Chapter 8
Scoring Modeling in Estimating the Financial Condition of Russian Agro-Industrial Companies

Oleg Y. Patlasov
Omsk Regional Institute, Russia

Olga K. Mzhelskaya
Omsk Humanitarian Academy, Russia

ABSTRACT

The chapter presents the authors' estimations according to the scoring modeling techniques; also, internationally spread models of bankruptcy forecasting are systematized. Advantages and disadvantages of dynamic modelling methods as applied to financial condition assessment are presented here. Methodological problems of financial modelling are explained here in detail. Regression, logit-regression, and discriminant models are built on the basis of data on the Rosselkhozbank and Sberbank of Russia regulations, taking into account the agrarian specifics of organizations and regional specificity of the Omsk region. An attempt has been made to balance the simplicity of calculations and the accuracy of predictions. Graphs, to be used for express analysis, are constructed on the basis of two core financial indicators.

INTRODUCTION

Nowadays managers' tasks include not just optimal combination of production factors, based on the knowledge of production technology and own organizational capabilities, but also on taking into account the current marketing situation, financial analysis and then making the right managerial decisions. Success of entrepreneurship is thus predetermined by natural and technological factors, and also organizational and sociopolitical factors and finally, by the variety of business risks. Contemporary management requires the knowledge of bankruptcy diagnostics, business financial position assessment, its operational prospects, possible actions of creditors, internal opportunities for debt restructuring etc.

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Depending on the economic analysis objectives, attention can be focused on the following aspect: company's liquidity and debt service indicators, important (for creditors); profitability and equity in their dynamics (for shareholders); labor costs, volume and efficiency of capital expenditures (for labor analysts); accuracy in calculations and payment of taxes (for public authorities' representatives). Arbitration managers should become convinced in the absence of premeditated and fictitious bankruptcy, and for this they should assess company's real net assets, the extent of overdue debts etc., the execution of the already announced court decisions. From the standpoint of managers, financial analysis and managerial accounting are management function; and from the standpoint of competitors' comparative analysis, economic analysis is part of benchmarking.

In the framework of economic analysis, the following forms of comparative analysis have become the most common:

1. Comparative analysis of financial ratios of the given economic subject with the average industry indicators.
2. Comparative analysis of financial indicators with the related data from competing enterprises.
3. Comparative analysis of financial indicators of separate structural units and separate divisions of a legal entity (its responsibility centers).
4. Monitoring of reporting according to the planned and/or regulatory financial indicators.

It is always easier to assess the merits and bottlenecks of any official analysis method in scientific terms, however, in practical terms, it is always not subject to correction because all corrections immediately become the prerogative of the official body that has approved and imposed this method. Complex methods of analysis are indisputably more labor-consuming, but they are necessary for organizations themselves, namely, for their more grounded managerial decision-making, whereas for external users (tax revenue offices, creditors, banks etc.) it is necessary to conduct more punctual analysis according to the already approved and well established methods.

The currently used methods of the organizations' financial condition analysis all have a serious drawback: their conclusions are often based only on the accounting reports' data, thus, they do not take into consideration the current stage of a company's life cycle and/or its potential future situation. For proper managerial decisions, it is advisable to conduct system analysis which includes, in addition to assessing the financial state of an organization, the current state of the external environment and the human factor too. The maximum effect from the conducted diagnostics is achieved when this diagnostics is of complex character, however, such procedures are, of course, much more challenging since they are time- and cost-demanding.

WESTERN BANKRUPTCY DIAGNOSTICS TOOLKIT

Different methods of predicting bankruptcy forecast various types of crises and, accordingly, estimations obtained with their help are also very different. The choice of specific methods is prescribed and adjusted in accordance with the specifics of a particular industry/branch in which the organization operates. As a result, a large number of different models for bankruptcy forecasting have been developed.

Financial analysis models differ depending on the research principles and analysis priorities. The key of them are as follows:

1. Descriptive models. They are based on scientific, theoretical literature mostly and also on the accounting toolkit (vertical and horizontal analyses of financial statements, balances' system construction, analytical coefficients' calculation).
2. Normative models are used mainly for carrying out an internal financial analysis. They are based on the required calculated indicators that are are compared with the recommended (normative) value.
3. Predictive models are used to make forecasts about future financial results and future financial condition of a firm. The models of situational analysis, of dynamic analysis, critical models can be singled out here.

Several groups of bankruptcy forecasting models can be distinguished basing on the characteristics of the used modelling techniques:

- Statistical models;
- Artificial intelligence models, and;
- Theoretical models.

The first two groups of models are characterized as positive ones, because they are focused on the symptoms of bankruptcy and are trying to explain, using inductive arguments, the reasons for some companies to become bankrupt. The last category (normative models) applies deductive argumentation to explain why a certain part of enterprises can become bankrupt.

Statistical models obtained through the use of various statistical methods to classify the problems of bankruptcy forecasting, include:

- Univariate analysis;
- Multiple discriminant analysis;
- Conditional probability analysis;
- The method of expert evaluations;
- Analogy method;
- The method of financial condition estimation, and;
- Survival analysis.

Among the artificial intelligence techniques, which have been successfully applied in bankruptcy forecasting, the following methods can be named:

- Decision tree; classification tree or recursive partitioning algorithm;
- Data mining;
- K-nearest neighbors algorithm, or k-NN;
- Genetic algorithm;
- Neural network;
- Rough sets theory, and;
- Support vector machines.

Recently a number of financial theories have been successfully applied in relation to bankruptcy forecasting problem, in particular:

- Entropy theory;
- Gambler's ruin theory, and;
- Option-priced theory.

Data obtained using various modelling techniques and their prediction accuracy indicate that the main studies in this field are mainly based on the statistical models of bankruptcy forecasting, and this can be explained by the chronology of various modelling technologies' emergence. However, these models show lower forecasting accuracy (84%) as compared to the models of artificial intelligence (88%) and theoretical ones (85%).

The adequacy degree of different types of models is determined by the errors in identifying the tested business entity. The following two types of basic errors are possible: the first type of error occurs when a financially unstable enterprise being on the verge of bankruptcy is defined as a financially secure one. And the second type of errors is connected with the erroneous classification of a financially stable company as a bankrupt organization. In foreign and domestic scientific literature the accuracy of forecasting among different types of models has been compared; high accuracy of the decision tree methods, multiple discriminate analysis, genetic algorithm etc. has been confirmed.

Currently, there are several key approaches to the theory of bankruptcy diagnostics. These methods are based on regression, discriminate factor models put forward by well-known Western economists.

The essence of this approach is to identify the factors significantly affecting financial condition of the company, to determine the type and the extent of its dependence on these factors and also formation of a probabilistic criterion for company bankruptcy.

Among the bankruptcy risk models based on logistic regression are the ones by Altman-Sabato (2007), Joo-Ha-Taehong (2000), Lin- Piesse (2004), Begley-Ming-Watts, Minussi-Soopramanien-Worthington, credit assessment (supervision of loans) model by Chesser (1974) and some others. Among other authors investigating the problems with accounting arrangement under the conditions of insolvency and bankruptcy we need to mention: Anderson H., Van Breda M.F., Caldwell D., Needles B., Reed S.F., Richard J., Hendricksen E.C..

For the prediction of bankruptcies some of the contemporary authors have also used vector machines (for example, Härdle, Lee, Schäfer, & Yeh, 2007) as well as neural networks (Tam, & Kiang, 1992; Altman, Marco, & Varetto, 1994). A number of modelling techniques raise concerns among academia since their financial ratios are calculated using the profit and loss account, and thus they often do not have a normal distribution (Ohlson, 1980; Wilson, & Sharda, 1994). Wei, Li, and Chen (2007) emphasize that LDA, inter alia, can treat the outcomes incorrectly since the covariance matrices of default and active companies are likely to be confusing in interpretation.

Linearly regression variants of LPM-models can give negative or exceeding estimated values for probabilities. Probit and logit models (respectively, with the standard normal and logistic transformation functions) are better in this sense because the transformation is monotonic, its output values are limited to zero and one, and tend to be zero and one on the distribution tails. All of the abovementioned is yet another confirmation that no event can be predicted with absolute certainty, even in the cases when probability is zero or one. Comparing logit methods with MDA, Collins and Green argue that, although the former give less error of the 1st kind, in general, their accuracy in terms of classification is not much better (Collins & Green, 1982).

C. Lennox has shown that in practice logit models allow much more effective bankruptcy risk assessments than MDA can provide theoretically (Lennox, 1999). The use of logit regression implies wide possibilities for carrying out various econometric tests allowing to evaluate the statistical significance of both the model as a whole and its individual forming variables. In contrast to MDA, logit regression allows not only making conclusions concerning the enterprise belonging to potential bankrupts, but also assessing the risk of this company's bankruptcy on a quantitative scale (Postin, Harmon, & Gramlich,1994). In addition, if we divide companies into 2 groups (bankrupt and non-bankrupt), it is necessary to establish the limits of reference to the group of financial stability when we use MDA. Logit models of bankruptcy risk do not require the development of decision-making ranges, and this simplifies results' interpretation: the resulting bankruptcy risk indicators obtained using these models are known to take values from 0 to 1 without ranges of uncertainty, and the conclusion about the degree of bankruptcy probability is made in the dependence from proximity of the calculated value of the final indicator to 0 (the minimum risk) or to 1 (the maximum risk).

Comparisons of neural network and MDA models are useful since we are able to compare a new, more stable method with known models where a priori assumptions about variables are adopted (Baestaens, Van Den Bergh, & Wood,1997). In this regard, we must note the use of neural networks when dealing with the problems of industrial corporations' bankruptcies and financial corporations' bankruptcies. In all such cases, only standard numeric variables reflecting the past state were used as input data, whereas it is preferable to use qualitative variables reflecting information about the future as well.

In contrast to discriminate forecasting models that are concentrating on linear dependence, logit models assume a non-linear dependence of bankruptcy probability from various factors (Ooghe & Balcaen, 2002).

An alternative to multiple discriminate analysis is a model with a discrete dependent variable, the basic principles of such models have been described in the works of D. McFadden, J. Tobin, and C. Gurieruks, W. Green.

The main difference between rating assessment of organizations' financial state and the integral models is that the weight coefficients in the model are obtained through expert analysis or by means of the coefficient value standardization, whereas in alternative integral models of estimation, the weight values of coefficients are obtained using mathematical tools (multiple discriminate analysis, probity regression, logistic regression etc.).

The world-known rating agencies, such as Standard and Poor's, Moody's Investors Service and Fitch Ratings, made a special contribution to the development of the investment attractiveness assessment methods, although in recent years these agencies have lost independence in risk assessments and have become politically biased, especially when it comes to credit ratings' understatement for Russia (in 2014-2015, for example).

Unfortunately, Russian university text books always present only the internationally promoted models, while other models, not that widely known in Russia, are able to show much better analytical capabilities. To these relatively new methods, practically unknown to a wider audience in Russia, belong the models by Keasey-McGuinness (Great Britain), Ooghe-Joos-Devos (Belgium), Meyers and Forgy (Myers, & Forgy, 1986); Cohen and Gilmore (Cohen, & Gilmore, 1990).

Among other related foreign studies it would be appropriate to mention: Edmister (1972); Altman, Sabato (2007); Vallini, Ciampi, and Gordini (2009), Pederzoli and Torricelli (2005).

In both scientific literature and in practical calculations, some attempts have been made to balance the simplicity of calculations and the accuracy of predictions. Insufficient accuracy of linear models has led to the necessity for transition to non-linear ones, while the insufficient predictive ability of two(three)-factor models has led to the necessity to construct 7-9-factor (or even more) models which is obviously associated with complication of calculations. Despite certain advantages demonstrated by the dynamic models, static linear models still have much wider practical application.

In order to strengthen the predictive role of static models, various proposals have been put forward regarding these models' and modeling techniques' transformation. A dynamic approach to the analysis of phenomena and processes in general as well as strategic analysis in particular is based on the concept of "instantaneous dynamics" (Voronin, 1994). According to this approach, the whole process (from its beginning to the very end) is not studied, but only certain moments (instants) of its implementation are. Therefore, the process of objects' changing is viewed as a successive change of their states. It is assumed that each state is the result of a shift from an immediately preceding state, which is primarily expressed quantitatively, since qualitative changes caused by structural shifts are mostly observed during a longer period of time. The paradigm of "instantaneous dynamics" is closely connected with the paradigm of time as a space for events. Within such a time space, there are many instantaneous events, or a sequence of instantaneous non-overlapping events, or a combination of the above mentioned. According to this interpretation, time space is considered to be one-dimensional, separate events are arranged in the order of their implementation in the form of a point or a segment on the time axis oriented "from the past through the present to the future" (the so-called "arrow of time"). For a more specific representation of events, the starting point and the scale of measurement are indicated on the time axis. In such a one-dimensional time space, it is possible to investigate only certain processes of objects' changing, which leads to a break in the links between them, or their totality as a whole, when connections and relationships are invisible. The concept of one-dimensional time is widely used in both natural and social sciences, whenever methodological aims are oriented towards analysis of complex objects and phenomena by means of separation into simple ones, and their subsequent studying separately from each other. With such an approach to the study objects (when only their structure is taken into account or only their structure is changed), all events are placed on a single time axis, so there is no need to revise the concept of one-dimensional time, which is confirmed by new scientific data in the field of natural sciences. At the same time, the one-dimensional time paradigm limits the possibilities for a holistic cognition of socio-economic systems, where the functioning importance belongs not only to individual objects, but also to their joint activities, mutual relations and interactions.

The values of time series represent the trend, cyclical, seasonal and random fluctuations. The method of simple dynamic analysis is used to construct the trend of a time series. Cyclical fluctuations are the ones referring to the trend line for the periods exceeding one year. Sometimes these fluctuations of financial indicators coincide with the business activity cycles: recession, recovery, growth and stagnation. Seasonal fluctuations are understood as periodic changes of the series values over a year, for example, when you grow plants in open ground, the main inflow of cash flows occurs in summer and in autumn. Random deviations are detected by determining the trend, cyclic and seasonal variations for the value of the analyzed indicator. When testing the forecasting model accuracy, a random deviation is taken into account. The method of simple dynamic analysis is based on the assumption that the predicted indicator varies in time proportionally.

Our research shows that official methods applied to analyze the financial state of organizations have a serious drawback - the conclusions are based on accounting data only, while the stage of organization's life cycle is not taken into account, thus, the future state is not predicted either. For crisis management, it is important to conduct system analysis taking into consideration the processes taking place in the business external environment and the human factor role too. Comprehensive methods of analysis are indisputably more labor-intensive, but they allow not only increase the reliability of the results obtained, but also to explore more deeply the hidden causes and consequences of the phenomena studied, and, thus, to improve the efficiency of crisis management for commercial organizations.

As it was noted above, the use of foreign and domestic methods for bankruptcy diagnostics have some drawbacks, in particular, the weight factors used in official methods require adjustments in relation to domestic, regional and sectoral conditions; the existing statistics does not fully reflect the actual situation of successful, average and underperforming enterprises in terms of their dynamics, structure of their equity and borrowed capital, current assets, liquidity etc. The main problem with data here is that it is rather complicated to collect all necessary financial information characterizing the actual financial situation from inside of an organization.

At present, on the one hand, the key problem with bankruptcy forecasting for individual enterprises is the absence of universally recognized effective methods to forecast bankruptcy and solvency of business entities. On the other hand, these techniques are oriented primarily to establish the fact of insolvency when the signs of bankruptcy are already too obvious.

HYPOTHESES AND PROBLEMS

There are a lot of discussions in scientific literature about the accuracy of models. When testing them, one should keep in mind the following useful questions:

1. How is the model result affected by the model's "age"? We will demonstrate that the Altman model of 1968, when compared with his latest models, shows a good result even on the example of Siberian agricultural enterprises.
2. How do the model characteristics influence its results? Let's take discriminant analysis vs logistic regression, for example. Discriminant models usually have a significant proximity due to the eroded boundaries of the integrated indicators' values as well as due to the presence of a "gray zone". Leitinen-Kankaanpaa studies (1999) were dedicated to comparing the accuracy of six alternative forcasting methods results: discriminant analysis, logistic regression, successive division method, survival analysis, decision-making analysis, and neural networks. These studies have come up with the conclusion that the results of one of the latest methods (neural networks) are also effective and accurate, as are the results of discriminant analysis, which was used more than thirty years ago (Laitinen, & Kankaanpaa, 1999).
3. What is the impact of the number of variables and their complexity on the result? In general, 2-3-factor linear models show rather low forecast accuracy; 4-5-factor nonlinear ones are relatively accurate; models with more than 6 factors are already cumbersome in calculations.
4. Is there a fundamental difference between Anglo-Saxon and European models in relation to Russia? In general, the differences between those two are not observed, however, there are some differences in Anglo-Saxon economic law and the continental one; in particular, European models are less focused on the stock quotes' performance.

5. What should be the ratio of financial and non-financial indicators in the model? In the study by Falkenstein, Boral, and Carty (2000), it is emphasized that the relationship between financial performance and the default risk is different for public and non-public companies. Pompe and Bilderbik in their work (Pompe, & Bilderbeek, 2005) note that it is more difficult to predict the bankruptcy probability for new firms than for long-established ones.

RESEARCH METHODOLOGY

Due to the fact that there are no universal methods to assess legal entities' solvency, some of the commercial banks have been developing their own regulations, thus, the conclusions from testing results for the same organization may turn out to be very much different when analyzed using different methodologies. In this regard, combination of models for assessing the legal entities' solvency allows entrepreneurs to have more possibilities to obtain a bank loan.

We have set the task to build a number of models for agroindustrial enterprises of Russia, proceeding from the commercial banks' regulations (namely, specialised banks functioning specifically in and for agriculture), primarily Sberbank of Russia and OJSC Rosselkhozbank.

Thus, in accordance with the Methodology for the Analysis and Assessment of Financial Condition for Borrowers of the OJSC Rosselkhozbank and taking into account their industry-specific features and organizational and legal forms approved by the Resolution of the Management Board of the OJSC Rosselkhozbank *(Protocol # 65 as of 25.11.2004),* the following indicators are used as the criteria for assessing the borrowers' financial condition:

- Financial soundness;
- Liquidity (solvency);
- Financial results (profit, loss),and;
- Cash flow for the term of credit.

As the estimates of the current financial condition, the following three groups of indicators are used:

- **Indicators of Financial Soundness (Independence):** Financial independence ratio; own funds ratio;
- **Liquidity Indicators:** Current liquidity ratio; absolute liquid ratio; quick liquidity ratio (or critical evaluation);
- **Indicators of Business Activity:** Turnover indicators; indicators of cost-efficiency (profitability).

In accordance with this Methodology the ratios are divided into:

- **Mandatory Ratios:** Financial independence ratio (K1), own funds ratio (K2), current liquidity ratio (K3), quick liquidity ratio (or critical evaluation) (K4), indicators of cost-efficiency (profitability) (K5), turnover of current assets (K6);
- **Voluntary Ratios (Used for Assessment if Necessary):** Absolute liquidity ratio, short-term receivables and payables; sufficiency of turnover in the bank.

Financial condition of a borrower is assessed taking into account the score points calculated using mandatory ratios. In accordance with this technique the following condition states can be singled out:

- **Good Financial Condition:** The number of scored points is equal to or more than 53.
- **Average Financial State:** The number of scored points is between 25 to 52 points.
- **Bad Financial Condition:** The number of scored points is less than 25.

Regulation on granting loans to legal entities and individual entrepreneurs by the Sberbank of the Russian Federation and its branches (approved by the Sberbank of Russia 30.06.2006, Protocol #322) concerning the assessment of borrowers' solvency in based on the following three groups of estimates:

1. **Liquidity Ratios:** Absolute liquid ratio (K1), quick liquidity ratio (K2), current liquidity ratio (K3);
2. Own funds ratio (K4);
3. **Turnover and Profitability Indicators:** Current assets turnover, receivables turnover, inventory turnover, profitability of products (profitability of sales) (K5), of enterprise profitability (K6), profitability of investments in this enterprise.

The main estimates are thus the K1, K2, K3, K4, K5 and K6 ratios (see Table 1 for more details). Evaluation of the results of these six ratios' calculation concludes with assigning a category for each of these indicators on the basis of the obtained values' comparison with the established sufficient ones.

In accordance with this methodology, we determine 3 classes of organizations' solvency:

1 Class: Lending is beyond doubt, S = 1.25 or less;
2 Class: Lending requires a balanced approach, S is in the range between 1,25 (exclusive) to 2,35 (inclusive);
3 Class: Lending is associated with an increased level of risks, S is 2.35 or above.

We have set a task to assess the solvency of 408 agroindusrial enterprises of the Omsk region on the basis of their annual accounting reports data for the period of 2003-2005 (369 organisations as of 01.01.2006, and 350 agricultural organizations in 2007). Moreover, the analysis has been carried out

Table 1. Indicators' subdivision into categories depending on their actual values

Ratios	1st Category	2nd Category	3rd Category
K_1	0,1 and higher	0,05-0,1	less than 0,05
K_2	0,8 and higher	0,5-0,8	less than 0,5
K_3	1,5 and higher	1,0-1,5	less than 1,0
K_4			
except trade and leasing companies	0,4 and higher	0,25-0,4	less than 0,25
for trade and leasing companies	0,25 and higher	0,15-0,25	less than 0,15
K_5	0.1 and higher	less than 0,10	unprofitable
K_6	0.06 and higher	less than 0,06	unprofitable

S = 0,05 * Category; K_1 + 0,10 * Category K_2 + 0,40 * Category K_3 + 0,20 * Category K_4 + 0,15 * Category K_5 + 0,10 * Category K_6.

according to the natural and economic zones of the Omsk Region: steppe zone (9 districts, 86 organizations), Southern forest-steppe zone (8 districts, 80 organizations), Northern forest-steppe zone (9 districts, 121 organizations) and Northern zone (6 districts, 82 organizations). Regression equations and graphs have been constructed basing on the analysis results.

AUTHORS' MODELS OF FINANCIAL CONDITION EVALUATION AIMED TO ANALYSE BORROWER'S SOLVENCY

At present, the most significant risk for the Russian banking sector is the credit one. Credit risk means the danger that a debtor will not be able to make interest payments or pay the principal amount of a loan in accordance with the terms specified in the loan agreement. Credit risk also means that payments can be delayed or not paid at all, which, in turn, may lead to the problems with cash flow and adversely affect bank's liquidity. Despite numerous innovations already implemented in the financial services' sector, credit risk is still the main cause of banking problems. More than 80% of the banks' balance sheets content is devoted to this risk management aspect. Taking into consideration some potentially dangerous consequences of credit risk, it is important to conduct a comprehensive analysis of the banks' capacities to assess, administer, monitor, control, implement and repay loans, advances, guarantees and other credit instruments. An overview of credit risk management includes the analysis of banks' policies and practices. This analysis should also determine the adequacy of financial information received from borrower which is by then used by a bank when making the decision to grant a loan.

Regression, logit-regression and discriminant models assessing borrowers' solvency have been built basing on the regulations of commercial banks, mainly, Rosselkhozbank and Sberbank and using the data on 369 agricultural organizations of the Omsk region as our study object. Analysis of the organizations' financial condition, determination of significant factors affecting their solvency level allows credit institutions to determine correctly the lending capacity of a particular organization, and the organization itself, after such an assessment, become more capable to manage these factors so that to increase own opportunity of obtaining a bank loan. This, indirectly, also confirms the practical importance of econometrics and multidimensional statistical research in general.

Rosselkhozbank Methodology

Having applied the data substitution method, we have experimentally determined the boundaries of the credit rating classes in points using the 100-point scale along with the Methodology for calculating financial condition indicators for agricultural producers (RF Government Decree # 52, as of January 30, 2003) as the basis: 1st class - 100 to 42,2 points (exclusive); 2nd class - from 42.2 (inclusive) to 26 points (inclusive); 3rd class - below 26 points (Patlasov, & Vasina, 2008). Indicators of the annual accounting reports data on all the Omsk region agricultural organizations for 2005-2007 have been used for the modelling here. Six basic coefficients were calculated, applying the Rosselkhozbank method.

From the obtained results it can be concluded that the solvency degree and the factors included in the model are closely related (the correlation ratio is equal to 0, 8917), and that the obtained regression equation is rather significant and cannot be the result of random sampling (the coefficient of determination is 0.82, and the calculated value of the Fisher test is higher than the tabulated value) (Table 2).

Table 2. Final results of the regression model estimation for the Omsk region as of 2007.

	Beta	Std. Err.	B	Std .Err.	t(343)	p-Level
Intercept			29,57775	1,384764	21,35942	0,000000
K1	0,685505	0,034189	37,80690	1,885584	20,05050	0,000000
K2	0,061420	0,033320	0,17393	0,094354	1,84336	0,066139
K3	0,233361	0,046195	0,23402	0,046325	5,05165	0,000001
K4	0,012488	0,045083	0,05036	0,181809	0,27700	0,781946
K5	-0,048720	0,033090	-0,23071	0,156694	-1,47237	0,141837
K6	0,036888	0,033157	0,28494	0,256119	1,11251	0,266697

Regression Summary for the Dependent Variable: Var7
R=, 89176679 R^2=, 82689464 Adjusted R^2=, 82036802
F(6,343)=96,052 p<0,0000 Std.Error of estimations: 15,706
Legend: K1 is the financial independence ratio, K2 - own funds' ratio, K3 - current liquidity ratio, K4 - quick liquidity ratio, K5 – profitability ratio, K6 - turnover of current assets ratio.

According to the analysis results, the following regression equations were obtained (Patlasov-Vasina regression model).

In 2007: Omsk region: $B = 29{,}57 + 37{,}80K_1 + 0{,}17K_2 + 0{,}23K_3 + 0{,}05K_4 - 0{,}23K_5 + 0{,}28K_6$ (Patlasov, Vasina, 2009);

Steppe zone: $B = 8{,}91 + 70{,}66K_1 + 1{,}47K_2 + 0{,}37K_3 - 0{,}53K_4 - 0{,}32K_5 + 4{,}91K_6$.

Southern forest-steppe: $B = 19{,}63 + 50{,}11K_1 + 1{,}17K_2 + 0{,}08K_3 + 0{,}61K_4 + 2{,}07K_5 - 6{,}21K_{6.}$

Northern forest-steppe: $B = 33{,}52 + 26{,}04K_1 + 0{,}11K_2 + 0{,}45K_3 - 0{,}30K_4 - 0{,}06K_5 -1{,}03K_{6.}$

Northern zone: $B = 16{,}71 + 53{,}77K_1 + 1{,}83K_2 + 0{,}28K_3 -0{,}36K_4 -0{,}02K_5 + 0{,}19K_{6\,.}$

The research thus shows that the assessment can be carried out on the basis of two indicators that have the most significant impact on the financial condition of agricultural producers:

- Own funds ratio (K4) with the error probability (p-level) being 0.0000;
- The current liquidity ratio (K3) for which the p-level is also equal to 0.0000.

During the research, the discriminant models assesing borrowers' solvency have been also constructed on the basis of data obtained from Omsk region agricultural enterprises and farms. The Methodology for calculating the indicators of the agricultural producers' financial condition (RF Government Decree # 52, as of January 30, 2003) is also the basis for the discriminant factor model here. This made it possible to classify the research objects into three groups according to their solvency level (financial condition) (see Table 3 for more details).

Thus, the system of equations (the discriminant model) is expressed in the following way:

Omsk Region:

Table 3. Discriminant analysis results for the agroindustrial enterprises of the Omsk region in 2007 According to the Rosselkhozbank Methodology

	Wilks' Lamda	Partial Lamda	F-Remove	p-Level	Toler.	1-Toler. (R-Sqr.)
Var1	0,863778	0,437144	220,1754	0,000000	0,972505	0,027495
Var2	0,392288	0,962546	6,6539	0,001462	0,995686	0,004314
Var3	0,378736	0,996989	0,5163	0,597161	0,538042	0,461958
Var4	0,380443	0,992516	1,2894	0,276761	0,543796	0,456204
Var5	0,385852	0,978601	3,7392	0,024750	0,993623	0,006377
Var6	0,384719	0,981484	3,2260	0,040930	0,994793	0,005207

Discriminate Function Analysis Summary
# of vars in model: 6; Grouping: Var9 (3 grps)
Wilks' Lambda:, 37760 approx. F (12,684)=35,760 p<0,0000

Table 4. Initial data for the equations by groups and for the Omsk region as of 2007

	1	2	3
Intercept	-4,04859	-3,50311	-1,69006
Var1	8,90478	4,14748	-0,87928
Var2	0,00755	-0,07138	-0,01675
Var3	0,00007	-0,00812	0,00334
Var4	0,06836	0,03775	-0,00420
Var5	0,02896	0,12736	0,06012
Var6	-0,01276	-0,15009	-0,01466

Classification Functions for Var9
Sigma-restricted parameterization

$$G_1 = - 4,05 + 8,90К_1 + 0,01К_2 + 0,001К_3 + 0,07К_4 + 0,03К_5 - 0,01К_6$$

$$G_2 = - 3,50 + 4,15К_1 - 0,07К_2 - 0,01К_3 + 0,04К_4 + 0,13К_5 - 0,15К_6$$

$$G_3 = - 1,69 - 0,88К_1 - 0,02К_2 + 0,003К_3 - 0,004К_4 + 0,06К_5 - 0,01К_6$$

Steppe zone:

$$G_1 = - 15,66 + 40,82К_1 - 0,39К_2 - 0,19К_3 + 0,54К_4 - 0,19К_5 + 4,94К_6$$

$$G_2 = -7,98 + 24,02К_1 - 0,46К_2 - 0,15К_3 + 0,42К_4 - 0,03К_5 + 4,09К_6$$

$$G_3 = -3,05 + 9,83К_1 - 0,73К_2 - 0,04К_3 + 0,10К_4 - 0,05К_5 - 0,19К_6$$

Southern forest-steppe zone:

$$G_1 = -10{,}75 + 22{,}42К_1 + 0{,}59К_2 + 0{,}004К_3 - 0{,}16К_4 + 2{,}13К_5 – 2{,}99К_6$$

$$G_2 = -4{,}80 + 11{,}04К_1 + 0{,}18К_2 + 0{,}001К_3 - 0{,}12К_4 + 1{,}31К_5 - 1{,}36К_6$$

$$G_3 = -2{,}80 - 1{,}00К_1 + 0{,}19К_2 + 0{,}01К_3 - 0{,}04К_4 + 1{,}32К_5 - 0{,}19К_6$$

Northern forest-steppe zone:

$$G_1 = - 2{,}84 + 4{,}26К_1 + 0{,}03К_2 + 0{,}05К_3 + 0{,}01К_4 + 0{,}54К_5 - 0{,}64К_6$$

$$G_2 = - 3{,}36 + 1{,}56К_1 - 0{,}05К_2 + 0{,}005К_3 + 0{,}01К_4 + 0{,}49К_5 - 0{,}33К_6$$

$$G_3 = - 1{,}72 - 0{,}81К_1 + 0{,}01К_2 + 0{,}01К_3 - 0{,}02К_4 + 0{,}46К_5 - 0{,}25К_6$$

Northern zone:

$$G_1 = - 29{,}26 + 62{,}70К_1 + 1{,}64К_2 - 0{,}10К_3 + 0{,}22К_4 + 1{,}99К_5 + 0{,}06К_6$$

$$G_2 = - 11{,}51 + 21{,}98К_1 + 0{,}51К_2 - 0{,}05К_3 + 0{,}12К_4 + 0{,}69К_5 - 0{,}47К_6$$

$$G_3 = - 5{,}17 + 13{,}12К_1 - 0{,}66К_2 - 0{,}02К_3 + 0{,}07К_4 + 0{,}26К_5 + 0{,}02К_6$$

Modelling Based on the Sberbank Methodology

Applying the data substitution method, we have experimentally determined the boundaries of the solvency classes in points using the 100-point scale, using the methodology for calculating the financial condition indicators for agricultural producers (RF Government Decree #. 52, as of January 30, 2003) as the basis: 1st class - 100 to 69 points, 2nd class - from 69 (not inclusive) to 42 points, 3rd class - below 42 points (not inclusive).

The following regression equations were obtained (Patlasov-Vasina regression model) for the Omsk region as a whole according to the data as of 01.01.2006:

B = 32,601 + 6,36 К1 + 0,77 К2 + 0,38 К3 + 23, 95 К4 + 6,70 К5 + 0,26 К6 [9],

where К1 - the absolute liquid ratio;

К2 - the interim coverage ratio;
К3 - the current liquidity ratio;
К4 - own funds’ ratio;
К5 – profit margin;
К6 - enterprise profitability (see Table 6 for more details on calculations).

Table 5. Statistics of errors for the Omsk region as a whole in 2007

	Observed	1	2	3	Highest	Second	Third
1	1	0,961004	0,035578	0,003419	1	2	3
2	1	0,981859	0,016702	0,001440	1	2	3
3	1	0,972165	0,025803	0,002032	1	2	3
4	1	0,979272	0,018116	0,002612	1	2	3
*5	2	0,532218	0,216568	0,251214	1	3	2
*6	3	0,479990	0,238672	0,281338	1	3	2
7	1	0,962986	0,033553	0,003462	1	2	3
*8	2	0,397159	0,250741	0,352100	1	3	2
*9	2	0,861896	0,103902	0,034202	1	2	3
10	1	0,939756	0,054205	0,006038	1	2	3
	etc.						
348	1	0,706537	0,165445	0,128018	1	2	3
349	3	0,056942	0,138546	0,804511	3	2	1
350	1	0,985607	0,013601	0,000792	1	2	3

Statistics for each case of incorrect classifications are marked with *
Analysis sample N = 350

Table 6. Regression Summary for the Dependent Variable

	Beta	Std. Err.	B	Std. Err.	t(362)	p-Level
Intercept			32,60066	1,267911	25,71210	0,000000
K 1	0,032463	0,035780	6,35794	7,007490	0,90731	0,364848
K 2	0,093219	0,042679	0,76985	0,352466	2,18417	0,029591
K 3	0,217814	0,042907	0,38442	0,075728	5,07636	0,000001
K 4	0,597020	0,037425	23,94968	1,501317	15,95245	0,000000
K 5	0,115490	0,038919	6,70405	2,259234	2,96740	0,003203
K 6	0,013951	0,039893	0,25719	0,735427	0,34972	0,726752

Regression Summary for the Dependent Variable: Var7
R=, 73398633 R^2=, 53873593 Adjusted R^2=, 53109067;
F(6,362)=70,467 p<0,0000 Std. error of estimations: 16,129.

The assessment can be carried out according to two indicators that have the most significant impact on the financial condition of agricultural producers:

- Own funds' ratio (K4) with the error probability (p-level) being 0.0000. It can also take a negative value;
- Current liquidity ratio (K3) where p-level is also equal to 0.0000.

The graphs are convenient for quicker analysis of enterprises and organizations, they allow classifying them into certain groups on the basis of two factors, and then the remaining indicators need to be calculated to assign organization/enterprise to a certain credit rating class (the financial condition group) more accurately.

Table 7 presents the general results of the six-factor regression model evaluation basing on the data for the Omsk Region as a whole, as of 2007.

The following characteristics of the constructed regression equation are given: R is the value of the selective correlation coefficient; R^2- the value of the coefficient of determination (its value shows what percentage of the total variation of the dependent variable is due to the regression constructed); adjusted R^2 - the value of the coefficient of determination corrected for the number of the degrees of freedom; F is the calculated value of the Fisher test used to test the hypothesis of the regression equation signifiance; p is the magnitude of the significance level; Std. error of estimate is the standard error of estimating the regression equation.

Thus, the correlation coefficient back in 2007 was equal to 0.9273. This indicates that the solvency degree and the factors included in the model are closely related.

In 2007, the coefficient of determination was 0.8132. This means that the constructed regression equation reproduces approximately 81% of the dependence of B on the factors (K1-K6), i.e., the effective indicator depends on these factors by 81%. The remaining 19% fall on the share of random and unaccounted factors. The calculated value of the Fisher test at the degree of freedom (6.334) was 93.212, which is higher than its tabular (theoretical) value for the confidence probability P = (1-0.05) = 0.95, and this, in turn, corresponds to the significance level of p being less than 0.0000. Therefore, the regression equation obtained is significant, and it is not the result of the random selection of observations.

According to the results of analysis on the agroindustrial enterprises in the Omsk Region as a whole, the following regression equations have been obtained for several natural-economic zones using the data as of 2007:

Table 7. General results of the regression model estimation for the Omsk region as of 2007

	Beta	Std. Err.	B	Std. Err.	t(343)	p-Level
Intercept			28,88420	1,365349	21,15518	0,000000
K1	0,027762	0,052598	0,27591	0,522750	0,52781	0,597975
K2	-0,014748	0,049176	-0,05948	0,198316	-0,29991	0,764427
K3	0,225652	0,053319	0,22629	0,053469	4,23212	0,000030
K4	0,694109	0,034647	38,21893	1,907740	20,03361	0,000000
K5	-0,044456	0,033853	-2,39926	1,826987	-1,31323	0,189982
K6	0,046040	0,033586	0,35563	0,259432	1,37081	0,171331

Regression Summary for the Dependent Variable: B

R=, 92730491 R^2=, 81984902 Adjusted R^2=, 81319915

F(6,343)=93,212 p<0,0000 Std.error of estimations: 5,854

Legend: K1 is the absolute liquid ratio; K2 - the interim coverage ratio; K3 - the current liquidity ratio; K4 - own funds' ratio; K5 - profit margin; K6 - enterprise profitability.

Omsk Region: $B = 28{,}88 + 0{,}27К_1 - 0{,}05К_2 + 0{,}22К_3 + 38{,}21К_4 - 2{,}39К_5 + 0{,}35К_6$ [10].

Steppe zone: $B = 7{,}30 - 2{,}96К_1 + 0{,}22К_2 + 0{,}55К_3 + 70{,}84К_4 - 6{,}82К_5 + 10{,}64К_{6.}$

Southern forest-steppe zone:

$B = 22{,}70 + 1{,}61К_1 + 0{,}34К_2 + 0{,}02К_3 + 48{,}96К_4 -4{,}61К_5 - 0{,}78К_{6.}$

Northern forest-steppe zone:

$B = 33{,}62 + 3{,}36К_1 - 0{,}13К_2 + 0{,}33К_3 + 26{,}23К_4 + 3{,}83К_5 - 0{,}25К_{6.}$

Northern zone: $B = 14{,}52 + 6{,}93К_1 - 2{,}54К_2 + 0{,}33К_3 + 57{,}50К_4 + 3{,}85К_5 + 0{,}21К_{6.}$

The research results show that, despite the importance of each equation, not all the factors are significant. So, if the p-level exceeds the given level of significance (α) 0.05, then these factors are insignificant in the regression equation. Significant factors having the greatest impact on the solvency degree are those that have the highest level of significance (p-level<0.05).

After the stepwise correlation, i.e., successively excluding the factors from the model according to the principle of their least significance, we have obtained the following results (see Table 8).

Thus, we have obtained the set of equations containing the most significant factors affecting the solvency degree:

Omsk Region: $B = 28{,}82 + 0{,}23К_3 + 38{,}20К_4 - 2{,}31К_5 + 0{,}35К_6$

Steppe zone: $B = 6{,}69 - 2{,}61К_1 + 0{,}56К_3 + 70{,}98К_4 + 6{,}70К_6$

Southern forest-steppe zone: $B = 22{,}80 + 2{,}35К_3 + 49{,}71К_4 - 5{,}44К_5$

Northern forest-steppe zone: $B = 33{,}49 + 4{,}75К_1 + 0{,}24К_3 + 26{,}64К_4$

Northern zone: $B = 13{,}78 + 6{,}99К_1 - 2{,}52К_2 + 0{,}35К_3 + 57{,}09К_4 + 0{,}20К_6$

Table 8. General results of the four-factor model assessment for the Omsk region, as of 2007.

	Beta	Std. Err.	B	Std. Err.	t(345)	p-Level
Intercept			28,82849	1,356994	21,24437	0,000000
K4	0,693766	0,034468	38,20003	1,897875	20,12778	0,000000
K3	0,235861	0,034310	0,23653	0,034406	6,87448	0,000000
K6	0,045907	0,033502	0,35460	0,258781	1,37027	0,171493
K5	-0,042866	0,033621	-2,31344	1,814517	-1,27496	0,203180

Regression Summary for the Dependent Variable: B
R=, 92710060 R^2=, 81952735 Adjusted R^2=, 81511608
$F(4,345)$=140,44 p<0,0000 Std. error of estimations: 5,815

According to the Sberbank methodology, the fragment of the dialog box is shown as in Table 9.

Thus, the system of equations (as per the discriminant model) looks as follows:

Omsk region:

$$G_1 = -5{,}05 - 0{,}16К_1 + 0{,}03К_2 + 0{,}03К_3 + 8{,}97К_4 - 0{,}68К_5 + 0{,}05К_6$$

$$G_2 = -3{,}89 - 0{,}17К_1 + 0{,}09К_2 - 0{,}001К_3 + 7{,}16К_4 - 0{,}04К_5 + 0{,}04К_6$$

$$G_3 = -1{,}20 - 0{,}03К_1 + 0{,}01К_2 - 0{,}001К_3 + 0{,}91К_4 + 0{,}01К_5 - 0{,}06К_6$$

Steppe zone:

$$G_1 = -15{,}42 - 0{,}59К_1 + 0{,}14К_2 + 0{,}04К_3 + 34{,}03К_4 + 6{,}92К_5 -2{,}51К_6$$

$$G_2 = -11{,}08 - 0{,}06К_1 + 0{,}04К_2 - 0{,}04К_3 + 28{,}23К_4 + 8{,}01К_5 - 2{,}82К_6$$

$$G_3 = -3{,}28 + 0{,}09К_1 - 0{,}05К_2 - 0{,}02К_3 + 12{,}4К_4 + 7{,}23К_5 - 3{,}79К_6$$

Table 9. Fragment of the dialog box according to the Sberbank methodology

	Wilks' Lamda	Partial Lambda	F-Remove	p-Level	Toler.	1-Toler. (R^2)
Var1	0,412334	0,995209	0,8232	0,439884	0,415680	0,584320
Var2	0,415740	0,987054	2,2427	0,107727	0,466326	0,533674
Var3	0,428441	0,957794	7,5352	0,000627	0,420867	0,579133
Var4	0,855155	0,479864	185,3508	0,000000	0,971287	0,028713
Var5	0,418419	0,980736	3,3588	0,035926	0,958499	0,041501
Var6	0,415083	0,988616	1,9691	0,141158	0,982213	0,017788

Discriminant Function Analysis Summary

# of vars in model: 6; Grouping: Var9 (3 grps)

Wilks' Lambda:, 41036 approx. F (12,684)=31,980 p<0,0000

Table 10. Initial data for the equations by groups for the Omsk region as a whole, as of 2007.

	G_1:1	G_2:2	G_3:3
Var1	-0,15632	-0,16826	-0,03101
Var2	0,03173	0,08752	0,01328
Var3	0,03289	-0,00081	0,00095
Var4	8,97384	7,16354	0,91444
Var5	-0,68149	-0,98190	0,01090
Var6	0,05198	0,03599	-0,05807
Constant	-5,04716	-3,89890	-1,20227

Classification Functions; grouping: Var9

Southern forest-steppe zone:

$$G_1 = - 1,67 + 0,07К_1 - 0,03К_2 - 0,002К_3 + 2,93К_4 - 0,36К_5 + 0,13К_6$$

$$G_2 = -2,75 - 0,07К_1 - 0,001К_2 - 0,006К_3 + 4,10К_4 + 0,30К_5 - 0,45К_6$$

$$G_3 = -1,96 - 0,19К_1 + 0,09К_2 + 0,004К_3 + 3,09К_4 - 0,03К_5 - 0,57К_6$$

Northern forest-steppe zone:

$$G_1 = -3,29 - 0,92К_1 - 0,10К_2 + 0,11К_3 + 3,88К_4 - 0,51К_5 - 0,10К_6$$

$$G_2 = -2,68 - 0,51К_1 + 0,04К_2 + 0,03К_3 + 3,15К_4 - 0,57К_5 - 0,32К_6$$

$$G_3 = -0,97 - 0,05К_1 - 0,01К_2 + 0,008К_3 - 0,45К_4 - 0,61К_5 - 0,31К_6$$

Northern zone:

$$G_1 = -32,93 - 0,16К_1 + 0,08К_2 - 0,03К_3 + 71,09К_4 + 1,17К_5 + 0,23К_6$$

$$G_2 = -24,05 – 0,24К_1 + 0,15К_2 – 0,06К_3 + 58,26К_4 – 2,22К_5 + 0,18К_6$$

$$G_3 = -5,05 – 0,13К_1 + 0,13К_2 – 0,02К_3 + 18,62К_4 – 1,05К_5 – 0,09К_6$$

Table 11. Fragment of error statistics for the Omsk region as of 2007

#	Observed	1	2	3	Highest	Second	Third
1	1	0,593849	0,368347	0,037803	1	2	3
2	1	0,745449	0,241932	0,012620	1	2	3
3	1	0,629958	0,346817	0,023225	1	2	3
4	1	0,897464	0,094120	0,008416	1	2	3
5	3	0,154512	0,262337	0,583152	3	2	1
6	3	0,142467	0,244370	0,613163	3	2	1
7	1	0,591174	0,375289	0,033536	1	2	3
8	3	0,110079	0,206023	0,683898	3	2	1
*9	3	0,394454	0,404863	0,200684	2	1	3
*10	2	0,548031	0,390896	0,061073	1	2	3
	Etc.						
348	2	0,291505	0,383828	0,324667	2	3	1
349	3	0,018692	0,062457	0,918851	3	2	1
350	1	0,730353	0,261720	0,007927	1	2	3

(Statistics for each case of incorrect classifications are marked with *)

Analysis sample N = 350

Note: The analyst has the opportunity to see the possibility to assign all 350 (in our case) organizations to the group of financial stability; here a fragment only is given. Information about the potentially incorrect organization classification is marked with an asterisk (*) in the table above and thus should be subject for a deeper analysis.

Thus, according to the annual accounting reports' data provided by the agricultural enterprises registered in the Omsk region, the following results of discriminant analysis have been obtained: the partition was obtained for 3 groups of solvency (financial) condition, a system of equations was established to classify the organization to a certain group of financial stability. To classify an organization to a group by financial position, the above systems of equations have been used to determine the largest value - **G**, indicating the organization's belonging to a particular group of financial stability. One of the positive aspect in using this toolkit is that it demonstrates the opportunity to assign a particular enterprise to a particular financial stability group. Besides that, asterisks in the first row mean mistakes in the initial classification into groups; and if additional information on these enterprises is added to the matrix for testing, the program will automatically assign them to the appropriate financial stability groups.

In order to build the log-regression model, financial indicators calculated on the basis of the annual accounting reports data on all agricultural enterprises of the Omsk Region were used. The basis for risk factors' selection for further classification is the methodology developed and used by the Sberbank of Russia.

For borrowers' solvency assessment, the Sberbank uses three groups of valuation indicators:

- **Liquidity Ratios:** Absolute liquid ratio (К1), quick liquidity ratio (К2), current liquidity ratio (К3);
- Own funds' ratio (К4);
- **Turnover and Profitability Indicators:** Current assets turnover, receivables' turnover, inventory turnover, profitability of products (profitability of sales) (К5), enterprise's profitability (К6), profitability of investments in the enterprise.

When constructing the logit-regression model, six basic coefficients were calculated, according to the Sberbank methodology.

Applying the data substitution method, we have experimentally determined the boundaries of classes in points using the 100-point system, using the Methodology for calculating financial condition indicators for agricultural producers (RF Government Decree #52, as of January 30, 2003) as the basis. According to the research results we have determined: 1st class of solvency - from 100 to 69 points (inclusive); 2nd class of solvency - from 69 (exclusive) to 26 points (inclusive); 3rd class of solvency being below 26 points.

In order to construct the regression equation, it is necessary to form the initial matrix. Data in matrices are formed by years, natural and economic zones and for the Omsk region as a whole. Annual accounting reports data provided by the Omsk region agricultural enterprises (as of 2005-2007) were used for the study. Data processing was carried out using the SPSS software. After entering the data presented in the matrix, the following information was obtained.

The forecast results can be put in the form of the following table (see Table 13).

A significant regression equation is obtained by using all six selected coefficients simultaneously. Based on the modelling results, the following regression equation has been obtained (Patlasov-Vasina logit regression model) (Patlasov, Vasina, 2013):

$$Y = -13{,}03 + 2{,}79K1 - 0{,}64K2 + 0{,}84K3 + 16{,}49K4 + 3{,}33K5 + 0{,}58K6.$$

Table 12. Dialog box fragment of the classification table for predicting the percentage of data correctness

	Observed		Predicted		
			VAR00007		Percentage Correct
			0,00	1,00	
Step 1	VAR00007	0,00	115	4	96,6
		1,00	2	149	98,7
	Overall Percentage				97,8

Classification Table (a)
a The cut value is, 500

Table 13. Generalized results of data forecasting

	VAR00007 = 1	VAR00007 = 0	Total
Totally according to the sampling	119	151	270
Forecast	117	153	270
Correct	115	149	264
Incorrect	4	2	6
% of correct	96,6	98,7	97,8
% of incorrect	0,4	1,3	2,2

Table 14. Data for regression equation construction

		B (Regression Coefficient of B)	Standard Error	Wald	Degree of Freedom	Significance	Exp(B) Inverse Function Ln
Step 1(a)	VAR00001	2,796	3,930	,506	1	,477	16,379
	VAR00002	-,639	,529	1,461	1	,227	1,528
	VAR00003	,844	,295	8,192	1	,004	2,325
	VAR00004	16,486	4,059	16,499	1	,000	14,243
	VAR00005	3,333	1,838	3,288	1	,070	28,009
	VAR00006	,579	,541	1,143	1	,285	1,783
	Constant	-13,030	2,955	19,443	1	,000	,000

Variables in the Equation
a Variable(s) entered on step 1: VAR00001, VAR00002, VAR00003, VAR00004, VAR00005, VAR00006.
Table values and coefficients' correspondence:
VAR00001 - K_1 (absolute liquid ratio);
VAR00002 - K_2 (interim coverage ratio);
VAR00003 - K_3 (current liquidity ratio);
VAR00004 - K_4 (own funds' ratio);
VAR00005 - K_5 (profit margin);
VAR00006 - K_6 (enterprise's profitability).

In this model, rather high error has the absolute liquidity ratio, own funds' ratio and profit margin. However, this model is built under the Sberbank regulation, so it is not appropriate to exclude from the model, for example, absolute liquid ratio, profit margin as they weakly reflect the actual financial situation in the agricultural sector.

The probability of loan payment delay is calculated by the formula:

$$P = \frac{1}{1 + e^{-y}}$$

If for p we get a value less than 0.5, then we can assume that bankruptcy does not come; otherwise, financial collapse is assumed.

The advantage of modelling in comparison with regulation is the ability to take into account industry's specificity, regional characteristics, the stage of company's life cycle, company's sizr and other business conditions.

In accordance with the proposed methodology, a set of logit regression models has been created allowing to predict the financial status and the solvency of organizations under various economic conditions. These models can be used by credit analysts of banks, financial analysts and managers of organizations with the purpose of forecasting the financial state of organizations.

The proposed methods for assessing the organization's solvency are acceptable for Russian conditions, since they are already somewhat adapted to the agricultural sector. The models are created on the regional data set and are presented in the context of the natural and economic zones of the regions, thus making it possible to better take into account the regional specificity and to develop a model that allows more accurate assessment of the financial condition of agricultural organizations located in different zones.

The proposed models allow organizations assess their financial condition from the viewpoint of banks and to obtain information on compliance with the requirements set by credit institutions. If you get such information in time, it will allow making more appropriate managerial decisions that would contribute to the organizations' financial condition improvement.

The models can be as well used by rating agencies to calculate the organizations' credit ratings and also by territorial state commissions in the course of financial recovery of agricultural producers.

CONCLUSION

Financial condition of any organization is characterized by a system of indicators reflecting the process of financial resources' formation and further use. Financial resources in this case include the aggregate of own money, income, raised and borrowed funds intended for the performance of financial obligations, financing of current costs and expenses associated with activities' expansion. The task of comprehensive analysis of organization's financial condition is not limited by establishing the solvency level according to official methods. It is necessary to conduct in-depth financial diagnostics taking into account sectoral and regional specifics. To determine the direction of in-depth analysis, a preliminary express analysis is first conducted. The key advantages of the indicators' system are systemic and integrated approaches, while the major disadvantage is higher degree of decision-making complexity.

In addition to the officially approved methods, there are other methods of analyzing financial and economic activities developed by scientists and practitioners working in consulting, audit, valuation firms, commercial banks, rating agencies and other organizations.

When analyzing company's financial condition, the following groups of financial indicators are distinguished: general indicators, liquidity and solvency analysis, financial stability, business activity, profit and profitability, cash flows and financial activity, business valuation, integral rating analysis. Among the methodological problems in forecasting of potential bankruptcy of organizations the following can be mentioned:

- Financial rather than economic analysis is carried out according to a complex methodology (while aggregated factor analysis is not carried out);
- Analysis involves mainly Form 1 and Form 2 of accounting reports, other forms with analytical capabilities are disregarded;
- Internal analysis is not always corroborated by environmental factors' analysis; financial analysis of economic entities' activities should be preceded by macroeconomic analysis (situation in the national economy, sectoral trends and regional characteristics);
- The problem of adaptation of Western methods for indicators' calculation as per Russian specifics of accounting and reporting persists;
- The difference between Russian accounting system (RAS) and the International Accounting System (IAS) and IFRS is maintained;
- Within the framework of our analysis, three following areas of economic activities are not studied thoroughly: operational, investment and financial ones;
- Within the framework of such an analysis business and management are not always assessed properly;
- As a rule, when constructing a graphical model of the break-even production, only the break-even point and the security edge are examined, the points of bankruptcy, profitability, minimum and full estimated profit remain without attention; the study of the corresponding points in the break-even graphical model is not corroborated by an analysis of the corresponding types of values (the liquidation value at the point of bankruptcy, the value of net assets at the point of profitability, the market value of the enterprise's property complex at the break-even point, the market value of business under traditional approaches to valuation at the point of minimum settlement profit and the market value of business as part of a strategic approach to valuation at the point of full estimated profit);
- Analysis is conducted with the involvement of limited information sources; there is hardly any information system for integrated analysis (data on accounting, taxation, statistics, managerial accounting and reporting, marketing research, enterprise itself etc.);
- During bankruptcy diagnostics, many intangible assets are not taken into account - the assets of intellectual capital, brand value etc.;
- The audit of initial information is not always carried out with the purpose of improving the quality of the information support system for further bankruptcy forecasting;
- The problem of indicators' choice and grouping under various financial analysis techniques is preserved, many of the vitally important indicators are often disregarded;
- Indicators sometimes correspond with each other or choose the inverse coefficients in the considered techniques and financial models;

- Company's investment attractiveness analysis does not actually provide a complete picture of its innovative activities;
- In the absence of standards (recommended values) of financial ratios, the integral indicator of economic activity cannot always be determined;
- Analysis of the best and/or the most effective business types is not conducted since benchmarking tool as such is;
- Specific features at various stages of bankruptcy (observation, financial recovery, external management, bankruptcy proceedings, settlement agreement) are not taken into account;
- As a rule, sectoral methods are limited to agriculture only, thus, when being applied to trade, for example, these methods do not sufficiently capture the specificity of accounting and/or analysis purposes as such;
- Analysis of added value is rarely carried out as such.

As of today, there is still no domestic model developed and available specifically for Russian insurance companies, commercial banks and non-bank credit organizations.

In general, in order to obtain more adequate conclusions about the financial state, it is advisable to apply a set of models in the analysis.

Thus, our research shows that official methods of financial analysis organization have a serious drawback - the basis for conclusions is formed by accounting data only, while the stage of organization's life cycle is not taken into consideration at all, thus, the future state cannot be really predicted as precisely as it is expected. For the aims of financial management it would be important to conduct system analysis, covering all processes in the external environment and the role of the human factor, in addition to organization's financial state assessment. Such comprehensive methods of analysis are indisputably more labor-intensive, but they allow not only increasing the reliability of the results obtained, but also exploring the hidden causes and consequences of all related phenomena. Consequently, this more comprehensive analysis would help raising the efficiency of commercial organizations' crisis management.

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KEY TERMS AND DEFINITIONS

Discriminant Analysis: A classification problem, where two or more groups or clusters or populations are known *a priori* and one or more new observations are classified into one of the known populations based on the measured characteristics.

Discriminant Function: A function of several variables used to assign items into one of two or more groups. The function for a particular set of items is obtained from measurements of the variables belonging to a known group.

Discriminant Score: The score of each respondent on the discriminate function in discriminant analysis.

Discriminant Variables: Characteristics used to distinguish one class from another; they should be measured either on the interval scale, or on the scale of relations. Thus, it becomes possible to calculate the mathematical expectations, variances, etc.

Discriminant Weights: Standardized discriminant weight (discriminant coefficient) of a certain sign and weight is assigned to each variable in computing of discriminant functions. When the sigh is ignored, each weight represents the relative contribution of its associated variable to that function, while independent variables with relatively larger weights contribute more to the discriminant power of the function than do variables with smaller weights.

F-Statistics: Consists of F-enter and F-remove: 1) The use of F-value. A variable is entered into the model if its F-value is greater than the Entry value and is removed if the F-value is less than the Remove value. Entry must be greater than the removal one, and both values must be positive. To enter more variables into the model, its author is supposed to lower the Entry value. To remove more variables from the model, the Removal value must be increased. 2) The use of probability with F. A variable is entered into the model if the significance level of its F-value is less than the Entry value and is removed if the significance level is greater than the Removal value. Entry must be less than Removal, and both values must be positive. To enter more variables into the model, one should increase the Entry value. To remove more variables from the model, the Removal value must be lowered. At each step, the predictor with the largest F-enter, the value of which exceeds the entry criteria, is added to the model.

Mahalanobis Distance: A measure of how much the particular case values of the independent variables differ from the average of all cases. Larger Mahalanobis distance identifies the case with the extreme values on one or more of the independent variables.

Raw Coefficients: Coefficients providing information about the absolute contribution of a variable to the value of the discriminant function.

Solvency: Is the ability of a company to meet its long-term financial obligations. Solvency is essential to staying in business as it asserts company's ability to continue operations into the foreseeable future. Liquidity should not be confused with solvency, however. Solvency is directly related to the ability of an individual or business to pay their long-term debts including any associated interest. To be considered solvent, the value of assets, company's or individual, must be greater than the sum of debt obligations.

Standardized Coefficients: Standardized coefficients refer to how many standard deviations a dependent variable will change per standard deviation increase in the predictor variable.

Structure Coefficients: Structure coefficients add to the information provided by β weights. Betas inform us as to the credit given to a predictor in the regression equation, while structure coefficients inform us as to the bivariate relationship between a predictor and the effect observed without the influence of other predictors in the model. If the coefficient is closer to zero, the relationship between the individual variable and the discriminant function is insignificant.

Tolerance: A variable defined as 1 minus the squared multiple correlation of this variable with all the other independent variables. Therefore, the smaller is the tolerance of a variable, the more redundant is its contribution to the regression (i.e., it is redundant with the contribution of other independent variables). If the tolerance of any of the variables in the regression equation is equal to zero (or is very close to zero), then the regression equation cannot be evaluated (the matrix is said to be ill-conditioned, and it cannot be inverted).

Wilks' Lambda: A measure of how well each function separates cases into groups. It is equal to the proportion of the total variance in the discriminant scores not explained by differences among groups. Smaller value of Wilks' lambda indicates greater discriminatory ability of the function.