European Research Studies Journal
Volume XXIV, Issue 1, 2021 *pp. 99-116*

Corporate Failure Prediction of Construction Companies in Poland: Evidence from Logit Model

Submitted 20/12/20, 1st revision 15/01/21, 2nd revision 02/02/21, accepted 18/02/21

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Abstract:

Purpose: *This paper aims to develop a corporate failure prediction model for construction companies in Poland that allow assessing their financial situation and credit risk.*
Design/Methodology/Approach: *For this purpose, the following research methods have been used, descriptive and comparative analysis, subject literature review, and logit analysis. The Polish construction companies' financial data in this research come from the Emerging Markets Information Service (EMIS). To achieve the main goal of the research, the logit model was built. The significance test, error matrix, and ROC curve were used to assess the quality of the estimated binary logit model.*
Findings: *Based on the research, we identify seven financial indicators that significantly impact the probability of poor financial condition. The following variables are current assets turnover, debt to assets ratio, operating profit to assets, gross profit to assets, operating profit plus amortization to short-term liabilities, current assets to assets ratio, and equity to assets ratio. The research results show that corporate failure prediction models are interesting and important tools to assess the financial situation. Based on the developed model, it has been found that the growth of debts increases the credit risk of construction companies. Moreover, the increase in the share of current assets in the total assets harms the financial condition. Also, the risk of insolvency decreases with growing profitability measured by the rate of return on assets.*
Practical Implications: *The built logit model can be beneficial for investment loan providers, insurance companies, and entities selecting contractors in construction projects due to the possibility of the credit risk assessment.*
Originality/Value: *The use of logit models to identify statistically significant corporate failure prediction factors for construction companies in Poland.*

Keywords: *Bankruptcy, bankruptcy prediction, construction company, logit analysis, discriminant analysis.*

JEL classification: *G17, G33.*

Paper type: *Research paper.*

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1. Introduction

Construction is one of the fundamental industry sectors in the Polish economy. In 2017, the gross value added (at basic prices) of the construction sector was 7.3% of the Polish GDP (Eurostat, 2018), while the employment in this industry reached 5.8% of the total employment in Poland (Statistics Poland, 2018, p. 23). Considering the close connection of the construction and other sectors, some studies show that the impact is even stronger. For instance, according to the data from Deloitte and the Polish Association of Employers – Construction Materials Manufacturers (2016), in 2014, the construction sector (means as building materials and services) created around 20.3% of the Polish GDP (directly, indirectly, and in terms of profit) and 18.7% of employment.

For the Polish construction companies, understood as building contractors, 2017 was a record year in which the construction and assembly production value increased by 10.9% in terms of fixed prices compared with the previous year, reaching almost PLN 186.8 billion. The highest share in this value belonged to companies performing mostly specialized construction activities (40.8%), followed by enterprises engaged in construction buildings (35.1%) and civil engineering works (24.1%). In 2017, the highest construction and assembly production dynamics was reported by construction buildings companies and civil engineering enterprises (year-on-year increase by 20.7% and 18.6%, respectively). The value of specialized construction companies' production was rather stable throughout the analyzed period (Statistics Poland, 2018b). The good economic situation on the Polish construction market was mostly connected with continuing infrastructural investments, mostly road and railway building, co-financed by the EU, and with the high demand on the residential real estate market, mostly induced by low mortgage interest rates and rising salaries (Deloitte, 2018). The high rate of increase in building production continued in 2018. According to Statistics Poland (2019a) estimates, in 2018, gross value added in the construction industry rose by 17.0% compared with the previous year.

Paradoxically, strong recovery on the Polish construction market has brought several problems that companies have to face in this sector. First, due to the significant accumulation of performed construction projects and low supply on the labor market, construction companies face a huge workforce shortage. According to the estimates, the Polish construction sector requires around 150 thousand employees (manual workers and highly qualified personnel). Over the recent years, construction enterprises have made efforts to fill the staff deficit by employing Eastern European workers, mainly Ukraine and Belarus. However, by considering the liberal immigration policy in Germany, it seems that this staff's availability could reduce significantly. This problem may involve significant limitation of the executive potential in the analyzed companies, causing a delay in realizing construction projects (BIG InfoMonitor and PZPB, 2019; Deloitte, 2018). Furthermore, a low labor supply induced a dynamic growth of salaries in the construction sector. According to the data published by Statistics Poland (2019b, p. 45), in 2018, monthly gross wages and salaries in the analyzed sector rose by 8.1% compared to the previous year.

Additionally, high project supply in the period from 2017 to 2018 also affected the rapid increase in the prices of construction resources and materials. According to InfoMonitor Economic Information Bureau and the Polish Construction Employers Association (2019), changes in building materials and resources' prices reached 30 to 70% in the analyzed period. Such rapid price increase is hazardous for large and long-term infrastructure projects, as the real cost of their execution significantly exceeds the investment expenditures assumed in the budget. Because previously applied indexation clauses do not reflect the current scale of price increase on the construction market, Statistics Poland has decided to adjust indexation to the present situation. At the same time, new price indexation rules have been introduced for all road, and railway construction contracts concluded from February 2019 onwards (BIG InfoMonitor and PZPB, 2018; 2019).

Another source of financial difficulties for Polish construction companies is current changes in tax policy. They particularly concern value-added tax on goods and services (VAT), which is the basic fiscal tool that influences buyers' behavior (Kučerová, 2017). An essential solution in this field is the reverse VAT charge mechanism, which was applied from January 2017 to October 2019 for construction services. It consisted of shifting the VAT settlement responsibility from the contractor to the buyer. Thus, subcontractors issued invoices for services performed exclusive of VAT. It resulted in an escalation of payment delays, an increase in debt, and financial costs. It also harmed construction companies' financial liquidity (BIG InfoMonitor and PZPB, 2018; Kaczmarczyk, 2017; Krupa-Dąbrowska, 2018).

The other tax legislation change that affects the construction industry is the introduction of split payment from November 2019. Using that mechanism, payments for sold goods and services are split into two parts. One is the net value received on the seller's bank account, while the other is VAT tax registered on a dedicated VAT settlement account. Considering this solution's character, several issues have been identified in the fields of currency invoicing, collective payment, trust accounts, factoring, etc., (Piskor, 2018).

Another problem faced by construction companies in Poland is significant payment arrears (Dankiewicz, 2018). In 2018, their value increased up to approx. PLN 4.8 billion. Payment delays exceeding 30 days concerned almost 41 thousand entities (BIG InfoMonitor and PZPB 2018). It has been confirmed by the research on payments conducted by Coface. It showed that particularly long payment delays are typical for the construction industry, reaching approx—105 days as of the end of 2018 (Coface, 2019). By considering the debt of construction companies, can be concluded that foreign capital is a dominant finance source in their activity. The analysis confirmed the analysis focused on the industry's largest entities, which showed that the average proportion of debt and income was approx. 72% as of the end of 2017 (Deloitte, 2018).

The identified problems concerning the activity of construction companies harm their financial situation. A decrease in business profitability and an increase in debt are observed, which impairs financial liquidity (Otto and Śmietana, 2018; Pałys, 2018). Ensuring financial liquidity, which is differently interpreted in the literature (Allen and Bolton, 2004), but universally defined as the capability to extinguish financial liabilities promptly (Kropsz, 2010), is a vital issue in the possibility of continuing business in the market conditions. Its importance is mainly determined by the fact that the loss of such capability is deemed a basic symptom of a deteriorating financial situation, leading to bankruptcy (Boratyńska, 2009; Tomczak, 2014). In that connection, the problem of financial liquidity is an important aspect of the analysis concerning construction companies' financial situation (Daryanto, Samidi and Siregar, 2018; Bolek and Wiliński, 2012).

2. Review of Corporate Failure Prediction Models

The capability to predict financial difficulties in companies, and consequently, the possibility of bankruptcy, is an important issue for a broad group of entities in the current economic reality. The significance of this problem has been proven in several studies conducted in recent years, focused on developing tools to allow effective prediction of financial problems (Gissel, Giacomino, and Akers, 2007). The subject's literature usually defines two basic failure business prediction models: bankruptcy prediction models and financial distress prediction models.

However, it is difficult to provide a conclusive definition of corporate failure in practice and make a clear division between bankruptcy and financial distress (Balcaen and Ooghe, 2006; Alaka *et al.*, 2018). In this regard, this part of the paper shall describe the general financial approach to predicting financial problems (Cultrera and Brédart, 2016). The first attempts in this field were made in the 1930s and 1940s, among others, by Fitzpatrick (1932), Mervin (1942), Chudson (1945). It consisted of determining the method of selection of financial indicators and analyzing them. The period of intensive development in this area started with the studies conducted in the 1960s. Extending the indicative analysis with a dichotomous classification test (Beaver, 1966) and the use of multiple discriminant analysis (Altman, 1968) is worth mentioning at this point. Dynamic development of those models followed it, e.g., Deakin (1972), Blum (1974), Moyer (1977), Fulmer, Moon, Gavin, and Ervin (1984), Gombola *et al.* (1987), Pantalone and Platt (1987), Koh and Killough (1990), Patterson (2001).

Besides that, other tools were developed. In 1980, Ohlson (1980) presented a pioneer application of logit models in failure business prediction. Ohlson's solution has been used by several researchers, among others, Gentry, Newbold and Whitford (1985), Zavgren (1985), Aziz, Emanuel, and Lawson (1988), Platt and Platt (1990), as well as Willekens and Gaeremynck (2003). In 1984, Zmijewski (1984) initiated the use of probit analysis in the analyzed field. It was further developed by Dopuch, Holthausen, and Leftwich (1987), Skogsvik (1990), Lennox (1999), and others.

Nevertheless, many new tools applicable in failure business prediction have appeared and evolved in recent years (Mai *et al.*, 2019). These include the analysis of neural network (Messier and Hansen, 1988), especially artificial neural network (Li and Wang, 2018; Zhang *et al.*, 1999), data envelopment analysis (DEA) (Cielen, Peeters and Vanhoof, 2004), genetic algorithm (Varetto, 1998), support vector machines (SVM) (Min, Lee, and Han, 2006), classification and regression trees (CART) (Li, Sun, and Wu, 2010; Siemiński, Wędrowska, and Krukowski, 2020). On top of that, the popularity of hybrid models, created by using two other models that could be parametric and/or non-parametric (Lee, Han, and Kwon, 1996) and a particular interest in Bayesian, Hazard, and Mixed Logit models (Trabelsi *et al.*, 2015), is worth noting.

Detailed considerations on developing the tools listed above, allowing to predict financial problems, are included in (Gissel, Giacomino, and Akers, 2007; Bellovary, Giacominot, and Akers, 2007; Balcaen and Ooghe, 2006).

The problem of bankruptcy threat assessment among Polish enterprises was not initiated until the 1990s. The Polish economic environment's specifics forced the necessity to develop properly adjusted models that would provide a better prognostic value (Balina and Bąk, 2016). For this reason, over the last few years, several tools have appeared, mainly based on discriminant analysis, e.g., Pogodzińska and Sojak (1995), Hadasik (1998), Hołda (2001), Hamrol, Czajka, and Piechocki (2004), and logit analysis, e.g., Stępień and Strąk (2004), Wędzki (2005a), Jagiełło (2013). Nonetheless, other techniques have also been developed recently, e.g., Ptak-Chmielewska (2014), Pisula, Mentel, and Brożyna (2015), Pawełek and Grochowina (2017), Wójcicka (2017).

The newly introduced models form a quite diverse category, not only in terms of statistical methods used but also in other characteristics. One of these features is the single or multi-industry character of the research sample. What must be noted, the higher is the uniformity of the analyzed population, the better is the prognostic capability of the model. Other factors significant in this area are the given community's territorial background and the stability of model parameters in time. The limited territory of the analysis and passing time generally reduces prognostic capability (Wędzki, 2005b). Therefore, sectoral models are suggested, emphasizing the need for constant updating (Prusak, 2015; Iwanowicz, 2018).

Certain publications in the subject literature refer to the use of failure business prediction models for the construction engineering sector (Koksal, Arditi and Asce, 2004; Horta and Camanho, 2013; Karas and Srbovȧ, 2019). In Poland, the research on forecasting financial difficulties of local construction companies has been initiated by Wędzki (2005b), Wawrzyniak and Batóg (2013), Król and Stefański (2014), Rusiecki and Białek-Jaworska (2015). Considering the significance of this sector in the Polish economy and the recovery on the construction market observed in recent years, and the accompanying problems, it seems reasonable to continue the research in this field.

3. Research Methodology

The analysis has been performed using financial data concerning the entities from the construction sector in Poland, taken from the EMIS database. The research sample included 3641 companies. The sample's final size was determined after the preliminary analysis, which consisted of cleaning the data from outliers and empty values. The financial data was describing the business activity of construction companies in 2017. A complete set of financial indicators is presented in Table 1.

Table 1. *Variables Used in the Logit Model*

Designation	Description	Designation	Description
X1	Return on Assets	X10	Operating profit / Assets
X2	Return on Equity	X11	Gross profit / Assets
X3	Operating profit margin	X12	Quick liquidity ratio
	Current assets turnover	X13	(Net profit +
X4	Assets turnover		amortization) / Liabilities
	Current liquidity ratio	X14	(Operating profit +
X5	Cash ratio		amortization) / Short-term
X6	Debt to equity ratio		liabilities
X7	Debt to assets ratio	X15	Current assets / Assets
X8		X16	Net cash / Assets
X9		X17	Equity / Assets

Source: *Own creation.*

The relationships between the binary, dependent variable (Y) and the set of explanatory variables (X) can be analyzed based on classification models defined in the literature. Basic models used for classification problems are the linear probability model (like Goldberger's model - see Wiśniewski, 2013, 2016), logit model, Probit model, and other models appropriate for machine learning methods.

The binary variable is indicated on the nominal scale, where the values 0 or 1 are attributed to a certain problem. In this study, the binary variable has been defined as the occurrence of a threat of bad financial condition (Y=1) and good financial condition (Y=0) – which is the opposite situation. The threat of corporate failure in construction companies has been determined based on the value of three financial indicators, i.e., EBITDA (earnings before interest and tax, depreciation, and amortization), EBIT (earnings before interest and tax), and net profit. The condition assignment of zeros and ones to variable Y takes the following form.:

$$Y = \begin{cases} 1, if\ EBITDA < 0 \wedge EBIT < 0 \wedge net\ profit < 0 \\ 0, if\ EBITDA > 0 \vee EBIT > 0 \vee net\ profit > 0 \end{cases} \quad (1)$$

The definition of binary variable Y is consistent with one proposed by Platt and Platt (2006). The authors pointed out that companies with reported negative values of EBITDA, EBIT, and net profit, are threatened with a bad financial condition, increasing the probability of bankruptcy.

The full research sample takes the value of 3641 companies, of which 347 companies were threatened with the bad financial condition (Y=1), while the other rest 2185 companies were in a good financial situation (Y=0). These companies have been selected based on the definition mentioned above. The data collected for the study were randomly divided into three subsets – training set, validation set, and testing set. The training dataset is used to train the logit model. This dataset is the largest and contains 70% of the available data. The validation dataset and test dataset are smaller, and each of them contains 15% of the available data. Evaluation of the model will be carried out based on the validation data set. The test dataset is used to obtain unbiased error estimates.

To explain the variability of variable Y, the logit model is used. The logit transformation allows replacing the limited probability interval 〈0,1〉 with unrestricted interval 〈-∞, + ∞〉 (Wiśniewski, 2016). Due to the Y variable's existing limitation, methods for the limited dependent variable must be applied. The linear probability model (LPM) is not appropriate, because probability values in this model go beyond the interval 〈0, 1〉. The LPM model can be used for preliminary analysis of the impact of explanatory variables on the probability of a defined event. Logit models are like Probit models. Both types of models can be used to solve the same problem. Hence, there is a relationship between them, and to analyze a selected problem, only one model can be chosen. The relationship between the parameters of both models takes the following form (Amemiya, 1981, pp. 481-536):

$$\hat{\beta}_{logit} \approx 1{,}6\hat{\beta}_{probit} \tag{2}$$

Based on the values of parameters of one model, it is possible to determine the values of parameters in the other model using the formula above. Another limitation to using the Probit model is the assumption that probabilities for the Y variable have normal or close-to-normal distribution, which is hard to achieve.

The logit model has the following general form:

$$ln\frac{p_i}{1-p_i} = logit(p_i) = x_i'\beta = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} \tag{3}$$

where $ln\frac{p_i}{1-p_i}$ is logit, p_i is probability of specific event, β is vector of the model parameters. To estimate the value of vector β, the maximum likelihood method (MLM see e.g., Marzec (2003), Gruszczyński (2012) is used. In case of a sample containing separate observations $Y_1, Y_2, \dots, Y_n$ (where $Y_i = 1$, for *i*=1,2, …, *n*), and probability $P(Y_i = 1) = p_i$, the probability of observation of value $Y_i = 1$ or $Y_i = 0$ can be expressed as $P(Y_i) = p_i^{Y_i}(1 - p_i)^{1-Y_i}$.

Results should be interpreted considering the marginal effects and the odds ratios. The sensitivity of probability p_i to endogenous variables is the function of a given model parameter and all predictors. The marginal effect of the change X_j on the value of probability p_i takes the form:

$$\frac{\partial p_i}{\partial x_{ji}} = \beta_j \lambda(x_i'\beta) = \beta_j p_i(1 - p_i) \quad (4)$$

The odds ratios are exp(βˆ_j) values, where βˆ_j are estimated parameters of the logit model. Because the econometric model is not a perfect tool, the developed model's quality needs to be assessed to ensure that the model has cognitive features proper for the analyzed research problem. To verify the quality of the model, we can use the error matrix, which allows checking the predicted accuracy based on a model. Using the error matrix (Gruszczyński, 2012), the following model quality measures can be determined: sensitivity, accuracy, and specificity.

4. Results and Discussion

For the aim of the analysis, 17 financial indicators have been used in model building. The set of variables is used to describe the financial situation of a company. Gissel, Giacomino, and Akers (2007) used a similar set of variables to describe the problem of corporate failure. The list of financial factors is presented in Table 1. To find the best combination of financial variables for predicting company failure, we employ logistics regression analysis and GLM estimator (Generalized Linear Model). Then we use the a-posteriori method to establish the final set of financial variables. We used a z-test to diagnose the significant factors that affect the binary variable (Y). The logit model of corporate failure is presented in Table 2.

Table 2. *Logit corporate failure prediction model for construction sector companies in 2017*

Predictors		Parameter assessment	Standard error	z
Constant	1	-2.517	0,983	2.56
Return on Assets	X1	0,233	0,209	1,115
Return on Equity	X2	0,00008	0,0002	0,659
Operating profit margin	X3	0,00008	0,00008	0,939
Current assets turnover	X4	-0,616	0,279	-2,209 **
Assets turnover	X5	0,154	0,342	0,45
Current liquidity ratio	X6	0,011	0,012	0,941
Cash ratio	X7	0,02	0,059	0,331
Debt to equity ratio	X8	-0,00003	0,000001	-0,473
Debt to assets ratio	X9	-0,013	0,006	-2,014 **
Operating profit / Assets	X10	-19,63	5,145	-3,815 ***
Gross profit / Assets	X11	-53,785	20,44	-2,631 ***
Quick liquidity ratio	X12	-0,029	0,06	-0,494
(Net profit + amortisation) / Liabilities	X13	0,061	0,448	0,136

(Operating profit + amortisation) / Short-term liabilities	X14	-0,286	0,26	-1,098
Current assets / Assets	X15	0,805	0,659	1,222
Net cash / Assets	X16	-1,02	0,796	-1,282
Equity / Assets	X17	0,368	0,908	0,405

Source: *Own creation.*

Next step of analysis was the elimination of insignificant variables. The final logit model, which was used in interpretations and prediction is presented in Table 3.

Table 3. *Logit model after a posteriori elimination*

Logit model variables		Parameter value	Standard error	Odds ratio	z
Constant	1	-2,38	0,435	-	-5,472 ***
Current assets turnover	X4	-0,511	0,092	0,600	-5,578 ***
Debt to assets ratio	X9	-0,012	0,006	0,988	-1,997 *
Operating profit / Assets	X10	-18,284	4,947	0,00001	-3,696 ***
Gross profit / Assets	X11	-31,713	4,926	0,000001	-6,438 ***
(Operating profit + amortisation) / Short-term liabilities	X14	-0,263	0,147	0,769	-1,793 *
Current assets / Assets	X16	0,936	0,462	2,549	2,025 **
Equity / Assets	X17	-0,683	0,285	0,505	-2,4 **

Source: *Own creation.*

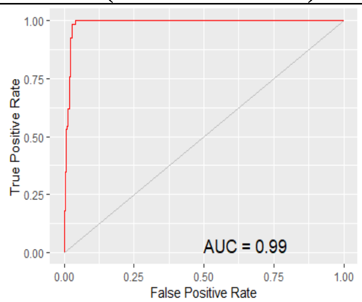
Based on the logit model, we identified the significant factors for the probability of corporate failure in construction companies. Seven out of 17 variables are significant for the probability of corporate failure at a significance level of at least p=10%. The factors affecting the variable Y include current assets turnover (X4), debt to assets ratio (X9), operating profit to assets (X10), gross profit to assets (X11), operating profit plus amortization to short-term liabilities (X14), current assets to assets ratio (X16) and equity to assets ratio (X17).

At this point, we can say that the probability of a corporate failure is decreasing when the company reports the increase in debt to assets ratio (X9), operating profit to assets (X10), gross profit to assets (X11), operating profit plus amortization to short-term liabilities (X14) and equity to assets ratio (X17). In the case of current asset turnover (X4), we can say that the increase in that variable is neutral for the probability of failure because the odds ratio is close to 1. However, the ratio of current assets to assets (X16) is the only variable that affects the probability of failure with a positive sign. It means the bigger value of the current assets to assets ratio, the bigger probability of financial failure. Also, the most important (according to the logit model) variables for reducing the probability of financial failure are the operating profits to asset ratio (X10) and gross profit to asset ratio (X11) (see Table 3).

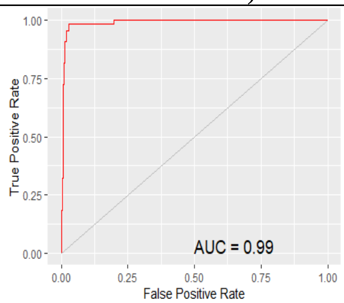
Then, the built logit model was assessed in terms of the use of new data. Using the validation and test datasets, the ROC curve was determined (Figures 1A and 1B), and the ratio of area under the ROC curve (AUC ratio) was calculated. These values make it possible to indicate the classification quality of the model. In the validation and test set case, the AUC value is 99%, which indicates the high classification quality of the constructed model.

Figure 1. *ROC curve and performance chart for logit model (case of validation and test data sets)*

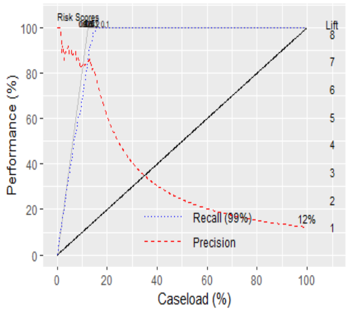
1A. ROC curve for logit model (validation data set)



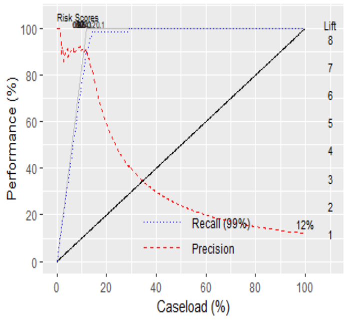
1B. ROC curve for logit model (test data set)



1C. Performance chart for logit model (validation data set)



1D. Performacne chart for logit model (test data set)



Source: *Own creation.*

In the classification problem, the classifier's quality (in this case, the logit model) is based on an understanding and measure of relevance. The relevance is measured with precision (positive predictive value) and recall (also called sensitivity). Based on that, we can say how many selected items are relevant and how many relevant items are selected (Durica, Valaskova, and Janoskova, 2019). Both measures are presented in figure 1, where the precision is marked in red, and the recall measure is marked in blue. The precision for the full sample of enterprises (the caseloads is equal to 100%) is equal to 12% (Figures 1C and 1D). This is because most of the companies included in the research have a good financial condition. On the other hand, the recall measure is equal to 99%, which means that in 99% of cases, the model (or classifier) correctly identifies companies with a bad financial condition. A detailed analysis will be carried out based on the error matrices presented in Tables 4A-4C.

Error matrix examines the classification model's ability to predict failure among a new set of companies (Durica, Valaskova, and Janoskova, 2019). Modeling companies' financial situation is an important factor for recognition of the early signs of deterioration of the financial condition. Micro-econometric models of financial threat are a specific group of models that should be considered in multiple fields, like the economy, analyzed sector, industry, and the time horizon. The purpose of the constructed model is to predict the future threats related to the deterioration of the financial situation in construction companies. The usefulness of the model is mainly connected with high sensitivity and specificity values that determine the proper classification capability of a given model. The quality of the model should be assessed based on the accuracy of the prediction of bad financial condition (Y=1) and good financial condition (Y=0) of construction enterprises (Table 4). The quality of the constructed classifier was assessed based on a training sample (Table 4A), a validation sample (Table 4B), and a test sample (Table 4C).

Table 4. *Error matrix for logit model (case of training, validation and test data sets)*

Table 4A.
Error matrix for training dataset

		Predicted	
		0	1
Empirical	0	2154 (85,1%)	31 (1,2%)
	1	61 (2,4%)	286 (11,3%)

Overall error: 3,6%
Averaged class error: 9,5%
Recall for *Y*=1: 82,4%

Table 4B.
Error matrix for validation dataset

		Predicted	
		0	1
Empirical	0	466 (86,0%)	10 (1,8%)
	1	7 (1,3%)	59 (10,9%)

Overall error: 3,1%
Averaged class error: 6,35%
Recall for *Y*=1: 89,4%

Table 4C.
Error matrix for test dataset

		Predicted	
		0	1
Empirical	0	474 (87,1%)	5 (0,9%)
	1	17 (3,1%)	48 (8,8%)

Overall error: 4,1%
Averaged class error: 13,6%
Recall for Y=1: 75%

Source: *Own creation.*

The most important measure, in terms of the developed model, is sensitivity (or recall). The recall is a fraction of the total amount of relevant instances that were retrieved. This means the recall measure indicates the percentage of construction companies with a company's correctly recognized status with a bad financial condition (Y=1). The sensitivity measure for the training dataset is equal to 82,4%. For the validation dataset, the sensitivity value has increased to 89,4%; however, this measure's test dataset value is equal to 75% (Table 4).

The logit model's cognitive value is determined based on the test data sample in which the error values in matrix error are unbiased and indicates that 3 out of 4 enterprises with bad financial conditions have been correctly identified by a classifier. The accuracy value for the logit model is 95.6%, which means nearly 96 percent of cases were correctly assigned to one group based on the applied set of predictors.

Comparison of the built model with others presented in the literature showed that there were only a few papers concerning a similar study subject. Król and Stefański (2014) developed several different discriminant functions for the Polish construction sector. The discriminant and logit analysis for bankruptcy prediction among the Polish construction companies has been applied by Rusiecki and Białek-Jaworska (2015). Their models showed overall efficiency exceeding 80%. The model was built based on 5 and 7 variables representing structural, profitability, debt, and liquidity indicators. Kapliński (2008) has noted that incorporate failure models, factors identified as significant allows assessing the symptoms of the financial condition of companies in a short period, while long-term analysis using that model was unreasonable due to changing economic situation (policy and accounting rules that have a major effect on financial results). However, as far as financial threat models are concerned, it is also more reasonable to use them in a short time perspective. For longer periods, political and economic conditions must be considered.

5. Conclusions

The logit corporate failure prediction model presented in this paper is a tool used to assess the financial condition of construction companies. Considering the growing payment arrears reported in the construction industry's recent period and the high significance of this sector and its relations with other sectors of the economy, the presented model might have a practical advantage. The model can be beneficial for investment loan providers, insurance companies, and entities selecting contractors in construction projects due to the possibility of the credit risk assessment. Most of the research on related topics is focused more on bankruptcy prediction models. In the context of rapid recovery in the Polish construction sector, it seems reasonable to identify the factors, which increase the probability of deterioration of the financial condition. The recognition of early warning signals is more important than the recognition of bankruptcy determinants.

The built model uses the following variables: current assets turnover, debt to assets ratio, operating profit to assets, gross profit to assets, operating profit plus amortization to short-term liabilities, current assets to assets ratio, and equity to assets ratio. The developed model is based on three financial indicators: profitability index, debt ratio, and structure index. The estimation of logit function parameters, analyzed in accounting and finances, allows formulating several conclusions. Above all, they confirm that debt increase is followed by a higher risk of deterioration in the financial and property situation. Additionally, a higher share of current assets in total assets harms the financial condition of construction companies. It seems to be rooted in this industry's specificity, distinguished by creating high-value stock, including materials, unfinished production, and unsold end products. According to the logit model estimation results, the risk of insolvency lowers along with the growing profitability measured by return on assets. Also, two out of seven factors (operating profit to assets and gross profit to assets) are significant in reducing poor financial condition probability.

The described model has been prepared based on the financial data of 2017, chosen due to the high availability of information concerning a wide group of Polish construction companies. The complete publication of data from financial reports of more recent years will allow verifying the prepared model and will be a starting point for further studies in this field.

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