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PRINCIPAL COMPONENT ANALYSIS IN THE FORECASTING BANKRUPTCY OF ENTERPRISES

Bankruptcy forecasting is one of the most studied subjects in accounting and finance. There are numerous articles, books, and research on finding the best method to predict possible future financial problems. This article examines Altman's (1968) multidimensional method, or Z-score, is one of the most ancient methods of predicting bankruptcy.

But given the fact that the economic situation in Ukraine is just beginning to stabilize, bankruptcy and liquidation of enterprises may destroy newly formed economic relations, which will lead to destabilization of the economy. In this regard, the problem of bankruptcy as a system of measures to remove an entity from the financial crisis is becoming more urgent . Insufficient and incomplete legislative and methodological normative framework for bankruptcy and the lack of a single coherent methodological tech approach to its financial and economic content and constrain the mechanism of implementing measures for bankruptcy in Ukrainian enterprises.

Keywords: *Altman's Z-score, bankruptcy forecasting, multidimensional method, solvency, insolvency, diagnostics, enterprise, monitoring, principal component method.*

Introduction. Bankruptcy forecasting is one of the most studied topics in finance and strategic management. The number of methods used to predict bankruptcy is huge, beginning with the Beaver method. Using one-factor ratios and moving on to recent studies such as logistic regression or hybrid models. Only one model has created countless articles, studies, and even books that have been produced with the primary purpose of developing them, and are now mostly trying to bring the oldest models closer to the 21st century. Although the new methods appear consistent, it seems that models developed in the mid-late 1900s have retained their positions in the top most popular.

Literature review. Bankruptcy models refer firms to one of two groups: a “good firm” group, which is likely to pay off any financial obligation; or a "bad firm" that is unlikely to pay any financial obligations [4]. Bankruptcy forecasting literature dates back to the 1930s, with the beginning of previous research on the use of the analysis factor to predict future bankruptcies [3]. Until the 1960s, prediction methods focused only on studies and formulas with a one-to-one ratio. The most recognizable for them is Beaver's original single method (1966). After that, models have developed multidimensional methods, of which the most recognizable is Altman's multidimensional Z-score (1968). The number of ratios in multidimensional formulas varies from two to 57.

Some aspects of corporate bankruptcy have been thoroughly covered in contemporary economic literature. This applies, in particular, works of I. O. Blank, V.O. Vasylenko, E. M. Andrushchak, T. G. Ben, L. O. Ligonenko, S. B. Dovbnya, N. Y. Demyanenko, C. V. Kalambet, M. M. Makarenko, A. M. Poddyerohin, V. P. Savchyk, J. L. Sazonets , O. O. Tereshchenko, S. Y. Salyga, A. M. Tkachenko and others. Thanks to the work of these scientists, the basis for further scientific research was created.

The purpose of this article is to answer the question of the possibility of modifying Altman's Z-account in such a way that it could be applied to the conditions of Ukraine. Apply the mathematical apparatus proposed in the work to the calculation of the numerical values of the coefficients of the model Z-calculus. You should also analyze, use factual data from company records to build the model and the ability to use the Z-account model to monitor the financial condition of enterprises that are in accordance with the current rules for assessing bankruptcy risk.

Result and discussion. Given the relatively high incidence of bankruptcies occurring by both publicly traded companies and private firms around the world, and the threat to suppliers and other stakeholders that rely on the solvency of firms for their own success, a reliable bankruptcy model with an ongoing predictable power is important business environment [5]. This underlines the importance of finding and possibly updating useful methods and models for bankruptcy forecasting. Not surprisingly, bankruptcy forecasting is such a well-studied field. Having a working method of bankruptcy forecasting is an important tool for a company. If future financial problems are identified in a timely manner, it can help save the company from another bankruptcy. For this reason, it is extremely important for researchers to develop models to obtain the most accurate results.

However, not only corporations use bankruptcy forecasts as a source of information about a company's financial future. Banks and other investors use this data as an information source when looking for and making new and viable investments. Lenders also gain useful knowledge of this data when considering their investments. As forecasting methods evolve, banks also benefit by receiving more detailed and accurate information about possible investments and making more solid investment decisions.

Predicting corporate failures is also important at different levels of the economy. For example, the bankruptcy of a medium-sized business in a small town is a major blow to the community economy. People who work for the company are losing their jobs and unemployment is rising. The community collects less taxes and is more likely to collect more debt. Other parties affected by these bankruptcies may be, for example, accounting firms that risk lawsuits if the auditor failed to notify the company in time of possible financial problems.

A popular way for lenders and investors to seek knowledge of the financial status of possible new investments is through credit rating agencies. These ratings tend to be more reactive than predictive, so it is more important for researchers to develop more accurate quantitative models of bankruptcy forecasting [6].

Bankruptcy is mostly predicted using the financial statements of companies. The basic idea behind this is that the differences between closed balance sheets of healthy and bankrupt companies and the ratios generated from these figures are significant. There is a small amount of research that uses qualitative information in addition to financial statements. [1].

Bankruptcy models are of two types: parametric and non-parametric. The most used parametric models are multivariate discriminant analysis (MDA) and logistic analysis (LA). MDA classifies companies into two groups: healthy and depressed. The classification is based on the financial characteristics of companies that are calculated by financial ratios. A discriminatory score allows you to classify two groups. Logistic analysis, on the other hand, takes into account the profitability of a company failure. The difference between the two is that logistic regression requires a logistic distribution [7]. Parametric models focus on the symptoms of bankruptcy and can be monotonous or multivariate, the variables of which are mainly financial ratios [2].

Edward I. Altman was the first to develop a multidimensional bankruptcy forecasting formula. His research was conducted with 66 companies, half of which went bankrupt and half healthy. Bankrupt companies have been going for quite a long time, because the data was not as readily available as it is now. Altman used only manufacturing companies for his research, making the original Z-score best used for manufacturing companies.

Altman began his research to find the right relationships. These ratios showed the largest changes between healthy and bankrupt companies. He started with 22 original financial ratios.

After conducting this part of the study, Altman ended up with five coefficients that he believed were most effective in trying to calculate the most informative Z-score. The coefficients were chosen by the appropriate ratio and how well they worked together under different formulas instead of their individual performance.

Finding a relation, Altman drew a linear function, also known as a Z-score. Its function consists of a weighted sum of financial ratios. The weights used were evaluated by statistical discriminant analysis. The calculation formula is given below:

$$Z = 0.012X_1 + 0.014X_2 + 0.0333X_3 + 0.006X_4 + 0.999X_5 \quad (1)$$

in which,

X_1 = net working capital / full capital;

X_2 = retained earnings / full capital;

X_3 = earnings before interest / full capital;

X_4 = market value of equity / book value of debt;

X_5 = sales / full capital.

Altman also specified, that only the first four ratios are used as percentages, and the last one is to be used as a natural number.

The results are classified into three groups. First the healthy companies, which get values at and above Z=2.99. The second group is the bankrupt companies, or companies with a high risk of facing financial distress, which get values at or less than Z=1.81. The third group is the so-called “grey area”. Companies in this grey area get a value for Z which falls between 1.81 and 2.99. These companies, according to Altman, do not have as easily classifiable financial future as the ones falling directly for either healthy or bankrupt values.

All of the five ratios have an area of financial stability that they measure. The first ratio X_1 measures liquidity. Altman had all in all three different ratios which he studied for the purpose of measuring liquidity, out of which he found the net working capital / full capital to be the most suitable.

The second ratio X_2 measures a company’s long-term profitability. For long-term profitability, retained earnings is a good fit, as it is a part of the company’s equity that is not divided to the shareholders. The long-term profitability ratio takes into notice the age of the company, which means that it classifies new companies highly sensitive for bankruptcy. This is not necessarily any different from reality, as new companies do tend to have a higher bankruptcy-rate.

The third ratio X_3 measures the profitability of a company relative to its total assets. As the main purpose of a company is usually to generate revenue and have high return on capital, excluding non-profit organizations, this ratio is ideal for the purpose.

The fourth ratio X_4 measures the financial solidity of a company. Out of all the five ratios, this is the only one which uses the market value of the asset, in this case equity. This makes the original Altman Z-score only applicable for publicly traded companies. Later on, Altman modified the formula to create a version which would be applicable for also private companies. This new Z-score uses book value of equity instead.

The fifth ratio X_5 shows how well a company uses its personal capital to generate sales. A low result on this tells that the company has not been able to raise its market share [8].

In the 1960's Altman's research was a major leap forward. It was a highly appreciated discovery that bankruptcy prediction could be done using scientific measures. Altman's multivariable formula is able to predict bankruptcy up to two years prior of any visible financial distress. In his initial testing, Altman found his research to be correct approximately in 72% of the cases. In his testing he found two types of errors that occurred: Type I (false positives) and Type II (false negatives). The percentage of type II errors was only 6%.

Altman used only industrial companies in his original research, and this seems to affect the formula that he mostly works only for similar companies. This is one of the difficulties of predicting bankruptcy using scientific methods; it is difficult to create a model that is generally accepted. Especially financial companies are advised not to use this formula.

Altman also received criticism when considering his data collection methods. The financial data he used in his research were collected over a 20-year period. At the time, though, it was a necessary act because getting the information you needed was a daunting task.

According to the results of these studies, it is proposed to use the principal component method to determine the level of financial and economic status and the degree of bankruptcy of industrial enterprises.

The proposed model can be represented in the following form: let the given $(p \times n)$ matrix be the observations of a random vector variable $\mathrm{X} = [X_1 \ldots X_p]'$ with a vector of averages $\mu_X = [\mu_1,...,\mu_p]'$ and a covariance matrix *Kx* that determines the structural dependence between the variables $X_j, j = 1,..., p$. It is necessary to find a linear transformation that allows to obtain a concise representation of the original data by a smaller number of variables without significant loss of the information contained in the initial matrix. Let's turn these observations $(p \times p)$ into an orthogonal matrix of appearance:

$$\Phi = [\varphi_1 \ldots \varphi_p]' \tag{2}$$

where $\varphi_j = [\varphi_{1j} \ldots \varphi_{pj}]', (j = 1,\ldots p)$ is the system of p-dimensional orthonormal vectors, that is, for scalar product rightly

$$(\varphi_i, \varphi_j) = \begin{cases} 1 \, with \, i = j, \\ 0 \, with \, i \neq j. \end{cases} \tag{3}$$

Then we obtain a random vector variable *Y* with uncorrelated components

$$\mathrm{Y} = [\mathrm{Y}_1 \ldots Y_p]' = \Phi \mathrm{X} \tag{4}$$

where Y_j there is a linear combination of the coordinates of the features $X_j, \; j = 1,..., p$

$$Y_j = \varphi_{1j} x_{j1} + \ldots + \varphi_{pj} x_{jp}, \, j = 1,..., p. \tag{5}$$

It follows from (3) that $\Phi\Phi' = \Phi'\Phi = \mathrm{I}$ *and* $\Phi' = \Phi^{-1}$,

The covariance matrix of data *X* (by definition):

$$\mathrm{K}_x = M\{(\mathrm{X} - \mu_x)(\mathrm{X} - \mu_x)'\}. \tag{6}$$

The determinant $|\mathrm{K}_x|$ of the covariance matrix $|\mathrm{K}_x|$ is called the generalized variance of the *X* data matrix .

The covariance matrix K_y of a random vector variable *Y* is defined by the expression

$$\begin{aligned} \mathrm{K}_y &= M\{(\mathrm{Y} - \mu_y)(\mathrm{Y} - \mu_y)'\} = M\{\Phi(\mathrm{X} - \mu_x)(\mathrm{X} - \mu_x)'\Phi'\} = \\ &= \Phi M\{(\mathrm{X} - \mu_x)(\mathrm{X} - \mu_x)'\}\Phi' = \Phi \mathrm{K}_x \Phi' \end{aligned} \tag{7}$$

Since K_x and Φ they are square matrices, the determinant of the covariance matrix K_y is equal

$$|\mathrm{K}_y| = |\Phi \mathrm{K}_x \Phi'| = |\Phi\Phi'||\mathrm{K}_x| = |\mathrm{K}_x| \tag{8}$$

that is, the generalized dispersions of the matrices *X* and *Y* are equal.

The best possible orthogonal transformation is to ensure as little redundancy as possible. This means that the matrix *Y* must have uncorrelated components $Y_j, \; j = 1, \ldots, p$. In other words, the matrix K_y must be diagonal

$$K_y = diag[\sigma^2_{y_1},...,\sigma^2_{y_p}] \quad (9)$$

where $\sigma^2_{y_j}$ - the variance of the j-th component of vector random variable Y . Denote $\lambda_j = \sigma^2_{y_j}, j = 1,..., p$ then:

$$|K_y| = \prod_{j=1}^{p} \lambda_j \quad (10)$$

Assume that the variances are ordered. If not all λ_j are equal, then the matrix Y can be compressed by discarding the components, neglecting small variances. Suppose $Y_1 - (n \times 1)$ that the vector is the first principal component of the matrix X : $Y_1 = \sum_{i=1}^{p} \varphi_{i_1} x_{1i}$. Let's find the variance of this principal component $\sigma^2_{y1} = \varphi_1^{'} K_x \varphi_1 = \sum_{r=1}^{p} \sum_{i=1}^{p} \varphi_{1_i} \varphi_{r_1} M[(X_1 - \mu_1)(X_1 - \mu_1)^{'}]$.

Will require that the first component Y_1 has the greatest variance if the orthogonality of the vectors $\sigma^2_{y_i}$ of the matrix Φ is preserved . Then the problem of finding the best transformation is reduced to finding the maximum of the function χ^2 under the condition $(\varphi_1^{'}, \varphi_1) = \sum_{j=1}^{p} \varphi^2_{1j} = 1$.

To solve this optimization problem, a Lagrange function is usually introduced

$$L(\varphi) = \varphi_1^{'} K_x \varphi_1 - \lambda_1(\varphi_1^{'} \varphi_1 - 1) \quad (11)$$

where λ_1 is the Lagrange multiplier. To obtain the necessary condition of the extremum by equating to zero the private derivatives $\partial L / \partial \varphi_1$:

$$\frac{\partial L}{\partial \varphi_1} = 2(K_x \varphi_1 - \lambda_1 \varphi_1) = 2(K_x - \lambda_1 I)\varphi_1 = 0 \quad (12)$$

where I - is a unit matrix. Since we are only interested in the solutions under which $\varphi_1 \neq 0$, then the condition on the determinant must be satisfied

$$|K_x - \lambda_1 I| = 0 \quad (13)$$

This implies that λ_1 there is an eigenvalue of the K_x matrix and φ_1 an eigenvector corresponding to that number . Expression (12) can be rewritten as $K_x \varphi_1 = \lambda_1 \varphi_1$.

Multiplying from left to $\varphi_1^{'}$ and considering relation (2), we obtain the following formula:

$$\varphi_1^{'} K_x \varphi_1 = \lambda_1 \varphi_1^{'} \varphi_1 = \lambda_1 \quad (14)$$

The left-hand side of equality (14) is $\sigma^2_{y_1}$, and since the maximization x_2 problem is solved, λ_1 there is therefore a maximal eigenvalue of the matrix K_x. To find the second major component $Y_2 = \varphi_2^{'} X$ will demand fulfillment of two conditions - the conditions of normalization $(\varphi_2^{'} \varphi_2) = \sum_{i=1}^{p} \varphi^2_{2i} = 1$, and orthogonality conditions: $(\varphi_1^{'}, \varphi_2) = 0$. The vector is now defined to be maximal when the two conditions are met. This task requires the use of two Lagrange multipliers λ_2, β . To maximize expression

$$\varphi_2^{'} K_x \varphi_2 - \lambda_2(\varphi_2^{'} \varphi_2 - 1) - \beta(\varphi_1^{'} \varphi_2 - 1) \quad (15)$$

Taking a derivative of expression (15) and equating it to 0, we find that, by condition (2), that β=0. Considering normalization condition, obsessed λ_2 which is the second largest eigenvalue K_x matrix equal dispersion of the second main component $\lambda_2 = \sigma^2_{y_2}$, and φ_2 - the corresponding eigenvector. The process is repeated until all eigenvalues are found and their eigenvectors associated with them are variances and coefficients of linear combinations of the principal components.

In terms of geometric interpretation, orthogonal transformation is the rotation of the coordinate system of a p-dimensional vector space around the origin. The total variance of the components of the vector quantity Y is equal $\sum_{j=1}^{p} \sigma^2_{y_j} = trM\{(Y - \mu_y)(Y - \mu_y)^{'}\} = trM\{\Phi(X - \mu_x)(X - \mu_x)^{'} \Phi^{'}\}$, using the property of the trace of the product of matrices, we have:

$$\sum_{j=1}^{p}\sigma_{y_1}^2 = trM\{(X-\mu_x)(X-\mu_x)'\Phi'\Phi)\} = trK_x = \sum_{j=1}^{p}\sigma_{x_j}^2$$

or

$$\sum_{j=1}^{p}\lambda_j = trK_y = trK_x \quad (16)$$

where trK_y, trK_z are the traces of the matrices K_y and K_x .

The relative contribution of a component to the total variance of a random vector variable Y_j is equal:

$$\frac{\sigma_{y_j}^2}{\sum_{j=1}^{p}\sigma_{y_j}^2} = \frac{\lambda_j}{\sum_{j=1}^{p}\lambda_j} = \frac{\lambda_j}{trK_x} \quad (17)$$

The resulting conversion maximized the dispersion of the first components Y_j, called principal components , to provide the best compression.

For the i-th principal component we have $Y_i = \varphi_i' X_i$ where φ_i the eigenvector corresponding to the eigenvalue λ_i of the matrix Kx . The importance of the i-th major component is determined by its contribution to the overall variance

$$\frac{\sigma_{y_j}^2}{\sum_{j=1}^{p}\sigma_{y_j}^2} = \frac{\lambda_j}{\sum_{j=1}^{p}\lambda_j} \quad (18)$$

Orthogonal transformation does not change the overall variance. If we limit r to the first components, then their share in the total variance will be $\frac{\sum_{i=1}^{r}\lambda_i}{\sum_{j=1}^{p}\lambda_j}$ residual variance will be equal $\sum_{j=r+1}^{p}\lambda_j$. Thus, the variance of the residuals is equal to the sum of the variances corresponding to the discarded components of the vector Y , and this is true for any orthonormal transformation.

This compression criterion is called dispersion. To use this method, you need to find the eigenvalues of the matrix K_x , arrange them in descending order, select the number of components r that will provide a given fraction of the residual dispersion:

$$\sigma_{\sigma_x}^2 = \frac{\sum_{j=r+1}^{p}\lambda_j}{trK_x} = \frac{\sum_{j=r+1}^{p}\lambda_j}{\sum_{j=1}^{p}\lambda_j} \quad (19)$$

You can use the dispersion criterion for sequential selection of components . The decision on when to stop the component selection procedure depends mainly on what is considered to be a small fraction of the variance. This technique allows to obtain p models of the form:

$$Z_i = C_{i1}X_1 + C_{i2}X_2 + \ldots + C_{ip}X_p,\ i=1,2,\ \ldots\ p. \quad (20)$$

From the models obtained, you must select one or more and bring them to a linear appearance. Given that the vector Z_i is the eigenvector of the correlation matrix K_x, which corresponds to the eigenvalue of λ_i , there are two options for solving this problem:

1). If the eigenvalue of λ_1 is much larger (predominant), the remaining numbers λ_2, $\lambda 3$, λp , then the first principal component is chosen as the determinant model of Z:

$$Z_1 = C_{11}X_1 + C_{12}X_2 + \ldots + C_{1p}X_p, \quad (21)$$

2). If not one of the numbers λ_i is not dominant, then the model will take the form:

$$Z = A_1Z_1 + A_2Z_2 + \ldots + A_pZ_p, \quad (22)$$

where, Z_1 , Z_2 , Z_p are the main components of the correlation matrix K_x , which are calculated by the formula (19), A_1, A_2, A_p are the values to be determined.

Since eigenvectors Z_1 , Z_2 , Z_p correspond to different size eigenvalues λ_1, λ_2, λ_p, then as A_1, A_2, A_p advisable to use values λ_1, λ_2, λ_p. Then the Z-score will take the form:

$$Z = C_1X_1 + C_2X_2 + \ldots + C_pX_p, \quad (23)$$

where C_1, C_2, C_p are determined by the formula:

$$C_i = \lambda_1C_{i1} + \lambda_2C_{i2} + \ldots + \lambda_pC_{ip} \quad (24)$$

Such an algorithm allows not only to obtain the model itself, but from the coefficients that are included in it to choose the most significant ones. If the value of a number λ_j is very small, then the corresponding coefficient can be excluded from the model without compromising its accuracy.

Let's demonstrate the application of the principal component method to construct an analogue of the Altman model on practical statistics. For example, let's take several enterprises in the same industry. Model will include the following parameters: return on investment (ROI) - X_1 , earnings per share (EP) - X_2 , return on assets (ROA) - X_3, quick ratio (QR) - X_4, cash to total assets (CTA) - X_5, debt ratio (DR) - X_6 (Table 1).

Table 1

Financial indicators of the enterprises of the Kirovograd region

Enterprises	ROI	EP	ROA	QR	CTA	DR
Year 2016						
LLC Dobrovelichkivka Cannery	-0,587	-0,105	-0,106	0,794	0,509	0,292
PrJSC Dolinsky bakery	0,981	0,201	0,201	3,062	0,516	0,872
PJSC Kirovogradolia	0,017	0,008	0,006	1,024	0,727	0,439
PJSC Novoarhangelsk cheese factory	8,235	0,092	0,069	2,012	4,564	0,676
PrJSC Alexandria Bakery	-3,221	-0,168	-0,149	0,543	1,856	-0,094
PJSC Svetlovodsk butter and cheese plant	0,118	0,009	0,009	3,467	0,901	0,226
Year 2017						
LLC Dobrovelichkivka Cannery	-0,159	-0,014	-0,015	0,903	0,541	0,137
PrJSC Dolinsky bakery	0,428	0,057	0,057	1,696	0,635	0,632
PJSC Kirovogradolia	0,018	0,009	0,004	0,683	0,322	0,800
PJSC Novoarhangelsk cheese factory	6,765	0,048	0,036	4,478	3,977	0,215
PrJSC Alexandria Bakery	-4,597	-0,144	-0,137	0,592	1,120	-0,198
PJSC Svetlovodsk butter and cheese plant	0,470	0,018	0,018	2,140	1,567	0,125
Year 2018						
LLC Dobrovelichkivka Cannery	-0,526	-0,034	-0,036	0,879	0,297	0,063
PrJSC Dolinsky bakery	-1,588	-0,412	-0,412	1,526	2,016	0,808
PJSC Kirovogradolia	0,001	0,001	0,000	0,786	0,125	0,819
PJSC Novoarhangelsk cheese factory	10,118	0,070	0,053	1,561	4,809	0,068
PrJSC Alexandria Bakery	-2,890	-0,079	-0,079	0,479	1,174	-0,260
PJSC Svetlovodsk butter and cheese plant	1,196	0,048	0,046	1,704	1,496	0,144

Source: calculated by the author [18].

Using the principal components method for existing data calculating the covariance matrix are presented in Fig. 1

$$Kx = \begin{pmatrix} 14.6858 & 0.2689 & 0.2389 & 2.1915 & 4.4717 & 0.2848 \\ 0.2689 & 0.0171 & 0.0166 & 0.0612 & 0.0196 & 0.0079 \\ 0.2389 & 0.0166 & 0.0161 & 0.0575 & 0.0113 & 0.007 \\ 2.1915 & 0.0612 & 0.0575 & 1.2508 & 0.6455 & 0.0817 \\ 4.4717 & 0.0196 & 0.0113 & 0.6455 & 2.1426 & -0.0654 \\ 0.2848 & 0.0079 & 0.007 & 0.0817 & -0.0654 & 0.1347 \end{pmatrix}$$

Fig. 1 Covariance matrix

The calculation of the eigenvalues of the covariance matrix K_x of transformed data are given in the Table 2.

Table 2

Calculated the eigenvalues the covariance matrix K_x of transformed data

Coefficients	Eigenvalue	Variance	Cumulative	$Chis_q$	Degrees of Freedom
Return on investment	16,471	90.27%	90.27%	323,823	20
Earnings per share	0,933	5.11%	95.38%	195,628	14
Return on assets	0,734	4.02%	99.41%	179,704	9
Quick Ratio	0,096	0.53%	99.94%	122,301	5
Cash to total assets	0,011	0.06%	100.00%	83,2209	2
Debt Ratio	0.000	0.00%	100.00%	0	0

Source: calculated by the author using OriginPro 2017.

A necessary condition for finding Z-model coefficients is to find the eigenvalues of eigenvectors. The calculations gave the following results are presented in Table 3.

Table 3

The eigenvalues of eigenvectors of Z-model coefficients

Coefficients	C_1	C_2	C_3	C_4	C_5	C_6
Return on investment	0,9417	-0.037	-0.320	-0.067	-0.065	0.002
Earnings per share	0,0163	0.045	-0.071	-0.138	0.684	-0.710
Return on assets	0,0144	0.045	-0.069	-0.140	0.691	0.703
Quick Ratio	0,1485	0.926	0.341	-0.032	-0.036	0.000
Cash to total assets	0,3005	-0.350	0.854	0.189	0.142	-0.001
Debt Ratio	0,0159	0.111	-0.200	0.958	0.166	0.000

Source: calculated by the author using OriginPro 2017.

Based on the calculations, obtained six equations that are presented in a compressed form, so the studied coefficients were optimized. The selection criterion and the possibility of simplification of the required model are sought due to the dominant eigenvalue of the vectors of the covariance matrix K_x of transformed data. Since the eigenvalue of λ_1 = 16.471 is much outweighed by the following eigenvalues λ_2, λ_3 ... λ_6, then as a model we get the equations of the form:

$$Z = 0{,}9417X_1 + 0{,}0163X_2 + 0{,}0144X_3 + 0{,}1485X_4 + 0{,}3005X_5 + 0{,}0159X_6 \qquad (25)$$

To determine the limits of the model (determination of interval values of the Z-model), which gives a direct characteristic of the threat of bankruptcy of enterprises, it is necessary to determine its value by the method of expert assessments.

Conclusions. Bankruptcy forecasting has paid much attention in recent decades to the accounting and finance literature. The main reason for developing new bankruptcy forecasting formulas was usually to improve the accuracy of these methods. Because there is no single theory of bankruptcy, research is largely based on empirical research for better predictions or statistical methods.

These results have some practical implications. Banks and other stakeholders who use bankruptcy forecasting formulas should modify them to meet the specific financial market. Models developed in one country over a period of time do not necessarily work in other countries and other time periods. Future research should also pay more attention to the development of bankruptcy forecasting models for further placement in different environments.

A coefficient analysis of the financial condition of enterprises is one of the most common methods and, in a certain sense, the classical method. It has a number of advantages and disadvantages, which are widely described in the economic literature. However, interest in such an approach in the implementation of economic analysis is constantly increasing.

Current trends in the theory and practice of financial analysis are associated with the problem of modifying the system of existing coefficient methods and the coefficients themselves in order to bring them into a form convenient for making adequate management decisions in the field of financial monitoring.

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ВИКОРИСТАННЯ МЕТОДУ ГОЛОВНИХ КОМПОНЕНТ В ПРОГНОЗУВАННІ БАНКРУТСТВА ПІДПРИЄМСТВ

Проблема. *Прогнозування банкрутства – одна з найбільш досліджених тем у фінансах та стратегічному управлінні. Кількість методів, що застосовуються для прогнозування банкрутства, є величезною, починаючи з методу Бівера (1966 р.) Використання однозмінних коефіцієнтів та переходу до останніх досліджень, таких як логістична регресія або гібридні моделі. Тільки для однієї моделі створено незліченну кількість статей, досліджень і навіть книг, виготовлених з основною метою їх розробки, і нині в основному намагаються наблизити найдавніші моделі до 21 століття. Хоча нові методи виглядають послідовно, але здається, що моделі, розроблені в середині кінця 1900-х років, зберігають свої позиції в топі найбільш популярних.*

Метою *статті є відповідь на питання про можливість модифікації Z-рахунку Альтмана таким чином, щоб з'явилася можливість його застосування для умов України. Застосуємо запропонований в роботі математичний апарат до розрахунку чисельних значень коефіцієнтів моделі Z-рахунку. Також слід проаналізувати, використовувати фактичні дані з облікових документів підприємств для побудови моделі та можливість використання моделі Z-рахунку для моніторингу фінансового стану підприємств, що входять у відповідності з діючими правилами оцінки платоспроможності в групу ризику банкрутства.*

Результати. *Враховуючи відносно високу частоту банкрутств, що відбувається як державними комерційними підприємствами, так і приватними фірмами по всьому світу, та загрозу для постачальників та інших зацікавлених сторін, які покладаються на платоспроможність фірм для власного успіху, надійною моделлю банкрутства з постійною прогнозованою силою є важливі для сучасного бізнес-середовища. Банкрутство здебільшого прогнозується, використовуючи фінансову звітність компаній. Альтман використовував у своїх оригінальних дослідженнях лише промислові компанії, і, схоже, це впливає на формулу того, що він здебільшого працює лише для подібних компаній. Це одна з труднощів передбачення банкрутства з використанням наукових методів; важко створити модель, яка є загальноприйнятою. Особливо фінансовим компаніям рекомендується не використовувати цю формулу. За результатами цих досліджень запропоновано для визначення рівня фінансового-економічного стану і ступеня загрози банкрутства підприємств промисловості, використовувати метод головних компонент.*

Наукова новизна. *Попередні дослідження свідчать про те, що точність моделі може бути сильно прив'язана до тієї галузі, в якій компанія займається своїм бізнесом. Оригінальна модель Альтмана, а останнім часом модель для приватних торгових компаній, яка використовувалася в цьому проекті, спочатку тестувались із виробничими компаніями. У зв'язку з цим було б сенс, що модель найкраще співпрацює з виробниками. Ці результати мають певні практичні наслідки. Банки та інші зацікавлені сторони, які використовують формули прогнозування банкрутства, повинні модифікувати їх з урахуванням конкретного фінансового ринку.*

Висновки. *Прогнозування банкрутства в останні десятиліття приділяло багато уваги літературі з питань бухгалтерського обліку та фінансів. Основною причиною розробки нових формул прогнозування банкрутства зазвичай було підвищення точності цих методів. Оскільки не існує єдиної теорії банкрутства, дослідження в основному ґрунтуються на емпіричному дослідженні для кращих прогнозів або статистичних методів. Моделі, розроблені в одній країні протягом певного періоду часу, не обов'язково працюють в інших країнах та інших періодах часу. Майбутні дослідження також повинні приділяти більше уваги розробці моделей прогнозування банкрутства для подальшого розміщення в різних середовищах.*

Ключові слова: *Z-рахунок Альтмана, прогнозування банкрутства, багатовимірний метод, платоспроможність, неспроможність, діагностика, підприємство, моніторинг, метод головних компонент.*

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