrupt; at $1{,}1 \leq Z \leq 2{,}6$–50% probability of bankruptcy; at $Z \geq 2{,}6$ – to the financially lities sustainable organization
Taffler R. J., Tisshaw H.	$Z = 0{,}53 \times TAF_1 + 0{,}13 \times TAF_2 + 0{,}18 \times TAF_3 + 0{,}16 \times TAF_4$, where TAF_1 – gross profit to average for the period current liabilities; TAF_2 – the ratio of current assets to total liabilities; TAF_3 – the ratio of current liabilities to total assets; TAF_4 – the ratio of revenues to an average total assets for the period	At $Z<0{,}2$ – bankrupt, at $0{,}2 \leq Z < 0{,}3$–50% probability of bankruptcy; $Z \geq 0{,}3$ – financially sustainable organization
Springate G.	$Z = 1{,}03 \times SP_1 + 3{,}07 \times SP_2 + 0{,}66 \times SP_3 + 0{,}4 \times SP_4$, where SP_1 – is the ratio of current assets to total assets; SP_2 – asset turnover by EBIT; SP_3 – provision of short-term liabilities with profit before taxation; SP_4 – turnover of total assets	At $Z < 0.862$ – bankrupt; $Z \geq 0.862$ – financially sustainable organization
Lis R	$Z = 0{,}063 \times LS_1 + 0{,}092 \times LS_2 + 0{,}057 \times LS_3 + 0{,}001 \times LS_4$, where LS_1 – is the ratio of current assets to total assets; LS_2 – profitability of assets by profit from sales; LS_3 – retained earnings to total assets; LS_4 – the ratio of equity to total liabilities	At $Z<0{,}037$ bankrupt; $Z \geq 0{,}037$ – financially sustainable organization
Saifulin R.S., G. Kadukov	$R = 2 \times SK_1 + 0{,}1 \times SK_2 + 0{,}08 \times SK_3 + 0{,}45 \times SK_4 + SK_5$, where SK_1 – is the ratio of working capital self-sufficiency in sources of funding; SK_2 – current liquidity ratio; SK_3 – the intensity of circulation of the prepaid capital; SK_4 – is the management ratio; SK_5 – return on equity	When $R<1$ – bankrupt; at $R \geq 1$ – financially sustainable organization
Chesser D.	$Y = -2{,}0434 - 5{,}24 \times CH_1 + 0{,}0053 \times CH_2 - 6{,}6507 \times CH_3 + 4{,}4009 \times CH_4 - 0{,}0791 \times CH_5 - 0{,}122 \times CH_6$, where CH_1 – is the share of disposable assets in total assets; CH_2 – proceeds to funds; CH_3 – EBIT assets turnover; CH_4 – ratio of total liabilities to total assets; CH_5 – the ratio of equity to net assets; CH_6 – the ratio of working capitalto revenue	The probability of bankruptcy is calculated as: $P = 1/(1 + e^{-y})$
Brîndescu-Olariu D.	$Z = 0{,}635 \times BO_1 \times 10-3 - 0{,}343 \times BO_2 - 0{,}243 \times BO_3 - 1{,}185 \times BO_4 - 0{,}544 \times BO_5 \times 10-6$, where BO_1 – is the period of repayment of the assignment of receivables; BO_2– the return sales; BO_3 – the ratio of cash flow to total liabilities; BO_4 – the ratio of non-current assets to total liabilities; BO_5 – net working capital	The probability of bankruptcy is calculated as: $P = 1/(1+e^{-Z})$
Zmijewski M. E.	$X = -4{,}3 - 4{,}5 \times ZM_1 + 5{,}7 \times ZM_2 - 0{,}004 \times ZM_3$, where ZM_1 – is the return on assets (ROA); ZM_2 – the ratio of total liabilities to total assets; ZM_3 – current ratio	At $X>0$ – bankrupt; at $X \leq 0$ – financially sustainable organization
Šorins R., Voronova I.	$Z = -2{,}4 + 2{,}5 \times SHV_1 + 3{,}5 \times SHV_2 + 4{,}4 \times SHV_3 + 0{,}45 \times SHV_4 + 0{,}7 \times SHV_5$, where SHV_1 – is the ratio of net working capital to total assets; SHV_2 – ratio of retained earnings to total assets; SHV_3 – EBIT return on assets; SHV_4 – book value of equity to total liabilities; SHV_5 – total assets turnover	At $Z<0$ – bankrupt; at $Z \geq 0$ – financially sustainable organization
Galvão R. K. H., Becerra V. M., Abou-Seada M.	$Z = 0{,}2173 \times GBA_1 + 0{,}3788 \times GBA_2 + 0{,}4666 \times GBA_3 + 0{,}1244 \times GBA_4$, where GBA_1 – the ratio of net working capital to total assets; GBA_2 – the ratio of retained earnings to total assets; GBA_3 – the ratio of book value of equity to total liabilities; GBA_4 – total assets turnover	At $Z<0{,}7548$ – bankrupt; at $Z \geq 0{,}7548$ – financially sustainable organization

Table 2
Predictive capability of the original standard values for companies, %

The author of the model	Manufacturing industry			agriculture			real estate			Construction			Transport			Hotels and catering			science			Trade		
	b	nb	o	b	nb	o	b	nb	o	b	nb	o	b	nb	o	b	nb	o	b	nb	o	b	nb	o
Altman E.	67	88,7	78,2	69,9	87,5	80,7	87,1	67,4	76,9	59,4	85,6	73,2	85,9	78,1	82	38,8	86,6	69,7	100	0	47,6	75,8	92,1	84,5
Taffler R.J., Tisshaw H.	9,1	95,9	54	42,3	85,9	69,2	8,6	93,4	52,6	7,4	96,0	53,91	6,5	95,2	50,5	7,5	98,8	66,6	10,7	97,2	56,1	3,3	99	54
Springate G.	56,3	89,8	73,7	79,9	65,6	71,1	45	73,2	59,6	44,1	89,1	67,7	38,7	83,4	60,9	65,7	89,4	81,1	46,8	89,3	69,1	41	94,2	69,3
Lis. R	65,8	85,1	75,8	83,9	74,8	78,3	78,5	63,4	70,7	74,1	89,4	82,1	80,9	79,1	0,8	77,6	78,5	78,2	66,9	88,3	78,1	61,7	91,6	77,6
Сайфулин Р.С., Кадыков Г.	89,7	72,2	80,6	87,5	66,7	74,7	87,4	44,3	65	86,5	65,7	75,6	85,1	60,7	73	79,1	68,3	72,1	85,6	71	77,9	76,4	76,8	76,6
Chesser D.	21,5	97,5	60,8	15,1	96,7	65,3	26,7	96,0	62,7	23,8	96,8	62,2	29,3	95,5	62,1	36,6	93,9	73,7	18,3	99	60,6	21	93,4	59,5
Brîndescu-Olariu D.	73,8	83,5	78,8	69,9	88,6	81,4	93,7	48,8	70,4	86,2	75,5	80,6	83,9	76,8	80,4	79,9	89,4	86,1	88,6	67,2	77,4	85,9	75,8	80,5
Zmijewski M.E.	85,6	79,9	82,6	73,8	90,2	83,9	88,3	67,6	77,6	92,1	63,6	77,1	89,1	71	80,1	86,6	72	77,1	87,5	70,7	78,7	83,2	82,9	75,2
Šorins R., Voronova I.	90,9	81	85,8	91,8	75,9	82	94	59,7	76,2	83,5	70,5	76,7	90,8	74,8	82,9	85,1	78,9	81,1	88,6	77,6	82,8	81,7	80,8	81,2
Galvão R.K.H., Becerra V.M., Abou-Seada M.	91,2	73	81,8	88,2	77,2	81,4	93,7	52,5	72,3	87,1	51,9	68,6	76,2	68,8	72,4	67,2	74,8	72,1	90,1	67,6	78,3	74,3	68,5	71,4

Notes: b – predictive capability for enterprises-bankrupts, nb – the same for non-bankrupts, o - total.

calculated values. Data show the high prediction accuracy of the proposed values for the evaluation of models. A detailed comparison of predictive capability of the original standard values of considered models and calculated industry values suggests the increase in the total predictive capability of all models for selected industries. However, in some cases, the total predictive ability of calculated normative values has decreased. A similar situation exists for those models where there is a high discrepancy between predictive bility for bankrupt companies and financially sustainable organizations. Thus, the new standard value designed to reduce the disproportion between the degree of prediction accuracy for the insolvent and financially stable companies, which will allow us to speak about higher efficiency of bankruptcy forecasting.

Average predictive capability of the proposed indicators is approximately equal to 77%, in many sectors and models it is higher than 80%. The minimum accuracy of the forecast model demonstrates the model of R. J. Taffl , H. Tisshaw for the transport sector; the maximum accuracy was noted in the model of D. Brindescu - Olariu for companies of the "hotels and catering" sector.

The analysis allowed us to suggest that distinguishing the most important financial indicators that compose the basis for the popular models of bankruptcy forecasting, their comprehensive processing and testing on a sample will allow to build a new model that demonstrate high validity of the results. A method of building a standard logistic regression model made it possible to develop the model presented below. Selecting indicators for this model, we were not limited to sample presented in table 1. We considered other coefficients used in the models not covered in this study.

$$\beta = -3{,}04+0{,}91x_1+2{,}41x_2-0{,}12x_3-0{,}25x_4+0{,}14x_5-0{,}19x_6,$$

where β – is the index value estimated for bankruptcy forecasting in accordance with the developed criteria; x_1 – current assets to total assets (model of G. Springate); x_2 – the difference of total liabilities and total assets.: 1 – total liabilities exceed total assets, 0 – total assets exceed total liabilities (model of J. Ohlson); x_3 – endowment of accumulated obligations with revenue (model of J. Ohlson); x_4 – product profitability (model of R. S. Sai fulina and G. Kadykova); x_5 – the natural logarithm of tan-gible assets (model of D. Fulmer); x_6 – natural loga-rithm EBIT interest to pay (model of D. Fulmer).

The generated model was tested on a sample of enterprises. For each industry a specific normative value was obtained for the evaluation of the developed model. Obtained normative values, indicating potential bankruptcy of the organization, and the degree of prediction accuracy are presented in table 5.

Analysis of the obtained values of the predictive capability of the model by industry reveals a high efficiently of its application. Overall accuracy of the forecasting is 80.2% minimum, and for most industries it exceeds 82%. For bankrupt companies and financially sustainable organizations the predictive capability of the model ranges by sectors from 78 to 89%, which also confirms its high degree of reliability. Minimal accuracy of prediction observed in respect of the bankrupt companies

Table 3
Updated values of the indicators calculated on the basis of bankruptcy forecasting models

The author of the model	The original indicator	Manu-facturing industry	Agricul-ture	real estate	Con-struction	Transport	Hotels and catering	science	Trade
Altman E	≤1,1	≤1,81142	≤6,47981	≤0,15331	≤0,19042	≤ –0,21887	≤1,97657	≤0,00571	≤1,16630
Taffler R. J., Tisshaw H.	<0,2	≤0,34437	≤0,54724	≤4,83639	≤0,67504	≤9,83118	≤6,78391	≤0,48352	≤0,56467
Springate G.	<0,862	≤ 1,03398	≤ 1,24036	≤ 1,03095	≤ 1,19964	≤1,06522	≤1,09941	≤1,16605	≤1,31559
Lis. R	< 0,037	≤0,03499	≤0,07097	≤0,00343	≤0,0484	≤0,00149	≤0,01502	≤0,0695	≤0,02621
Сайфулин Р.С., Кадыков Г.	<1	≤ –0,16499	≤ 0,5659	≤ 0,1299	≤ 0,52184	≤ –0,14699	≤ –7,61240	≤0,47582	≤0,72510
Chesser D.	≥0,5	>0,05408	>0,03879	>0,06967	>0,04215	>0,13779	>0,00092	>0,00463	>0,75
Brîndescu-Olariu D.	≥0,5	>0,73127	>0,84858	>0,9999	>0,75534	>0,61164	>0,52036	>0,88857	>0,59634
Zmijewski M. E.	>0	>0,06109	>0,47175	>1,42149	>1,35579	>0,85425	>1,2636	>1,04318	>1,30393
Šorins R., Voronova I.	<0	≤–0,69983	≤–0,34777	≤–4,30897	≤–2,23809	≤–0,8809	≤–1,59827	≤–0,90125	≤–1,64359
Galvão R. K. H., Becerra V. M., Abou-Seada M.	< 0,7548	≤ 0,45293	≤ 0,30151	≤ 0,2423	≤ 0,08854	≤ –0,0584	≤ 0,15091	≤ 0,1779	≤ 0,13328

in the agriculture sectors, maximum - for the bankrupt companies operating in the field of transportation.

The considered model is best adapted for use in manufacturing and construction industries, while the lowest predictive capability is shown in the industry trade. Such results can be partly explained by the fact that many of the indicators in the model are associated with the assets of the company (including material), composition and structure of which differs significantly in trade and industry. This fact again shows the usefulness of updating of bankruptcy forecasting models considering the industry in which the company operates.

We compared the results of determining the probability of bankruptcy using the proposed and the classical prediction models. It turned out that the financial ratios included in the new model are as neutral as possible regarding industry specificities of companies. This conclusion is based on significant alignment of indexes of overall predictive capability to forecast accuracy for bankrupt companies and financially sustainable companies by sectors. For construction and transport industries, the value of reliability of the forecast, according to our method, exceed the values resulting from the application of any of the considered prediction models. This fact once again confirms the maximum adaptation of proposed model for application in the construction and transport industry.

Any model of bankruptcy forecasting needs to take into account the industry affiliation of reviewed company to improve the prediction accuracy and validity of the results. The use of the found sectoral values of the considered models will allow to increase efficiency of bankruptcy forecasting in practice that will have a positive impact on overall statistics on bankruptcy of legal entities in the national economy, as well as with regard to industry. The developed model demonstrates high predictive capability for companies of all considered industries, after verification on broader sample and proper elaboration it can be implemented in practice that will significantly improve the accuracy of bankruptcy predicting for companies in various industries.

Table 5
Normative values and predictive capability of the model

Industry	standard value	Predictive capability, %		
		b	nb	o
The manufacturing industry	> –0,64630	84,1	86,0	85,0
Agriculture	> –0,47827	74,2	86,8	82,0
Real estate	> –0,43117	83,1	82,0	82,5
Construction	> –0,53444	85,0	84,5	85,9
Transport	> –0,82901	89,8	78,3	84,1
Hotels and catering	> –0,89084	83,6	82,5	82,9
Science	> –0,53033	77,9	88,9	83,7
Trade	> –0,55229	75,7	84,2	80,2

Notes: b – predictive capability for enterprises-bankrupts, nb – the same for non-bankrupts, o – total.

Table 4

Bankruptcy prediction accuracy with the application of the proposed ratios

Author of the model	The manufacturing industry			Agriculture			Real estate			Construction			Transport			Hotels And catering			Science			Trade		
	b	nb	o	b	nb	o	b	nb	o	b	nb	o	b	nb	o	b	nb	o	b	nb	o	b	nb	o
Altman E.	70,5	85,4	78,2	91,8	55,8	69,6	84,2	75,9	79,9	53,5	90,7	73,0	81,9	84,6	83,3	88,1	84,2	85,5	74,1	84,1	79,4	76,1	92,1	84,6
Taffler R.J., Tisshaw H.	27,7	93,4	61,7	79,6	62,1	68,8	96	17,8	55,4	23,2	71,5	60,8	61,5	11,1	36,5	97,0	32,9	55,5	46,0	89,7	68,9	31,1	90,5	62,8
Springate G.	72	87,3	79,9	90,3	51,6	66,4	59,3	66,6	63,1	29,6	81,1	72,2	50,1	79,4	64,6	76,9	86,2	82,9	67,7	85,9	77,2	64,1	88,4	77,0
Lis. R	64,3	85,4	75,2	97,5	46,2	65,9	66,2	91,5	79,3	38	87,2	83,8	73,5	89,2	81,3	72,3	88,6	82,9	92,9	68,3	79,9	59,9	94,7	78,4
Сайфулин Р.С., Кадыков Г.	69,6	85,1	77,6	83,9	74,1	77,9	81,1	54,6	67,4	39,4	78,5	80,6	78,2	73,3	75,8	52,2	93,9	79,2	79,9	83,1	81,6	72,2	82,6	77,7
Chesser D.	45,4	93,7	70,4	51,6	83,7	71,4	50,4	91,3	71,6	26	90,4	73,5	54,8	91,2	72,9	70,9	80,1	76,8	52,9	96,2	75,6	21	94,2	59,9
Brîndescu-Olariu D.	64	92,6	78,8	58,8	95,1	81,2	77,7	83,3	80,6	35,2	92,3	83,7	75,9	87,7	81,8	76,1	92,7	86,8	75,3	94,1	85,2	82,9	84,5	83,8
Zmijewski M.E.	88,5	73,3	80,6	68,5	92,2	83,1	75,6	86,5	81,3	38,6	88,8	85,2	86,4	79,6	83	79,1	84,6	82,6	71,1	90,7	81,4	67,1	90,8	79,7
Šorins R., Voronova I.	86,4	84,8	85,6	90,3	77,9	82,7	70,5	93,6	82,5	34,8	91,8	83	88,8	79,1	84	79,1	88,2	85	84,8	85,5	85,2	73,7	92,6	83,8
Galvão R.K.H., Becerra V.M., Abou-Seada M.	88,2	83,2	85,6	76	87,1	82,8	87,7	71,9	79,5	34,5	91,2	82,4	61,5	90,9	76,1	56,7	89,4	77,9	80,6	90,3	85,7	78,1	69,7	73,9

Notes: b – predictive capability for enterprises-bankrupts, nb – the same for non-bankrupts, o - total.

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