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The Prediction of Bankruptcy in a Construction Industry of Russian Federation

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The problem of the firm bankruptcy prediction was investigated by foreign researchers in the 1930s and it still remains relevant. Since the publishing of Altman's (1968) major work, based on multiple discriminant analysis (MDA), this methodological area has considerably changed. Taking into consideration that new data have appeared in the course of time, companies' average size has changed, and the accounting standards have changed (Altman, Haldeman, & Narayanan, 1977), methods and models should be renewed so as to be appropriate for current situation. The purpose of this paper[1] is to reveal factors causing bankruptcy and use models appropriate for prediction bankruptcy in the area of a construction industry during the financial crisis. This investigation has been carried out on the basis of logit and probit analysis. The main reasons of bankruptcy revealed in the course of this investigation are the following: (1) non-optimal capital structure formation; (2) ineffective liquidity management; (3) decrease in assets profitability; and (4) decrease in short-term assets turnover. The most reliable indicators which give warning of bankruptcy ahead of others are financial instability and liquidity ratios.

Keywords: bankruptcy prediction, construction industry, logit and probit analysis

Introduction

Since the increasing popularity of bankruptcy prediction in the 1930s, a large number of various methods have been created. A lot of models based on the data from the developed and developing countries have been tested. Russian researchers began to study this matter only at the end of the 1990s after the transition to the market economy. The amount of the investigations of this type has increased considerably after the crisis of 1998. The second wave of interest emerged after the world crisis in the period of 2008-2009. The collapse in a banking industry provoked related and dependent sectors to erosion. The most erupted industry, not only in this crisis period but also before, is the construction industry (Repin, 2011). The list of the main damaging symptoms includes the mortgage crediting lowering from 4.03% in 2008 to 0.75% in 2009 relative to the whole pool of credits in Russia, decrease of price index from 116.9 to 100.1 with cost share in sales growth from 91.3% to 92.1% in 2008 and 2009 correspondingly, and the rise of specific weight of unprofitable organizations[2]. Yu and Zi (2007) showed that cost inefficiency had been a core problem in Korean construction companies. Furthermore, share of capital investment has fallen from 4.60% to 3.50% in these years, and gross

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[1] JEL classification: G12, G13, G32, G33.
[2] Retrieved from http://www.gks.ru.

added value relative to gross domestic product (GDP) reduced from 6.30% to 5.50%. With more than 5% in GDP and a stable share (7.5%-8%) of employers, the construction industry has remained strategically important[3]. Decrease in crediting in that industry was depicted also by Kovalenko and Urtenov (2010). Thus, it is necessary to reveal the key factors leading to bankruptcy in this industry by taking into account the aggravating influence of crisis prior to bankruptcy to observe the change in these measures and their dynamics. Consequently, the purpose of this paper is to reveal factors causing bankruptcy of Russian firms in construction industry. The corresponding tasks could be determined in the following way: (1) revealing of separate bankruptcy factors; (2) definition of the most relevant method; and (3) observation of the whole set of these factors' dynamics. The remainder of this paper is organized as follows. The first part is devoted to a review of investigation in the field of bankruptcy prediction and in the construction industry in particular. In the following sections, the used methodology and initial hypotheses are presented. In the last three practical sections, description of data, factor set, and results are shown. And finally, the summary of the results is presented.

Literature Review

In the middle of the 20th century, the most popular method used to predict bankruptcy was classical ratio analysis pioneered by Beaver (1966). The main drawback of this method is the difficulty of a cut-off point choice, since its value depends completely on the sample. However, this tool remains significant in the investigations, being this area the base for other advanced methods.

The first multiple-factor linear model was constructed by Altman (1968) on the grounds of the multiple discriminant analysis (MDA). He used this method to find a linear combination consisting of five variables which were chosen with the help of the correlation analysis. As Slesarenko (2010) pointed out, this model did not take account of all the financial sources of a firm. In 1977, Altman improved his model by taking into account the changes in a quoted companies list, a significant increase in the companies' asset size, and some arguable points in previous investigation. Kucherenko (2008) used this method for investigation of agricultural firms and obtained the model with the classification accuracy of 91.07% for one year prior to bankruptcy. A. A. Friland and D. Friland (2002), on the basis of this technique, developed the IFFR[4] index for bankruptcy prediction in commercial aviation. The classification accuracy of this index was about 85%-90%. Having compared Altman's (1968) and Beaver's (1966) methods, Deakin (1972) showed an unambiguous superiority of the MDA-based model. Abidali and Harris (1995) with the help of MDA analysis on the sample formed from construction industry showed that *Z*-score method could only increase the confidence in future failure, although there were a lot of non-financial indicators that could be taken into consideration. Kovalenko and Urtenov (2010) used the adjacent method based on the same premises—cluster analysis.

Nevertheless, the MDA method has a lot of disadvantages in view of tough premises. For instance, a sample should consist of multivariate normally-distributed observations with equal variance-covariance matrices. Moreover, ex ante failure probability should be known. Neglecting these problems in most cases leads to test biases (Balcaen & Ooghe, 2006). Under these conditions, the popularity of the MDA method declined considerably after the 1980s along with the emergence of methods based on the logit and probit methods, neural networks, envelopment analysis, and other advanced methods which partially helped to avoid these premises.

[3] Retrieved from http://www.gks.ru.
[4] Future financial responsibility index (IFFR).

The logit analysis which was pioneered by Ohlson (1980) became a broadly-used method in the bankruptcy prediction area. Among Russian researchers, Evrostopov (2008) built the model for the fourth and second years prior to bankruptcy via this method. The probit model in this sense was firstly used by Zmiewski (1984). Grise and Dugan (2001) checked the sensitivity of Zmijewski's (1984) and Ohlson's (1980) models to the industry effect, generality, and stability over time. They showed that both models' accuracy decreased with time. However, none of them was heavily sensitive to the industry effect. Koksal and Arditi (2004) on the basis of multinomial logit model got 80.40% classification accuracy for the construction industry firms.

There are also a lot of more advanced methods to predict bankruptcy probability. Among them, neural network (NN), data envelopment analysis, option models, and some others could be pointed out. For instance, Back, Laitinen, Sere, and van Wezel (1966) tested the MDA, logit methods, and the NN method. With this technique, the construction of an NN from "neurons" calculated on the basis of financial statements is assumed. The model obtained via this method for one year prior to bankruptcy has a classification error of about 2.7%, whereas the logit model and the MDA model have errors of about 3.51% and 14.86% respectively. However, for the second year, the best model was built with the help of the MDA method. In the study of Kapliński (2008), superiority of NN on MDA method was revealed for construction industry in Poland. However, he got low prediction accuracy for both tools: 70%-80% and 60%-75% correspondingly. Pompe and Bilderbeek (2005) compared the two methods mentioned in the previous investigation (NN and MDA) and the dichotomous classification test used by Beaver (1966). As the results showed, the MDA models based on stepwise selection presented better results than the ones based on the factor analysis. In this factor analysis, the MDA and NN models gave very close results. Cielen, Peeters, and Vanhoof (2004) compared the models based on the data envelopment analysis (DEA), linear programming, and the rule induction models. They conclude that the DEA model exceeds the others with the level of classification accuracy of 85.1%. Premachandra, Bhabra, and Sueyoshi (2009) in their paper compared the DEA and the logistic regression methods. The authors found that the DEA method gives better results (74%-86% against 67%) using out-of-sample data, while logistic regression is favorable for within-sample datasets. For studying construction industry, that tool was used by You and Zi (2007) for different efficiency-analyzing types.

One more approach based on the market parameters and call-option approach described by Agarwal and Taffler (2008) showed results similar to the accounting-based models. As the authors said, the option models were more up-to-date, whereas the value of the accounting-based models was in catching a trend in the company's performance.

As it has been shown, there are a lot of different methods used to predict firms' financial failure. Comparison of the accounting-based methods with more advanced ones shows controversial results. Taking into account the relative simplicity of the basic techniques, their performances should be checked before going to the second stage of analysis with the help of advanced tools.

Methodology

In this work, three main accounting-based methods have been employed—multiple discriminant, logit, and probit analysis. This set of techniques was chosen on the bases of frequency testing in most famous articles and its comparative simplicity. MDA method is implemented through finding linear combinations of measures that make it possible to define which of the two groups the firm belongs to (bankrupt or sound firm). In place of usual specification, canonical discriminant analysis would be in use due to more sophisticated analysis realization possibilities (Kim, Myuller, & Klekka, 1989). Under this tool, there are some strong assumptions. The strongest ones are factor independency, correspondence to multivariate normal distribution of joint variables, and equivalence of covariance matrices. The canonical discriminant function could be presented in the following way:

$$f_{km} = u_0 + u_1 X_{1km} + u_2 X_{2km} + \ldots + u_p X_{pkm} \tag{1}$$

where:

k is the group number or class number;

m is the unit number, for which values of independent variables $X_1, \ldots, X_p$ are presented;

u_i is the coefficients which are responsible for the distance between classes.

For relative influence of factors analyzing, it is necessary to transform derived coefficients to standardized form:

$$c_i = u_i \sqrt{\frac{w_{ji}}{n-g}} \tag{2}$$

where:

n is the amount of observations;

g is the amount of classes.

To appreciate the discriminant function quality, it is possible to use such tools as canonical correlation coefficients and Wilk's lambda statistic, having a Fisher's distribution. The first instrument allows ascertaining the dependence between classes and discriminant function and allows for the information contained in eigenvalues. Directly, it helps to estimate the discriminant function usefulness. The second is used in case of inconsistency of a sample to the initial population due to possibility of a spurious dependence.

As Kim, Myuller, and Klekka (1989) pointed out, necessity of prior probability knowledge for chosen classes is another disadvantage of this method. However, the features of the object complicate this task because of impossibility to define inherited properties of initial population in discrete time due to its dynamic nature.

Another type of instruments which allows avoiding tough premises is connected with the method described above—binary choice models (logit and probit). In general, such kind of model specification is the following:

$$E(y_t) = 1 * P(y_t = 1) + 0 * P(y_t = 0) = P(y_t = 1) = F(x_t^{'} * \beta) \tag{3}$$

where:

$x_t^{'} * \beta$ is the determinate part from linear regression model;

$y_t = x_t^{'} * \beta + \varepsilon_t$, where $t = 1, \ldots, n$ and is the observation number;

$\beta = (\beta_1, \ldots, \beta_k)^{'}$ is the set of unknown parameters—coefficients;

ε_t is the random error with mean of zero and variance σ^2.

In this model, the specific dependence of binary variable value is assumed:

$$\begin{aligned} y_t &= 1,\_if\ \_y_t^* \geq y_{cutoff} \\ y_t &= 0,\_if\ \_y_t^* \lhd y_{cutoff} \end{aligned} \tag{4}$$

For logit model, the distribution function has the logistic form: $F(u) = \Lambda(u) = \dfrac{e^u}{1+e^u}$; and for probit model, standard normal: $F(u) = \dfrac{1}{2\sqrt{\pi}} \int\limits_{-\infty}^{u} e^{-\frac{x^2}{2}} dx$.

In both cases, likelihood function is maximized $L = L(y_1,...,y_n) = \prod\limits_{yt=0}(1 - F(x_t^{'} * \beta)) \prod\limits_{yt=1} F(x_t^{'} * \beta)$. Derived value of this function is supposed to be one of model quality criterion along with Akaike, Schwarz, and F-statistic under the test for explanatory power of variables. However, coefficients in these models could not be interpreted in the direct way. To appreciate the relative effect of variables, it is necessary to calculate marginal effects $\dfrac{\partial P(y=1)}{\partial x} = F^{'}(x^{'}\beta)\beta = p(x^{'}\beta)\beta$.

The models for each year prior to bankruptcy are supposed to be constructed using each of the methods. For instance, if the model for three years prior to bankruptcy is obtained, according to this model, the failed firm tends to go bankrupt in three years with calculated probability.

Hypotheses

In the course of this investigation, the following hypotheses have been formed on the bases of the relevant purpose and tasks which have been proposed. The first hypothesis refers to the whole applicability of the basic methods, such as logit, probit, and discriminant analyses for prediction of Russian firms' bankruptcy from construction industry. Before using such advanced methods as NN or DEA, it is necessary to check the base methods' validity for possible simplification of the instrument employed.

H1: The base methods are applicable for prediction of Russian firms' bankruptcy from construction industry.

The similar hypothesis was implicitly verified in the paper of Kovalenko and Urtenov (2010).

The next hypothesis is connected with the final factor set used in the prediction process. Some authors in their investigations got the same factors on the base of different methods using different samples of non-financial companies. This hypothesis was used in the basic works of Beaver (1966), Altman (1968), and Ohlson (1980).

H2: The best prediction ability factor set does not depend on the method of analysis which is in use.

If the final set of measures is not the same as the results of the other investigations based on the multi-industry samples, then it means that factors of insolvency are unique for such industry companies. On the other hand, results of Beaver's (1966) and Grise and Dugan's (2001) investigations are not determined by the industry.

H3: The factors causing bankruptcy depend on industry.

For verification of these hypotheses, the models depicted above are to be constructed using the sample described in the following section.

Data

The sample includes 120 Russian firms: 60 bankrupt in the first group and 60 sound analogues from construction industry in the second one. Data were collected from the database Ruslana (bureau VanDijk). For selection of sound firms, the matched sample method was chosen to partially and carefully smooth the covariance matrixes' difference for the correct realization of MDA. That procedure was carried out under the following criteria (Altman, 1968; Premachandra, Bhabra, & Sueyoshi, 2009): (1) six-digit industry code (by OKVED[5]); (2) assets size; (3) legal form; and (4) periods of the financial statement available.

There are only construction firms in the sample from two legal forms: open corporations along with closed ones. Iwasaki (2006) showed that in the privatization period, the choice between these legal forms was more political than economic in view of a great number of insiders. Furthermore, managers preferred the closed form because of the scantiness of financial market sources and desire for control keeping. Thus, the two forms can be gathered in one sub-sample in this research in the economic context. The sample includes yearly data from 2002 to 2010: five observation years for every company. After averaging of stock variables, there are four years for analyzing: from the 4th to the 1st year prior to bankruptcy. Because of the fact that in most cases, a firm begins the competitive production procedure one year after the last financial statement, the bankruptcy period covers years of 2006-2011.

Factor Set

The initial factor set consists of 22 variables (see Table 1) which have been chosen according to the mentioned frequency in the literature and their performances in previous investigations of the foreign and Russian authors (Abidali & Harris, 1995; Back, Laitinen, Sere, & van Wezel, 1996; Slesarenko, 2010). These 22 measures for each company for each year prior to bankruptcy were calculated. Six basic groups were assigned on the bases of the correlations and economic logic for which these variables could be referred to: liquidity, turnover, profitability, solidity, size, and cash flow ratios. This was similar to the classification which was presented in Beaver's (1966) work.

Table 1

List of Ratios in the Initial Factor Set

Liquidity	Size	Turnover	Solidity	Profitability	Cash flow
Cash/current liabilities (cashcl)	Ln total assets (lnta)	Account receivable/sales (ars)	Interest coverage (intcov)	EBIT[6]/total assets (ebitta)	Cash flow/total assets (cfta)
Quick assets/current liabilities (qacl)		Inventory/sales (invs)	Total debts/total assets (tdta)	Sales/total assets (sta)	Cash flow/total debts (cftd)
Current assets/current liabilities (cacl)		Current assets/sales (cas)	Long-term debts/total assets (ltdta)	EBIT/sales (ebits)	
Cash/total assets (cashta)			Ln tangible assets (lntang)	Net income/total debts (nitd)	
Working capital/total assets (wcta)					
Current liabilities/total assets (clta)					
Working capital/total debts (wctd)					
Current assets/total assets (cata)					

[5] Общероссийский классификатор видов экономической деятельности (OKVED) is the Russian classification of economic activities.

[6] Earnings before interest and taxes (EBIT).

On the basis of the descriptive statistics analysis (see Tables 2-7), it is revealed that the factors increasing bankruptcy probability, such as turnover coefficients (see Table 2), debt to assets ratio (see Table 6), are significantly higher for bankrupt group, while the factors with opposite influence exceed counterparts in the second group. For the main factor of the financial stability, the mean for the first year before bankruptcy for the bankrupt firms is significantly more than one (see Table 6) with average negative balance value of equity.

For almost every coefficient, the standard deviation is not great after the initial correction of the sample for outliers. This tendency intensified during the year before bankruptcy, because the final stage of distress was coming.

Table 2

Descriptive Statistics: Turnover Ratios

	bankr	qas1	ars1	cas1	qas2	ars2	cas2	qas3	ars3	cas3	qas4	ars4	cas4
Mean	0	0.57	0.21	0.73	0.42	0.17	0.62	0.77	0.18	0.82	0.75	0.19	0.77
Sd.	0	0.54	0.22	0.74	0.36	0.15	0.61	1.66	0.21	1.73	1.82	0.28	1.75
Cv.	0	0.93	1.05	1.00	0.84	0.89	0.99	2.15	1.17	2.12	2.41	1.42	2.27
Min.	0	0.05	0.01	0.09	0.05	0.00	0.12	0.07	0.00	0.08	0.06	0.00	0.14
Max.	0	2.50	1.39	3.39	1.84	0.86	3.72	10.52	1.24	9.73	10.45	1.35	10.42
Mean	1	1.46	1.05	2.82	1.05	0.67	1.89	0.47	0.22	0.76	0.54	0.24	0.76
Sd.	1	1.86	1.65	3.42	3.15	2.23	5.42	0.29	0.17	0.68	0.89	0.28	0.99
Cv.	1	1.27	1.57	1.21	2.99	3.35	2.88	0.61	0.78	0.90	1.64	1.18	1.29
Min.	1	0.00	0.00	0.10	0.07	0.00	0.16	0.09	0.00	0.17	0.11	0.00	0.17
Max.	1	11.67	10.07	16.72	24.51	17.27	41.84	1.40	0.94	4.85	6.47	1.63	6.88

Table 3

Descriptive Statistics: Liquidity Ratios

	bankr	cashcl1	qacl1	cacl1	cashta1	wcta1	clta1	wctd1	cata1
Mean	0	0.25	1.07	1.43	0.09	0.06	0.62	0.41	0.68
Sd.	0	0.52	0.94	1.21	0.12	0.34	0.28	1.18	0.27
Cv.	0	2.09	0.88	0.85	1.33	5.96	0.44	2.89	0.40
Min.	0	0.00	0.04	0.04	0.00	-0.91	0.07	-0.96	0.04
Max.	0	3.17	4.91	7.33	0.58	0.63	1.14	6.23	0.99
Mean	1	0.02	0.64	0.86	0.02	-0.56	1.28	-0.26	0.72
Sd.	1	0.03	1.19	1.23	0.04	0.93	0.86	0.35	0.24
Cv.	1	2.03	1.86	1.42	2.08	-1.67	0.67	-1.35	0.33
Min.	1	0.00	0.01	0.02	0.00	-4.64	0.09	-0.98	0.02
Max.	1	0.16	9.36	9.77	0.15	0.84	4.74	0.74	0.99
	bankr	cashcl2	qacl2	cacl2	cashta2	wcta2	clta2	wctd2	cata2
Mean	0	0.36	1.38	1.77	0.09	0.08	0.59	0.70	0.68
Sd.	0	0.80	1.91	2.19	0.11	0.32	0.30	2.18	0.24
Cv.	0	2.19	1.39	1.23	1.12	3.86	0.51	3.09	0.36
Min.	0	0.00	0.04	0.05	0.00	-0.91	0.05	-0.95	0.05
Max.	0	4.39	11.98	14.62	0.47	0.73	1.28	13.63	0.99
Mean	1	1.03	0.56	0.90	0.02	-0.17	0.87	-0.13	0.70
Sd.	1	0.07	0.31	0.46	0.06	0.37	0.32	0.36	0.24
Cv.	1	2.69	0.55	0.52	2.72	-2.14	0.36	-2.84	0.34
Min.	1	0.00	0.02	0.02	0.00	-1.56	0.18	-0.98	0.02
Max.	1	0.53	1.38	2.82	0.44	0.39	2.13	0.74	0.99

(Table 3 continued)

	bankr	cashcl3	qacl3	cacl3	cashta3	wcta3	clta3	wctd3	cata3
Mean	0	0.25	1.31	1.64	0.08	0.10	0.60	0.45	0.71
Sd.	0	0.45	1.39	1.47	0.12	0.31	0.27	1.01	0.23
Cv.	0	1.84	1.06	0.89	1.38	2.95	0.46	2.26	0.32
Min.	0	0.00	0.16	0.18	0.00	-0.72	0.05	-0.75	0.11
Max.	0	2.55	8.87	9.19	0.58	0.85	1.05	4.49	0.99
Mean	1	0.04	0.63	0.97	0.03	-0.10	0.81	-0.08	0.71
Sd.	1	0.07	0.37	0.49	0.05	0.31	0.27	0.34	0.24
Cv.	1	1.84	0.58	0.50	1.78	-3.10	0.33	-4.37	0.33
Min.	1	0.00	0.06	0.06	0.00	-1.13	0.10	-0.94	0.04
Max.	1	0.41	1.84	3.11	0.35	0.51	1.50	0.69	0.97
	bankr	cashcl4	qacl4	cacl4	cashta4	wcta4	clta4	wctd4	cata4
Mean	0	0.22	1.04	1.36	0.10	0.05	0.63	0.27	0.68
Sd.	0	0.40	0.83	0.86	0.13	0.29	0.25	0.70	0.22
Cv.	0	1.80	0.79	0.64	1.35	5.74	0.39	2.61	0.33
Min.	0	0.00	0.06	0.09	0.00	-0.86	0.05	-0.91	0.09
Max.	0	2.34	4.69	4.72	0.67	0.63	1.09	2.55	0.99
Mean	1	0.06	0.62	0.97	0.04	-0.08	0.78	-0.07	0.69
Sd.	1	0.10	0.30	0.56	0.08	0.27	0.22	0.36	0.24
Cv.	1	1.74	0.49	0.58	1.81	-3.17	0.28	-4.95	0.34
Min.	1	0.00	0.06	0.07	0.00	-1.07	0.16	-0.93	0.03
Max.	1	0.48	1.53	4.29	0.43	0.53	1.32	1.08	0.99

Table 4

Descriptive Statistics: Cash Flow Ratios

	bankr	cfta1	cftd1	bankr	cfta2	cftd2	bankr	cfta3	ftd3	bankr	cfta4	cftd4
Mean	0	0.02	0.07	0	0.01	0.06	0	0.01	0.02	0	0.04	0.15
Sd.	0	0.11	0.40	0	0.11	0.43	0	0.16	0.48	0	0.14	0.55
Cv.	0	5.13	5.77	0	10.12	6.74	0	11.63	27.55	0	3.56	3.59
Min.	0	-0.17	-0.92	0	-0.44	-0.63	0	-0.77	-2.89	0	-0.38	-0.82
Max.	0	0.38	2.49	0	0.35	2.84	0	0.52	1.39	0	0.59	3.17
Mean	1	-0.01	-0.01	1	-0.01	-0.01	1	-0.01	-0.01	1	0.01	0.01
Sd.	1	0.06	0.05	1	0.05	0.04	1	0.07	0.09	1	0.08	0.12
Cv.	1	-3.13	-5.16	1	-3.78	-4.36	1	-12.5	-13.72	1	7.63	9.52
Min.	1	-0.28	-0.36	1	-0.21	-0.17	1	-0.29	-0.31	1	-0.17	-0.34
Max.	1	0.12	0.12	1	0.08	0.09	1	0.21	0.33	1	0.32	0.45

Table 5

Descriptive Statistics: Profitability Ratios

	bankr	ebitta1	sta1	ebits1	nitd1	bankr		bankr	ebitta2	sta2	ebits2	nitd2
Mean	0	0.12	1.64	0.05	0.22	0	Mean	0	0.11	1.74	0.08	0.23
Sd.	0	0.18	1.13	0.39	0.58	0	Sd.	0	0.15	1.10	0.17	0.51
Cv.	0	1.56	0.68	7.85	2.68	0	Cv.	0	1.42	0.63	2.19	2.25
Min.	0	-0.31	0.04	-2.66	-0.36	0	Min.	0	-0.45	0.13	-0.35	-0.45
Max.	0	1.10	5.12	0.86	4.02	0	Max.	0	0.47	6.21	0.99	2.97
Mean	1	-0.18	0.71	-0.59	-0.18	1	Mean	1	-0.04	1.08	-0.39	-0.08
Sd.	1	0.32	0.69	1.09	0.31	1	Sd.	1	0.15	0.90	2.36	0.13
Cv.	1	-1.80	0.97	-1.84	-1.67	1	Cv.	1	-3.74	0.84	-6.09	-1.71

(Table 5 continued)

	bankr	ebitta1	sta1	ebits1	nitd1	bankr		bankr	ebitta2	sta2	ebits2	nitd2
Min.	1	-2.05	0.01	-6.95	-1.21	1	Min.	1	-0.54	0.01	-18.04	-0.49
Max.	1	0.08	2.60	0.19	0.21	1	Max.	1	0.29	5.52	0.49	0.11
	bankr	ebitta3	sta3	ebits3	nitd3	bankr		bankr	ebitta4	sta4	ebits4	nitd4
Mean	0	0.12	2.02	0.08	0.18	0	Mean	0	0.09	2.06	0.06	0.15
Sd.	0	0.15	1.43	0.13	0.36	0	Sd.	0	0.18	1.29	0.13	0.32
Cv.	0	1.27	0.71	1.58	1.96	0	Cv.	0	1.98	0.63	2.02	2.19
Min.	0	-0.42	0.01	-0.26	-0.60	0	Min.	0	-0.89	0.02	-0.49	-0.56
Max.	0	0.49	8.47	0.81	1.54	0	Max.	0	0.53	5.77	0.74	1.84
Mean	1	0.01	1.46	-0.00	-0.03	1	Mean	1	0.03	1.60	0.01	-0.01
Sd.	1	0.10	0.99	0.18	0.11	1	Sd.	1	0.11	1.11	0.08	0.11
Cv.	1	11.89	0.68	-1.06	-4.29	1	Cv.	1	4.25	0.69	6.62	-9.14
Min.	1	-0.48	0.04	-0.93	-0.38	1	Min.	1	-0.19	0.02	-0.19	-0.35
Max.	1	0.17	4.32	0.49	0.26	1	Max.	1	0.44	4.70	0.26	0.26

Table 6

Descriptive Statistics: Financial Solidity Ratios

	bankr	intcov1	tdta1	ltlta1	lntang1	bankr		bankr	intcov2	tdta2	ltlta2	lntang2
Mean	0	0.24	0.69	0.07	11.27	0	Mean	0	0.12	0.68	0.09	11.09
Sd.	0	0.77	0.28	0.15	1.56	0	Sd.	0	0.82	0.32	0.19	1.50
Cv.	0	3.18	0.40	2.04	0.14	0	Cv.	0	6.62	0.46	2.04	0.13
Min.	0	-0.02	0.07	0.00	7.09	0	Min.	0	-4.07	0.05	0.00	7.03
Max.	0	5.73	1.22	0.73	15.45	0	Max.	0	4.20	1.74	0.82	15.34
Mean	1	-0.46	1.42	0.13	9.88	1	Mean	1	-0.22	0.98	0.10	10.70
Sd.	1	1.80	0.95	0.45	1.57	1	Sd.	1	3.36	0.27	0.17	1.40
Cv.	1	-3.88	0.67	3.35	0.16	1	Cv.	1	-14.9	0.27	1.69	0.13
Min.	1	-10.08	0.43	-0.02	6.74	1	Min.	1	-23.0	0.36	0.00	7.65
Max.	1	1.28	4.93	3.23	13.50	1	Max.	1	7.95	2.17	0.80	13.71
	bankr	intcov3	tdta3	ltlta3	lntang3	bankr		bankr	intcov4	tdta4	ltlta4	lntang4
Mean	0	0.17	0.68	0.08	10.82	0	Mean	0	0.15	0.69	0.06	10.56
Sd.	0	0.38	0.27	0.17	1.60	0	Sd.	0	0.40	0.28	0.16	1.72
Cv.	0	2.32	0.40	2.13	0.15	0	Cv.	0	2.57	0.40	2.55	0.16
Min.	0	-1.22	0.06	0.00	6.27	0	Min.	0	-0.47	0.05	0.00	5.55
Max.	0	1.51	1.06	0.71	15.28	0	Max.	0	1.98	1.74	0.86	15.03
Mean	1	0.61	0.91	0.09	10.73	1	Mean	1	0.02	0.84	0.05	10.75
Sd.	1	2.06	0.21	0.19	1.15	1	Sd.	1	2.44	0.19	0.13	1.26
Cv.	1	3.39	0.23	2.02	0.12	1	Cv.	1	1.07	0.23	2.45	0.11
Min.	1	-2.29	0.51	0.00	7.60	1	Min.	1	-15.3	0.43	0.00	7.61
Max.	1	12.74	1.52	0.89	13.16	1	Max.	1	9.73	1.33	0.68	13.39

Table 7

Descriptive Statistics: Size Ratio

	bankr	lnas1	lnas2	lnas3	lnas4
Mean	0	13.01	12.72	12.59	12.18
Sd.	0	0.98	1.04	0.99	0.99
Cv.	0	0.07	0.08	0.07	0.08
Min.	0	11.27	10.93	10.89	10.16

(Table 7 continued)

	bankr	lnas1	lnas2	lnas3	lnas4
Max.	0	15.98	15.81	15.73	15.40
Mean	1	12.13	12.55	12.60	12.41
Sd.	1	1.09	0.97	1.06	1.05
Cv.	1	0.09	0.07	0.08	0.08
Min.	1	9.89	10.74	11.05	11.03
Max.	1	14.87	15.56	16.82	16.75

Results

The initial analysis has shown that the main assumptions which are under the MDA being presumed are not held at all. The results of Doornik and Hansen's (1994) test have shown that only the distribution of few variables complies with the standard normal law. Furthermore, the revealed tendency is not typical either for bankrupt sound firms' groups. Moreover, the covariance matrices are not equal, meaning that the same group proportions introduced through the sample formation is well-founded. The in-sample classification accuracy has decreased with time before the bankruptcy. For the first year, it is about 86.44%. For the second and third years, it fell to 75.43% and 71.19% correspondingly. And in the fourth year prior to bankruptcy, the classification accuracy was 67.80%. From the error-type view, the first model is the most accurate, because the I-type error is lower and potentially bankrupt firm would be classified as sound with the smaller probability (see Table 8).

Table 8

Discriminant Analysis Models' Quality

	1-I-type error (%)	1-II-type error (%)	Class accuracy (%)	Prob Wilks' lambda	Canon corr.
$t-1$	89.83	83.05	86.44	0.0000	0.7006
$t-2$	77.88	77.97	77.93	0.0000	0.4786
$t-3$	67.80	74.58	71.19	0.0000	0.4743
$t-4$	67.80	67.80	67.80	0.0009	0.3389

The extremely small *P*-values of Wilk's lambda statistic indicate that these discriminant functions are sufficient for classification. Values of canonical correlation coefficient also become lower with a decrease in classification accuracy. In Table 9, intervals for *Z*-scores are presented. Obviously, there is no any strict dependency between the year prior to bankruptcy and *Z*-score interval width and asymmetry. However, the first year interval is narrower than that of Abidali and Harris's (1995) *Z*-score for the UK firms from construction industry but is broader than in Altman's (1968) work.

Table 9

Z-Score From t – 1 to t – 2 Year Prior to Bankruptcy

$t-1$	-1.82	Z1	2.21
$t-2$	-0.95	Z2	1.29
$t-3$	-2.33	Z3	2.23
$t-4$	-2.10	Z4	2.31

While choosing the final set of variables, the factor analysis and stepwise selection were carried out. In the fourth year prior to bankruptcy, two measures—sales to total assets and total debt share in total assets (with the prevalent influence of the second factor), meaning that the core reasons of future distress leading to bankrupt stage are non-optimal capital structure formation and decrease in profitability (see Table 10). Standardized coefficients for the $t - 3$ period showed absolutely similar results. However, in the second year prior to bankruptcy, main indicators are profitability, liquidity, and turnover measures in the lowering influence order. The main role has profitability of assets as before and more sort-run indicator—profitability of sales under operating profit. In the first and the most critical period, measures of size and interest coverage coefficients have been added, and the liquidity coefficient has the least influence that is illogical under the generally accepted conception of bankruptcy. That fact could be described through the crisis phenomenon that facilitates inherit problems in companies that lead to bankruptcy not at the critical stage. However, this method is not completely confirmed as valid by tests, because the *P*-value for Wilks' lambda is extremely small, indicating a spurious dependence because of the inconsistency between initial population and the sample in use (Kim, Myuller, & Klekka, 1989).

Table 10

Standardized Coefficients in Discriminant Analysis Models

	Standardized coefficient			
	$t - 1$	$t - 2$	$t - 3$	$t - 4$
ebitta1	-0.50			
lnas1	-0.36			
cashcl1	-0.13			
ars1	0.33			
intcov1	-0.28			
sta2	-0.29	-0.65		
cashcl2		-0.55		
invs2		0.13		
ebits3		-0.50		
sta3			-0.50	
tdta3	0.47		0.91	
sta4				-0.54
tdta4				0.84

Table 11

Quality of Logit and Probit Models

	$t - 1$		$t - 2$		$t - 3$		$t - 4$	
	logit	probit	logit	probit	logit	probit	logit	probit
LR stat.	85.97	85.84	50.04	47.16	39.16	42.54	12.5	12.24
P-value (LR stat.)	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.002
L max.	-38.81	-38.87	-56.77	-58.21	-62.21	-60.52	-75.54	-75.67
Rsq. (McFadden)	52.55%	52.48%	30.59%	28.83%	23.94%	26.01%	7.64%	7.48%
AIC	87.62	87.74	121.54	124.43	130.42	129.04	157.08	157.34
BIC	101.47	101.59	132.63	135.51	138.73	140.12	165.39	165.65
Predict +	88.14%	86.44%	83.05%	84.75%	83.05%	89.83%	66.10%	64.41%
Predict −	84.75%	84.75%	71.19%	71.19%	67.80%	64.41%	64.41%	64.41%
Predict whole	86.44%	85.59%	77.12%	77.97%	75.42%	77.12%	65.25%	64.41%

Notes. (1) LR stands for the likelihood ratio; (2) AIC is Akaike information criterion; and (3) BIC is Bayesian information criterion.

The results of binary choice models are slightly different and better in average. Classification accuracy falls also as in the discriminant analysis case. However, the I-type error is relatively smaller than in the previously-used method (see Table 11).

Values of AIC and Schwartz increase along with the other indicators' deterioration (LR statistic, McFadden R^2, and likelihood function maximum) towards the most distant year prior to bankruptcy, but are sufficiently high. Thus, the first initial hypothesis has been rejected only partially. For both specifications, logit and probit, the coefficient results are extremely similar with the exception in the second and third years (see Table 12).

Table 12

Logit and Probit Models Results

Variable	log1	pr1	log2	pr2	log3	pr3	log4	pr4
lnas1	-1.3^{***}	-0.748^{***}						
cashcl1	-12.2^{*}	-6.72^{*}						
cas1	1.05^{**}	0.577^{**}						
tdta3	4.44^{*}	2.63^{**}		1.68^{*}		1.6^{*}		
ebitta2				-2.47^{*}				
cashcl2			-7.57^{*}	-3.66^{*}				
ars2			2.06^{*}					
tdta2			2.82^{*}					
ebitta3					-7.22^{**}	-2.8^{*}		
cashcl3					-7.72^{**}	-3.82^{**}		
wcta4							-1.49^{*}	-0.951^{*}
ebits4							-5.07^{*}	-2.74^{*}
_cons	12.2^{**}	6.94^{**}	-2.45^{*}	-1.02	1.04^{***}	-0.836	0.159	0.0782

Note. Legend: * $p < 0.05$; ** $p < 0.01$; and *** $p < 0.001$.

Table 13

Logit and Probit Models Marginal Effects

Variable	log1	pr1	log2	pr2	log3	pr3	log4	pr4
lnas1	-0.31^{**}	-0.29^{**}						
cashcl1	-2.88^{**}	-2.60^{*}						
cas1	0.25^{*}	0.22^{**}						
tdta3	1.05^{*}	2.02^{**}		0.59^{*}		0.62^{*}		
ebitta2				-0.87^{*}				
cashcl2			-1.67^{**}	-1.30^{**}				
ars2			0.46					
tdta2			0.62^{*}					
ebitta3					-1.69^{**}	-1.07^{*}		
cashcl3					-1.81^{**}	-1.47^{**}		
wcta4							-0.37^{*}	-0.38^{*}
ebits4							-1.27^{*}	-1.09^{*}

Note. Legend: * $p < 0.05$; ** $p < 0.01$.

The probit specification insignificantly differs in quality criteria from the logit model. In the fourth and third years prior to the critical state of insolvency, there are two main indicators, i.e., liquidity and profitability, at which the influence of the second is more meaningful (see Table 13). In the fourth year, there are working capitals to total assets and profitability of sales under the operating profit. In comparison with MDA results, the last mentioned indicator had influence on the third period, and in place of the liquidity measure, the debt share was derived. In the third year, there is only difference between testable specifications—Debt share in total assets in the probit model is presented. In two residual models, this factor is included with different lags. For the second year, the account receivable turnover in the logit model and profitability of total assets in probit specification are inserted. For the most critical year before the bankruptcy announcement, such additional factors as size and current assets turnover were appended. It is necessary to note that the most significant factor for the bankruptcy prediction is absolute liquidity coefficient. Derived results coincided with those of Abidali and Harris (1995), who also depicted profitability, leverage, and liquidity. That reasoning gives the ground to the second initial hypothesis rejection.

As the binary choice models overcome the discriminant analysis tool and probit specification, the final results explanation would be in this model frame. Thus, the universal indicators augmenting the bankruptcy probability are the liquidity coefficients. The second-level factors are profitability and leverage, and the most short-term indicators are turnover and size. The last mentioned measure has a crucial role only at the last stage before bankruptcy, because it is easier to take a credit in crisis period for a big construction company. The current assets and significant factors of account receivable turnover for such type of a company are due to advanced payment financing system. In the middle of the first crisis year, the construction companies faced a lack of current assets, and their expectations about the summer peak of construction were not realized (Kovalenko & Urtenov, 2010). However, the third hypothesis was not proved in the course of similar investigation. For instance, Back, Laitinen, Sere, and van Wezel (1966) also showed that absolute liquidity coefficient had meaningful influence on the whole period before bankruptcy. The rest of derived measures are similar to the factors presented in basic works of Beaver (1966), Altman (1968), and Ohlson (1980). Although Kaplinski (2008) pointed out that the method should be adapted to industry, it could be done to increase classification accuracy and predictive ability.

Conclusions

In the course of the financial crisis of 2008-2009, one of the most erupted industries was the construction industry. It was determined by the substantial decrease in mortgage crediting, price index, capital investment, and level of cost growth. Due to the importance of that industry in the country economy, it is necessary to define the main risk factor leading to the bankruptcy of companies of such type. This research has been carried out to reveal corresponding indicators. Used sample contained 138 Russian firms from construction industry, 69 out of 138 companies were bankrupt. In this investigation, three main accounting-based methods are presented: canonical discriminant, logit, and probit analysis. The Wilk's test showed invalidity of the first method, and quality criteria led to the selection of the probit specification as superior. The profitability coefficients have the crucial role in every period as the liquidity measures. The latter coincided with the results of Back, Laitinen, Sere, and van Wezel's (1966) work. Among meaningful measures, total debt share in total assets and size could be pointed out. The specific factor for this industry, current assets turnover, was derived (Kovalenko & Urtenov, 2010). However, the received factors correspond to the factors presented in works carried out on multi-industry samples. The models may be adapted for various lists of ratios to increase classification quality considering predictive ability.

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Appendix A

Table A1

Correlation Analysis: Turnover Ratios

	qas1	ars1	cas1		qas2	ars2	cas2
qas1	1.00			qas2	1.00		
ars1	0.84	1.00		ars2	0.98	1.00	
cas1	0.76	0.77	1.00	cas2	0.98	0.97	1.00
	qas3	ars3	cas3		qas4	ars4	cas4
qas3	1.00			qas4	1.00		
ars3	0.33	1.00		ars4	0.36	1.00	
cas3	0.90	0.26	1.00	cas4	0.98	0.40	1.00

Table A2

Correlation Analysis: Liquidity Ratios

	cashcl1	qacl1	cacl1	cashta1	wcta1	clta1	wctd1
qacl1	0.52	1.00					
cacl1	0.61	0.96	1.00				
cashta1	0.64	0.27	0.27	1.00			
wcta1	0.25	0.44	0.48	0.24	1.00		
clta1	-0.26	-0.39	-0.43	-0.21	-0.94	1.00	
wctd1	0.82	0.70	0.80	0.39	0.52	-0.48	1.00
cata1	-0.00	0.19	0.22	0.11	0.33	-0.00	0.21
	cashcl3	qacl3	cacl3	cashta3	wcta3	clta3	wctd3
qacl3	0.55	1.00					
cacl3	0.55	0.96	1.00				
cashta3	0.66	0.21	0.18	1.00			
wcta3	0.36	0.67	0.74	0.15	1.00		
clta3	-0.40	-0.57	-0.64	-0.04	-0.72	1.00	
wctd3	0.63	0.74	0.80	0.25	0.76	-0.66	1.00
cata3	-0.01	0.21	0.22	0.16	0.48	0.25	0.24
	cashcl2	qacl2	cacl2	cashta2	wcta2	clta2	wctd2
qacl2	0.78	1.00					
cacl2	0.73	0.97	1.00				
cashta2	0.68	0.44	0.38	1.00			
wcta2	0.39	0.53	0.57	0.35	1.00		
clta2	-0.42	-0.49	-0.52	-0.29	-0.78	1.00	
wctd2	0.71	0.96	0.98	0.37	0.55	-0.49	1.00
cata2	0.00	0.12	0.15	0.14	0.45	0.20	0.16
	cashcl4	qacl4	cacl4	cashta4	wcta4	clta4	wctd4
qacl4	0.51	1.00					
cacl4	0.46	0.86	1.00				
cashta4	0.85	0.30	0.24	1.00			
wcta4	0.41	0.65	0.77	0.30	1.00		
clta4	-0.33	-0.64	-0.73	-0.10	-0.65	1.00	
wctd4	0.61	0.77	0.87	0.36	0.82	-0.69	1.00
cata4	0.15	0.14	0.21	0.27	0.57	0.24	0.31

Table A3

Correlation Analysis: Cash Flow Ratios

	cfta1		cfta2
cftd1	0.67	cftd2	0.70
	cfta3		cfta4
cftd3	0.90	cftd4	0.81

Table A4

Correlation Analysis: Profitability Ratios

	ebitta1	sta1	ebits1		ebitta2	sta2	ebits2
sta1	0.23	1.00		sta2	0.36	1.00	
ebits1	0.50	0.31	1.00	ebits2	0.21	0.14	1.00
nitd1	0.75	0.19	0.32	nitd2	0.65	0.16	0.13
	ebitta3	sta3	ebits3		ebitta4	sta4	ebits4
sta3	0.30	1.00		sta4	0.26	1.00	
ebits3	0.63	-0.03	1.00	ebits4	0.68	-0.08	1.00
nitd3	0.80	0.14	0.46	nitd4	0.76	0.18	0.49

Table A5

Correlation Analysis: Financial Solidity Ratios

	intcov1	tdta1	ltlta1		intcov2	tdta2	ltlta2
tdta1	-0.12	1.00		tdta2	-0.05	1.00	
ltlta1	0.02	0.39	1.00	ltlta2	0.05	0.20	1.00
lntang1	0.23	-0.31	0.10	lntang2	0.01	-0.16	0.33
	intcov3	tdta3	ltlta3		intcov4	tdta4	ltlta4
tdta3	0.04	1.00		tdta4	0.04	1.00	
ltlta3	0.07	0.16	1.00	ltlta4	-0.01	0.31	1.00
lntang3	0.00	-0.14	0.22	lntang4	-0.12	-0.15	0.05