

The Evaluation and Prediction of the Viability of Construction Enterprises

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Abstract

This paper provides a comprehensive method for the evaluation of a company. Specifically, it concerns the prediction of the viability of Czech construction companies. The construction industry is a very specific industry. This is primarily due to the nature of the product. The use of many production factors to convert to a form (a house, a factory building, etc.) is assumed. Each contract of a construction company (apart from the exceptions) is usually unique. In addition, the field produces long-term assets. As the generic name suggests, the product is used by a consumer (a household or firm) over a long period of time. Such a product is seen to some extent as a consumer one in the consumer market. However, it enters the market of production factors in the form of fixed assets. Due to this fact, construction is usually a field which first inhibits its activity and suffers a loss in times of crisis. On the other hand, it also becomes the first field which enters a phase of growth after a crisis period. The offered method is not only a suitable tool for managers of individual companies, but it may indicate the stage of the economic cycle in the particular country or in a particular market at a correct selection of those monitored companies. The methodology of the formation in an offered model is applicable not only in the Czech Republic but it is also transferable to other countries in Europe and the world, where it will also be able to take into account the specifics of local markets, too, after its application.

Keywords: construction company, financial health of the company, bankruptcy and credibility models, binary logistic regression, discriminant analysis

Introduction

The world economy, as well as the Czech economy, has been going through an economic recession for several years. The recession was created by the crisis in the mortgage market in the USA approximately between 2008 and 2009 (some sources state even earlier date). It spread from there throughout almost all of the world; neither the EU nor the Czech Republic was spared.

The crisis, actually an economic recession, is proved by a drop in the economic growth or a decline of the state domestic product, followed by an increase in unemployment, but it also is involved with changing the attitudes and moods of the country's population. The economy, previously drawn by a household demand, stagnates or falters and people, who are already nervous due to the negative news about the development of the world as well as the European and Czech economies, wait whether to see if there will be any change.

However, in the case of growth, which was driven by a household demand and a trend towards consumerism and spending, the situation is much more complicated because it concerns a change of the mood and the psyche of these households. Currently, there is another serious problem that we can identify in relation to the European Union. Even in the event that the Czech Republic had a tendency to increase its demand and thus the growth of the economy, the country is bound by the mood of the inhabitants of the neighboring countries.

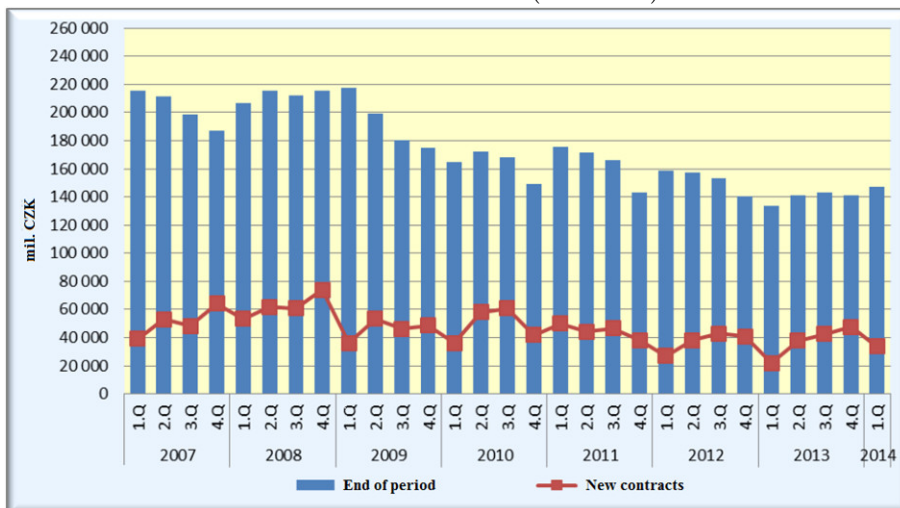
At the time when the economy of one of 27 EU Member States has been faltering, it is not such a disadvantage. These economic ties, on the other hand, can be positively seen as a stabilizing factor. At this moment, when the recession extends almost within the entire EU, the situation is more complicated since, on the contrary, the often very complex ties tend to apply a certain rigidity of the system. We should try to revive the system, which has a downward trend, rather than preserving or stabilizing this downward trend. The question is whether the right driving force of the economy is a household demand. As it follows from the discussions of the experts, it is not probable. The first impulse, which says that the economy is growing or declining, is a development of the construction sector in a given state. It is doubly true for the Czech Republic, especially when taking into account the fact that a historically maximum of the construction enterprises went bankrupt in the year 2012 (MPO, 2013). This, in itself, may indicate that a return to the growth will be relatively long and complex.

However, all of the data should be monitored in both space and time. Table No 1 shows the development of the value of the construction contracts in the Czech Republic in millions of Czech Crowns.

The value of the contracts of construction companies has been continuously declining from 2007 until the fourth quarter of 2013 (MPO, 2014; MPO, 2013). Subsequently, there is a slight increase in the total sum of these contracts in the first quarter of the following year (MPO, 2014b). However, this cannot be said for new contracts. Thus, the data show a certain correlation between the bankruptcies of construction companies and in the volume of contracts in the industry over time. It is possible to deduce that the situation is not likely to change in the near future from the trend of these contracts.

Construction companies are subjected to high pressure, to which they respond with savings within their operation by searching for new markets and with increasing the efficiency of their financial management, of course.

Table 1: The value of construction contracts (CZK mil.)



Source: The Data from the Czech Statistical Office , a figure of the Ministry of Industry of the Czech Republic (MPO, 2014b)

In practice, there are a number of methods that are employed when assessing the financial situation of a company. Bankruptcy models, value models, the economic added value, the market added value, benchmarking methods and others are employed. Most of these methods, however, do not respect the specifics of the construction industry and building businesses.

Bankruptcy models have a great potential. It should be noted that they are currently used more as a supplement of financial analyses. Although they work with relatively accurate data, their structure assumes a certain inaccuracy. This is mainly caused by a used database and by employing the data from companies of many sectors.

This paper therefore aims to create a bankruptcy model that will be used exclusively for the evaluation of construction enterprises.

The Analysis of the Current State of the Researched Problem

One dimensional discriminant analysis was used in the construction of the first bankruptcy models (Mohd-Sulaiman, 2013; Ho, McCarthy, Yang and Ye, 2013; Korol, 2013). Bankruptcy models were subsequently able to provide information on whether a particular enterprise is able to survive any financial distress or whether it is heading for bankruptcy. Then the use of multiple discriminant analysis spread and it was followed by a logit analysis (Altman and Saunders, 1998). Many classical statistical methods have been developed and described by these authors: Altman and Saunders (1998), Altman (1984), Taffler (1984), Jones (1987), Keasey and Watson (1987), Ooghe and Balcaen (2002), Dimitras, Zanakakis and Zopudinis (1996), Altman and Narayanan (1997).

Currently a logit analysis, a probit analysis and linear probability models are also employed. These methods are used in the development of models of the evaluation of conditional probability (Douplos and Zopoudinis, 1999). They consist of a combination of variables, with the best possibility to discern those failing enterprises within groups or, conversely, those which are able to survive any financial hardship. The nonlinear maximum likelihood estimation of the logit analysis was used to estimate the parameters of the following logit model (Hosmer and Lemeshow, 2000; Gujarati, 2003; Meloun, Militký and Hill, 2005):

$$P_1(X_i) = \frac{1}{1 + \exp - (B_0 + B_1X_{i1} + B_2X_{i2} + \dots + B_nX_{in})} = \frac{1}{1 + \exp - (D_i)}$$

where $P_1(X_i)$ = probability of failure with regard to the vectors of attributes X_i ;
 B_j = attribute coefficient j , for $j = 1, \dots, n$ and B_0 = limited section,
 X_{ij} = attribute values j (for $j = 1, \dots, n$) for company i ,
 D_i = "logit" for company i .

Material and Methods

The data set consists of the absolute and relative indicators of those companies operating in construction (section F classification CZ-NACE) in the years 2003–2012, i.e.:

- Building Construction:
 - o Development activity.
 - o Construction of residential and non-residential buildings.
- Civil engineering:
 - o Construction of roads and railways.
 - o Construction of engineering networks.
 - o Construction of other buildings.
- Specialised construction activities:
 - o Electrical, plumbing and other construction installation activities.
 - o Completion and finishing work.
 - o Other specialized construction activities.

The file was generated from the Albertina database and it contains 67,492 recording lines. Each row contains 191 characteristics of each company. These are the statements from the financial statements (balance sheet data, income statement and statement of cash flows), non-financial indicators and ratios.

The following assumptions will be considered in order to create the method:

- It will be a bankruptcy model (the enterprise development will be evaluated in two variables: the survival of the company or the tendency to bankruptcy. A dependent variable will be only 0 or 1).
- Absolute indicators will be used for the model (but I will assess the potential relevance of selected ratios when creating the method).
- Analyzed data do not follow a normal distribution.
- A development of a model is an iterative process that is cyclically repeated by the efforts for an improvement.
- The analyzed sample is a representative specimen of the population surveyed.
- The goal is to create a model that is as simple as possible that explains sufficiently enough of the behaviour of the dependent variable. The dependent variable is of a binary character.
- The model will have some generalizing properties; it can be used for predicting (the efficiency of classification into groups would be better than the one with a by chance basis, i.e. the classification efficiency should be higher than 50%).
- The quantitative variables of the discrete nature (e.g. the number of the employees) will be regarded as a continuous variable (a used software does not enable a better access).
- Each model is inadequate or inaccurate to a certain extent and it distorts the reality, but some models are (or can be) more useful than others.

The Mathematical Model of the Assignment Problem

The focus will be given to the nature of the problem only on the so-called binary logistic regression. In this case, the value of a dependent variable takes only two conditions. In the case of the binary variable in our context, it will be the dependent variable, defined as:

$$Z = \begin{cases} 1 & \text{if a result ends in the success} \\ 0 & \text{if a result ends in the failure} \end{cases}$$

with probabilities of $\Pr(Z = 1) = \pi$ and $\Pr(Z = 0) = 1 - \pi$. If we have an n of such mutually uncorrelated variables $Z_1, Z_2, \dots, Z_n$, where $\Pr(\text{Rev} = 1) = \pi$ for $j = 1, 2, \dots, n$, the random variable Y can be defined; it will be represented by the sum of all n random variables Rev , $j = 1, 2, \dots, n$. A variable Y represents the total number of “achievements” in the n performed experiments. The density probability of a variable Y , ie. a probability function, is possible in this case note as:

$$Pr(Y = y) = \binom{n}{y} \pi^y (1 - \pi)^{n-y}, y = 0, 1, 2, \dots, n.$$

Certainly, one can imagine a more general situation in which can be obtained n of such values $y_1, y_2, \dots, y_n$ by performing experiments and observations. These values represent a number of "achievements" in the n various groups. The individual groups themselves may vary in different conditions of our experiment, i.e. values of predictors (in our approach to various indicators of financial statements).

If we want to study subsequently the relative frequency of "achievements" in different groups depending on various explanatory variables, we can use generalized linear models to determine the probability of π_i by the model:

$$g(\pi_i) = \beta' \mathbf{x}_i.$$

The symbol $\mathbf{x}_i$ here is the column vector of explanatory variables for the i -th observation, a β column vector represents search parameters. The function $g(\cdot)$ then presents the so-called linker, or the binding function (Meloun, Militký and Hill, 2005).

The simplest method of predicting the relative frequencies of success lies in the assumption that the so-called canonical linker function $g(\cdot)$ is an identical function. A classic linear model in the form of $\pi_i = \beta' \mathbf{x}_i$ is obtained. It is not very suitable for the probability modeling as the predicted values may lie outside the interval $[0; 1]$. To eliminate the problems that arise when using a classical linear model, it is possible to use distribution functions where:

$$\pi = \int_{-\infty}^t f(s) ds$$

The probability density of an $f(s)$ is called the tolerance distribution. An appropriate choice of the tolerance distribution can reach e.g. a logit or probit model. In the case of the probability modeling it is likely to be advantageous to use the logit linker function and the model enter as:

$$\text{logit}(\pi(\mathbf{x}_i)) = \ln \left(\frac{\pi(\mathbf{x}_i)}{1 - \pi(\mathbf{x}_i)} \right) = \beta' \mathbf{x}_i$$

The objective of a logistic regression¹ consists in the modeling of the conditional mean of the dependent variable y at certain values of $\mathbf{x}$, i.e. via logistic functions. Formally, therefore:

$$E(y|\mathbf{x}) = \pi(\mathbf{x}) = \frac{\exp(\beta' \mathbf{x})}{1 + \exp(\beta' \mathbf{x})}$$

¹In essence, the name of the logistic regression is derived from the so-called linker function (the so-called logit transformation of the dependent variable is employed)

In order to estimate the unknown parameters of the logistic model, denoted by a symbol β , the method of maximum likelihood can be used. Its principle can be expressed as follows. When considering a pair of measurements, which are obtained by observation or experiment, i.e. $(\mathbf{x}_i, y_i)$, then the contribution of the information contained in this observed pair to the likelihood function can be expressed as:

$$\pi(\mathbf{x}_i)^{y_i} [1 - \pi(\mathbf{x}_i)]^{1-y_i}$$

as variables $y_i \sim \text{Bi}(1, \pi(\mathbf{x}_i))$. If we further assume that the individual measurements are independent of each other, then the likelihood function can be expressed as the product of all these contributions, since it is in essence the associated probability function, i.e. we obtain the following likelihood function:

$$l(\beta) = \prod_{i=1}^n \pi(\mathbf{x}_i)^{y_i} [1 - \pi(\mathbf{x}_i)]^{1-y_i}$$

Results and Discussion

The Preparation of the Data File

The division into the training and testing parts, according to the businesses, was carried out. The variables “test” and “sample” were added. We also added the variable “bankruptcy” which acquires the value 0 provided that the business is not declared bankrupt, and which acquires the value 1 provided that the business is declared bankrupt or going into liquidation.

The Primary Screening of the Variables

According to the methodology, we subsequently eliminated the variables with no links to the variable “bankruptcy”, i.e. the variables which did not contribute to the discrimination between well prospering and not prospering businesses.

Firstly, we carried out a set of tests whose objective was to reveal the variables which did not depend on the variable bankruptcy yes(1)/no(0). We eliminated the variables with insufficient number of observations at the next stage.

Afterwards, the overly correlated variables were removed and a correlogram was created. We also removed the variables of a purely categorical character for the model creation itself, which did not enter into the analysis, in order to make the final file in the smallest possible way. We created the data matrix in this way, which was subsequently used for the final model creation.

The Model Creation

A logistic regression was carried out. It was necessary to analyse the results, above all using the tests of the significance of the regression coefficients. Subsequently, suitability and predication qualities of the model were evaluated.

Firstly, the likelihood-ratio test type 1 and 3 were performed. The results of the second one are indicated in table No. 1.

Table 1 Likelihood-ratio test type 3(significant values only)

Effect	Bankruptcy-Likelihood-ratio Test type 3 (data) Division:BINOMIAL, link function: LOGIT Modelled probability bankruptcy=0			
	Degrees of freedom	Ln-likelihood	Chi-square	p
Unbilled revenue	1	-5444.37	4.84539	0.027720
Current assets	1	5454.39	24.88395	0.000001
Original capital – CZK K	1	-5444.27	4.64226	0.031194
Bank loans and accommodation (short-term)	1	-5462.30	40.70408	0.000000
Output consumption – CZK K	1	-5454.34	24.79270	0.000001
Change in reserves and provisions relating to operating activities and complex costs	1	-5456.04	28.19159	0.000000
Total financial cost	1	-5445.35	6.80446	0.009093
Cost to the government	1	-5444.00	4.10276	0.042813
Instant liquidity	1	-5448.62	13.35169	0.000258
Labour productivity of personnel – CZK K/month	1	-5456.07	28.24996	0.000000
Quick test	1	-5459.75	35.61390	0.000000
Ratio of receivables to assets - %	1	-5448.31	12.72688	0.000360
Ratio of financial assets to assets-%	1	-5460.68	37.46638	0.000000
Other liabilities in the ratio of liabilities-%	1	-5444.54	5.19664	0.022631

Note: In order to simplify, the table contains only the items that are important for further solution of the logistic regression.

Source: Authors

The regression coefficients were estimated as the last ones. The actual values are indicated with the individual items in table No. 2.

Thereafter, a repeated choice of variables was carried out. All the variables with insignificant regression coefficients were eliminated from the analysis. Each of the three tests marked some coefficients as significant and, on the contrary, some others as insignificant. It is then essential to incorporate all the significant coefficients from all three tests into the analysis.

The final model for the evaluation of the viability of construction enterprises has the following form: $\text{logit}\pi(\mathbf{x}_i) = \log \frac{\pi(\mathbf{x}_i)}{1 - \pi(\mathbf{x}_i)} = \hat{\beta}'\mathbf{x}_i = -2.78018 + 0.02346 \times \text{Number of employees}_i + 0.98379 \times \text{Profit/Loss}_i - 0.00004 \times \text{Actual capital-K CZK}_i - 0.00005 \times \text{Retained earnings of the recent years-K CZK}_i + 0.00013 \times \text{Short-term bank loans}_i - 0.00017 \times \text{Loan indebtedness-\%}_i + 0.00065 \times \text{Repayment period of debt from cash flow years}_i + 0.0004 \times \text{Gross cash flow liquidity-\%}_i - 0.01893 \times \text{Capital coefficient of total assets-\%}_i + 0.01352 \times \text{Ratio of receivables to assets -\%}_i + 0.01350 \times \text{Bank loans and accommodation in the ratio of liabilities-\%}_i$

Table 2 The estimation of the regression coefficients (significant values only)

Bankruptcy-Estimation of parameters (data) Division:BINOMIAL, link function: LOGIT Modelled probability bankruptcy=0								
Effect	Level effect	Column	Estimate	Standard error	Wald. Stat.	Lower LS 95%	Upper LS 95%	p
Absolute value		1	4.177385	0.088481	228.978	4.003965	4.350806	0.000000
Current assets		5	-0.000001	0.000000	16.547	-0.000001	0.000000	0.00004
Original capital – CZK K		6	-0.000001	0.000000	4.974	-0.000002	0.000000	0.02572
Bank loans and accommodation (short-term)		9	-0.000003	0.000001	32.287	-0.000004	0.000002	0.000000
Output consumption – CZK K		10	-0.000001	0.000000	25.119	-0.000001	0.000000	0.000000
Change in reserves		13	0.000010	0.000002	25.860	0.000006	0.000014	0.000000
Total financial cost		18	0.000005	0.000002	6.316	0.000001	0.000009	0.01196
Cost to the government		20	0.000005	0.000003	3.869	0.000000	0.000011	0.04918
Instant liquidity		25	0.000993	0.000244	16.487	0.000514	0.000514	0.00004
Labour productivity of personnel – CZK K/month		26	0.000594	0.000117	25.677	0.000364	0.000823	0.00000
Quick test		28	-0.132134	0.021764	36.859	-0.174792	0.089477	0.00000
Ratio of receivables to assets - %		30	-0.003107	0.000969	10.285	-0.005005	0.001208	0.00134
Ratio of financial assets to assets - %		31	0.008031	0.001330	36.438	0.005423	0.010639	0.00000
Other liabilities in the ratio of liabilities - %		33	-0.006266	0.002310	7.361	-0.010793	0.001739	0.00666

Note: In order to simplify, the table contains only the items that are important for further solution of the logistic regression.

Source: Authors

Table 3 the Goodness of Fit - Hosmer-Lemeshow Test (Part 1)

Bankruptcy – Goodness of fit: Hosmer-Lemeshow Test (data) Division:BINOMIAL, link function: LOGIT Hosmer Lemeshow= 116.23, p value = 0												
Response	Group1	Group2	Group3	Group4	Group5	Group6	Group7	Group8	Group9	Group10	Row Tot.	
0: Observ. Predict.	314	155	105	79	56	69	49	32	24	20	903	
	216	114	102	93	86	79	71	62	51	31		
1: Observ. Predict.	3812	3971	4021	4047	4070	4057	4077	4094	4102	4114	40365	
	3910	4012	4024	4033	4040	4047	4055	4064	4075	4103		
All groups	4126	4126	4126	4126	4126	4126	4126	4126	4126	4134	41268	

Source: Authors

Table 4 The Goodness of Fit - Hosmer-Lemeshow Test (Part 2)

		Bankruptcy-Goodness of fit statistics (model-zf) Division:BINOMIAL, link function: LOGIT Modelled probability Bankruptcy = 0	
Stat.	SV	Stat.	Stat/sv
Deviation	41235	8.165706E+03	1.980285
Deviation in scale	41235	8.165706E+03	1.980285
Pearson 's Chi2	41235	4.879660E+15	1.183378E
Scaled P. Chi2	41235	4.879660E+15	1.183378E
AIC		8.231706E+03	
BIC		8.516425E+03	
Cox-Snell R2		1.259661E-02	
Nagelkerke R2		6.634722E-02	
Log-likelihood		-4.082853E+03	

Source: Authors

On the basis of the sensitivity analysis, the threshold of 0.500997 was determined. The construction enterprises whose model value reaches 0.500997 or above will probably survive the potential financial crisis. Otherwise, they will have problems and go bankrupt in the case of a financial crisis.

The Validation of the Model on a Specific Case Solution in Practice

The quality of the model will be evaluated by means of the Hosmer-Lemeshow Test (in table No. 3 and 4), fuzzy matrix (in table No. 5) and ROC (The Received Operation Characteristic curve).

The P-value of the Hosmer-Lemeshow Test and the other characteristics indicate the suitability of the model.

The fuzzy matrices for the training data are indicated in table No. 5.

Table 5 The Fuzzy Matrices for the Training Data

Observation	Predicted YES	Predicted NO	Percentage of correct predictions
YES	13928	16	99.89 %
NO	285	9	3.06 %

Source: Authors

Let us examine the obtained fuzzy matrix in detail. There are predicted frequencies in lines and after that the frequencies on the basis of real observations of the data in the columns of this table. The inner elements of the fuzzy matrix – the contingency table has their established names:

- TP – True positive (Observed YES; Predicted YES) number of the correctly classified cases of the bankruptcy of the entity.
- FP – False positive (Observed YES; Predicted NO) number of the incorrectly classified cases of the bankruptcy.
- TN – True negative (Observed NO; Predicted NO) number of the correctly classified cases when the enterprise is without difficulties.
- FN – False negative (Observed NO; Predicted YES) number of the incorrectly classified cases when the enterprise is without difficulties.

On their basis, the relative indicators of the effectiveness of the classification are determined. The first indicator, and probably the most important one, is the so-called Accuracy which is defined as the sum of the absolute frequency of the main diagonal to the total number of classified.

Formally written as:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

As shown in Table No.4, the ratio in case of our model: $(13928+9) / (13928+9+16+285)=0.9901$, i.e. 97.89 %.

Other relative measures are as follows:

- The True Positive Fraction: the sensitivity which indicates the probability that our model will mark a really failing enterprise as a failing enterprise. The sensitivity can be obtained as follows:

$$TPF = \frac{TP}{TP + FN} = 54.38\%$$

- The False Positive Fraction: it is supplementary to the specificity and indicates the probability that our model will mark the enterprise as failing although it will be without difficulties in reality. The ratio as follows:

$$FPF = \frac{FP}{FP + TN} = 2.12\%$$

- The True Negative Fraction: it has become usual to use the name “specificita” in Czech, which indicates the probability that the model will mark the non-failing enterprise as not failing. The specificity can be obtained as follows:

$$TNF = \frac{TN}{FP + TN} = 97.88\%.$$

- The False Negative Fraction: it is supplementary to the sensitivity and indicates to what extent our model is not able to reveal the presence of the observed phenomenon, i.e. the bankruptcy of an enterprise. This indicator can be obtained as follows:

$$FNF = \frac{FN}{TP + FN} = 45.62\%.$$

The fuzzy matrix obtained on the basis of the training data gives a biased estimate of the effectiveness of the established model, since it is obtained on the basis of the training data that is used to the construction of the model. Therefore, it is important to use the validation data set. The fuzzy matrix for the validation part of the data is presented in table No. 6, from which it is apparent that the estimate of the classification effectiveness of our regression model makes (ACC) 97.824%.

Table 6 Fuzzy Matrix for the Validation Data

Observation	Predicted YES	Predicted NO	Percentage of correct predications
YES	40339	26	99.93 %
NO	872	31	3.43 %

Source: Authors²

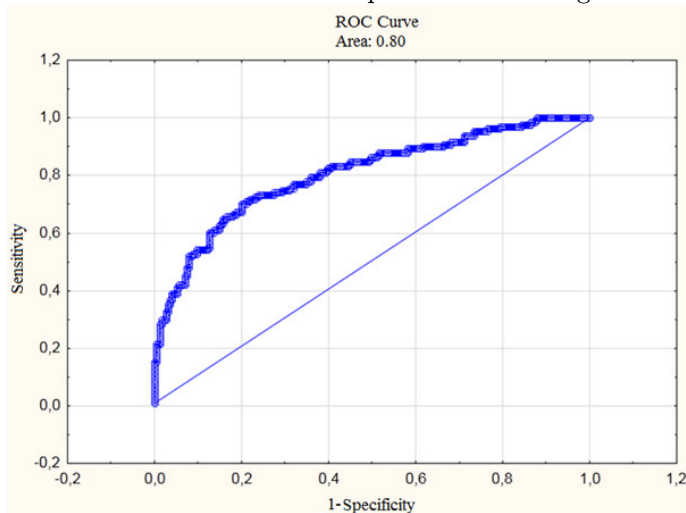
²Other characteristics are: TPF=36 %, FPF=2 %, TNF=98 %, FNF=64 %.

The Received Operation Characteristic Curve

Another possibility of evaluation of the predication abilities of our model is the so-called ROC curve.

Picture No. 1 presents the ROC curve for the training data base.

Picture 1 The ROC Curve Graph for the Training Data Base

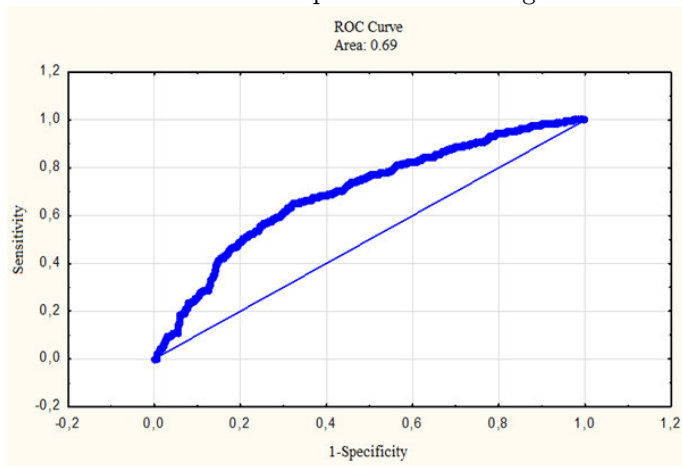


Source: Authors

The graph of the ROC curve model with null predication ability is the line segment connecting points $[0;0]$ and $[1;1]$.

Picture No. 2 presents the ROC curve for the validation data base.

Picture 2 ROC Curve Graph for the Training Data Base



Source: Authors

It is obvious that the predication ability of the model is influenced by the choice of the threshold to some extent. We can say that it is necessary to opt for such a threshold (substantially it is about probability) for which the relevant point on the ROC curve is as close as possible to the point with the coordinates $[0;1]$. Assuming the determination of the threshold values based on the validation data base, we would probably focus on the area of the highlighted rectangle because it is the closest to the point with the coordinates $[0;1]$.

From a visual perspective of the graph, it is possible to deduce that the ROC curve and the fuzzy matrix coincide, i.e. the efficiency model is on the level of 99.9%.

Conclusion

In the introduction and in the theoretical part of this paper, the problem and the need were redefined, or more precisely, the nationwide need of a solution. A method to easily predict the viability of a construction company in the Czech Republic does not exist yet.

Creating a new model for a comprehensive evaluation of construction companies is built on the principles of binary logistic (logit) regression. The assumptions of the model creation were defined; the procedure of the data analysis of the Czech construction companies as a prerequisite for creating the test file in order to validate the proposed model was described as well. After applying the chosen methodology, a model was found whose predictive power is high (97 824%). We can say with certainty that a model was created, or rather, a new method for evaluating the viability of the Czech construction companies was found. This tool is applicable to both the management of these companies, as a top indicator of business management, and the other interest groups (the stakeholders), the lender, the owner, the competitors and others. This model offers guidance on the methodology to prepare similar models in different countries of the world to some extent; (it is not possible to say that the developed model is generally applicable to the whole world), but the methodology is certainly applicable. If the predictive power of such models obtained by these models anywhere in the world is greater than 50%, then we can speak of a valid model. A model preparation for the individual countries of Europe or the world appears to be a challenge for a further solution. The new developed models ought to respect the local conditions.

If there is a connection between the development of construction enterprises and the entire economy, a newly constructed model applied to a correct sample file of the construction enterprises in a particular country can be understood as an indicator of future economic development. We will be able to indicate fairly accurately whether the economic crisis or boom is coming.

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