THE METHODICAL APPROACH OF BANKRUPTCY PROBABILITY ESTIMATION IN AN ANTI-CRISIS MANAGEMENT SYSTEM OF ENTERPRISE

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ABSTRACT

The purpose of this study was to define an effective methodical approach to bankruptcy probability estimation in an anti-crisis management system using the example of metallurgical enterprises in Ukraine. The leading research methods were discriminatory analysis, the factorial analysis method, and the three-sigma rule. For research purposes, the financial funding of 20 metallurgical plants in Ukraine during the period of 2001 to 2017 was used. The overall number of observations was 112 financial indicators. In order to define enterprise bankruptcy risk indicators, the method of discriminant analysis was applied. Factor analysis of enterprise bankruptcy indicators enabled us to distinguish the variance, which describes the input of every indicator into the formation of the results and therefore defines the significance of the indicators in bankruptcy risk estimation. The range of integrated solvency index values by the class of enterprises with regard to bankruptcy risks was refined with regard to the 3-sigma rule. The elaborated methodical approach is the instrument for preventive anti-crisis management in Ukrainian enterprises due to its direction of determining early marks of insolvency. Approbation results for the elaborated methodical approach for metallurgical enterprises testified high bankruptcy risk caused by the enterprises' loss-making activities, which has a negative impact on the current financial standing and poses the potential threat of bankruptcy resulting from the lack of self-finance sources, thus reducing the enterprises' financial stability and creditworthiness.

Keywords: anti-crisis management, insolvency, bankruptcy risk, financial standing, financial stability

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INTRODUCTION

The functioning of Ukrainian enterprises under the present conditions is accompanied by their loss-making activity, leading to an increase in the amount of enterprises for which bankruptcy proceedings have been instituted, or have ceased their functioning as a result of their inability to meet their credit grantors and investors' claims. This financial standing of these enterprises comes from a reduction in the enterprise solvency level, which upsets the financial equilibrium and threatens their further existence. In accordance with the official data provided for January through September of 2018, the share of loss-making enterprises amounts to 29.8% of the total amount of functioning enterprises, in comparison with the value of this index of 27.6% by the end of 2017, 27% in 2016, and 26.7% in 2015. The downward trend of the share of loss-making enterprises in 2015-2018, along with the steady reduction of their number (15.89% of large and 5.43% of medium-sized enterprises in 2018), indicates that the need to upgrade the methodical provisions for preventive enterprise bankruptcy risk estimation has become highly relevant (State Statistics Service of Ukraine, 2019).

The topicality of the problem under scrutiny at the legislative level is proved by the Concept of Provision of National Security in the Financial Sector (ordinance of the Cabinet of Ministers of Ukraine of 15 August 2012 № 569-р.) (On Approval of the Concept of Provision of National Security in the Financial Sector, 2012), in compliance with strategic finance security management in the real economy, and thus national security, which is streamlining anti-crisis management. The essence of the problem of enterprise bankruptcy, with regard to its negative impact, lies in its interference with existing financial relations, decrease in the ability to raise capital, and loss-making activity, all of which are due to a decline in market shares. This explains the existence of a great variety of anti-crisis diagnostics and management techniques. Bankruptcy risk diagnostics plays an important role in providing sustainable development and functioning because timely, adequate diagnostics have a preventive nature and thus enable the indication of marks of insolvency at early stages by means of responding to the negative impact of external and internal factors, thereby preventing insolvency from developing. The main factor in how the Ukrainian economy functions destructively have been metallurgical enterprises: in 2011-2012, in comparison with the performance of industrial enterprises, the activity of metallurgical enterprises in Ukraine was loss-making; in 2013 the amount of losses made by metallurgical enterprises exceeded the amount of losses made by industrial enterprises by 2.8 times; in 2014, the share of losses made by metallurgical enterprises amounted to 21.14% of industrial enterprises net losses; in 2015, it was 23.56% of losses; and in 2016, 33.73%. In 2017, the situation seen in 2011-2012 recurred when, with the added value of 56124,0 mln UAH of the bottom line in the industry, the losses of metallurgical enterprises totaled 9803,2 mln UAH (State Statistics Service of Ukraine, 2019). Therefore, this study defines an effective methodical approach to developing an anti-crisis management system using the example of metallurgical enterprises in Ukraine. This approach is based on the introduction of a system for permanent monitoring of robust financial flows in these enterprises, with the aim of preventing financial insolvency in metallurgical enterprises. The paper is divided into several sections as follows: Section 2 reviews the literature, followed by an outline of the factors and hypotheses of this study in Section 3, which also describes the research methodology; Section 4 describes the data collection; the data analysis and results are discussed in Section 5; Section 6 summarizes the conclusions of this study; and finally, Section 7 presents outlines and recommendations.

LITERATURE REVIEW

Diagnostic techniques based on the analysis of external enterprise bankruptcy factors and built on the basis of GDP growth indices, consumer price standards, producer price standards, and unemployment levels include: the Through The Cycle Estimation (TTC) method (Hamilton, Sun & Ding, 2011), which is applied by the Basel Committee on Banking Supervision; the Wilson Model (Wilson, 1997), Hoggart model, Sørensen-Zikchino model, and Alves model; and the Troyler-Weiner model, which is used by the World Bank and World Monetary Fund to assess financial sector stability. These techniques are grounded on the statement that bankruptcy of enterprises has a cyclical nature and its probability increases with economic recession. Models based on macroeconomic indicators have a number of advantages, which is proved by their use by the Basel Committee, the World Bank and World Monetary Fund. These advantages lie in the possibility to obtain short-term and long-term estimates of bankruptcy risks that take into account the cyclical nature of economic development, the accessibility of analytical data, and resilience to various economic conditions, as opposed to current bankruptcy risks estimates, which change along with the economic situation. The drawback of these techniques, however, is their inability to define bankruptcy risks for every enterprise because the analysis is done at the level of economic segments.

A technique that analyzes internal enterprise bankruptcy factors is the coefficient method (Hosaka, 2019; Antunes, Ribeiro & Pereira, 2017), the essence of which lies in conducting enterprise financial analysis to determine liquidity ratios, business solvency, business activity, and cost effectiveness. These form the basis for short-term bankruptcy risk analysis via estimating the current and potential threat level of bankruptcy in the enterprise and the ability eliminate it. Coefficient methods for enterprise bankruptcy diagnostics provide for the complex analysis of financial status. The drawbacks of the diagnostics methods under scrutiny are high labour intensity, insufficient argumentation of financial ratio standards, neglect of industrial specialization, and ambiguous interpretation of results, all of which result in a decrease in the accuracy of diagnostics, thus limiting the use of this method in the system of enterprise bankruptcy risk management.

Among economic and mathematical methods, the most widely used are models built using the application of the discriminatory analysis (Azayite & Achchab, 2016; Kočišová & Mišanková, 2014), on the basis of the holistic financial indicators' analysis, taking into account relativity theory and the integrated index definition to calculate enterprise bankruptcy risk. The most widely used discriminatory models for enterprise risk diagnostics are the two-factor enterprise bankruptcy risk diagnostics model, Altman Z-Score (Altman & Hotchkiss, 2006), Toffler-Tishaw model (Toffler & Tishaw, 1977), Springate model (Springate, 1978), Fulmer model (Fulmer et al., 1984), and the Tereshchenko model (Tereshchenko & Stetsko, 2017; Tereshchenko & Pavlovskyi, 2016). The advantages of discriminatory analysis are unambiguous interpretation and high accuracy of enterprise bankruptcy risk estimation results, which also take into account industrial specialization and timing in domestic models. Despite this, the drawbacks of the domestic discriminatory models are inconsistency of results obtained, low forecast accuracy, and the application of static measures with no regard to their dynamic characteristics.

Another instrument that forms the basis for the enterprise bankruptcy diagnostics model is linear logistic regression, an analytical model in which the dependent variable gains the discrete type (in the simplest form of 0 or 1), which aims at the definition of the probability of the cause variable to take the value of 0 or 1. Contemporary representatives of the field of enterprise insolvency diagnostics are L. Koval (Koval 2008), S. Jabeur (Jabeur, 2017), J. Pereira, M. Basto, and A. da Silva (Pereira, Basto & da Silva, 2016). The advantage, in comparison with discriminatory analysis, of applying logistic regression instruments for forecasting enterprise bankruptcy in the system of enterprise management is the possibility of describing the nonlinear relationships between variables in the model, thus providing for higher accuracy of results. These models are also characterized by the simplicity and unambiguity of interpreting the results; however, they are more vulnerable to multicollinearity as compared to discriminatory models. A common drawback of discriminatory and logistic models is the fact that they produce qualitative evaluations of enterprise bankruptcy risks and do not calculate the numerical value of bankruptcy risks. The provided statistic data in the introduction and the drawbacks of the existing methods prove the objective necessity to improve the methodical provision of the bankruptcy risk management process, particularly for metallurgical enterprises.

METHODS AND MATERIALS

Improving the methodical provision for enterprise bankruptcy risk management processes can be conducted by means of solving the given tasks: defining enterprise bankruptcy indicators; calculating the integrated enterprise solvency index; building an integrated solvency index interval by enterprise class in relation to bankruptcy risks; and finally, defining enterprise bankruptcy risks.

In order to define the enterprise bankruptcy risk indicators, the method of discriminatory analysis was applied. The discriminatory analysis method enables the definition of the indicators, which provide maximum accuracy in categorizing the objects of research and do not demand a quantitative composite indicator. Generally, the task of discrimination is formulated in the following way. If observation of the object results in building m-vector random variable $X = (X_1, X_2, \dots, X_m)$, where $X_1, X_2, \dots, X_m$ are object features, it is necessary to make a rule (build a discriminatory function) in which the object is referred to one of the possible populations π_i , $i = 1, 2, \dots, n$ by the value of vector X components (Dai & Li, 2018).

Discriminatory functions take the form of (Dai & Li, 2018):

$$f_{im} = u_0 + u_1 X_{1im} + u_2 X_{2im} + \cdots + u_p X_{pim}, \qquad (1)$$

where X_{1im} is the value of the discriminant value X for i-object in the group;

u_i is the index, which provides the necessary conditions.

Index u_i of the discriminatory function is determined so that its mean observation values for various populations have maximum difference. The input matrix for the discriminatory analysis is formed by the indices of metallurgical enterprises' financial status. These indices are the following ratios: net working capital resilience; day-to-day (overall) liquidity; instant liquidity; absolute liquidity; assets fluidity; net working capital provision; stock availability and costs coverage from net working capital; stock cover; autonomy; financial dependence; financial risks; working capital fluidity; long-term investment coverage system; long-term investment promotion; financial self-sufficiency of capitalized sources; assets turnover; fixed assets turnover; working assets turnover; inventory turnover; finished goods turnover; receivables turnover; equity funds turnover; payables turnover; assets payability; return on equity; net equity profitability; margin on sales; gross profit margin of the core activity; return on business operations; net margin of the marketed goods; capital assets pay ability; working assets pay ability.

The necessary prerequisite of conducting the discriminatory analysis is preliminary classification of the objects or research. Researching the problem of bankruptcy, these classes are: class A, comprised solvent enterprises with 0% bankruptcy risks, which have a high level of financial capacity (Neskorodeva & Pustovgar, 2015) and are capable of timely and fully settling accounts with contractors; and class B, consisting of enterprises in default, against which bankruptcy proceedings had been initiated and a resolution on their liquidation had been made by the end of 2017. In order to form class B, financial indicators values of enterprises, which were liquidated during the previous year, were taken for the relevant year. These enterprises are: "Kostiantynivka Metallurgical Plant" (liquidated in 2004), "Makiivka Metallurgical Plant" (2012), "Kramatorsk Metallurgical Plant named after Kuibyshev" (2010), Public Joint Stock Company "Kerch Metallurgical Combine" (2011), Public Joint Stock Company "Kirov Plant of Manufacturing Metal Bodies from Powder" (2009), Public Joint Stock Company "Steel Production Plant" (2007), Public Joint Stock Company "Sarny Plant "Metallist" (2009), Public Joint Stock Company "Starokostiantynivka Plant "Metallist" (2008), and Public Joint Stock Company "Stakhanov Plant of Metal Manufactures" (2007).

The financial statements of 20 Ukrainian metallurgical plants for the period of 2001to 2017 were used for research. The last year was 2017 due to the absence of official figures from annual financial statements for 2018. The overall number of observations is 112: 56 observations referred to class A, and 56 observations referred to class B. The input data array was formed with the view of comparing the dimension of classes. The integrated enterprise solvency index was calculated on the basis of the data array applied in the discriminatory analysis, and the factorial analysis method was formed on the basis of values obtained in the discriminatory analysis of indicators. The calculations were made using the Statistica 8 software suite.

In compliance with the factorial analysis method, the composition of indicators is determined based on the factor loading values of indicators with the corresponding factor referring to the factor model (Menke, 2018):

$$x_i = a_1 * f_1 + a_2 * f_2 + \ldots + a_i * f_i + dv, \qquad (2)$$

where x_i is the standardized value of the factor;

a_i – factor loading;

f_i – factor score;

dv – model residuals.

Factor loading calculation is made in accordance with the hypothesis for the normal law of distribution x_i, absence of correlation between the factors f, and the normal law of residuals distribution dv. The optimality criterion in this is minimization of deviations for the covariance matrix obtained in the factor loading estimation from the original values covariance matrix (Menke, 2018).

The main purpose of the factor analysis is data reduction; however, in the given research, this kind of analysis is used with the aim of calculating the integrated index by the formula:

$$I = \sum_{i=1}^{n} X_i \times w_i + \varepsilon, \qquad (3)$$

in which I is the integrated enterprise solvency index value;

X_i is the value of factor i (factor i for enterprise bankruptcy indicator);

w_i is the weighing factor for factor i, which corresponds to the percent of variance for factor i;

ε is the error (impact of factors unaccounted in the model);

n – the number of factors (n=5).

The factor analysis enables the calculation of the percent of factor variance. The number of factors corresponds to the number of indexes: 5.

The following stage of improving the methodical provisions is defining the range of integrated solvency index values by class of enterprises with regard to bankruptcy risks. The range of values corresponds to the minimum and maximum values of the integrated index calculated in Formula 3 for classes A and B. In order to eliminate random variables, the obtained values were refined with regard to the 3-sigma rule, in compliance with which the range of index values is defined by the formula (Rousseau, Egghe & Guns, 2018):

$$[\bar{X} - 3 \times \sigma;\ \bar{X} + 3 \times \sigma], \qquad (4)$$

in which $\bar{X}$ is the mean observation for the integrated index for enterprises, which formed classes A and B separately;

σ is the mean square deviation of the indicator for the enterprises, which form classes A and B.

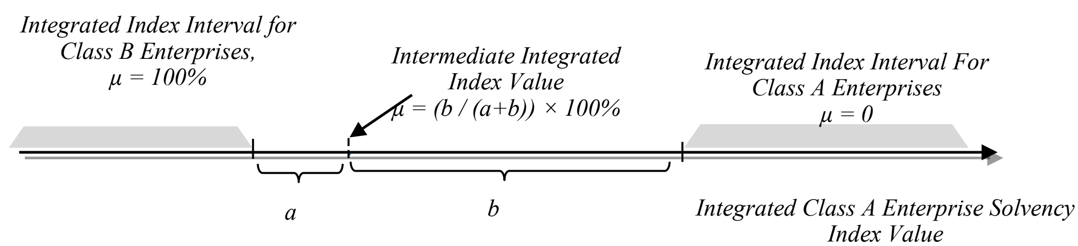

Figure 1. Flow Chart for Enterprise Bankruptcy Risks Estimation Model.
Source: Developed by the authors.

If the value of the integrated solvency index lies within the given spectrum (Formula 4) calculated for class A, the bankruptcy risk is μ = 0. If the value of the integrated solvency index lies within the given spectrum calculated for class B, the bankruptcy risk is μ = 100% (Fig. 1). The bankruptcy risk for enterprises, which are intermediate in classes A and B, is calculated on the basis of the distance to the upper boundary for class B and the lower boundary for class A.

The enterprise bankruptcy risk estimation model can be analytically presented in the form of a system:

$$\begin{cases} \mu = \frac{b}{a+b} \times 100\%; \\ a = I' - I_{Б}^{max}; \\ b = I_{А}^{min} - I' \end{cases} \quad (5)$$

in which I' is the value of the integrated enterprise solvency index;

$I_{Б}^{max}$ is the upper boundary of the integrated index for class B enterprises;

$I_{А}^{min}$ is the lower boundary of the integrated index for class A.

RESULTS

The discriminatory analysis, conducted with the application of the Statistica 8 software suite, the variables, which are valuable within enterprise risk evaluation, were selected based on Fisher's variance ratio and p-levels (Table 1).

Table 1. Indexes, which are discriminatory within the process of Ukrainian metallurgical enterprises bankruptcy risk identification

Index	Criterion for evaluation of the statistical significance of indicators				
	Wilks' lambda	Finite lambda	F-criterion	p-level	Tolerance
Working capital ratio	0,41	0,82	32,48	0,00	0,58
Asset turnover ratio	0,36	0,93	11,78	0,00	0,86
Net margin ratio	0,34	0,98	3,12	0,01	0,97
Net margin ratio for the sold goods	0,34	0,96	3,68	0,00	0,91
Ratio of correlation of net assets to the registered capital	0,39	0,86	24,14	0,00	0,94

Source: Developed by the authors.

In Table 1, the statistical value of indicators included in the insolvency diagnostics model for metallurgical enterprises is proved by the F-criterion, the actual value of which is higher for all variables than the critical point of 2.38, by the p-level, the value of which approaches 0, and the tolerance level, which is higher than the borderline of 0.01 (Dai & Li, 2018), which testifies to the high discriminatory effect of the variables added to the model. Therefore, the working capital ratio, asset turnover ratio, sales profitability ratio, and net profitability ratio for sold goods, as well as the ratio of correlation of net assets to the registered capital, are discriminatory variables in bankruptcy risk identification of metallurgical enterprises.

In order to prove the statistical significance of the distinguished financial indicators, which identify the bankruptcy risk of metallurgical enterprises, the class of enterprises was modeled on the basis of these indicators using the figures from the input array. The results of the quality assessment for the discriminatory analysis are presented by the classification matrix (Table 2).

Table 2. Metallurgical Enterprises Classification Matrix upon the Insolvency Level

Actual number of enterprises by class	Number of enterprises by insolvency levels defined with discriminatory models			
	Number of Class A enterprises, units	Number of Class B enterprises, units	Total number of enterprises, units	Percent of correct classification, %
Number of Class A enterprises, units	56	0	56	100
Number of Class B enterprises, units	0	56	56	100
Total number of enterprises,units	56	56	112	100

Source: Developed by the authors.

According to the figures in Table 2, the percent of correct classification is 100%, which proves the possibility of applying the outcomes of the conducted discriminatory analysis, i.e. the defined financial indicators for bankruptcy risk estimation for metallurgical enterprises, in practice. The 100% correctness of the classification is stipulated by the fact that, in order to conduct discriminatory analysis, enterprises, which could produce a firm conclusion as to bankruptcy risks and financial status, were considered in two classes. Class A encompassed profitable and financially stable enterprises with sufficient net cash flows, while class B included enterprises with negative equity capital, who had initiated court proceedings (bankruptcy or liquidation proceedings), or had liquidated the enterprises.

The factor analysis of enterprise bankruptcy indicators (Table 1) enabled variances to be distinguished, which describes the input of every indicator into the formation of the results, and therefore, the significance of the indicators in bankruptcy risk estimation. The values of the bankruptcy risk indicators variance for metallurgical enterprises are presented in Table 3.

Table 3. Values of Ukrainian Metallurgical Enterprises Bankruptcy Risk Indicators Variance

Indicator	Percent of variance, %	Weight ratio for integrated estimation model
Working capital ratio	31	0,31
Asset turnover ratio	25	0,25
Sales profitability ratio	18	0,18
Net margin ratio for the sold goods	13	0,13
Correlation ratio of net assets and the registered capital	9	0,09
Cumulative variance value	96	-

Source: Developed by the authors.

The figures presented in Table 3 demonstrate that the working capital ratio, which defines bankruptcy risks by 31%, is most resilient to changes in the financial status of metallurgical enterprises in Ukraine. The asset turnover ratio defines bankruptcy by 25%, whereas the sales profitability ratio determines bankruptcy by 18%, the net margin ratio for sold goods determines profitability by 13%, and the correlation ratio of net assets and registered capital defines bankruptcy by 9%. With account taken for the given weight ratios, the bankruptcy risk integrated estimation model, built on the basis of formula 3, is written as:

$$I = 0,31 \times X_1 + 0,25 \times X_2 + 0,18 \times X_3 + 0,13 \times X_4 + 0,09 \times X_5, \quad (6)$$

in which X_1 is the value of the working capital ratio;

X_2 is the value of the asset turnover ratio;

X_3 is the value of the sales profitability ratio;

X_4 is the value of the net margin ratio for the sold goods;

X_5 is the value of the correlation ratio of net assets and the registered capital.

The percent of cumulative variance is 96%. This means that the error rate of the built integrated estimation model (Formula 6) is 4%, with the common tolerable level f 5%. Therefore, the built model may be used in bankruptcy risk estimation of metallurgical enterprises.

The range of values for the integrated enterprises solvency index, calculated with regard to classes, in accordance with Formula 6 is:

Class A – [1.5; 3.8];

Class B – [0.11; 0.34].

With account taken for the 3-sigma rule (Formula 4), the range of values for the integrated index is:

Class A – [1,1; 3,5];

Class B – [0,12; 0,31].

The given ranges were obtained based on the values of the financial indicators for the enterprises under scrutiny. Taking into account, however, the fact that for Class A enterprises, all the indicators (working capital ratio, asset turnover ratio, sales profitability ratio, net margin ratio for the sold goods, correlation ratio of net assets and the registered capital) do not have the maximum allowable limit, the range of values is:

Class A – [1,1; +∞].

For Class A enterprises, the minimum allowable value of the working capital ratio and the asset turnover ratio is «0». For other ratios, the minimum allowable limit is absent, thus, the range of integrated index values is modified into:

Class B – [-∞; 0,31].

With an integrated index value of [1,1; +∞], the enterprise is classified as Class A – the class of solvent enterprises, for which bankruptcy risk equals zero. With an integrated index value of [-∞; 0,31] and a risk of 100%, asserting bankruptcy of the enterprise can be possible. For enterprise bankruptcy risks under the intergraduated integrated index values of 0.31 < I < 1.1 Formula 5 proposes a calculation, which has the following form for Ukrainian metallurgical enterprises:

$$\begin{cases} \mu = \frac{b}{a+b} \times 100\%; \\ a = I' - 0,31; \\ b = 1,1 - I' \end{cases} \quad (7)$$

The developed model was practically approved for the Ukrainian metallurgical that were not included in the input data heap that was the basis for modelling. The 2017 financial statements for metallurgical enterprises that have affected financial status, but do not expressly have features of bankruptcy, were taken for practical approval. The bankruptcy risk for these enterprises, which was calculated with Formulas 6-7, is presented in Table 4.

Table 4. Metallurgical Enterprises Bankruptcy Risk by the End of 2017

Enterprise	Bankruptcy risk, %
«Dneprospetsstal», PJSC	73
«Ilyich Iron and Steel Works of Mariupol», PJSC	52
«Zaporizhstal», PJSC	61
«Kremenchuk Metal Structure Plant», PJSC	52
«Chernihiv Metalwork and Metal Equipment Plant», PJSC	46
«Kievmetallоprom», PJSC	41
«MetallProm», PrJSC	81
«Metaloprylad Kamianets-Podilskyi Plant», PrJSC	88
«Dnieper Metallurgical Combine», PJSC	66
«EVRAZ-Dnipropetrovsk Metallurgic Plant», PJSC	59

Source: Developed by the authors.

The figures provided in Table 4 proved the possibility of applying the developed enterprise bankruptcy risk estimation model because no enterprise was misclassified as A or B; rather, all of them are intermediate.

DISCUSSION

This specific Ukrainian metallurgical enterprise bankruptcy risk estimation model was developed with the aim of improving the anti-crisis management system within the given research. Statistical indicators from the discriminatory and factor analysis, as well as sample sufficiency, considerable time range, and practical approval outcomes testify the possibility of applying the developed bankruptcy risk estimation model for Ukrainian metallurgical enterprises to anti-crisis management at enterprises. The uniqueness of the presented methodological approach to assessing the probability of risk of bankruptcy is that it allows the quantitative level of the probability of bankruptcy to be determined for any enterprise, taking into account the specifics of the industry and current financial condition. This allows the determination of the most effective preventive measures to restore the solvency of the enterprise, in contrast to such approaches as: the TTC method (Hamilton, Sun & Ding, 2011); the Wilson model (Wilson, 1997); and the model of Hoggart, Sorensen and Zikchino, Alves, Troitler and Weiner (Chan-Lau, 2006); all of which focused on assessing the bankruptcy of an enterprise's macro-environment.

The methodological approach that was developed to assess the bankruptcy of a company was based on the discriminant analysis method, which, when compared with widely used methods such as coefficient analysis (Hosaka, 2019; Antunes, Ribeiro & Pereira, 2017) and the logistic regression method (Jabeur, 2017; Pereira, Basto & da Silva, 2016), allows for the determination of key indicators of the insolvency of an enterprise, taking into account the industry. The higher the value of this indicator, the lower the likelihood of bankruptcy. These research results can complement the findings of previous research (Azayite & Achchab, 2016; Springate, 1978; Fulmer et al., 1984; Tereshchenko & Stetsko, 2017). In contrast to the proposed methods, however, a decrement analysis was used with the three-sigma method, which allowed for the determination of specific quantitative indicators. This allowed us to classify metallurgical industry enterprises according to their solvency level. The presented approach greatly simplifies the diagnosis of metallurgical industry enterprises' financial positions to systematize information about solvent and insolvent enterprises; in other words, the shortest possible time to make decisions on necessary measures for crisis management.

It should be noted that the methodological approach to assessing the bankruptcy of an enterprise is a universal technology for diagnosing the solvency of an enterprise, especially since the applied algorithm can be used to assess the likelihood of bankruptcy for enterprises in other sectors of the economy. In the framework of this study, however, the statistical basis only used the financial statements of the metallurgical industry. As such, the main findings cannot be applied to enterprises in other sectors of the Ukrainian economy. The features of determining key indicators of enterprises' bankruptcy, depending on the industry sector and the levels of classification of their solvency, have determined our further scientific priorities and will be considered in the next study.

CONCLUSIONS

The following conclusions were drawn from this empirical study. In the current conditions of how the Ukrainian market functions, its metallurgical enterprises are the most vulnerable to bankruptcy. The methodological approach to assessing the probability of bankruptcy that was developed in this study testified that the main indicators of the solvency of enterprises in the industry are the ratios of: working capital, asset turnover, sales profitability, net profitability for the sold goods, and the correlation of net assets to registered capital. Based on the integrated solvency indicator, Ukrainian metallurgical enterprises must be classified into bankruptcy probability according to Class A [1,1; +∞] and Class B [-∞; 0,31]. The identified solvency classes of enterprises could be a basis for improving the crisis management systems for enterprises in the metallurgical industry.

The outcomes of practical approval of the developed model, built on the basis of financial statements provided by Ukrainian metallurgical enterprises that have affected financial statuses but do not have express signs of bankruptcy, testified to the problem of high enterprise bankruptcy risk (>40% by the end of 2017), stipulated primarily by low profitability levels. Lack, or insufficient levels, of profit negatively characterizes the current financial status of enterprises, creating potential bankruptcy risks due to the lack of self-funding sources, thereby decreasing enterprises' financial sustainability and solvency.

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