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Static Model Classification Status: Taking Into Account Emerging External Factors

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Analysis of the problem of predicting bankruptcy shows that foreign and domestic models included only internal factors of enterprises. But the same indicators of internal factors in the rapidly changing external environment can lead to bankruptcy, and not in others. External factors are the most dangerous, because the possible influence on them is minimal and the impact of their implementation can be devastating. This paper focuses on the same factors to assess the impact of the macroeconomic indicators (external factors) on the parameters of static models predicting a local approximation of the crisis at the plant. To accomplish the purpose, a Spark set of 100 companies was compiled, including 50 companies which officially declared bankruptcy in the period of 2000-2009 and 50 stable operating companies with a random sample of the same time period. External factors were extracted from the Joint Economic and Social Data Archive[1]. The author compared two data sets: (1) microeconomic indicators—money to the total liabilities, retained earnings to total assets, net profit to revenue, Earnings Before Interest and Taxes (EBIT) to assets, net income to equity, net profit to total liabilities, current liabilities to total assets, the totality of short-term and long-term loans to total assets, current assets to current liabilities, assets to revenue, equity to total assets, and current assets to revenue; and (2) external factors—index of real gross domestic product (GDP), industrial production index, the index of real cash incomes, an index of real investments, consumer price index, the refinancing rate, unemployment rate, the price of electricity, gas prices, oil price, gas price, dollar to ruble, ruble euro Standard & Poor (S&P) index, the Russian Trading System (RTS) index, and region. The aim of the comparison results paging classes “insolvent” and “non-bankrupt” is achieved using two methods: classification and discrimination. In both methods, computational procedures are realized with the use of algorithms: linear regression, artificial neural network, and genetic algorithm. In the 2-m model, data set includes both internal and external factors. The results showed that the inclusion of only the microeconomic indicators, excluding external factors, impedes models about two times.

Keywords: bankruptcy prediction, external factors, methods of classification and discrimination

The Notion of “Emerging”

Conventional wisdom is that the bankruptcy and the crisis at the plant—the concepts are synonymous, bankruptcy, in fact, is seen as an extreme manifestation of the crisis. In reality, this is not the case—the company is subjected to various types of crises (economic, financial, and managerial) and bankruptcy is just one of them (Eytington, 2007). Worldwide under the financial crisis, bankruptcy is commonly understood as

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[1] Retrieved from http://www. stat.hse.ru.

the inability of the company to fulfill its current obligations. In addition, the company may be experiencing economic crisis (a situation where resources are used inefficiently) and crisis management (ineffective use of human resources, which often means low competence management, and consequently, inadequate management decisions with the environment). Accordingly, different methods of predicting bankruptcy, as it is accepted to name them in domestic practice, in fact, predict various types of crises.

State of the Problem

Types of Models

Attempts to develop models for predicting bankruptcy were initiated in the mid-1930s and continue to this day. In summary, the results of previous studies can be divided into three groups.

Bankruptcy prediction models:

(1) Statistical model (statistical models);

(2) A model of artificial intelligence (AI);

(3) The theoretical model (theoretical models).

Statistical models were obtained through the use of different statistical methods of classification:

(1) This single factor (a one-dimensional analysis);

(2) Multifactor linear discriminant of such (multiple discriminant analysis);

(3) The conditional probability (conditional probability analysis);

(4) Survival (survival analysis).

A model of AI applied in this issue includes:

(1) Decision tree (tree);

(2) Genetic algorithm (genetic algorithm);

(3) Neural networks (neural networks);

(4) The theory of fuzzy sets (rough sets theory);

(5) Method of support vectors (support vector machine).

Among the theoretical models include:

(1) Entropy theory (the theory of entropy);

(2) Ruin theory (theory of ruin player);

(3) Theory of the auditors of the option (option price theory).

Comparison of frequency of use and the accuracy of the predictions showed that 64% of previous studies were associated with statistical models for predicting bankruptcy, 25% with models of AI, and 11% with the development of theoretical models. The prediction showed the superiority of models of AI: 88%, with theoretical models showing 85% and 84% for statistic models forecasting accuracy (see Table 1) (Aziz & Dar, 2004; Zhurov, 2010).

Table 1

Comparison of Accuracy of Forecasting Developed Models

Modeling technique	This study				The average precision in foreign studies (Aziz & Dar, 2004)
	The overall accuracy of the original data set classification	Procedure for comparative validity			
		Error type 1	Error type 2	Overall accuracy	
Single factor analysis	83.10%	21.40%	14.80%	80.70%	81%

(Table 1 continued)

Modeling technique	This study				The average precision in foreign studies (Aziz & Dar, 2004)
	The overall accuracy of the original data set classification	Procedure for comparative validity			
		Error type 1	Error type 2	Overall accuracy	
Multifactor analysis of linear discriminant	85.30%	14.30%	16.20%	84.80%	86%
Analysis of conditional probability	85.30%	14.30%	16.20%	84.80%	87%
Decision tree	95.50%	17.10%	10.00%	86.40%	87%
Genetic algorithm-neural network	95.80%	9.00%	10.00%	90.50%	89%
The theory of fuzzy sets	90.00%	12.90%	11.90%	87.60%	91%
Method of support vectors	89.10%	10.00%	15.20%	87.40%	87%

Notes. Here, under the error of type 1 means the result when the bankrupt enterprise is wrongly classified as an enterprise model— non-bankrupt. Error type 2 is recorded when the non-bankrupt company is classified as bankrupt.

Interim Conclusions From the Analysis of the Problem, the Purpose of the Study, and the Choice of Methodology

Analysis of the problem shows that the Russian (Zaitseva, 1998; Zaichenko & Rogoza, 2010; Kovalev & Privalov, 2001; Hooks & Egorychev, 2001; Kryukov, 2006; Nedosekin, Maximov, & Pavlov, 2003; Prudnikova, 1998; Strekalov & Zaripov, 1997; Fomin, 2003; Furmanov, 2005; Haydarshina, 2009; Chelyshev, 2006; Yurzinova, 2005; Davydov & Belikov, 1999) and foreign (Ezzamel, Brodie, & Mar-Molinero, 1987; Hardle, Moro, & Schifer, 2005; Lennox, 1999; Ohlson, 1980; Taffler, 1983) models take into account only the internal factors of enterprises. From overseas practices of countries with developed market economies, it has been realized that internal factors of risk of bankruptcy, due to the erroneous actions of management, are responsible for up to 80% of cases of economic insolvency of companies. This is due to the relatively stable value of external factors (constants in the construction of models do not appear).

Since Russia external factors are changing rapidly, the models of domestic enterprises may occur. It is clear that the same indicators of internal factors in the rapidly changing external environment can lead to bankruptcy, and not in others.

External factors are the most dangerous, because the possible influence on them is minimal and the impact of their implementation can be devastating.

In accordance with the conclusions of the analysis of the problems in the goal, the paper focuses on the same factors of Russian enterprises to evaluate the impact of macroeconomic indicators (external factors) on the parameters of the static model prediction approach local crisis at the company.

Sample Size

In order to accomplish the objectives of the Spark database has compiled a set of 50 companies officially recognized bankrupt during the period of 2000-2009 and 50 stable enterprises with random sampling of the same time period.

Indicator Sets

Calculations were made with two sets of data: (1) only microeconomic indicators; and (2) in addition, microeconomic indicators were taken into account external factors relevant time-fixing internal factors. A set of internal (microeconomic) enterprises is taken:

(1) Cash to total commitments;
(2) Retained earnings to total assets;
(3) Net profit in the proceeds;
(4) Earnings before interest and taxes (EBIT) to total assets;
(5) Net profit/equity ratio;
(6) Net income to total liabilities;
(7) Current liabilities to total assets;
(8) Set of short- and long-term loans to total assets;
(9) Present value (PV) to assets;
(10) Current assets in short-term obligations;
(11) Assets to revenue;
(12) Shareholders' equity to total assets;
(13) Current assets to revenue.

At 2-ohms dataset to calculate prediction models, pre-crisis state enterprises in addition to the 1st set of external factors are taken into account:

(1) Index of real gross domestic product (GDP);
(2) The index of industrial production;
(3) Index of real cash incomes;
(4) Index of real investment of the fixed assets;
(5) Consumer price index;
(6) Refinancing rate;
(7) The unemployment rate;
(8) Electricity prices by region;
(9) Gas prices by region;
(10) The price of oil;
(11) Price of gas;
(12) Dollar to ruble;
(13) Euro rate to the ruble;
(14) Standard & Poor (S&P) index;
(15) Russian Trading System (RTS) index;
(16) Region.

Calculation Methods

The aim of comparison results paging classes "insolvent" and "non-bankrupt" allows one to apply the two methods: classification and discrimination.

As applying statistical packages is in conflict with the normal law of distribution and multicollinearity in the source data, to solve the problems that had arisen, the author used package-mining company PolyAnalist Megaputer Intelligents.

In both methods, computational procedures are realized with the use of algorithms:

(1) Linear regression;
(2) Artificial neural network;

(3) Genetic algorithm.

In the two latter algorithms, result is presented in the form of higher-order polynomials, which makes it difficult to use them in practice.

Since the objective of the study was not to achieve the highest precision, and assessing the impact of external factors, the following are the results of applying only the linear regression algorithm.

The Results of the Research

Model Discrimination

The results of applying the methodology of discrimination with the algorithm and a set of linear regression only microeconomic indicators are as follows:

Straightly, between class “bankrupt” and class “non-bankrupt”, has the form:

If the value of the prediction expression (see below) more than the record belongs to 0.5814 Class 1 (class 1) or not (0).

Prediction expression is:

$$0.5814 < (+0.496044 + 2.93727e - 003 * r3 + 1.94875e - 001 * r7 - 7.53875e - 002 * r8 - 8.44984e - 001 * r11)$$

Legend is given in Table 2.

Table 2

Calculation of Indicators

Cash flow ratios	Calculation	Indicator
Cash flow to total liabilities	DC/commitments	r1
Profitability ratios		
Retained earnings to total assets	Profit/assets	r2
Net profit to net sales	Net profit/sales	r3
EBIT to total asset	EBIT/total assets	r4
Net income to total equity	Return on equity (ROE)	r5
Net income to total liabilities	Profit/commitments	r6
Leverage ratios		
Total current liabilities to total assets	Short-term liabilities/assets	r7
Total debt to total asset	Short-term and long-term debt/total assets	r8
Debt to equity	Debt/equity	r9
Equity to asset	Capital/assets	r10
Liquid asset ratios		
Cash and bank to total assets	DC/assets	r11
Short-term solvency ratios		
Current asset to current liabilities	Current assets/current liabilities	r12
Activity ratios		
Turnover of assets	Assets/revenue	r13
Current asset to sales	Current assets/revenue	r14

The results of model calculations of discrimination using a linear regression algorithm and data sets of micro and macro indicators are as follows:

If the value of the prediction expression (see below) more than the record belongs to 0.6477 Class 0 (class 1) or not (0).

Prediction expression is:

$$0.3406 < (+2.09434e-007*r3+2.56384e-006*r6+1.54082e-005*r7-4.73087e-006*r8+1.17210e-007*r9 -6.54962e-005*r11-3.13720e-006*\text{"}\mathit{Index\ of\ the\ real\ income\ of\ the\ fixed\ assets}\text{"}+1.02195e-006*\text{"}\mathit{Index\ of\ real\ investments}\text{"}+1.31177e-005*\text{"}\mathit{Refinancing\ rate}\text{"}-1.14226e-005*\text{"}\mathit{Dollar\ to\ ruble}\text{"} +1.25165e-005*\text{"}\mathit{Euro\ to\ Russian\ ruble}\text{"})$$

Type 1 and type 2 errors are presented in Table 3.

Table 3

Error in the Method of Discrimination

Valid/predicted	Micro		Micro & macro		Undefined
	0	1	0	1	
0	39	8	34	13	0
1	25	25	4	46	0

Statistical significance coefficients for both internal and external factors are illustrated in Table 4.

Table 4

Factors

The name	Micro & macro			Micro		
	The coefficients	Standard deviation	*F*-ratio	The coefficients	Standard deviation	*F*-ratio
r3	2.094e-003	7.824e-004	7.166	2.937e-003	8.967e-004	10.73
r6	2.564e-002	2.509e-002	1.044			
r7	1.541e-001	5.838e-002	6.966	1.949e-001	6.626e-002	8.65
r8	-4.731e-002	3.892e-002	1.477	-7.539e-002	4.617e-002	2.666
r9	1.172e-003	1.135e-003	1.066			
r10	-6.55e-001	4.11e-001	2.539			
r11	-3.137e-002	7.132e-003	19.35	-8.45e-001	4.702e-001	3.229
Index of the real income of the fixed assets	1.022e-002	3.617e-003	7.981			
Index of real investments	1.312e-001	1.899e-002	47.73			
Refinancing rate	-1.142e-001	2.67e-002	18.3			
Dollar to ruble	1.252e-001	2.209e-002	32.11			
Euro to Russian ruble	2.094e-003	7.824e-004	7.166			

Error separation sample classes “bankrupt” and “non-bankrupt” are illustrated in Table 5.

Table 5

Error in the Method of Discrimination

Probability	Micro (%)	Micro & macro (%)
Error classification for class 0	17.02	27.66
Error classification for class 1	50	8
General error classification	34.02	17.53
The probability of a correct classification	65.98	82.47
Efficacy classification	29.79	63.83
P-value	3.775e-011	6.144e-006

The calculation results for discriminatory method set only the variables in the form of internal indicators, and additional view of external factors shows the inclusion in the model of macroeconomic indicators.

Reduced error classifications are as follows:

(1) General error classification two times (with 34.02% to 17.53%);

(2) For class “bankrupt”, it is more than six times (from 50% to 8%);

(3) Increased the probability of a correct classification with 65.98% and 82.47%;

(4) The classification efficiency increased from 29.79% to 63.83%.

The results of applying the algorithms in a discriminatory method of artificial neural network and genetic algorithm are not listed here.

A Classification Model

The results of the classification method for predicting the pre-crisis conditions differ somewhat from the above method of discrimination. So, dividing line is of the form:

If the value of the prediction expression (see below) is greater than the value of the class, then 0.5814 is TRUE (class 1), otherwise, it is set to be FALSE (0).

Prediction expression is:

$$0.5814 < (+0.496044 + 2.93727e - 007 * r3 + 1.94875e - 005 * r7 - 7.53875e - 006 * r8 - 8.44984e - 005 * r11)$$

The results of calculations using the classification in the joint account, both internal and external factors, are given below:

If the value of the prediction expression (see below) is greater than the value of the class, then 0.3406 is TRUE (class 1), otherwise, it is set to be FALSE (0).

Prediction expression is:

$$\begin{gathered}0.3406 < (+2.09434e - 007 * r3 + 2.56384e - 006 * r6 + 1.54082e - 005 * r7 - 4.73087e - 006 * r8 + 1.17210e - 007 * r9 \\ -6.54962e - 005 * r11 - 3.13720e - 006 * "\textit{Index of the real income of the fixed assets}" + 1.02195e - 006 * "\textit{Index of} \\ \textit{real investments}" + 1.31177e - 005 * "\textit{Refinancing rate}" - 1.14226e - 005 * "\textit{Dollar to ruble}" \\ + 1.25165e - 005 * "\textit{Euro to Russian ruble}")\end{gathered}$$

First and second types of error classification are presented in Table 6.

Table 6

Error Classification Methods

Valid/predicted	Micro		Micro & macro		Undefined
	0	1	0	1	
0	39	8	34	13	0
1	25	25	4	46	0

Error separation sample classes “bankrupt” and “non-bankrupt” are illustrated in Table 7.

Table 7

Error Classification

Probability	Micro (%)	Micro & macro (%)
Error classification for class 0	17.02	27.66
Error classification for class 1	50	8
General error classification	34.02	17.53
The probability of a correct classification	65.98	82.47
Efficacy classification	29.79	63.83
P-value	3.775e-011	6.144e-006

The statistical significance of the coefficients in a method of classification is given in Table 8.

Table 8

Factors

The name	Micro & macro			Micro		
	The coefficients	Standard deviation	*F*-ratio	The coefficients	Standard deviation	*F*-ratio
r3	2.094e-003	7.824e-004	7.166	2.937e-003	8.967e-004	10.73
r6	2.564e-002	2.509e-002	1.044			
r7	1.541e-001	5.838e-002	6.966	1.949e-001	6.626e-002	8.65
r8	-4.731e-002	3.892e-002	1.477	-7.539e-002	4.617e-002	2.666
r9	1.172e-003	1.135e-003	1.066			
r11	-6.55e-001	4.11e-001	2.539	-8.45e-001	4.702e-001	3.229
Index of the real income of the fixed assets	-3.137e-002	7.132e-003	19.35			
Index of real investments	1.022e-002	3.617e-003	7.981			
Refinancing rate	1.312e-001	1.899e-002	47.73			
Dollar to ruble	-1.142e-001	2.67e-002	18.3			
Euro to Russian ruble	1.252e-001	2.209e-002	32.11			

Grouping Variables Factor Analysis

In addition, the paper attempts to explain the correlation between the observed variables using factor analysis, the union of the variable, thus revealing the existence of some common causes behind them (or several reasons—the latent variables). Factor analysis allows us not only to obtain information to help us identify the latent variables, but also provides investigators with a way to quantify the value of the latent variable for each observation.

It is obvious that some factors are more important, others are less important for the explanation of individual variables. However, there is a metric by which the author could characterize the weight (importance) of factor for explaining all the variables included in the analysis. As this indicator is used the sum of squares of the weights of all variables on this factor. This figure is computed for display before the rotation factor bears the name of its own value factor (eigenvalue).

The use of factor analysis is not a variable, as mentioned above, and the application of factor analysis to the observations will split the company bankrupt on cluster groups and go to the dynamic problem of performance analysis of each group to produce scenarios of deterioration of their performance prior to the bankruptcy. The last task of the volume is not covered here.

For the variable factor analysis, the author applied statistical package for social science (SPSS).

All the variables explain 90.237% dispersion grouped in nine major components. Of the nine groups in models with microeconomic and macroeconomic indicators are eight components (see Table 9). One group (component 7) with variables r13 and r14 was not included in the model. All groups have an economic interpretation. Mixed teams with micro and macro indicators were observed. It follows that as the number of variables increases, such as micro and macro, it is possible to replace them with a much smaller number of latent variables.

Table 9

Grouping Variables

	Component								
	1	2	3	4	5	6	7	8	9
r1	-0.05932	0.060086	0.150043	0.031665	0.002056	**0.800149**	-0.01982	-0.00042	0.024
r2	0.053418	**0.976152**	-0.08038	-0.11418	0.007719	0.088058	0.039567	0.029417	0
r3 (profitability ratios)	0.045001	**0.922583**	-0.10796	-0.12675	-0.05222	-0.01603	-0.22203	0.045308	0.022
r4	0.037326	**0.97375**	-0.04838	-0.11197	0.012202	0.113744	0.036169	0.021192	0.001
r5	0.052977	**0.976047**	-0.0827	-0.11409	0.008038	0.087283	0.039134	0.029851	0
r6 (profitability ratios)	0.031162	0.114554	0.018302	-0.01002	0.020004	**0.852994**	-0.00461	-0.00656	-0.026
r7 (leverage ratios)	-0.02785	-0.49657	0.017108	**0.84419**	0.004241	-0.09881	-0.00094	-0.01896	0.013
r8 (leverage ratios)	0.009583	-0.09171	-0.00093	**0.967364**	0.015713	-0.05013	-0.01439	-0.00559	-0.015
r9 (leverage ratios)	-0.02981	0.016344	-0.05242	0.012766	0.069732	-0.02977	-0.0017	-0.01118	**0.882**
r10 (leverage ratios)	0.018372	**0.407548**	-0.00666	-0.8707	-0.01888	0.111886	-0.0041	0.011251	0.009
r11 (liquid asset ratios)	-0.03375	0.143006	-0.01905	**0.884868**	-0.03456	0.190747	-0.02513	-0.01111	0.01
r12 (short-term solvency ratios)	0.070785	0.05355	-0.05276	-0.03935	0.032435	**0.910284**	-0.02073	-0.02387	-0.042
r13 (activity ratios)	0.006472	-0.03385	-0.01469	-0.01891	-0.00427	-0.02466	**0.993659**	-0.02967	-0.007
r14 (activity ratios)	0.006588	-0.03283	-0.01481	-0.01906	-0.0044	-0.02468	**0.99365**	-0.02973	-0.007
Index of real GDP	0.606109	-0.04731	**0.757781**	-0.01243	0.178003	0.068431	-0.00475	-0.027	0.065
Index of industrial production	**0.853129**	0.019491	0.431874	0.036616	-0.03374	0.085161	0.050251	0.020669	-0.124
Index of real cash incomes	-0.04297	-0.12682	**0.960432**	-0.01338	0.204864	0.034369	-0.02958	0.024585	0.013
Index of real investment	-0.02432	-0.11575	**0.96937**	-0.02586	0.086893	0.01202	-0.03627	0.086313	-0.043
Consumer price index	**0.46544**	0.066387	-0.68776	-0.08996	0.000684	-0.06071	-0.06734	-0.19372	0.326
Year of bankruptcy	0.386125	-0.05129	**0.586726**	-0.00691	0.435599	0.102673	-0.00641	-0.15158	0.277
Refinancing rate	**-0.7453**	-0.06139	0.036467	-0.06302	-0.58793	-0.08338	-0.07329	-0.01798	0
The unemployment rate	**-0.87798**	-0.02348	0.084412	0.031888	0.153289	0.035506	0.024979	0.016132	-0.062
Electricity prices by region	-0.1065	0.142057	0.155776	0.005108	-0.03281	-0.05263	-0.05748	**0.902237**	0.155
Gas prices by region	0.006519	-0.02361	-0.02395	-0.03881	0.016884	0.01552	-0.00758	**0.909312**	-0.168
The price of oil	**0.972007**	0.039454	-0.01373	-0.05993	-0.10986	-0.02777	-0.03386	-0.05459	0.049
Price of gas	**0.733246**	-0.0392	0.137058	-0.19004	-0.02467	-0.14086	-0.16263	-0.10454	0.273
Dollar to ruble	-0.16861	-0.013	0.152963	0.003293	**0.956804**	0.007508	-0.00535	-0.00807	0.003
Euro rate to ruble	0.073766	-0.02592	0.321251	-0.03026	**0.913458**	0.014001	-0.03005	0.002033	0.089
S&P index	**0.765777**	0.02352	-0.23448	0.068521	0.420985	0.049286	0.081859	0.055446	-0.231
RTS index	**0.927406**	0.093659	-0.06357	0.071641	0.00255	0.091269	0.08901	-0.01857	-0.137

Notes. (1) Extraction method: Principal component analysis; (2) Rotation method: Varimax with Kaiser normalization; (3) Rotation converged in six iterations; (4) Underlined: Background variables included in the model of discrimination; (5) Figures in bold: Background variables dominating the main component; and (6) Columns in grey: Principal components that define the background model prediction of crisis situations in the enterprise.

Conclusions

Thus, in the work on the platform of the package of PolyAnalist Megaputer Intelligents' data-mining models of discrimination and classification, separating the internal financial indicators of enterprises and external macroeconomic indicators for emerging and stable by a linear procedure (linear regression)—both internal and external factors are included in the model, which only worsens the separation efficiency of microeconomic indicators in patterns of discrimination and classification of approximately two times. Bankruptcy prediction methods: linear discrimination and linear classification have identical results.

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