Corporate Bankruptcy Prediction Using the Principal Components Method

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Abstract

A huge number of articles and papers devoted to the study of bankruptcy prediction problems. Solving the problem of predictive ability many difficulties arise from the processing of data ending with the choice of models and algorithms. Efficiency is formed on the basis of three key aspects, such as tools, data quality and algorithms, formed based on the correct formulation of the problem.

This research raises the problem of predicting the probability of bankruptcy using the method of neural network modeling. The paper proposes an effective prediction algorithm, in comparison with conventional parametric methods and is able to correctly classify on average more than 94% of observations in the sample of Russian small, medium and large businesses. Also during the research, the issue of data processing was touched upon.

By the principal components method of neural networks, factors affecting the bankruptcy and key turning points that could lead to destabilization of the company's normal operations were discovered. Increasing the accuracy of the forecast can be achieved by using more sophisticated algorithms, which are hybrid models.

Keywords: corporate bankruptcy, bankruptcy prediction, profitability, liquidity, principal components method, neural simulation

JEL classification: C38, C53, G33

Introduction

In recent years the Russian economy has been exposed to most complex stress tests, therefore the issue of corporate bankruptcy still appears relevant. It is related to many factors: high risk strategies, currency fluctuations, sanctions imposed by the USA and Western countries in order to destabilize the Russian economy and financial system, geopolitical environment in the Russian Federation. The result is that the Russian economy is subjected to serious fluctuations. In the environment of instability companies are virtually incapable of conducting their business. Sometimes even in a stable economic environment due to wrong strategies or internal problems some companies find themselves in a pre-bankruptcy state. Bankruptcy of large, strategically important industry participants may result in problems not only for directly associated economic agents, but for the economy in general. A proper tool which predicts beforehand critical states and possible bankruptcy of a company may prevent wrong resolutions of management, investors, banks and other creditors. The correct risk assessment related to financial instability of a company may prevent economic downturn in general in case of a crisis.

Warning signs of corporate bankruptcy may be formal and informal. The formal warning sign of an enterprise bankruptcy is its insolvency, that is its inability to fulfill its obligations of making payments to creditors for a long time. The informal warning signs are used mainly in order to improve the prediction accuracy.

The informal warning signs of bankruptcy comprise inefficient performance of financial services and the company information system, sharp changes in statement items, a decrease or steep increase of corporate liquid assets, lack of opportunities for growth and efficient investment, increase of the share of accounts receivable, reduction of material assets, turnover slowdown, debts to employees, shareholders, financial bodies etc.

The present paper is of relevance because it is necessary to improve the bankruptcy prediction mechanism, search for factors which influence the company financial standing. From the scientific point of view this research comprises the idea of increase of the predictive power of the bankruptcy model. But on the practical side it may be applied as one of the versions of an effective methodology. In the article the emphasis is made on small and medium companies because these groups are subjected to financial instability more than large companies. However, large companies also need control over financial stability.

In this research we used neural networks to build the bankruptcy prediction model. The sample multitude consists of Russian small, medium and large companies which conducted business or became bankrupt within 2015–2016 and which fall into the same industry and are of the same size. We use the principal components method as a means of factors dimension reduction and also verify its superiority over the standard model which comprises all considered variables.

The result of the paper will be a positive influence of the offered algorithm on the predictive power of the bankruptcy model as an assessment of Russian companies' standing. The need in improvement of the predictive power is a relevant and unanswered issue because the methods applied in practice are reduced to standard parametric methods with low predictive power.

Literature Review

Corporate Bankruptcy Factors

The interest to bankruptcy prediction arose in the early 1960-ies because cases of destabilization became more frequent. The researchers Beaver [1] and E.I. Altman [2] are considered to be the ground breakers in this sphere.

The possibility to build a bankruptcy model was mentioned for the first time in the research by Beaver [1] who analyzed the indicators of corporate performance as the factors which could predict bankruptcy. In his paper the author considers a selection of 158 American companies from 38 industries which comprises two types of companies: bankrupt and functioning ones, represented in equal proportion. He chose five out of over 30 factors and eliminated all factors which have the smallest influence on the company standing. The research considers three groups of values: non-bankrupts, those which became bankrupt in one or five years.

Altman [2] applied the multiple discriminant analysis method. The selection consisted of 66 companies divided into the companies which became bankrupt in the period of 1946 and 1965, and financially sound ones as of 1966. The author included 22 factors but in the course of the research established that only five indicators were of importance. The result of his research was the Z-score indicator of a considered company. The lower this indicator the less financially sound and more prone to bankruptcy was the company. Altman defined three main groups of values of the Z-score indicator. The companies with the value less than 1.81 fall into the group of potential bankrupts. Altman called the interval of 1.81 to 2.99 an uncertainty range with a high probability of a classification error. The companies with the indicator exceeding 2.99 are considered to be financially sound ones. This method helped to predict the possibility of bankruptcy of approximately 95% of all considered companies.

Nowadays the main emphasis of papers is on improvement of the methodology of bankruptcy models building in order to obtain better predictive models. But one of important aspects is choice of factors which influence the financial standing of a company. The financial indicators such as profitability, liquidity, business activity, capital structure, debt servicing capacity, company size and its growth opportunity are of frequent occurrence in researches. In this article we consider each group of indicators as factors of corporate bankruptcy for small, medium and large companies.

Table 1. Profitability indicators used in the bankruptcy prediction models

Indicator	Indicator explanation	Authors who used the indicators in the bankruptcy prediction models
EBIT/TA	earnings before interest and taxes to total assets	Geng et al., 2015 [10]; Loukeris, Eleftheriadis, 2015 [11]
RETA	retained earning to total assets	Tseng, Hu, 2010 [12]; Ahmadi et al., 2012 [13]; Lee, Choi, 2013 [14]
ROA	return on assets	Bredart, 2014 [15]; Hamdi, Mestiri, 2014 [9]; Tserng et al., 2014 [6]; Geng et al., 2015 [10]; Tudor et al., 2015 [16]
ROE	return on equity	Hamdi, Mestiri, 2014 [9]; Tudor et al., 2015 [16]
ROCE	return on capital employed	Yim, Mitchell, 2005 [8]; Tian et al., 2015 [7]

Table 2. Liquidity indicators used in the bankruptcy prediction models

Indicator	Indicator explanation	Authors who used the indicators in the bankruptcy prediction models
WCTA	working capital to total assets	Alifiah et al., 2013 [19]; Lu et al., 2016 [18]; Tserng et al., 2014 [6]; Loukeris, Eleftheriadis, 2015 [11]
CACL	current assets to current liabilities	Makeeva, Bakurova, 2012 [5]; Bredart, 2014 [15]; Tserng et al., 2014 [6]
ALR	liquid assets to current liabilities	Kasgari et al., 2013 [20]; Geng et al., 2015 [10]; Loukeris & Eleftheriadis, 2015 [11]
TCTA	total cash to current liabilities	Lennox, 1999 [17]; Tseng, Hu, 2010 [12]; Fedorova et al., 2013 [21]
CATA	cash assets to total assets	Fedorova et al., 2013 [21]; Bauer, Agarwal, 2014 [22]
QLR	change in cash to total liabilities	Tseng, Hu, 2010 [12]

Profitability

Profitability is one of the key indicators of corporate performance. The company activity is possible due to a positive amount of profit. Purchase of raw materials and supplies, administration and operating expenses, accounts payable, debt repayment is impossible without a source of funds. In case of lack of funds the company is forced to use borrowed funds which are received by creditors on the basis of the company financial indicators. In case of lack of cashflows or a security to repay the debt the company will be limited in obtaining of borrowed funds. The company profit is the source of its expansion and growth by means of reinvesting funds into companies, development of process-oriented manufacturing, scientific research or investment in profitable projects.

The company profitability has a positive impact on its status. The companies which generate profit are less prone to financial instability as they have an opportunity to mitigate or avoid the influence of instability factors on their activity. This conclusion was first studied in the papers dedicated to developed [2]; [3]; [4]; [5]; [6]; [7] and emerging markets [8]; [9] (table 1).

Liquidity

Liquidity should be understood to mean the ability to pay off debts in short time. The company assets may be divided into highly liquid, low liquid and nonliquid ones, and it implies the speed of sale of an asset at a price close to the market price. The highly liquid assets comprise monetary funds and realizable securities. The low liquid assets are accounts receivable, stock of commodities and materials. Nonliquid assets are buildings, equipment and construction in progress.

The main reason for bankruptcy is the company inability to pay off its debts [12]. An enterprise with liquid assets is subjected to financial instability less than companies with nonliquid assets on the balance sheet. Availability of highly liquid assets helps a company to pay its accounts payable, loans and debts, thus, reducing the likelihood of bankruptcy. It should be noted that a marginally profitable company predeterminedly has a small amount of highly liquid assets.

The negative relation between corporate assets liquidity and possibility of corporate bankruptcy is confirmed by a range of empiric studies dedicated to advanced countries [2]; [3]; [17]; [5]; [18]; [6]. Researches of emerging markets also confirm this kind of influence [19]; [20] (table 2).

Business Activity

The company business activity affords assessment of efficiency of the corporate assets use. A high turnover of reserves, accounts receivable and accounts payable is characteristic of a company with high business activity and high quality of conducting of business activity, and the speed of such activity is indicative of profitability. Consequently, one can sum up that this indicator influences negatively on the possibility of default (table 3).

Capital structure

Bankruptcy is lack of opportunity to settle with creditors and bank. Such situation may be caused by a large debt. The management has to maintain the financial leverage. A large amount of borrowed funds may result in financial instability and a company will be unable to settle its liabilities, its access to the borrowed funds market will be limited making it impossible to stabilize the financial standing. From this we can deduce that the more well-balanced the financial leverage, the lower the possibility of default [1].

Empiric researches of developed markets confirmed Beaver's [1] assumption of interconnection between the capital structure and possibility of bankruptcy. This confirms a positive effect on the possibility of bankruptcy for emerging markets of Iran [13]; [20] and Brazil [8]. The paper by Ciampi [26] dedicated to prediction of bankruptcy of small, medium and large companies also confirms Beaver's ideas (table 4).

Table 3. Indicators of business activity used in the bankruptcy prediction models

Indicator	indicator explanation	Authors who used the indicators in the bankruptcy prediction models
WCT	work capital turnover	Foreman, 2003 [4]
AT	assets turnover	Altman, 1968 [2]; Odom, Sharda, 1990 [23]; Zhang et al., 1999 [24]; Alifiah et al., 2013 [19]; Hamdi, Mestiri, 2014 [9]
ART	accounts receivable turnover	Lennox, 1999 [17]; Geng et al., 2015 [10]
APT	accounts payable turnover	Tserng et al., 2014 [6]
FAT	fixed assets turnover	Chi, Tang, 2006 [25]; Geng et al., 2015 [10]
IT	inventory turnover	Chi, Tang, 2006 [25]; Geng et al., 2015 [10]
CLT	current liabilities turnover	Fedorova et al., 2013 [21]; Kasgari et al., 2013 [20]
TLT	total liabilities turnover	Fedorova et al., 2013 [21]

Table 4. Indicators of capital structure used in the bankruptcy prediction models

Indicator	Indicator explanation	Authors who used the indicators in the bankruptcy prediction models
TLTA	ratio of total liabilities to total assets	Ohlson, 1980 [3]; Tseng, Hu, 2010 [12]; Kasgari et al., 2013 [20]; Tinoco, Wilson, 2013 [27]; Bauer, Agarwal, 2014 [22]; Geng et al., 2015 [10]; Loukeris, Eleftheriadis, 2015 [11]
TLE	ratio of total liabilities to equity	Chi, Tang, 2006 [25]; Makeeva, Bakurova, 2012 [5]; Fedorova et al., 2013 [21]; Ciampi, 2015 [26]; Geng et al., 2015 [10]
TDTA	ratio of total debt to total assets	Beaver, 1966 [1]; Ahmadi et al., 2012 [13]; Alifiah et al., 2013 [19]; Tserng et al., 2014 [6]; Tian et al., 2015 [7]
TDTL	total debt to total liabilities ratio	Foreman, 2003 [4]
TDE	ratio of total debt to equity	Tudor et al., 2015 [16]

Table 5. Indicators of growth opportunity used in bankruptcy prediction models

Indicator	Indicator explanation	Authors who used the indicators in the bankruptcy prediction models
S_growth	sales growth	Lu et al., 2016 [18]; Tudor et al., 2015 [16]
TA_growth	total assets growth	Serrasqueiro, 2011 [28]; Lee, Choi, 2013 [14]; Tudor et al., 2015 [16]
NI_growth	net income growth	Tudor et al., 2015 [16]

Table 6. Indicators of the company size used in the bankruptcy prediction models

Indicator	Indicator explanation	Authors who used the indicators in the bankruptcy prediction models
LnTa	logarithm of total assets	Chi, Tang, 2006 [25]; Serrasqueiro, 2011 [28]; Lu et al., 2016 [18]; Tudor et al., 2015 [16]
LnS	logarithm of sales	Ohlson, 1980 [3]
Lnemp	company size through employees number	Lennox,1999 [17]

Debt servicing capacity

The ability to pay credit interest is also indicative of financial stability of a company and availability of funds to repay a credit and potential capability of raising additional borrowed funds. As long as the degree of debt servicing is directly related to the company capability to discharge its liabilities this factor has a negative influence on the degree of default.

This was shown in the research by [27] for British companies, as well as for Italian ones [26]. The variable (EBIT/IntExp)$^{-1}$ was used as an indicator of debt servicing.

Growth opportunities

Growth is indicative of the capability to develop and reduce the chance of financial destabilization. A positive effect of growth opportunities on the possibility of bankruptcy was found out for Portuguese small, medium and large companies [28] (table 5).

On the basis of a literature review concerning corporate bankruptcy one may assume that the greatest influence on the possibility of bankruptcy is produced by the indicators of profitability, liquidity and business activity due to frequency of their use in researches. After analysis of the abovementioned articles we will define the main methods and their upgraded approaches which have been offered by the above authors.

Company size

Often in literature the company size is considered as a factor which influences the company size. Small companies are prone to financial destabilization due to limited access to the borrowed funds market. Large companies are more sensitive to high risks which may entail bankruptcy.

Researches dedicated to influence of the company size give no specific answer to the question of influence of the company size on its financial instability. One group of authors considers that as a company grows the possibility of its bankruptcy decreases [3]; [17]; [27], another group points out a positive influence of the company size on the possibility of default [25]; [18]. Serrasqueiro [28] on the basis of a selection of Portuguese companies discovered a positive effect of this indicator on the probability of default (table 6).

Methodology and Data

Principal Components Method

On the basis of a literature review from the point of view of the factors of corporate financial instability 35 variables were chosen (table 1, Appendix B). These factors consist of the indicators of profitability, liquidity, business activity, capital structure, debt servicing, growth opportunities and company size.

In order to reduce dimension of bankruptcy indicators we considered the means of indicators' aggregation. One of the problems of a large number of variables is the danger of network over-training [8]. It is also rather difficult to fetch out of a group of indicators precisely the factors which are most capable of bankruptcy prediction. In view of this in this paper we offer to have recourse to aggregation of input variables my means of the principal components method.

In order to check the assumption of the efficiency of use of the principal components method from the point of view of improvement of the predictive capability of the bankruptcy probability model it is necessary to verify the following hypotheses.

Hypothesis 1. *Aggregation of indicators for prediction of bankruptcy probability of Russian small, medium and large companies using the principal components method has a better effect from the point of view of predictive capability of the model in comparison with use of the variables selected separately from each group of factors.*

The essence of the principal components method consists in reduction of data dimension losing as little information as possible. This method implies redistribution of data in such a way that the considered variables were generalized as relating to a small number of factors (principal components) which record the maximum possible amount of information contained in the source data. This method may also be phrased as a necessity to find factors $z=\left[z_1,z_2,\ldots,z_p\right]$ which represent the linear dependence $u=\left[u_1,u_2,\ldots,u_p\right]'$ and initial variables $x=\left[x_1,x_2,\ldots,x_p\right]$ which provide for the maximal variance.

Factor z_1 is a linear combination of initial variables x with the maximal variance. The second component contains the information not included in and not correlated to the first component. The principal components method consists in maximization of variance of the factors $z = xu$, which $u'u=1$, or eigenvalue decomposition of the correlation matrix.

The principal components method is consigned to solution of the following equation:

$$(R-\lambda I)u=0, \quad (1)$$

where R – variables correlation matrix x;

λ – eigenvalue;

u – eigenvector.

Eigenvalues λ are the variance of relevant factors z. The share of the variance of the initial variable x_i corresponding to the first factors represents a sum of squares of factor loadings:

$$\sum_{k=1}^{c} f_{ik}^2 \quad (2)$$

The factor loadings are a correlation of initial variables x

And components z:

$$F=cor(x,z)=uD^{\frac{1}{2}}, \quad (3)$$

where D – is the diagonal matrix of components' covariants z: $D=diag(\lambda)$.

The method is used only if there is a correlation between the variables. After transformation z the factors do not correlate to each other. Due to a large number of considered variables it is highly probable that there is a high correlation between the indicators. This encourages application of this method.

Data

The selection of Russian companies was made using the Ruslana database created by Bureau Van Dijk. For the research we analyzed approximately 10 thousand small, medium and large companies which became bankrupt in the period of 2015–2016. The research does not consider earlier periods because financial instability of 2014 resulted in increase of bankruptcy cases in the indicated time. The economic situation in general influences greatly the company standing. Therefore, this period is to be analyzed separately within the issue of influence of political factors on corporate bankruptcy which is an exceptionally interesting issue.

Standards of Ordinance of the Russian Federation Government of July 13, 2015 No. 702 "On Threshold Values of Proceeds of Sales of Goods (Works, Services) for each Category of Small and Medium-Sized Business Entities" were used as criteria of small, medium and large business. In this paper small and medium-sized business is represented by the companies which sales proceeds from goods, works or services net of VAT vary in the range of 150 million roubles to over 2 billion roubles.

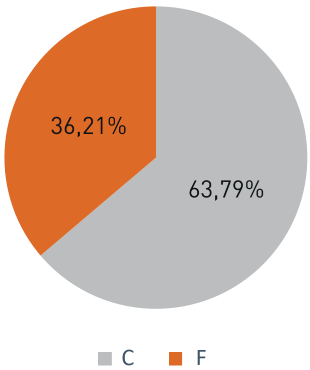
We consider two selections in the paper. The first selection touches upon the industrial sector C which comprises 6,800 companies and the second one also includes the construction sector F and comprises 10,700 companies.

In order to build the bankruptcy probability model, we used the data one year before the bankruptcy had taken place (2015–2016). The result of such model is the company predictive power for one year. We do not build models in this paper two or three years before the bankruptcy because empiric results of the papers dedicated to default probability prediction show a decrease of predictive power with increase of the time horizon between the bankruptcy fact and used data. Thus, a model built on the basis of the data related to one year before the bankruptcy can define potential bankrupts most correctly.

After calculation of the variables necessary for the research and processing of observations with missing values in the selection of bankrupts used for building of the bankruptcy probability model the offered separation and division into stacks method was applied.

Division of companies into industry sectors in accordance with the Russian National Classifier of Types of Economic Activity is presented in fig. 1. The selections consider manufacturing (C – 63.8%) and construction companies (F – 36.21%).

Figure 1. Companies' industry sectoral affiliation



Division of companies in accordance with their status is presented in fig. 2. The selection consists of financially sound companies (1 – 88.80%) and bankrupts (0 – 11.20%).

Figure 2. Companies' status

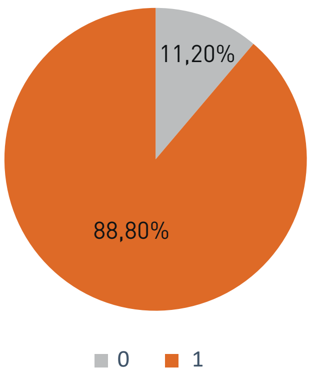


Table 7 comprises descriptive characteristics of variables of manufacturing companies.

Table 7. Descriptive characteristics of variables of manufacturing companies

"Indicator"	N	Range	Min	Max	Sum	Average		Standard deviation	Variance
	Statistics	Statistics	Statistics	Statistics	Statistics	Statistics	StdErr	Statistics	Statistics
Bnkrpt_status	6879	1	0	1	6385	0,93	0,003	0,258	0,067
Rev	6879	281292	100	281392	17165287	2495	122	10121	102441791
EBIT/TA_16	6879	84,85	-68,86	15,99	637,78	0,09	0,01	0,92	0,85
EBIT/TA_15	6879	47,75	-1,63	46,12	772,59	0,11	0,01	0,58	0,33
RETA_16	6879	25365,92	-4,42	25361,50	26745,43	3,89	3,69	305,78	93501,85
RETA_15	6879	184,13	-132,50	51,63	1649,41	0,24	0,02	1,79	3,22
ROA_16	6879	4038,01	-1025,61	3012,40	2252,07	0,33	0,46	38,38	1473,40
ROA_15	6879	47,58	-1,93	45,66	396,60	0,06	0,01	0,57	0,33
ROE_16	6879	6368,80	-1864,40	4504,40	9412,62	1,37	0,90	74,36	5529,13
ROE_15	6879	38094,31	-31091,11	7003,20	-36035,52	-5,24	5,22	432,55	187098,14
ROS_16	6879	41,72	-30,07	11,65	69,06	0,01	0,01	0,59	0,34
ROS_15	6879	21,21	-18,11	3,10	78,65	0,01	0,00	0,34	0,12
ROCE_16	6879	5743,93	-108,53	5635,40	10022,03	1,46	0,86	71,67	5135,92
ROCE_15	6879	18180,29	-14319,89	3860,40	-6264,40	-0,91	2,17	180,02	32406,54
WCTA_16	6879	1010,09	-1009,10	0,99	-25,28	0,00	0,15	12,23	149,45
WCTA_15	6879	12,50	-4,83	7,67	1050,90	0,15	0,00	0,38	0,14
CACL_16	6879	184,78	0,00	184,78	17957,42	2,61	0,07	5,50	30,28
CACL_15	6879	245,91	0,02	245,93	16839,69	2,45	0,07	5,62	31,57

"Indicator"	N	Range	Min	Max	Sum	Average		Standard deviation	Variance
	Statistics	Statistics	Statistics	Statistics	Statistics	Statistics	StdErr	Statistics	Statistics
ALR_16	6879	159,83	-0,03	159,80	3745,83	0,54	0,04	3,05	9,28
ALR_15	6879	92,39	-0,27	92,12	3405,61	0,50	0,03	2,51	6,30
TCTA_16	6879	0,97	-0,02	0,95	631,65	0,09	0,00	0,13	0,02
TCTA_15	6879	1,17	-0,21	0,96	610,37	0,09	0,00	0,13	0,02
CATA_16	6879	31488,10	0,00	31488,10	59389,29	8,63	5,12	424,53	180229,77
CATA_15	6879	78974,50	0,00	78974,50	244894,81	35,60	17,45	1447,25	2094521,29
QUICK_LR_16	6879	165,64	0,00	165,64	10548,54	1,53	0,05	3,93	15,45
QUICK_LR_15	6879	105,62	0,00	105,62	9690,77	1,41	0,04	3,58	12,80
WCT_16	6879	76355,23	-26856,33	49498,90	197001,70	28,64	11,41	946,15	895207,61
WCT_15	6879	379136,62	-16661,75	362474,87	747099,81	108,61	69,06	5728,01	32810123,67
AT_16	6879	49498,89	0,01	49498,90	75071,98	10,91	7,25	601,54	361845,16
AT_15	6879	1286,05	0,00	1286,05	15091,50	2,19	0,19	15,69	246,05
ART_16	6879	11294,15	0,03	11294,19	100102,50	14,55	1,92	159,61	25476,08
ART_15	6879	12850,79	0,00	12850,79	91358,07	13,29	1,93	159,81	25540,01
APT_16	6879	1808,41	0,00	1808,41	70775,10	10,29	0,43	35,46	1257,51
APT_15	6879	10904,65	0,00	10904,65	79854,89	11,61	1,84	152,73	23327,47
FAT_1_16	6879	91,81	0,00	91,81	2827,27	0,41	0,02	1,66	2,75
FAT_1_15	6879	92,92	0,00	92,92	3019,90	0,44	0,02	1,86	3,48
IT1_1_16	6879	13,64	0,00	13,64	2127,44	0,31	0,01	0,49	0,25

"Indicator"	N	Range	Min	Max	Sum	Average		Standard deviation	Variance
	Statistics	Statistics	Statistics	Statistics	Statistics	Statistics	StdErr	Statistics	Statistics
IT1_1_15	6879	29,77	0,00	29,77	2321,99	0,34	0,01	0,75	0,57
IT2_1_16	6879	14,11	0,00	14,11	1694,73	0,25	0,01	0,43	0,18
IT2_1_15	6879	34,33	0,00	34,33	1828,90	0,27	0,01	0,69	0,47
CLT_16	6879	1111,22	0,00	1111,22	49082,07	7,14	0,28	23,07	532,24
CLT_15	6879	10904,65	0,00	10904,65	52619,84	7,65	1,59	131,90	17397,64
TLT_16	6879	1112,16	-0,94	1111,22	39507,11	5,74	0,27	22,29	496,62
TLT_15	6879	10905,84	-1,20	10904,65	42856,98	6,23	1,59	131,67	17336,94
CAT_16	6879	49498,88	0,02	49498,90	85761,90	12,47	7,26	602,11	362541,51
CAT_15	6879	1286,05	0,00	1286,05	22472,32	3,27	0,19	15,84	251,05
ET_16	6879	70414,01	-20915,11	49498,90	369197,77	53,67	11,79	977,67	955833,66
ET_15	6879	173559,15	-119114,13	54445,02	270707,51	39,36	20,83	1727,41	2983940,96
TLTA_16	6879	1012,59	-2,59	1010,00	5844,23	0,85	0,15	12,23	149,63
TLTA_15	6879	7,13	-1,44	5,70	4734,90	0,69	0,00	0,39	0,16
TLE_16	6879	58128,50	-4035,00	54093,50	198408,95	28,84	8,63	715,74	512282,28
TLE_15	6879	291412,08	-184627,25	106784,83	127279,02	18,51	31,50	2612,61	6825714,05
TDTA_16	6879	50,07	-2,70	47,37	1752,67	0,25	0,01	0,72	0,52
TDTA_15	6879	6,53	-1,47	5,07	1740,77	0,25	0,00	0,33	0,11
TDTL_16	6879	1,17	-0,12	1,04	2195,10	0,32	0,00	0,30	0,09
TDTL_15	6879	1,12	-0,10	1,02	2257,29	0,33	0,00	0,31	0,10

"Indicator"	N	Range	Min	Max	Sum	Average		Standard deviation	Variance
	Statistics	Statistics	Statistics	Statistics	Statistics	Statistics	StdErr	Statistics	Statistics
TDE_16	6879	9231,82	-787,88	8443,94	45644,01	6,64	1,54	128,03	16391,07
TDE_15	6879	126895,90	-94128,63	32767,28	7763,86	1,13	14,68	1217,29	1481790,88
EBIT_IE_1_16	6879	2500,65	-188,46	2312,18	4781,71	0,70	0,35	28,62	819,02
EBIT_IE_1_15	6879	1376,08	-643,43	732,65	3310,02	0,48	0,18	15,22	231,78
S_GROWTH_16	6879	9267,76	-0,99	9266,77	11330,94	1,65	1,35	111,75	12488,15
S_GROWTH_15	6879	96088,14	-0,99	96087,15	101799,70	14,80	13,97	1158,56	1342256,21
TA_GROWTH_16	6879	31488,10	-1,00	31487,10	54738,09	7,96	5,12	424,53	180224,71
TA_GROWTH_15	6879	78974,46	-0,96	78973,50	197672,21	28,74	16,31	1353,02	1830676,05
NI_GROWTH_16	6879	12313,14	-9785,14	2528,00	-24796,77	-3,61	2,10	173,80	30206,16
NI_GROWTH_15	6879	53363,33	-23806,00	29557,33	24867,59	3,62	6,40	530,70	281640,81
LN_TA_16	6879	17,78	-4,61	13,17	41292,00	6,00	0,02	1,69	2,85
LN_TA_15	6879	17,60	-4,61	12,99	40743,09	5,92	0,02	1,70	2,90
LN_S_16	6879	7,94	4,61	12,55	44076,15	6,41	0,02	1,35	1,83
LN_S_15	6879	16,29	-3,65	12,64	43377,75	6,31	0,02	1,41	2,00
LN_EMP_NUM_16	6879	10,27	0,00	10,27	35114,52	5,11	0,01	1,18	1,40
LN_EMP_NUM_15	6879	9,63	0,69	10,32	34853,15	5,07	0,01	1,23	1,52

Table 8 comprises descriptive characteristics of variables of construction companies.

Table 8. Descriptive characteristics of variables of construction companies

"Indicator"	N	Range	Min	Max	Sum	Average		Standard deviation	Variance
	Statistics	Statistics	Statistics	Statistics	Statistics	Statistics	StdErr	Statistics	Statistics
Bnkrpt_status	3905	1	0	1	3191	0,82	0,006	0,387	0,149
Rev	3905	276334	101	276434	4396635	1126	105	6545	42843092
EBIT/TA_16	3905	932,17	-724,98	207,19	-266,87	-0,07	0,21	13,40	179,49
EBIT/TA_15	3905	15,31	-13,00	2,31	186,93	0,05	0,00	0,30	0,09
RETA_16	3905	303,94	-219,84	84,10	412,93	0,11	0,08	5,15	26,56
RETA_15	3905	6206,11	-5,91	6200,20	7797,02	2,00	1,59	99,49	9898,89
ROA_16	3905	436,94	-286,50	150,44	-554,03	-0,14	0,10	6,32	39,92
ROA_15	3905	17,45	-15,17	2,28	80,24	0,02	0,00	0,29	0,09
ROE_16	3905	5163,23	-2559,83	2603,40	3707,34	0,95	1,08	67,54	4561,61
ROE_15	3905	314,50	-76,45	238,05	1862,74	0,48	0,10	6,00	36,02
ROS_16	3905	46,45	-34,06	12,38	-103,85	-0,03	0,01	0,81	0,65
ROS_15	3905	399,21	-385,34	13,87	-426,97	-0,11	0,10	6,20	38,49
ROCE_16	3905	6385,07	-3552,40	2832,67	5865,06	1,50	1,29	80,59	6495,11
ROCE_15	3905	331,36	-84,71	246,64	2956,36	0,76	0,12	7,47	55,84
WCTA_16	3905	1953,83	-1952,83	1,00	-2565,32	-0,66	0,51	32,03	1025,86
WCTA_15	3905	13,08	-12,08	1,00	238,32	0,06	0,01	0,38	0,14
CACL_16	3905	590,85	0,00	590,85	7836,65	2,01	0,20	12,20	148,72

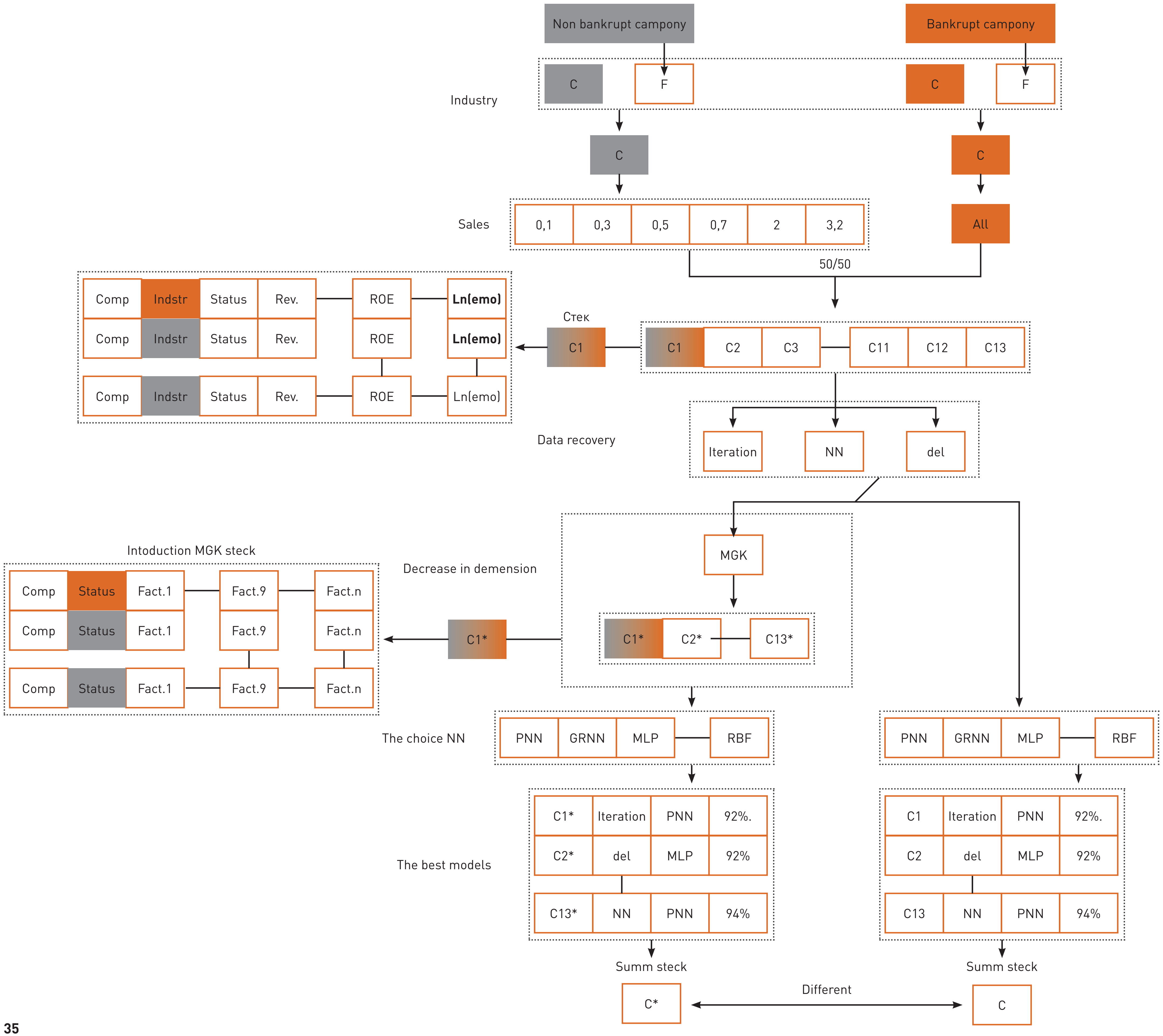
"Indicator"	N	Range	Min	Max	Sum	Average		Standard deviation	Variance
	Statistics	Statistics	Statistics	Statistics	Statistics	Statistics	StdErr	Statistics	Statistics
CACL_15	3905	173,06	0,03	173,10	6181,60	1,58	0,06	3,81	14,48
ALR_16	3905	270,85	-0,03	270,82	1757,03	0,45	0,08	4,74	22,43
ALR_15	3905	67,33	0,00	67,33	1334,83	0,34	0,03	1,69	2,85
TCTA_16	3905	1,03	-0,03	1,00	480,68	0,12	0,00	0,16	0,03
TCTA_15	3905	2,04	0,00	2,04	464,64	0,12	0,00	0,16	0,03
CATA_16	3905	45645,70	0,00	45645,70	138762,30	35,53	15,08	942,51	888321,27
CATA_15	3905	51611,39	0,01	51611,40	560891,17	143,67	34,26	2140,66	4582423,26
QUICK_LR_16	3905	590,75	0,00	590,75	5739,67	1,47	0,18	11,23	126,04
QUICK_LR_15	3905	99,03	0,00	99,03	4390,53	1,12	0,04	2,72	7,37
WCT_16	3905	450340,36	-52887,86	397452,50	750194,23	192,16	110,35	6895,08	47542142,07
WCT_15	3905	710494,40	-261773,00	448721,40	397146,32	101,75	133,88	8363,75	69952375,24
AT_16	3905	29577,39	0,01	29577,40	150371,96	38,51	11,88	742,66	551543,96
AT_15	3905	4774,27	0,00	4774,27	16059,57	4,11	1,30	81,22	6596,39
ART_16	3905	12253,13	0,02	12253,14	103559,28	26,55	5,40	337,07	113613,90
ART_15	3905	57274,67	0,00	57274,67	89867,05	23,05	14,73	920,00	846403,66
APT_16	3905	172226,00	0,00	172226,00	289553,11	74,17	45,37	2835,09	8037725,47
APT_15	3905	5404,86	0,00	5404,86	26771,54	6,86	1,52	94,76	8980,13
FAT_1_16	3905	107,08	0,00	107,08	2102,37	0,54	0,06	3,56	12,70
FAT_1_15	3905	16623,44	0,00	16623,44	20681,24	5,30	4,26	266,23	70880,09

"Indicator"	N	Range	Min	Max	Sum	Average		Standard deviation	Variance
	Statistics	Statistics	Statistics	Statistics	Statistics	Statistics	StdErr	Statistics	Statistics
IT1_1_16	3905	34,77	0,00	34,77	1463,25	0,37	0,02	1,19	1,41
IT1_1_15	3905	200,89	0,00	200,89	2130,89	0,55	0,06	3,85	14,84
IT2_1_16	3905	23,17	0,00	23,17	1165,12	0,30	0,01	0,89	0,79
IT2_1_15	3905	31,80	0,00	31,80	1416,31	0,36	0,02	1,20	1,45
CLT_16	3905	34404,66	0,00	34404,67	111394,79	28,53	10,33	645,37	416502,02
CLT_15	3905	5404,86	0,00	5404,86	22504,83	5,76	1,49	93,28	8700,84
TLT_16	3905	34404,66	0,00	34404,67	110435,04	28,28	10,33	645,37	416498,03
TLT_15	3905	5404,86	0,00	5404,86	21625,15	5,54	1,49	93,28	8700,35
CAT_16	3905	29577,39	0,01	29577,40	151874,43	38,89	11,88	742,37	551110,43
CAT_15	3905	4774,27	0,00	4774,27	17948,58	4,60	1,30	81,22	6597,42
ET_16	3905	416672,39	-19219,89	397452,50	1280528,63	327,92	111,77	6984,42	48782154,94
ET_15	3905	19341,11	-1362,53	17978,58	417001,71	106,81	10,72	669,57	448327,10
TLTA_16	3905	2007,67	0,00	2007,67	6134,19	1,57	0,53	32,87	1080,68
TLTA_15	3905	13,08	0,00	13,08	3248,30	0,83	0,01	0,40	0,16
TLE_16	3905	183157,22	-25125,72	158031,50	472686,38	121,05	43,41	2712,83	7359458,83
TLE_15	3905	38557,86	-9992,84	28565,02	312434,64	80,01	12,57	785,81	617496,49
TDTA_16	3905	53,88	-0,04	53,83	571,40	0,15	0,01	0,91	0,82
TDTA_15	3905	14,29	-1,21	13,08	516,64	0,13	0,00	0,31	0,10
TDTL_16	3905	1,07	-0,07	1,00	561,61	0,14	0,00	0,22	0,05

"Indicator"	N	Range	Min	Max	Sum	Average		Standard deviation	Variance
	Statistics	Statistics	Statistics	Statistics	Statistics	Statistics	StdErr	Statistics	Statistics
TDTL_15	3905	3,40	-2,40	1,00	574,81	0,15	0,00	0,23	0,05
TDE_16	3905	21719,42	-3217,78	18501,64	64001,99	16,39	5,99	374,11	139957,89
TDE_15	3905	6625,62	-3764,04	2861,58	18677,47	4,78	1,54	96,30	9272,93
EBIT_IE_1_16	3905	373,36	-219,70	153,66	881,74	0,23	0,09	5,36	28,77
EBIT_IE_1_15	3905	444,77	-337,43	107,34	504,15	0,13	0,12	7,26	52,75
S_GROWTH_16	3905	64062,47	-0,97	64061,50	76399,32	19,56	16,49	1030,45	1061832,00
S_GROWTH_15	3905	4680,32	-1,00	4679,32	22385,91	5,73	1,58	98,73	9747,44
TA_GROWTH_16	3905	45645,70	-1,00	45644,70	135635,24	34,73	15,08	942,53	888359,97
TA_GROWTH_15	3905	51611,36	-0,96	51610,40	560178,40	143,53	34,41	2149,86	4621890,47
NI_GROWTH_16	3905	39956,20	-13973,80	25982,40	-3349,66	-0,86	8,22	513,54	263721,90
NI_GROWTH_15	3905	8073,00	-6872,50	1200,50	-21100,95	-5,41	2,85	178,07	31710,07
LN_TA_16	3905	17,64	-4,96	12,68	22131,47	5,67	0,03	1,67	2,78
LN_TA_15	3905	17,33	-4,96	12,37	21997,10	5,63	0,03	1,71	2,93
LN_S_16	3905	7,92	4,61	12,53	23311,57	5,97	0,02	1,03	1,06
LN_S_15	3905	18,76	-6,21	12,54	22859,50	5,85	0,02	1,28	1,65
LN_EMP_NUM_16	3905	11,39	0,00	11,39	17677,37	4,53	0,02	0,97	0,93
LN_EMP_NUM_15	3905	11,39	0,00	11,39	17460,72	4,47	0,02	1,09	1,19

As we see from table 7 and 8, 35 indicators will be used for calculation. However, it will be somewhat difficult to define the influence of each indicator and for this purpose we will use the principal components method which affords aggregation of indicators and development of the system of indicators' groups which are characteristic of each industry sector.

Figure 3. Algorithm with added aggregation stage and analysis of effectiveness of this method



Separation

The stage of dividing the current revenue company and the formation of primary blocks by revenue

Formation

The stage of adding bankrupts to the formed stacks in different shares

Recovery

At this stage, data recovery occurs. Ultimately, the best recovery method is chosen

Aggregation

The stage of reducing factor dimension by the method of principal components

Education

The stage of choosing the best neural network tool

Creature

The end result is a model consisting of blocks that include stacks of the best models

The Choice

Choosing the best way to predict

Figure 4. Comparative analysis of the predictive power of a forecast as exemplified by the trainable, tested and validation selections for manufacturing sectors

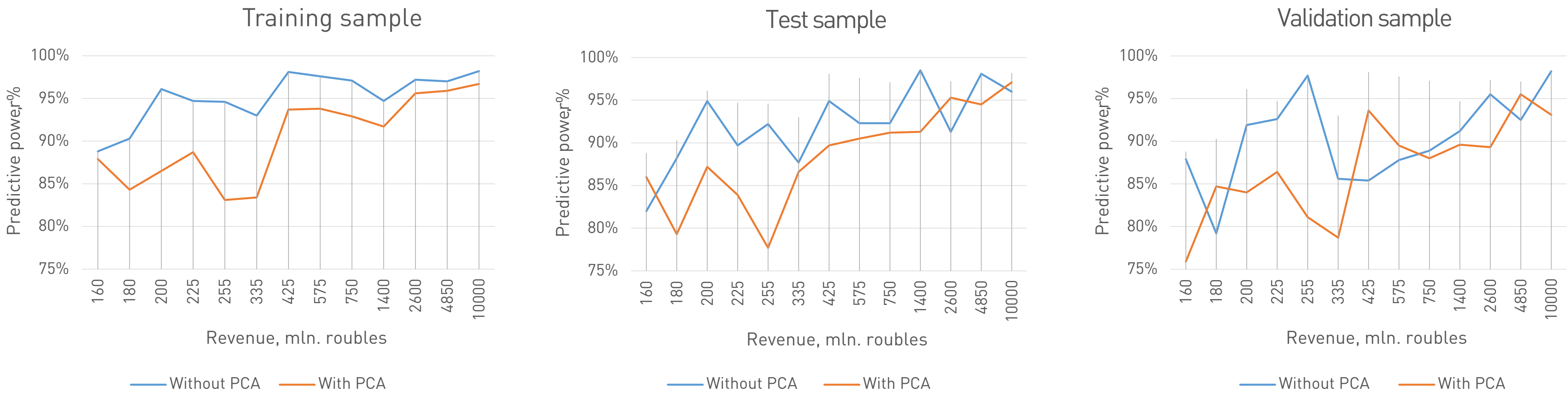
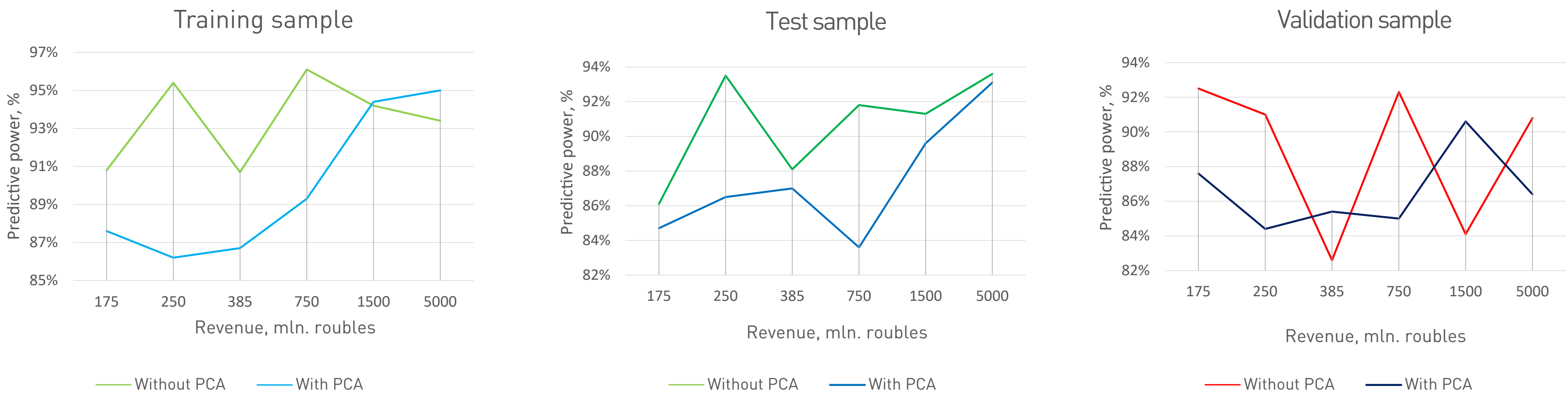


Figure 5. Comparative analysis of the predictive power of a forecast as exemplified by the trainable, tested and validation selections for the construction sector



As we see from fig. 4 for the companies from manufacturing sectors, almost at all stages the principal components method has rather big deviations for 5–15%. This result is typical at virtually all intervals of company sizes, apart from the interval of 425–430 million roubles.

Fig. 5 shows for the companies of the construction sector F a more interesting situation. The principal components method affords smoothing over of sharp outlying data and, thus, during the test of the validation selection there arise outlying data, but this is true only for a small group of validation selections.

Econometric Analysis and its Results

Our selection consists of 1,200 bankrupt companies and 8,700 financially sound companies which totals to 10 thousand companies. We will use the offered method presented in fig. 3 as a forecast and try to define the influence of the method on the predictive power.

After forming the aggregate indicators we started the procedure of prediction and defining the significant factors. Analysis of interconnection between the main components and bankruptcy probability at each stack in the correlation matrix is indicative of a significant influence of two to four main components (at the 20% significance level as an assumption). Therein, the majority of correlation coefficients between the main components are of significance and do not exceed 0.5 in absolute magnitude.

The hypothesis of improvement of the predictive power applying the principal components method is rejected but it has a set of assumptions at which the hypothesis will still be accepted in case of presence in the selection of a large amount of outlying data and relevantly small validation selection.

Conclusion

A large number of articles is dedicated to improvement of quality of bankruptcy prediction. Modern methods in this sphere consist in development of complex composite hybrid models which consist not just of neural networks but of genetic algorithmization. Such models may provide the maximum predictive capability, however, this is an issue for a new research, while the offered method has an opportunity for further improvement of methodology. A high predictive power of the model helps investors, banks and other creditors to foresee potential financial problems of a company with s greater accuracy. Therefore, in this article we study the quality of methodology applied for assessment of business solvency of Russian small, medium and large companies from the point of view of the ability to predict correctly the bankruptcy probability. To do this the separation algorithm was offered.

The forecasting was done using neural simulation. 35 indicators which characterize profitability, liquidity, business activity, capital structure, debt servicing, growth opportunities, company size were used. They were selected on the basis of a literature review and were aggregated applying the principal components method. It was found out that use of the principal components method does not increase the predictive power of a model in comparison to use of the variables selected separately from each group of factors.

The conclusion of this research is that it is necessary to increase accuracy of the forecast of the models which are used in practice for assessment of business solvency of Russian small, medium and large companies. It is possible to improve the methodology by means of applying advanced methodologies accompanied by complicating of models, employment of additional underlying behavioral factor, use of methods of data recovery and hybrid networks.

For further study of this issue it is interesting to consider the problem of accuracy of processing of lost or missing data applying genetic algorithmization and dynamic models.

References

1. Beaver W.H. Financial ratios as predictors of failure. *Journal of Accounting Research*. 1966;4:71-111. DOI: 10.2307/2490171

2. Altman E.I. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*. 1968;23(4):589-609. DOI: 10.2307/2978933

3. Ohlson J.A. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*. 1980;18(1):109-131. DOI: DOI: 10.2307/2490395

4. Foreman R. D. A logistic analysis of bankruptcy within the US local telecommunications industry. *Journal of Economics and Business*. 2003;55(2):135-166. DOI: 10.1016/S0148-6195(02)00133-9

5. Makeeva E.Yu., Bakurova A.O. Predicting bankruptcy of oil and gas companies using neural networks. *Korporativnye finansy = Journal of Corporate Finance Research*. 2012;6(3):22-30. DOI: 10.17323/j.jcfr.2073-0438.6.3.2012.22-30 (In Russ.).

6. Tserng H.P., Chen P.-C., Huang W.-H., Lei M.C., Tran Q.H. Prediction of default probability for construction firms using the logit model. *Journal of Civil Engineering and Management*. 2014;20(2):247-255. DOI: 10.3846/13923730.2013.801886

7. Tian S., Yu Y., Guo H. Variable selection and corporate bankruptcy forecasts. *Journal of Banking & Finance*. 2015;52:89-100. DOI: 10.1016/j.jbankfin.2014.12.003

8. Yim J., Mitchell H. A comparison of corporate distress prediction models in Brazil: Hybrid neural

networks, logit models and discriminant analysis. *Nova Economia*. 2005;15(1):73-93.

9. Hamdi M., Mestiri S. Bankruptcy prediction for Tunisian firms: An application of semi-parametric logistic regression and neural networks approach. *Economics Bulletin*. 2014;34(1):133-143.
10. Geng R., Bose I., Chen X. Prediction of financial distress: An empirical study of listed Chinese companies using data mining. *European Journal of Operational Research*. 2015;241(1):236-247. DOI: 10.1016/j.ejor.2014.08.016
11. Loukeris N., Eleftheriadis I. Support vector machines networks to hybrid neuro-genetic SVMs in portfolio selection. *Intelligent Information Management*. 2015;7(3):123-129. DOI: 10.4236/iim.2015.73011
12. Tseng F.-M., Hu Y.-C. Comparing four bankruptcy prediction models: Logit, quadratic interval logit, neural and fuzzy neural networks. *Expert Systems with Applications*. 2010;37(3):1846-1853. DOI: 10.1016/j.eswa.2009.07.081
13. Ahmadi A.P.S., Soleimani B., Vaghfi S.H., Salimi M.B. Corporate bankruptcy prediction using a logit model: Evidence from listed companies of Iran. *World Applied Sciences Journal*. 2012;17(9):1143-1148. URL: https://docplayer.net/12755133-Corporate-bankruptcy-prediction-using-a-logit-model-evidence-from-listed-companies-of-iran.html
14. Lee S., Choi W.S. A multi-industry bankruptcy prediction model using back-propagation neural network and multivariate discriminant analysis. *Expert Systems with Applications*. 2013;40(8):2941-2946. DOI: 10.1016/j.eswa.2012.12.009
15. Bredart X. Bankruptcy prediction model using neural networks. *Accounting and Finance Research*. 2014;3(2):124-128. DOI: 10.5430/afr.v3n2p124
16. Tudor L., Popescu M.E., Andreica M. A decision support system to predict financial distress. The case of Romania. *Romanian Journal of Economic Forecasting*. 2015;18(4):170-179. URL: http://www.ipe.ro/rjef/rjef4_15/rjef4_2015p170-179.pdf
17. Lennox C. Identifying failing companies: A re-evaluation of the logit, probit and DA approaches. *Journal of Economics and Business*. 1999;51(4):347-364. DOI: 10.1016/S0148-6195(99)00009-0
18. Liang D., Lu C.-C., Tsai C.-F., Shih G.-A. Financial ratios and corporate governance indicators in bankruptcy prediction: A comprehensive study. *European Journal of Operational Research*. 2016;252(2):561-572. DOI: 10.1016/j.ejor.2016.01.012
19. Alifiah M.N., Salamudin N., Ahmad I. Prediction of financial distress companies in the consumer products sector in Malaysia. *Jurnal Teknologi*. 2013;64(1):85-91. DOI: 10.11113/jt.v64.1181
20. Kasgari A.A., Divsalar M., Javid M.R., Ebrahimian S.J. Prediction of bankruptcy Iranian corporations through artificial neural network and Probit-based analyses. *Neural Computing and Applications*. 2013;23(3-4):927-936. DOI: 10.1007/s00521-012-1017-z
21. Fedorova E.A., Gilenko E.V., Dovzhenko. S.E. Models for bankruptcy forecasting: Case study of Russian enterprises. *Studies on Russian Economic Development*. 2013;24(2):159-164. DOI: 10.1134/S1075700713020044
22. *Bauer J., Agarwal V. Are hazard models superior to traditional bankruptcy prediction* approaches? A comprehensive test. *Journal of Banking & Finance*. 2014;40:432-442. DOI: 10.1016/j.jbankfin.2013.12.013
23. *Odom* M.D., *Sharda*, R. A neural network for *bankruptcy* prediction. In: 1990 International Joint Conference on Neural Networks (San Diego, June 17-21, 1990). 1990:163-168. DOI: 10.1109/IJCNN.1990.137710
24. Zhang G., Hu M.Y., Patuwo B.E., Indro D.C. Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis. *European Journal of Operational Research*. 1999;116(1):16-32. DOI: 10.1016/S0377-2217(98)00051-4
25. Chi L.C., Tang T.C. Bankruptcy prediction: Application of logit analysis in export credit risks. *Australian Journal of Management*. 2006;31(1):17-27. DOI: 10.1177/031289620603100102
26. Ciampi F., Gordini N. Using economic-financial ratios for small enterprises default prediction modeling: An empirical analysis. Oxford Business and Economics Conference Proceedings (Oxford, June 22-24, 2008). 2008:1-21.
27. Hernandez Tinoco M., Wilson N. Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. *International Review of Financial Analysis*. 2013;30:394-419. DOI: 10.1016/j.irfa.2013.02.013
28. Serrasqueiro Z. Are capital structure decisions of service SMEs different? Empirical evidence from Portugal. *Management Research Review*. 2011;34(1):34-57. DOI: 10.1108/01409171111096469