

# MODELING AND FORECAST OF SOCIO-ECONOMIC PROCESSES

DOI: 10.15838/esc.2019.2.62.7

UDC 330.43, LBC 65.054

© Stel'makh V.S.

## Methodological Aspects of Predicting the Probability of Bankruptcy on the Example of Pharmaceutical Companies



**Veniamin S. STEL'MAKH**

Khabarovsk State University of Economics and Law

Khabarovsk, Russian Federation, 134, Tikhookeanskaya Street, 680042

E-mail: Vs-stel@ya.ru

**Abstract.** When it comes to the development of industrial enterprises, there is always the possibility of a crisis; therefore, for continuous sustainable operation it is necessary to develop preventive tools to predict the crisis processes in advance. The present paper covers the objective of developing and testing models for estimating the probability of bankruptcy based on logistic regression for sustainable development of domestic industrial enterprises. The study was conducted within the pharmaceutical industry, yet the methods of development and the testing technique can be applied in other industries. The paper presents the stages of model development (predictor formation, correlation and regression analysis) and its testing (evaluation of statistics parameters, comparative analysis with existing models). The use of the logistics model of bankruptcy assessment helps analyze the correlation between the indicators of enterprise's economic condition and its degree of bankruptcy. Moreover, such a model can quantify the probability of bankruptcy at an industrial enterprise. The reliability and validity of the presented results is confirmed by the generalization of theoretical and methodological studies of experts in this field, the applied results are based on a large amount of financial information of domestic pharmaceutical enterprises and confirmed by the use of algorithms of economic and mathematical modeling recognized in the scientific community. The study used indicators of economic condition based on public reporting of 266 pharmaceutical companies, where one hundred companies were engaged in model development and the rest – its testing. The developed model is able to predict the probability of bankruptcy of pharmaceutical enterprises two

---

**For citation:** Stel'makh V.S. Methodological aspects of predicting the probability of bankruptcy on the example of pharmaceutical companies. *Economic and Social Changes: Facts, Trends, Forecast*, 2019, vol. 12, no. 2, pp. 115-127. DOI: 10.15838/esc.2019.2.62.7

years ahead. The small amount of calculations and lack of highly technical calculations helps quickly obtain information about the economic condition and versatile calculation makes it possible to conduct a comparative analysis of enterprises in the context of one industry.

**Key words:** crisis management, modelling, logistic regression, probability of bankruptcy, correlation and regression analysis, elimination method, industrial enterprises, pharmaceutical industry.

### Introduction

When it comes to the development of industrial enterprises, there is always the possibility of a crisis. The most important objective of crisis management is to prevent a crisis caused by management errors and ensure most painless recovery amid objectively developing crisis processes [1]. Therefore, crisis processes should be quickly detected in order to prevent them and maintain the functioning of industrial enterprises since timely identification of a crisis helps minimize losses during management.

It is advisable to use models of bankruptcy assessment to identify the crisis, but the methodological issue of this process lies in taking into account industry characteristics. Ignoring such information may lead to incorrect assessment and, as a result, accelerated development of crisis processes at enterprises [2]. In the present article, the research object is pharmaceutical enterprises. The choice of pharmaceuticals is due to intensive development of the industry, its strategic importance for the state and the population, as well as lack of tools for assessing bankruptcy in this area [3].

In order to determine the functional type of relations between the indicators of economic condition and the degree of bankruptcy of an industrial enterprise, the methods of correlation and regression analysis are used. Common methods for assessing bankruptcy are those based on discriminant analysis and logistic regression.

As a result, there is an objective to develop and test a new model of bankruptcy assessment adapted to Russian pharmaceutical companies through econometric modeling.

### Literature review

In Economics, modeling and estimating the probability of bankruptcy arose in the 1940s. In works of that time, models were used only for assessing credit capacity and monitoring credit risks. For example, D. Duran developed credit-score models which included only financial aspects of company's activities, such as solvency and credit debt [4].

The area under review rapidly developed in the 1960s. E. Altman began to use discriminant analysis in the development of models for assessing bankruptcy [5]. It was found that the basic condition for using such analysis for modeling is the subordination of discriminant variables to the multinormal law, and the model is the dependence of degree of bankruptcy on basic financial ratios of an enterprise. It should be noted that in certain samples of bankrupt enterprises it is either difficult to determine the normal distribution, or it is not executed at all [6–8]. Moreover, when calculating the integrated index in the models of foreign [8–10] and Russian [11–14] economists, there is an uncertainty interval, in which it is impossible to make an unambiguous conclusion about the probability enterprise's of bankruptcy.

In addition to discriminant analysis since the 1980s, for example, in the work by J. Ohlson [15], models were developed based on logit

regression (logit-model). In [15–17], logit-models are constructed in the absence of the problem of “uncertainty” since the value of a continuous dependent variable is calculated, which takes values in the range from 0 to 1. To construct such models, we need data on both bankrupt and operating enterprises [18–21]. Consequently, logit-models make it possible to analyze the correlation between indicators of enterprise’s economic condition and its probability of bankruptcy, while other models only classify an enterprise according to a certain degree of bankruptcy. Moreover, logit-models can not only classify an enterprise, but also quantify the probability of bankruptcy, thus they are more flexible than their analogies.

Despite the advantages of logit-models, [22–24] note a certain subjectivity in calculations of the probability threshold of bankruptcy and the presence of multicollinearity of predictors, which is a factor reducing the model accuracy. This problem is explained by the national peculiarities of accounting policy and industry characteristics of enterprises, which is confirmed in domestic studies.

Russian researchers continued to develop this area, with a great contribution to the development of domestic models and comparative analysis with foreign models noted in works [11, 12, 20, 21]. The analysis of works shows that the authors agree on the high error values in using foreign methods of predicting the probability of bankruptcy; among the applied methods, models based on discriminant analysis and logistic regression have higher assessment accuracy, and the use of models for various industries leads to incorrect research results since each industry has its own characteristics, which affects the inclusion of indicators in the model and their weighing factors.

### 1. Stages of development of the bankruptcy assessment logit-model

When assessing bankruptcy using the logit model, it is assumed to assess the probability of bankruptcy using enterprise performance. The very nature of such a model is a linear correlation between the base logarithm of integrated index of economic condition (response) and the linear combination of indicators of enterprise functioning [15; 22] and is expressed by the following formula:

$$\ln\left(\frac{S}{1-S}\right) = a_0 + \sum a_i k_i, \quad (1)$$

where  $S$  – probability of bankruptcy of an enterprise,  $S/(1-S)$  – odds ratio, which determines how many times more often the response takes value 1 than 0,  $k_i$  – the predictor (a factor characterizing a certain aspect of the economic condition),  $a_0$  – a free member,  $a_i$  – the weighing factor of each predictor.

The presented equation reflects the linear dependence of the probability of bankruptcy depending on the set of values of the enterprise’s economic factors. Theoretically, regardless of the regression coefficients  $a_i$  and predictors  $k_i$ , the model takes any value. Note that the term *logit* comes from the fact that it is possible to get away from linearity in this model using logit-transformation, thus the value of the model will be on the interval  $[0, 1]$ , which indicates the probability of bankruptcy, where 0 is minimum probability, 1 – maximum. To interpret the coefficients and to simplify the model the exponential form (parts of the equation are exhibited) of the model is typically used:

$$S = \frac{e^{a_0 + \sum a_i k_i}}{1 + e^{a_0 + \sum a_i k_i}} = \frac{1}{1 + e^{-a_0 - \sum a_i k_i}}. \quad (2)$$

Thus, the first stage of constructing a bankruptcy assessment model using logistic regression is the formation of predictors ( $k_i$ ).

### 1.1. Forming an array of predictors

The information framework for the model includes financial statements of pharmaceutical companies<sup>1</sup>. The indicators in the sample were calculated for two groups of enterprises:

1. 72 operating enterprises, as of the beginning of 2018 (excluding enterprises in the process of liquidation or reorganization through merger, division and accession to another legal entity, as well as those in bankruptcy proceedings),  $S=0$ ;
2. 28 bankrupt enterprises from 2004–2017, for such enterprises  $S=1$ .

In our opinion, when forming an array of predictors it is necessary to conduct a dynamic analysis of indicators, which helps determine the development of the industry and crisis periods. For example, due to the crisis processes taking place in the Russian economy in 2014–2015, the indicators of enterprises sharply changed, which affected the deterioration of the overall economic condition, while pharmaceutical enterprises did not go bankrupt. Therefore, the calculation of indicators for such atypical periods may lead to incorrect model values and its low quality.

For bankrupt enterprises, the indicators are calculated for two years before going bankrupt (for example, if the enterprise is declared bankrupt in 2015, the predictors for the array were calculated at the end of 2012). We believe that the two-year period is optimal for introducing anti-crisis measures in order to maintain the functioning of industrial enterprises. For the enterprises of the first group, data for 2014–2015 (crisis periods) and 2016 (did not pass the two-year lag) were not used. It is advisable to use data for 2013, which

is more relevant today and quite a favorable period for the pharmaceutical industry.

Thus, the forecast horizon of the constructed model is two years. Note that in the existing models there is either a short forecasting period [21; 23] when the company does not have time to “prepare” for the crisis; or an increase in the forecast horizon [18; 19], which reduces the model accuracy, since the distribution of outcomes for the two groups of enterprises becomes the same.

As a result, the formed sample is an array of data for a certain reporting date, where  $i$ -th pharmaceutical enterprise corresponds to a set of indicators of its activity  $k_1, k_2, \dots, k_n$ , and depending on the status of an enterprise ( $S$ ), the operating or the bankrupt one is assigned either 0 or 1, respectively.

It should be noted that after the development of the logistic regression model, there may be a problem with the low accuracy of the forecast, the reason for which is the insufficient amount of historical sampling (observed in the developments of models [11; 14; 21; 24]). The choice of the minimum sample size depends on the distribution of dependent variable values. Under normal distribution, nine or ten predictors are sufficient to describe systems of any complexity, where at least ten observations are required for each predictor [25].

Thus, the historical sample will include 100 enterprises. One of the limitations in constructing a logistic model is the small amount of bankrupt enterprises and reporting on them. As a result, 58 bankrupt enterprises were selected (half of the sample was used for construction, the remaining – for testing). We do not present in-depth analysis of the shares in which to select operating and bankrupt enterprises, the sample quality is still the criterion accuracy of the model. Note that the authors either correlate these groups in equal

<sup>1</sup> The statements of pharmaceutical companies can be found official websites of companies, corporate information disclosure portals and in the system of professional market and company analysis (SPARK Interfax).

volumes [5, 7, 13, 15, 21], or the sample is dominated by the operating enterprises [6, 7, 12, 14, 18–20], since the number of bankruptcy procedures in the industry is always less than the number of normally operating enterprises. We should also add that the fact of enterprises being among historical and test samples is random.

Based on these provisions, we form a sample of indicators according to financial statements of 100 pharmaceutical enterprises. To do this, we select from a set of indicators those that have the following properties:

1. make economic sense and provide an informative, consistent ideas of the economic situation;
2. are not highly technical indicators and are calculated according to the data of public reporting;
3. correspond to the nature of the model of bankruptcy assessment and meet the goals and objectives of crisis management of industrial enterprises.

Thus, we selected 18 indicators characterizing enterprises from different perspectives (liquidity, profitability, asset and capital structure, financial viability): sufficiency of own working capital ( $K_1$ ), flexibility of own current assets ( $K_2$ ), share of receivables in assets ( $K_3$ ), share of short-term liabilities in the capital structure ( $K_4$ ), ratio of immobilized and mobilized assets ( $K_5$ ), current liquidity ( $K_6$ ), quick liquidity ( $K_7$ ), absolute liquidity ( $K_8$ ), financial leverage ( $K_9$ ), financial dependence ( $K_{10}$ ), debt coverage ( $K_{11}$ ), return on equity ( $K_{12}$ ), gross margin ( $K_{13}$ ), return on assets ( $K_{14}$ ), return on equity ( $K_{15}$ ), sales margin ( $K_{16}$ ), return on working assets ( $K_{17}$ ), degree of solvency ( $K_{18}$ ).

The sample did not include turnover indicators as they have underestimated values at industrial enterprises. Instead, liquidity and profitability indicators, which quickly respond

to changes in the economic condition of enterprises, are included.

Next, it is necessary to check the distribution of selected indicators for normality. To test the hypothesis that the sample belongs to the normal distribution law (empirical distribution corresponds to expected distribution), we use the Kolmogorov-Smirnov test.

The exclusion of indicators from further calculation should be determined by the significance level. If  $p > 0.05$  then empirical distribution under study corresponds to normal distribution, in the opposite case the distribution differs from normal. For example, the distribution of values of variables  $K_1$  and  $K_3$  is not statistically different from normal since  $p > 0.05$  and error probability is negligible.  $K_2$  variable has a significance level below the set level, therefore, the values do not obey normal distribution and it is necessary to exclude this indicator from further model construction.

According to the results of normality test, the following indicators are selected for further model construction:  $K_1, K_3, K_4, K_6, K_7, K_{10}, K_{11}, K_{13}$ .

## 1.2. Correlation analysis

Within this stage it is necessary to:

1. create a matrix of paired correlation indices;
2. using the Chaddock scale, identify mutually correlated indices (a negative value indicates the opposite correlation between variables), one of which is excluded from further calculation. Such a reduction in the number of indicators can reduce their number, while the level of economic condition assessment of an enterprise is not reduced;
3. select the indices without a strong and close correlation, in which the critical level of the correlation index is not more than 0.7. The selected indices are the basis for further construction of the logistic regression equation.

Table 1. Matrix of pair correlation indices

K	K <sub>1</sub>	K <sub>3</sub>	K <sub>4</sub>	K <sub>6</sub>	K <sub>7</sub>	K <sub>10</sub>	K <sub>11</sub>	K <sub>13</sub>
K <sub>1</sub>	1.000	0.306	-0.663	0.872	0.658	-0.606	0.813	0.179
K <sub>3</sub>	0.306	1.000	0.227	0.121	0.445	0.032	0.290	0.284
K <sub>4</sub>	-0.663	0.227	1.000	-0.717	-0.523	0.749	-0.438	-0.119
K <sub>6</sub>	0.872	0.121	-0.717	1.000	0.735	-0.588	0.762	0.154
K <sub>7</sub>	0.658	0.445	-0.523	0.735	1.000	-0.502	0.607	0.279
K <sub>10</sub>	-0.606	0.032	0.749	-0.588	-0.502	1.000	-0.673	-0.097
K <sub>11</sub>	0.813	0.290	-0.438	0.762	0.607	-0.673	1.000	0.052
K <sub>13</sub>	0.179	0.284	-0.119	0.154	0.279	-0.097	0.052	1.000

During the analysis of matrix pair correlation indices presented in *Table 1* it is advisable to exclude from further research:  $K_p$ ,  $K_q$ ,  $K_r$ . The sufficiency of own working capital ( $K_1$ ) index is closely correlated with debt coverage ( $K_{11}$ ) index and current liquidity ( $K_6$ ) index. In turn,  $K_6$  has a high pair index with the majority of indicators. Besides being closely correlated to  $K_6$ , the share of short-term liabilities in the capital structure ( $K_4$ ) index is also highly interdependent with the financial dependence ( $K_{10}$ ) index.

According to the results of the correlation analysis, further development of the logistic regression model for assessing the bankruptcy of pharmaceutical enterprises will be based on the following indices with normal distribution, where paired correlation indices are not closely correlated with the indicators:

1. share of receivables in assets ( $K_3$ );
2. quick liquidity ( $K_7$ );
3. financial dependence ( $K_{10}$ );
4. debt coverage ( $K_{11}$ );
5. gross margin ( $K_{13}$ ).

### 1.3. Regression analysis

This stage implies the construction of the logistic regression equation. We note that it is inappropriate to have an absolute term in the equation. From the theoretical point of view, if all economic indicators (predictors) equal 0,

the probability of bankruptcy will be calculated based on the size of the absolute term. In real economic processes, if all indicators equal 0, the industrial enterprise does not function, therefore it is recognized non-operating.

Thus, the logistic regression model will not contain free term, *Formula 2* is transformed into the following equation:

$$S = \frac{e^{\sum a_i k_i}}{1 + e^{\sum a_i k_i}} = \frac{1}{1 + e^{-\sum a_i k_i}} \quad (3)$$

The regression equation was constructed using the method of eliminating (backward likelihood ratio) the remaining indices. This method involves the inclusion of all predictors in the regression equation. Later, at each step there is an exclusion of the least "useful" ones, that is, predictors with minimum  $F$ -statistic value, this value should be less than the pre-selected threshold. The  $F$ -statistic assessment helps exclude predictors with an insufficient influence on the explained variable. The IBM SPSS Statistics 17.0 complex, in which the model is calculated, calculates  $p$ -value, and the exclusion of predictors ends when all of them satisfy the expression  $p_i < p$ , where  $p_i$  – significance level of each predictor,  $p$  – a threshold value of 0.01.

*Table 2* demonstrates statistic characteristics of the regression analysis for the construction of

Table 2. Parameters of logistic regression model

Step	Predictor ( $K_i$ )	Predictor weighing factor ( $a_i$ )	Standard error	Walt test	Degree of freedom	Level of significance ( $p$ )
1	$K_3$	-0.755	1.850	0.167	1.000	0.683
	$K_7$	-1.154	0.977	1.394	1.000	0.238
	$K_{10}$	2.336	0.807	8.378	1.000	0.004
	$K_{11}$	-0.479	0.576	0.693	1.000	0.405
	$K_{13}$	-4.183	1.449	8.332	1.000	0.004
2	$K_7$	-1.339	0.891	2.259	1.000	0.133
	$K_{10}$	2.183	0.699	9.741	1.000	0.002
	$K_{11}$	-0.502	0.578	0.754	1.000	0.385
	$K_{13}$	-4.147	1.437	8.331	1.000	0.004
3	$K_7$	-1.947	0.598	10.584	1.000	0.001
	$K_{10}$	1.984	0.633	9.829	1.000	0.002
	$K_{13}$	-3.970	1.415	7.875	1.000	0.005

a logistic model for assessing bankruptcy. Based on the presented data, two predictors were excluded, as the significance level was 1% higher than the threshold value:

1. at the first step, share of receivables in assets ( $K_3$ ) index is excluded:  $0.683 > 0.01$  (condition  $p_i < p$  is not met);
2. at the second step, debt coverage ( $K_{11}$ ) index is excluded:  $0.385 > 0.01$  ( $p_i < p$  is not met).

The indices of the regression equation ( $a_i$ ) determine the effect of the corresponding indicators (predictors) on the integrated index of the economic condition of an industrial enterprise. Based on this, gross margin ( $K_{13}$ ) index has the largest contribution to the value of the final indicator. By the last step, the values of Wald test as a criterion for the significance of each  $a_i$  for the corresponding predictor do not have strong deviations among themselves, which indicates that the model is appropriate.

Further, calibration test will be applied for testing the model and evaluating the obtained indices of the regression equation. The test determines the degree of correspondence between estimated probabilities of bankruptcy predicted by the model and the real probabilities of defaults.

Based on statistics of 100 Russian pharmaceutical enterprises divided into operating enterprises and bankrupt enterprises, with the use of normality test, correlation analysis and the likelihood ratio method, we constructed a logistic model which determines the probability of bankruptcy 2 years before its occurrence.

In order to improve the regression analysis procedure and, as a consequence, improve the quality of models for assessing bankruptcy, methodological aspects of construction were clarified:

1. the use of data on enterprises of one industry: each industry has its own functioning characteristics; the inclusion of enterprises from other industries changes the levels of predictors and creates a multidirectional assessment (the aspect is not taken into account in models [15; 18–20]);
2. the inclusion in the study of at least a quarter of enterprises declared bankrupt: a small amount of actual data on bankrupt enterprises underestimates the final assessment (a small amount of such data is present in the models [19; 23; 24]);
3. adding to the analysis the normality test of distribution of each predictor in the data array (absent in models [17; 20; 22]).

According to *Formula 3* and based on data from *Table 2*, the logistic model is the following:

$$S = \frac{1}{1 + e^{1.95K_{ql} - 1.98K_{fd} + 3.97K_{gm}}}, \quad (4)$$

where  $S$  – probability of bankruptcy (an integral indicator of the economic condition of a pharmaceutical enterprise),  $K_{ql}$  – quick liquidity (ratio of current assets minus inventories to short-term liabilities),  $K_{fd}$  – index of financial dependence (share of borrowed funds in the capital structure),  $K_{gm}$  – gross margin (ratio of gross profit to sales revenue).

The development of logit models does not involve an interval assessment of the final indicator ( $S$ ) since the point value of the probability of bankruptcy is calculated. But it should be noted that when using this model for management decision-making, it is necessary to take into account the critical levels. Applying the method [20] taking into account the actual distributions of model values for the calculated sample, two levels were identified that determine the stable (favorable) economic condition ( $S < 20\%$ ) and the zone of acute crisis at a pharmaceutical enterprise ( $S > 80\%$ ).

**2. Testing the developed model of bankruptcy assessment**

For practical application of the developed model it is necessary to test the model for accuracy of predicted results. In our opinion,

the testing process should be carried out in two stages.

**2.1. Estimation of statistical parameters of the model based on the initial sample**

Let us consider the results of observed and predicted outcomes (bankruptcy) with the null model and the final model presented in *Table 3*.

The null model represents the equation of logistic regression, where weighting factors ( $a_i$ ) of every predictor equal 0. In turn, the final model is constructed by elimination and is reflected in *Formula 4*. It should be noted that the boundary for division of predicted outcomes is 50%, with 1 – the enterprise is declared bankrupt, 0 – the enterprise is operating.

The resulting regression model has forecasting power if its accuracy is higher than the accuracy of the null model. In the initial model, the total percentage of correctly predicted bankruptcies is 28%, but in the final model it increases almost three times to 79%. We specify that the considered accuracy shows the degree of correct outcomes calculated using the regression model for the historical (initial) sample of pharmaceutical enterprises.

To justify the appropriateness of the model we consider the statistical criteria for assessing the quality of the final model.

The value of the ( $-2LogL$ ) logarithm function of the likelihood ratio in the final model decreased by 41% compared to the initial

Table 3. Observed and predicted outcomes of historical sample

Null model		Predicted outcomes		Share of correct outcomes
		0	1	
Observed outcomes	0	0	72	0%
	1	0	28	100%
Total accuracy of null model				28%
Final model		Predicted outcomes		Share of correct outcomes
		0	1	
Observed outcomes	0	63	9	88%
	1	12	16	57%
Total accuracy of null model				79%

model and amounted to 81.23. The decrease in this indicator, which is the result of comparing two models, indicates an improvement in the forecast capacity of the model.

As a rule, to assess the quality of regression models the determination index is used, but for logistic models, the determination index is not the basic parameter for determining the accuracy, unlike linear regression models. Therefore, the pseudo determination coefficient *Nagelkerke R-square* is calculated – 0.582, which is an approximation of the determination index taking into account the function  $-2LogL$  and  $X$ -square. The indicator characterizes the degree of change in the probability of bankruptcy depending on indicators included in the model; therefore, the change in the probability of bankruptcy of pharmaceutical enterprises 58.2% depends on the indices of quick liquidity, financial dependence and gross margin. Low  $R$ -square values for logit models are normal. In contrast to linear regression, it is impossible to suggest constant variance in logistic regression: the binary variable variance depends on the frequency of value distribution of the variable itself, so the calculated determination indices are an approximate measure [11].

Therefore, for additional evaluation of the model and its parameters we consider the

calibration test via the Hosmer-Lemeshow goodness-of-fit test. This test calculates the intervals between observed and predicted frequency distributions of bankrupt and operating enterprises. The value of the index under review should be higher than the significance level of 0.05. In the author’s model, the significance level is 0.31 (at  $X$ -square=9.39 and  $df=8$ ), which is six times higher than the established level.

Thus, the considered characteristics indicate that the obtained model is well calibrated, is sufficiently accurate in terms of forecasting bankruptcy and can be effectively used in practical calculations.

**2.2. Accuracy assessment and comparative analysis with existing models in the test sample**

To confirm the results and apply the developed model an important condition is its testing at pharmaceutical enterprises that are not included in the initial (historical) sample. For the second testing stage a similar array of data on the economic condition of pharmaceutical enterprises was formed:

1. for 136 operating enterprises;
2. for 30 bankrupt enterprises.

*Table 4* presents the results of the author’s model of bankruptcy assessment using the initial and tested samples. The intercept margin of outcomes is maintained at 50%.

Table 4. Observed and predicted outcomes of historical sample

Initial sample		Predicted outcomes		Share of correct outcomes
		0	1	
Observed outcomes	0	63	9	88%
	1	12	16	57%
Total accuracy of initial sample				79%
Tested sample		Predicted outcomes		Share of correct outcomes
		0	1	
Observed outcomes	0	109	27	80%
	1	8	22	73%
Total accuracy of tested sample				79%

It should be noted that the 50% intercept margin is conventional and does not fully reflect the accuracy of the model. The forecasted probability of bankruptcy of some operating enterprises fluctuates around this boundary. For example, when the intercept margin is increased by 10 percentage points (up to 60%), the model accuracy for existing enterprises increases by 7 p.p. and the overall model accuracy for the tested sample is 83%. Despite this, the share of correct outcomes according to the calculations on each sample fluctuates at the same level, which characterizes the adequacy of the model.

Having determined the accuracy criteria of the developed model, we proceed to the comparative analysis of the model with other common models of bankruptcy assessment adapted to industrial enterprises.

Since comparative analysis uses logit- and MDA-models a necessary condition for proper studies is the distribution of enterprises into equal groups according to the probability of bankruptcy.

For logit-models (author's, Zhdanov's [21], Khaidarsina's [20]) five groups with the same

interval of probability of bankruptcy (20 p.p. each) are distinguished, where the group "0%–20%" characterizes minimum risk of bankruptcy, and "80%–100%" – maximum.

Groups of bankruptcy probabilities (five groups) of Muradov [11] and Irkutskaya [12] models will correspond to similar groups for logistic models. Groups of bankruptcy probabilities according to Vishnyakov's model [14] correspond to groups "0%–40%" with minimum and "60%–100%" with maximum risk of bankruptcy. Bankrupt enterprises according to Kolyshkin's model [13] will be part of the group "60%–100%", prosperous ones – "0%–40%", the remaining groups will be in uncertainty zone.

Thus, the distribution of pharmaceutical enterprises of the tested sample was obtained in five groups for comparative analysis of models for enterprises recognized as bankrupt and for operating enterprises (see *Table 5*).

In our opinion, when the models use extended grouping of enterprises, the subject of management, when choosing a more accurate model and its further application, is

Table 5. Distribution of pharmaceutical companies by group of bankruptcy probabilities

Model	Groups of bankruptcy probability					Total enterprises
	0%–20%	20%–40%	40%–60%	60%–80%	80%–100%	
Distribution of bankrupt pharmaceutical enterprises						
Author's	4	2	4	3	17	30
Khaidarshina's	15	–	–	–	15	30
Kolyshkin's	6	–	1	1	22	30
Zhdanov's	11	1	–	–	18	30
Irkutskaya's	10	–	1	–	19	30
Muradov's	5		8	17		30
Vishnyakov's	5		–	25		30
Distribution of operating pharmaceutical companies						
Author's	94	10	14	14	4	136
Khaidarshina's	122	4	–	1	9	136
Kolyshkin's	85	12	11	13	15	136
Zhdanov's	103	1	3	3	26	136
Irkutskaya's	89	1	6	7	33	136
Muradov's	77		38	21		136
Vishnyakov's	56		–	80		136

required to compare the share of enterprises whose economic condition was incorrectly forecasted. For example, this aspect is very important for analyzing bankrupt enterprises, where it is necessary to identify the minimum forecasted probability of bankruptcy at actual bankruptcy. Incorrect forecasting may lead to inadequate assessment of the enterprise's economic condition, lack of anti-crisis measures and early liquidation of business. As a result, the calculation of accuracy of models will be determined by the following formula:

$$P = 1 - \frac{\sum N_{S > S_k}}{N}, \quad (5)$$

where P – model accuracy, N – total number of enterprises,  $N_{S > S_k}$  – number of enterprises with the calculated probability ( $S_j$ ) greater than (less than) the set level ( $S_k$ ): for bankrupt enterprises  $S < 40\%$ , for operating enterprises  $S > 60\%$ . The interval “40%–60%” represents the uncertainty zone, the average probability for evaluation, so the enterprises in this interval are excluded from the calculation of accuracy.

According to the results of calculating the accuracy presented in *Table 6*, the total accuracy of only three models is higher than 80%: Kolyshkin's model, Khaidarshina's model and the model proposed by the author.

Significant drawbacks of Khaidarshina's logistics model is the highest predictive power for operating ( $P=92.6\%$ ) and at the same time the lowest for bankrupt enterprises ( $P=50.0\%$ ),

as well as a large number of indicators in the model. Vishnyakov's model has a similar forecasting imbalance showing the lowest accuracy for operating enterprises ( $P=41.2\%$ ) and one of the best results for bankrupt enterprises ( $P=83.3\%$ ).

It is necessary to highlight Kolyshkin's model showing relatively similar accuracy for the two groups of enterprises. But since this model is based on discriminant analysis it is impossible to determine the exact probability of bankruptcy. Moreover, 27.7% of enterprises are in zone of uncertainty (average probability), which makes it difficult to assess and predict future business development (according to the author's model, only 10.8% of all enterprises are in the group “40%–60%”).

The author's model has the highest accuracy ( $P=85.5\%$ ) among the analyzed models; it has no significant differences in the degree of accuracy between operating and bankrupt enterprises.

**Conclusion**

In the course of the study, using correlation and regression analysis, a model for assessing the probability of bankruptcy of industrial enterprises (for example, enterprises of the pharmaceutical industry) was developed and tested.

The process of construction and testing is based on financial statements of 266 domestic pharmaceutical companies, so the industry aspects are fully taken into account. The

Table 6. Accuracy of models for assessing the bankruptcy of pharmaceutical enterprises

Model	Bankrupt enterprises	Operating enterprises	All enterprises
Author's	80.0%	86.8%	85.5%
Khaidarshina's	50.0%	92.6%	84.9%
Kolyshkin's	83.3%	84.6%	84.3%
Zhdanov's	80.0%	79.4%	79.5%
Irkutskaya's	60.0%	78.7%	75.3%
Muradov's	66.7%	70.6%	69.9%
Vishnyakov's	83.3%	41.2%	48.8%

absence of a large amount of calculations and highly technical calculations helps quickly obtain information about the economic condition. The model uses three indices describing enterprise activities from different aspects: liquidity, financial stability, profitability. The flexibility of calculations makes it possible to conduct a comparative analysis of the economic condition of enterprises in the context of one industry. The model determines the probability of bankruptcy two years ahead, which gives a sufficient opportunity to implement anti-crisis measures for maintaining sustainable development of a business.

The article also outlines stages and highlights methodological aspects of constructing a model for assessing the probability of bankruptcy not taken into account in the existing studies, which are aimed at increasing the forecast quality.

The necessary steps in model development are checking the indicators for normality of distribution and excluding closely correlated

indicators, which increases its effectiveness. When testing the model, it is advisable not only to calculate the statistical parameters of the equation, but also to assess the accuracy of a new sample of enterprises and conduct comparative analysis using the existing methods.

The application of the proposed methodology for monitoring enterprises helps forecast crises, detect their causes, prevent bankruptcy and maintain sustainable business development. The algorithms of development and testing discussed in the article can be applied to other economic sectors.

The research materials can be used by: owners and managers of enterprises in order to build a monitoring system; commercial banks in corporate lending and credit risk monitoring; consulting organizations and investors to conduct analytical studies in the industry and assess investment climate; executive authorities for implementing the industrial policy and performing control and supervisory functions.

## References

1. Ryakhovskaya A.N., Kovan S.E. Anti-crisis management: a modern concept and the main instrumentarium. *Upravlencheskie nauki=Management Science*, 2015, no. 3, pp. 45-55. DOI: 10.26794/2304-022X-2015--3-45-55. (In Russian).
2. Stel'makh V.S. Theoretical and methodological features of crisis monitoring. *KANT*, 2018, no. 1, pp. 225-229. (In Russian).
3. Stel'makh V.S. Monitoring the company's value in the system of crisis management of a pharmaceutical enterprise. *Upravlenie ekonomicheskimi sistemami=Management of Economic Systems*, 2017, no. 6. Available at: <http://uecs.ru/teoriya-upravleniya/item/4427-2017-05-29-10-52-43> (accessed 25.10.2018). (In Russian).
4. Durand D. *Risk Elements in Consumer Installment Financing: technical edition*. New York: National Bureau of Economic Research. 1941. 237 p.
5. Altman E. Financial Ratios. Discriminant Analysis, and the Prediction of Corporate Bankruptcy. *Journal of Finance*, 1968, no. 4, pp. 589-609. DOI: 10.1111/j.1540-6261.1968.tb00843.x.
6. Fulmer G. A Bankruptcy Classification Model For Small Firms. *Journal of Commercial Bank Lending*, 1984, pp. 25-37.
7. Beaver W. Financial Ratios and Predictions of Failure. *Empirical Research in Accounting Selected Studies, Supplement to Journal of Accounting Research*, 1966, no. 6, pp. 71-87. DOI: 10.2307/2490171.
8. Lin L. Identification of corporate distress in UK industrials – a conditional probability analysis approach. *Journal of Applied Financial Economics*, 2004, no. 14, pp. 73-82. DOI: 10.1080/0960310042000176344.

9. Aziz M. Predicting Corporate Bankruptcy: Whither do we stand? *Corporate Governance*, 2006, no. 6, pp. 18-33. DOI: 10.1108/14720700610649436.
10. Dewaelheyns N. Aggregate Bankruptcy Rates and the Macroeconomic Environment: Forecasting Systematic Probabilities of Default. *Tijdschrift voor Economie en Management*, 2007, no. 4, pp. 541-545. DOI: 10.2139/ssrn.1025805.
11. Muradov D.A. *Prognozirovanie i otsenka bankrotstva neftegazovykh kompanii : dis. ... kand. ekon. nauk: 08.00.05* [Forecast and Assessment of Bankruptcy of Oil and Gas Companies. Candidate of Sciences (Economics) dissertation]. Moscow, 2011. 217 p.
12. Davydova G.V., Belikov A. Yu. Methods of quantitative assessment of bankruptcy risks. *Upravlenie riskom=Risk Management*, 1999, no. 3, pp. 13-20.
13. Kolyshkin A.V. *Prognozirovanie razvitiya bankrotstva v sovremennoi Rossii : dis. ...kand. ekon. nauk : 08.00.05* [Forecasting the Bankruptcy in Modern Russia. Candidate of Sciences (Economics) dissertation]. Saint Petersburg, 2003. 152 p.
14. Vishnyakov Ya.D. Assessment and analysis of financial risks amid hostile business environment. *Menedzhment v Rossii i za rubezhom=Management in Russia and Abroad*, 2000, no. 3, pp. 106-111. (In Russian).
15. Ohlson J. Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, 1980, no. 6, pp. 12-45. DOI: 10.2307/22490395.
16. Back B. Choosing Bankruptcy Predictors Using Discriminant Analysis, Logit Analysis and Genetic Algorithm. *Proceedings of the 1st International Meeting on Artificial Intelligence in Accounting, Finance and Tax*, 1995, no. 4, pp. 337-356.
17. Gruszczynski M. *Modele mikroekonometrii w analizie i prognozowaniu zagrozenia finansowego przedsiebiorstw*. Warsaw: Polska Akademia Nauk, Instytut Nauk Ekonomicznych, 2003. 33 p.
18. Joo-Ha N. Bankruptcy prediction: evidence from Korea listed companies during the IMF crisis. *Journal of International Financial Management and Accounting*, 2000, no. 11, pp. 178-197. DOI: 10.1111/1467-646X.00061.
19. Minussi J. *Statistical modelling to predict corporate default for Brazilian companies in the context of Basel II using a new set of financial ratios*. Lancaster: Lancaster University Management School. 2007. 35 p.
20. Khaidarshina G.A. *Metody otsenki riska bankrotstva predpriyatiya: dis. ...kand. ekon. nauk : 08.00.10* [Methods to assess bankruptcy risks of an enterprise. Candidate of Sciences (Economics) dissertation]. Moscow, 2009. 253 p.
21. Zhdanov V.Yu. *Diagnostika riska bankrotstva promyshlennykh predpriyatii : dis. ...kand. ekon. nauk : 08.00.05* [Detecting the risk of bankruptcy at industrial enterprises. Candidate of Sciences (Economics) dissertation]. Moscow, 2012. 193 p.
22. Begley J. Bankruptcy classification errors in the 1980s: An empirical analysis of Altman's and Ohlson's models. *Review of Accounting Studies*, 1996, no. 1, pp. 267-284. DOI: 10.1007/BF00570833.
23. Ginoglou D. Predicting corporate failure of problematic firms in Greece with LPM, logit, probit and discriminant analysis models. *Journal of Financial Management and Analysis*, 2002, no. 15, pp. 1-15.
24. Lennox C. Identifying Failing Companies: A Re-evaluation of the Logit-, Probit- and DA Approaches. *Elsevier Science Inc*, 1999, no. 4, pp. 181-210.
25. Saaty T. *The Analytic Hierarchy Process*. New York: McGraw Hill. 1980. 287 p.

### Information about the Author

Veniamin S. Stel'makh – Graduate Student, Khabarovsk State University of Economics and Law (134, Tikhookeanskaya Street, Khabarovsk, 680042, Russian Federation; e-mail: Vs-stel@ya.ru)

Received October 29, 2018.