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Bankruptcy Prediction Models for Construction Companies in the Russian Federation

A.V. VoikoFinancial University,
Moscow, Russia<https://orcid.org/0000-0002-2387-3440>

ABSTRACT

The article is concerned with determining the main predictors of bankruptcy in construction organizations in the Russian Federation. Probabilistic prediction of bankruptcy is relevant for both individual companies and sectors of the national economy. Developed a long time ago, the existing bankruptcy prediction methods do not consider the industry specifics of organizations. The article investigates the mechanism for probabilistic prediction of bankruptcy based on logit models. Criteria affecting the bankruptcy probability were substantiated; a mathematical model was proposed to calculate the probability. The provided model was tested in a real company. Based on the sample of small and medium-sized construction companies, the author proposed a logit model reflecting the main factors affecting the financial state of construction companies in Russia and, therefore, the likelihood of their bankruptcy. Testing the model on the actual data from the construction enterprises showed its high predictive power. The study results allow predicting the bankruptcy in construction organizations by means of logit models.

Keywords: bankruptcy; construction companies; bankruptcy prediction; regression; logit model

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INTRODUCTION

In accordance with the Federal Law of December 25, 2018 No. 478-FZ "On amendments to Federal Law "On Joint Participation in Construction of Apartment Buildings or Other Real Estate and on Amendments to Several Legislative Acts of the Russian Federation" and Separate Legislative Acts of the Russian Federation", from 1 July, 2019, real estate developers are required to use escrow accounts to attract and store cash from property buyers. At the same time, the construction is supposed to be financed by credit funds provided by banks. The funds of the buyers remain on the escrow accounts until the construction ends or

are returned to the buyers in case of termination of the shared construction participation agreement.

The construction companies have to service a loan obtained from an authorized bank which increases their volume of expenses and cash outflows.

The question now arises: how difficult this innovation will be for construction companies and if this will lead to bankruptcies among developers?

Forecasting defaults of enterprises, including companies in the construction sector as one of the most important sectors determining the development of the country's econo-

my, is Russia's urgent problem, since the construction industry is among the most at risk of bankruptcy [1]. In the IV quarter of 2018, one of the main indicators of the business climate in the construction sector, the business confidence index (BCI) was equal to -19% . This means that the forecast for the industry as a whole is negative, despite the presence of such successful large companies as PIK or Donstroy.

It is important to understand the special features of the construction sector distinguishing it from other sectors in the economy. These differences are caused by the specificity of the final product and the complexity of the applied production and labor technologies. The characteristics inherent in the field of construction include the following aspects:

- nonhomogeneity of the construction process and final products;
- relationship between all technological operations in the construction process. The sequence of production processes is important. The time shift of one of the construction stages directly affects the entire construction plan;
- uneven ratio of construction and installation works by their labor costs and varieties. This makes it difficult to plan the required number of workers, as well as their qualification;
- a large number of companies involved in the construction process: several organizations can be involved at the same time (general contractor and subcontractor);
- high material consumption of the construction industry. Material expenses account for 50–70% of the total estimated cost of construction projects;
- impact of climatic and regional conditions on the construction process. Different labor and production costs may be required depending on the region and its climatic conditions. The construction process is influenced by such factors as weather conditions, terrain, wetlands and the ability to deliver the necessary materials to the construction site [2].

Thus, the construction industry is rather difficult to do business due to the number of specific features.

According to Rosstat statistics, from 2013, there has been a steady increase in the number of construction companies in Russia.

In *Fig. 1* we see that the number of operating construction companies has grown over 5 years from 217 961 in 2013 to 279 496 in 2017. The number of companies operating in this industry increased from 2% to 17% every year. There is also a noticeable increase in the scope of work performed in the construction industry.

Over 5 years, the scope of work performed by the type of economic activity "construction" increased from 6019.5 billion rubles in 2013 to 7573 billion rubles and 8385.7 billion rubles in 2017 and 2018 correspondingly.

The following statistics can be seen along with these indicators. The number of loan arrears to the construction industry has grown significantly over the past few years. The number of construction companies that overdue their loan obligations as of January 1, 2013 was equal to 68,241, which amounted to 8% of the total number of debtor companies in Russia. This indicator was rapidly growing, and as of January 1, 2019, the number of companies that overdue their loan obligations amounted to 287,294, or 15% of the total number of companies.

The business confidence index helps assess the climate in the construction industry. According to Rosstat, in the IV quarter of 2016, the BCI was -21% , and at the end of 2017 and 2018 it was -20% and -19% , respectively. In the IV quarter of 2018, construction companies distinguish the following factors limiting their activities: high taxes (38%), high cost of materials (30%), lack of work orders (27%), insolvency of customers (25%), unfair competition from other construction firms (26%), lack of financing (21%), a large percentage of loans (17%), and incompetence of workers (12%).

Thus, the construction industry is currently in unstable. Its recovery after the crisis slows

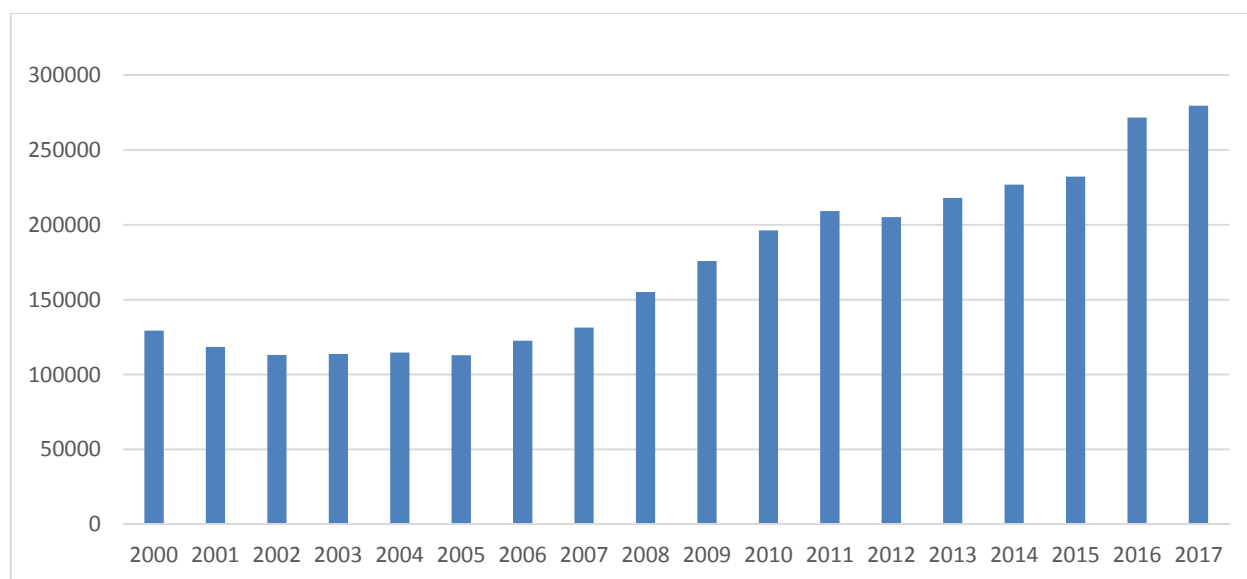


Fig. 1. Number of operating construction companies in the Russian Federation

Source: URL: http://www.gks.ru/free_doc/doc_2018/stroit-2018.pdf (accessed on 15.07.2019).

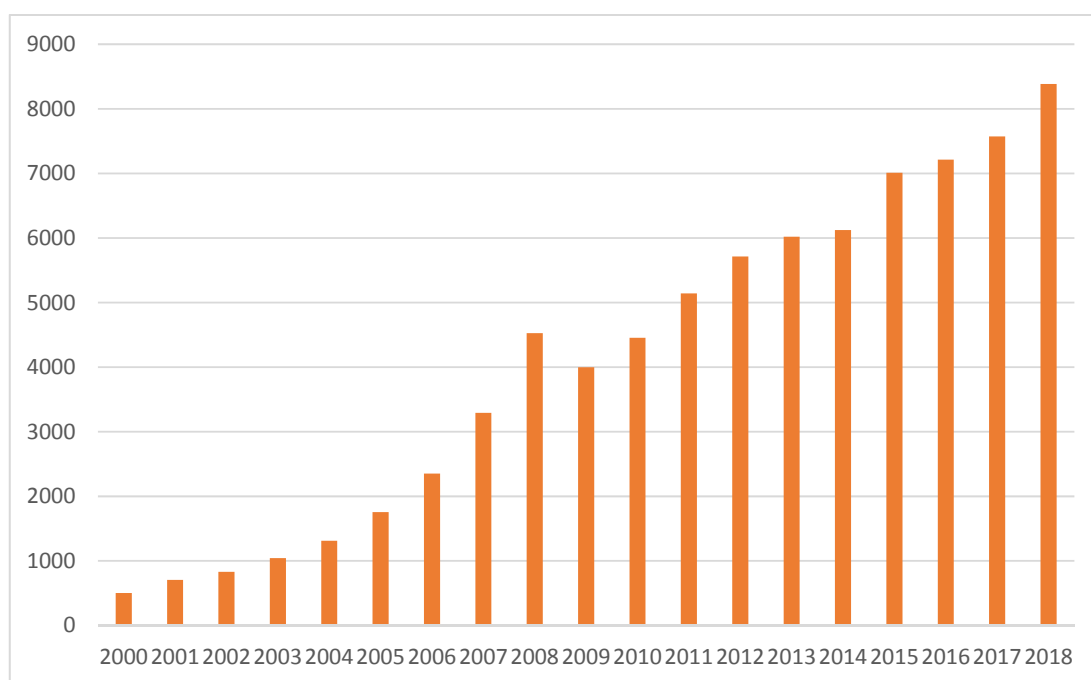


Fig. 2. Scope of work performed by the type of economic activity "construction"

Source: URL: http://www.gks.ru/free_doc/doc_2018/stroit-2018.pdf (accessed on 15.07.2019).

down due to lower incomes and persistent inflation risks. In the IV quarter of 2018, the balance of the number of concluded agreements amounted to -5% . This means that the majority of respondents noted a decrease in this indicator compared to the previous period. Due to the deterioration of the business climate in the construction industry, the problem of

company bankruptcies is becoming significant. According to a survey of entrepreneurs in 2017, 16–17% of contraction companies assess their condition as pre-bankrupt, i.e. their financial condition worsens over 3–4 quarters.

Therefore, with increasing sales volumes (see Fig. 2) and an increasing number of market participants (Fig. 1), the number of con-

struction companies with signs of bankruptcy is also growing. It is necessary to determine the factors influencing the probability of bankruptcy of construction companies, as well as to select a model that will help find and study these indicators and, most importantly, predict the financial insolvency of construction companies. This issue may attract the attention of not only top-level managers of developers, but also lenders to construction companies, as well as their shareholders.

There is no single model for predicting bankruptcy of a company. It is also necessary to consider the market characteristics of each individual country, since applying foreign models to Russian companies will not always provide an accurate forecast [3, 4].

RESEARCH RESULTS

Today, there are enough works on predicting bankruptcy of companies. They differ in the factors in the considered models, their number, as well as in the methods used to build models. This is noted in the work by Yu.N. Zakharova and N.N. Yaromenko [5].

Modern approaches to the financial condition of an enterprise and the probability of its bankruptcy involve not only discriminant analysis models, but also models based on neural networks allowing analysis with lack of information and complex non-linear relationships between variables. This conclusion was obtained by T.V. Varkulevich and O. Yu. Shchukina, in the study devoted to modern approaches to forecasting bankruptcy of enterprises [6].

Besides, one should consider not only internal, but also external factors potentially affecting the probability of bankruptcy of enterprises [7].

Nevertheless, the Altman model (1968) remains one of the most famous and popular models for predicting bankruptcy, being one of the first examples of the multiple discriminant analysis (MDA) method [8]. The author compiled a sample of 66 American companies from 1946 to 1965 (33 operating companies and 33

bankrupt companies). This model showed fairly accurate prediction abilities: the probability of correct predicting for the year ahead is 95%, for two years — is 83%. However, the Altman model (1968) cannot be called universal, since it can be applied only to the companies whose shares are traded on the stock market. E. Yu. Fedorova, M.A. Chukhlantseva and D.V. Chekrizov noted the indicated feature of the Altman model in [9].

Besides, the differences in business conditions in the USA and Russia are too significant making the Altman model (as well as the Taffler model) difficult to apply due to inaccurate predictions. This thesis is also confirmed in the work by G.V. Davydova and A. Yu. Belikov [10].

Logit models for predicting bankruptcy of enterprises gained little recognition in scientific publications. A fundamental contribution to the study of logit models for predicting bankruptcies was made by J. A. Ohlson (1980) [11]. This method uses regression analysis of binary selection models. The predicted variable “bankruptcy” in these models can take “0” values if the company has not gone bankrupt, and “1” values if the company has done. Another advantage of logit models is that they can be used to construct nonlinear factor dependencies in models. As a result, Ohlson developed the following regression formula:

$$Y = -1.3 - 0.4X_1 + 0.6X_2 - 1.4X_3 + 0.1X_4 - 2.4X_5 - 1.8X_6 + 0.3X_7 - 1.7X_8 - 0.5X_9, \quad (1)$$

where X_1 — is the natural logarithm of the ratio of assets to the GDP deflator index;

X_2 — is the ratio of short-term and long-term debt to assets;

X_3 — is the operating capital to assets ratio;

X_4 — is the ratio of current liabilities to current assets;

X_5 — is the net profit to assets ratio;

X_6 — is the ratio of net profit and depreciation to the amount of short-term and long-term debt;

X_7 — equals to 1 if total liabilities exceed total assets, or equals to 0 in the opposite situation;

X_8 — equals to 1 if net profit was negative in the last two years, or to 0 if it was positive;

X_9 — is the ratio of the difference in net profit for the last reporting period and net profit for the previous reporting period to the modulus of the amount of these financial indicators [11].

Having calculated the Y value, it is possible to find the probability of bankruptcy by the logistic regression formula [5]:

$$P = \frac{1}{1 + e^{-Y}}, \quad (2)$$

where e — is the exponent (Euler's number); and P — is the probability of bankruptcy of the enterprise.

It is more difficult to apply logit models as they often use high-quality variables. Nevertheless, they are characterized by a sufficiently high forecast accuracy, which makes it possible to use them when the probability of bankruptcy cannot be described only by financial variables.

For example, Russian author G. A. Khaidarshina (2009) built a logit model to assess the risk of bankruptcy of Russian enterprises [12]. The sample included 350 enterprises from different industries that vary in scale of activity. As a result, the author identified 11 significant variables, including the age of the enterprise, its credit history, current liquidity ratio and the Central Bank of Russia refinancing rate. The study results show the accuracy of the model built by G. A. Khaidarshina, accounted for 85.6%, which is a fairly high result proving the applicability of logit analysis to predicting bankruptcy of Russian companies. Also, the high predictive ability of logit models was noted in the article by O. E. Bol'shakova A. G. Maksimov and N. V. Maksimova who tested small and medium-sized enterprises [13].

In this article we will try to build a logit model for predicting bankruptcy of Russian construction companies. The specifics of the

industry requires considering not only financial, but also non-financial indicators of enterprises, which is what logit models are for. Besides, logistic models, in contrast to discriminant analysis models, not only help determine whether companies are bankrupt or not, but also show the probability of a company to become bankrupt [14].

The following advantages distinguishing the model from other methods of predicting bankruptcy can be specified:

- the ability of the model to determine the probability of bankruptcy of companies;
- data should not necessary to have a normal distribution, in contrast to the discriminant analysis model;
- the results are easy to interpret;
- the model can consider specific variables for different industries;
- high accuracy of the results [15].

Since the considered examples of logit analysis for predicting bankruptcies of companies (for example, the model of G. A. Khaidarshina) showed rather high predictive accuracy, there is a reason to believe that by applying this type of model to the construction sector, one can also obtain a highly effective estimate of the probability of bankruptcies of construction companies.

The generated database includes 526 Russian construction companies specializing in the construction of residential and non-residential buildings. In this paper, microenterprises, small and medium enterprises were considered. The information about the organizations and their financial statements were taken from the Spark information source.

The sample consists of open financial statements of construction companies for 2014–2017. The sample includes the data for the crisis period from 2014 to 2015. It was decided not to exclude these data, since such fluctuations in the market can be quite expected in the future and including this information can improve the predictive qualities of the model. On the contrary, the choice of a specific time period (recession period or

recovery period) would lead to the fact that the built model could assess the probability of bankruptcy only considering the current situation in the construction industry, which would worsen its predictive accuracy and narrow the applicability.

The sample contains information on 370 operating companies and 156 companies that were liquidated or are in the process of bankruptcy as of December 31, 2017. Most of these organizations have an open legal form. The companies were selected based on the fact that public companies are more demanding of their reporting, as it is open to a wide range of people.

The dependent variable in the model is binary and takes “1” values if the company is bankrupt, and “0” values if it is operating. For bankrupt companies, the latest accounting reports made before the bankruptcy were only included in the sample, since it is very difficult to say exactly when the organization became financially insolvent. Besides, the period between the moment when the company first experiences financial problems and the time when the arbitral tribunal decides to declare the company bankrupt can vary from few to a few years [16].

SELECTING EXPLANATORY VARIABLES FOR A LOGIT MODEL

One of the main objectives of this work is to select indicators affecting the probability of bankruptcy of construction companies. The author analyzed many works on logit analysis to predict the default of companies, and selected the most suitable factors for the model under review. In this work, the most significant indicators from the other empirical studies are taken as explanatory variables. These include both classical studies on predicting bankruptcy (E.I. Altman (1968) [8], J.A. Ohlson (1980) [11]) and modern studies (V. Yu. Zhdanov, O.A. Afanas'eva (2011) [15], S.A. Gorbakov, S.A. Farkhieva (2018) [17]).

The financial indicators have been chosen based on the definition of bankruptcy. As not-

ed earlier, bankruptcy means the company has no funds to pay off debt [18]. This is expressed in the fact that the organization cannot create new cash flows or attract external financing. As a result, the company does not have enough funds to meet its obligations.

An indicator demonstrating a company's ability to pay current liabilities is the current liquidity ratio (*curLiq*), calculated as the ratio of current assets to short-term liabilities. Also, important is the solvency ratio (*SvsO*), equal to the ratio of equity to all liabilities. The solvency ratio shows how much the company is dependent on its creditors and is stable in a crisis situation when attracting foreign investment is difficult.

To verify the profitability and effectiveness of company management, the following indicators were selected:

- ROE — is the ratio of net profit to equity. This index allows to evaluate the effectiveness of invested equity in the company. If the company functions well, this indicator should be more than 1;
- ROA (Return on assets) — is the net profit ratio to all company assets. The ROA allows to evaluate what net profit each unit of assets can make. This ratio makes it possible to evaluate the effectiveness of the company's management.
- ROS (Return on sales) — is the ratio of net profit to company revenue. ROS is another important indicator for evaluating the performance of a company. It allows to compare the profitability of firms within one industry.

The indicators reflecting liquidity (*curLiq*), solvency (*SvsO*) and the company's profitability (ROE, ROA, ROS) became even more significant for construction companies after the new amendment to Federal Law dated 01.07.2018 No. 214-FZ. The above ratios reflect the company's ability to pay for its obligations on time and effectively manage the invested funds.

Let us check some hypotheses about the influence of non-financial indicators on the probability of bankruptcy of a company. For example, B.B. Demeshev and A.S. Tikhonova

(2014) tested the following hypothesis: the older the company is, the lower the probability of bankruptcy is [19]. The age of the company can really play an important role in its functioning. Having completed another project, construction organizations will potentially have a more own funds to be spent on business development. This can reduce the company's dependence on external financing and reduce the probability of bankruptcy.

Another hypothesis is the negative relationship between the size of the company (comp_size) and the probability of bankruptcy. For small companies or the ones that just start their development is extremely difficult to attract credit funds for the projects. Many of them may bankrupt due to lack of own funds to meet their current obligations.

To check the relationship between the probability of bankruptcy and the size of the company, a revenue logarithm indicator (ln-Revenue) was introduced. As the revenue generated by companies from the sample varies greatly between the firms, the logarithm of this indicator was taken to simplify the interpretation.

The econometric model for assessing the bankruptcy factors of construction companies is as follows:

$$Y = F(\text{curLiq}, \text{SvsO}, \text{ROA}, \text{ROE}, \text{ROS}, \text{lnRevenue}, \text{comp_size}, \text{age}). \quad (3)$$

The probability of bankruptcy of an enterprise can be calculated by the following formula:

$$P_i = \frac{1}{1 + e^{-\left(a_0 + a_1 \text{curliq}_i + a_2 \text{SvsO}_i + a_3 \text{Roe}_i + a_4 \text{ROS}_i + a_5 \text{lnRevenue}_i + a_6 \text{ROA}_i + a_7 \text{comp_size}_i + a_8 \text{age}_i + \varepsilon_i \right)}}, \quad i = 1 \dots 526, \quad (4)$$

where P_i – is the probability of bankruptcy of the i -th company, α_0 is a constant value;

$\alpha_1 \dots \alpha_{10}$ – are parameter estimates obtained as average values for the sample;

ε_i – is an error of the log model, reflecting deviations of the actual value of the depend-

ent variable from the predicted value. It is generally taken to be zero.

BUILDING A LOGIT MODEL TO ASSESS BANKRUPTCY FACTORS OF CONSTRUCTION COMPANIES

To assess the impact of the selected ratios on the bankruptcy of construction companies, we use the Stata14 package to solve statistical problems. It helped build a logit model including all explanatory variables. *Table 1* shows the model obtained after constructing the regression.

The statistics above shows that almost all regression coefficients are significant at any reasonable level of significance. Significant variables include the ROA and age.

The ROA may be insignificant since potential bankrupt companies already experience financial problems a year before the default. They start selling off their assets as they hope to get over the crisis. By doing so, businesses can overestimate the ROA.

The age index also relates to insignificant variables and shows how long the company exists. This result can be obtained due to the ambiguous influence of the age of the company on its financial stability and management efficiency. On the one hand, the older the company is, the more counterparties it has acquired within its lifetime and the more orders it may have. On the other hand, a large number of acquired relationships can also have a negative effect on the company's activities. Due to the loyalty between the company and its constant counterparties, the effectiveness of payment and debt management decreases. This may lead the company to increase late payments and to bankruptcy proceedings if the relations with the counterparties worsen. Therefore, the age of the company can have both positive and negative effects on the probability of bankruptcy of the company and is not significant.

The insignificant age and ROA variables were removed from the second stage of building the logit model. *Table 2* reflects the updated regression statistics.

Table 1

Logit model 1

```
. logit bankrupt sLiq SvsO ROE ROA ROS lnRevenue i.comp_size age
```

```
Iteration 0: log likelihood = -287.25978
Iteration 1: log likelihood = -203.61352
Iteration 2: log likelihood = -183.00905
Iteration 3: log likelihood = -179.7727
Iteration 4: log likelihood = -179.57507
Iteration 5: log likelihood = -179.5747
Iteration 6: log likelihood = -179.5747
```

```
Logistic regression                Number of obs    =      526
                                   LR chi2(9)           =     215.37
                                   Prob > chi2           =     0.0000
Log likelihood = -179.5747         Pseudo R2        =     0.3749
```

bankrupt	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
sLiq	-1.213096	.2926656	-4.14	0.000	-1.78671	-.6394814
SvsO	-.1557101	.0302781	-5.14	0.000	-.2150541	-.096366
ROE	-.3968591	.141142	-2.81	0.005	-.6734923	-.1202259
ROA	-.0806657	.1795676	-0.45	0.653	-.4326118	.2712804
ROS	-2.244519	.6220966	-3.61	0.000	-3.463806	-1.025232
lnRevenue	.2428741	.0616831	3.94	0.000	.1219775	.3637708
comp_size						
2	-1.052509	.2899157	-3.63	0.000	-1.620733	-.4842847
3	-1.954751	.4936351	-3.96	0.000	-2.922258	-.9872436
age	-.0180554	.027371	-0.66	0.509	-.0717016	.0355907
_cons	-2.999704	1.050806	-2.85	0.004	-5.059246	-.9401619

Source: calculated by the author.

Table 2

Logit model 2

```
. logit bankrupt sLiq SvsO ROE ROS lnRevenue i.comp_size
```

```
Iteration 0: log likelihood = -287.25978
Iteration 1: log likelihood = -204.96912
Iteration 2: log likelihood = -181.46575
Iteration 3: log likelihood = -179.90752
Iteration 4: log likelihood = -179.90087
Iteration 5: log likelihood = -179.90086
```

```
Logistic regression                Number of obs    =      526
                                   LR chi2(7)           =     214.72
                                   Prob > chi2           =     0.0000
Log likelihood = -179.90086         Pseudo R2        =     0.3737
```

bankrupt	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
sLiq	-1.242342	.2902214	-4.28	0.000	-1.811165	-.6735183
SvsO	-.155542	.0303183	-5.13	0.000	-.2149649	-.0961191
ROE	-.4197041	.1341943	-3.13	0.002	-.6827201	-.1566882
ROS	-2.283701	.6205705	-3.68	0.000	-3.499997	-1.067405
lnRevenue	.2403916	.0617658	3.89	0.000	.1193328	.3614503
comp_size						
2	-1.049589	.2886773	-3.64	0.000	-1.615386	-.4837917
3	-1.921264	.4889267	-3.93	0.000	-2.879543	-.9629856
_cons	-3.072688	1.028905	-2.99	0.003	-5.089304	-1.056072

Source: calculated by the author.

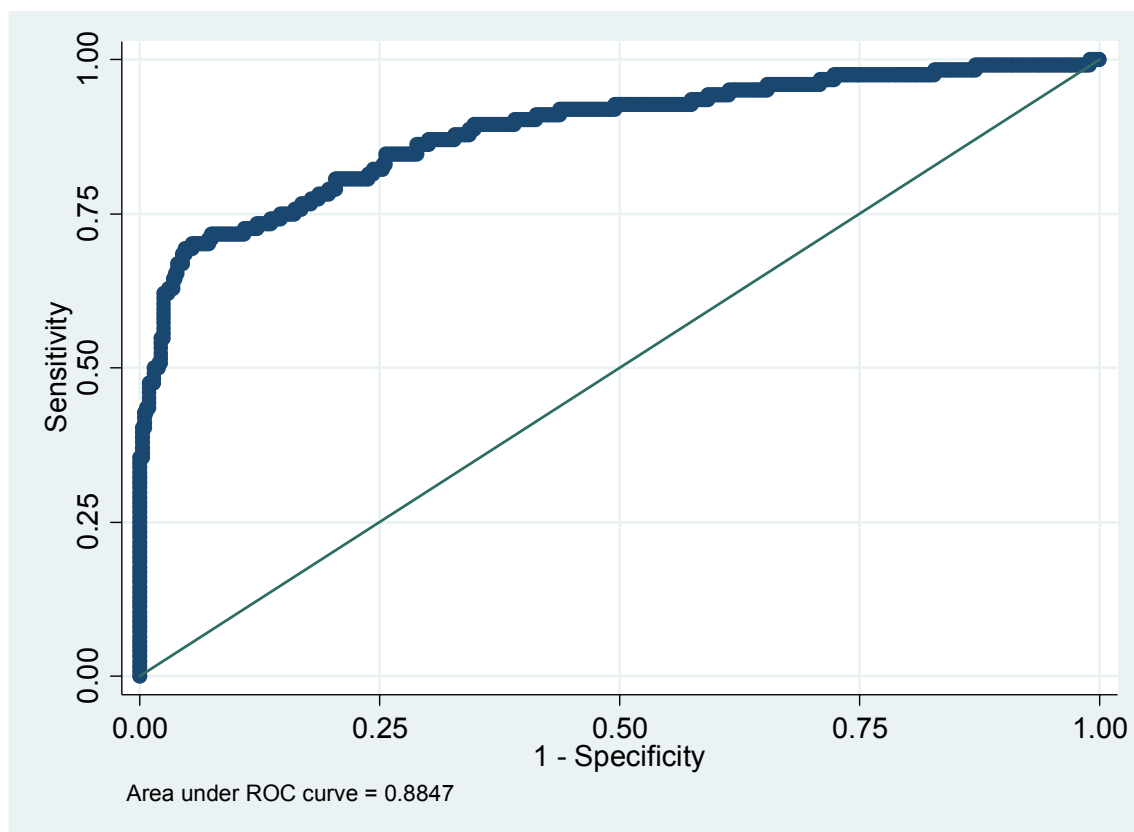


Fig. 3. ROC-analysis

Source: compiled by the author.

After the ROA and age variables were excluded, all remaining coefficients turned out to be significant at any reasonable level of significance.

The quality control procedure of the binary specification was also verified. ROC analysis suits here. When conducting this test, the main attention is paid to the AUC indicator considered as the area of the figure located under the ROC curve and can be calculated by the formula:

$$AUC = \int f(x) dx = \sum_i \left[\frac{X_{i+1} + X_i}{2} \right] \times (Y_{i+1} - Y_{i+2}). \quad (5)$$

Fig. 3 shows the ROC curve and the value of the AUC.

The AUC was 0.8847, which is close to 1. The classifier turned out to be qualitative. The AUC indicator can be interpreted as follows: a randomly selected bankrupt company with a probability of 88.47% will be evaluated by the

classifier of the model higher than a randomly selected existing company.

To check our assumptions and the influence of each coefficient on the probability of bankruptcy of companies, the marginal effects were calculated. The results are presented in Table 3.

According to the results, the ROS (return on sales) coefficient in the logit model has the greatest impact on the probability of bankruptcy of construction companies. An increase in the ROS variable by one base unit reduces the probability of bankruptcy by 22.3%. The specifics of the construction industry include a high share of cost in sales. Here, the relationship between the control of the structure and volume of expenses and the financial sustainability of the construction organization is quite obvious. Continuing increase in new orders in most efficient operating companies allows to increase the revenue growth rate com-

Table 3

Marginal effects calculation

	Delta-method				[95% Conf. Interval]	
	dy/dx	Std. Err.	z	P> z		
sLiq	-.1215719	.0226323	-5.37	0.000	-.1659303	-.0772135
SvsO	-.0152209	.0032094	-4.74	0.000	-.0215111	-.0089306
ROE	-.041071	.0125199	-3.28	0.001	-.0656096	-.0165324
ROS	-.2234761	.0782119	-2.86	0.004	-.3767687	-.0701836
lnRevenue	.023524	.0059113	3.98	0.000	.011938	.03511
comp_size						
2	-.1264242	.0386485	-3.27	0.001	-.2021738	-.0506746
3	-.1748416	.0410354	-4.26	0.000	-.2552694	-.0944137

Source: calculated by the author.

pared to the cost growth rate due to the effect of production leverage.

The size of the company may influence the probability of bankruptcy. One can see that the comp_size variable is categorical. The sample includes three types of companies: micro, small and medium. The limiting effect for this type of variable is interpreted as follows: how much the dependent variable changes when moving from one category to another. Table 3 shows that micro-companies were considered for the base category. If the company is small, then the probability of its bankruptcy is 12.6% lower than that of a micro-enterprise. Based on these results, medium-sized enterprises are least affected by bankruptcy. The probability of their default is 17.5% lower than that of microenterprises. In most cases, medium-sized companies have more equity than small organizations. As a result, medium-sized companies have a greater resource for paying off their obligations and investing in new projects than small and micro-enterprises.

Also, the current liquidity has a fairly strong effect on the probability of bankruptcy of construction companies. If this ratio increases by one, the probability of bankruptcy decreases by 12.2%. Current liquidity reflects the company's ability to pay its current liabilities as soon as possible. Many contractors working with construction companies, includ-

ing credit organizations, are guided by this indicator. Therefore, the greater the current liquidity indicator of a company is, the fewer signs of bankruptcy it has.

The ratio of equity to all liabilities also turned out to be significant. If this indicator increases by one, the probability of default decreases by 1.5%. Indeed, if a company takes on too many obligations (the SvsO coefficient decreases), then it risks not to pay it on time and become financially insolvent.

ROE (return on equity) is the second significant coefficient of profitability. If return on equity increases by one base unit the company's chance to become bankrupt decreases by 4.1%. ROE is an extremely important indicator for attracting investments and evaluating policies pursued by the company management.

The last significant indicator in the considered logit model is the natural logarithm of revenue (lnRevenue). If this indicator increases by a unit, it increases the probability of bankruptcy by 2.4%. Despite the fact that the size of the company is in negative correlation with the probability of its bankruptcy, this dependence can be explained. An increase in construction revenue means more likely an increase in receivables than an increase in cash flow during the observation period. However, it always means the growth of short-term obligations that must be paid. This fact provokes

Table 4

Values of variables for JSC "BALTSTROY"

Significant coefficient	Value
sLiq	0.999451
SvsO	0.016284
ROE	-5.52443
ROS	-0.56243
lnRevenue	20.89492
comp_size	3

Source: compiled by the author.

further research on the impact of the dynamics of revenue volumes and financial stability of construction organizations.

Let us test the predictive ability of the logit model on a real company that faced the problem of bankruptcy. For example, JSC "BALTSTROY" company, whose financial statements are presented by the electronic resource Spark. In August 2018, the Arbitration Court of St. Petersburg and the Leningrad Region introduced a monitoring procedure for this company as part of the bankruptcy proceedings of this company.

Due to the real financial statements of JSC "BALTSTROY" for 2017, we can check whether the logit model built in this work is applicable for predicting bankruptcies of construction companies in practice. Therefore, for the selected company, the coefficients significant in the model should be calculated. Table 4 shows the values of these indicators for JSC "BALTSTROY".

We substitute these values into formula (4) to calculate the probability of default of JSC "BALTSTROY" one year before its actual bank-

ruptcy. The results of the calculations are following:

$$P = \frac{1}{1 + e^{-\left(-3.073 + 1.243 \times 0.999 + 0.156 \times 0.016 - 0.42 \times (-5.524) - 2.284 \times (-0.562) + 0.24 \times 20.89 - 1.92 \right)}} = 0.92.$$

As a result, the probability of bankruptcy of JSC "BALTSTROY" one year before the monitoring procedure by the Arbitration Court of St. Petersburg and the Leningrad Region is 92%.

It can be concluded that the constructed logit model really has rather high predictive qualities and can be used to assess the probability of bankruptcies of construction companies in practice.

CONCLUSIONS

The proposed bankruptcy prediction model for construction companies is highly reliable in predicting their potential financial insolvency. The logit model is characterized by simple calculations; the explanatory variables have a strong logical relationship with the financial

activities of construction organizations, considering the industry specifics. Moreover, the model allows including new significant variables, non-financial ones, based on the individual working conditions of specific organizations. This circumstance adds an applied character to the presented logit model for predicting bankruptcy.

It should definitely be noted that the sample used in this article is limited. Today, according to Spark, there are more than 200 thousand companies in Russia involved in the construction of residential and non-residential buildings. This study included only 526

construction companies into the sample. The database spread-out can potentially change the significance and marginal effects of some coefficients and be more accurate in reflecting the situation on the Russian construction market.

Nevertheless, the logit model presented in the article has good predictive characteristics both at the level of medium and small enterprises. It helps assess the chance of bankruptcy of construction enterprises considering the scale of their activities. There are plenty opportunities for further research that can improve this model.

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ABOUT THE AUTHOR



Aleksandr V. Voiko — Cand. Sci. (Econ.), Associate Professor, Department of corporate finance and corporate governance, Financial University, Moscow, Russia
AVVoyko@fa.ru

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