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V РОССИЙСКИЙ ЭКОНОМИЧЕСКИЙ КОНГРЕСС

Том XIV

тематическая конференция

«ЭКОНОМИКА ФИРМЫ, ОТРАСЛЕВЫЕ РЫНКИ И ПРОМЫШЛЕННАЯ ПОЛИТИКА»

(сборник тезисов докладов)

Москва
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НОВАЯ ЭКОНОМИЧЕСКАЯ АССОЦИАЦИЯ
Институт экономики Российской академии наук, Уральский государственный экономический университет, Институт экономики Уральского отделения Российской академии наук, Уральский государственный горный университет, Уральский институт управления – филиал РАНХиГС, Центральный экономико-математический институт Российской академии наук и экономический факультет Московского государственного университета имени М.В. Ломоносова

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Сопредседатели Программного комитета
А. А. Аузан, В. М. Полтерович, А. Я. Рубинштейн

Составители:
Г. Б. Клейнер, И. Л. Любимов, Ю. В. Симачев

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Default prediction for auto repair firms using non-financial data

Introduction and a brief literature review.

Default prediction is conventionally performed with financial ratios as the predictors. This approach was proved to be efficient by numerous researchers, including works of Edward Altman (E. I. Altman, 1968), which is known as the founder of default prediction, and a lot of new research (Altman et al., 2010; Matenda et al., 2020).

However, as it is shown in (Afanasev, 2023), the financial ratios of Russian services firms may not reflect the real condition of the business, because of high level of shadow operations and business disaggregation. Thus, the quality of default prediction may be low for Russian services firms.

This study aims to discover:

- whether the latter statement is true for car repair industry;

- whether the quality of default prediction for car repair industry can be increased if one uses non-financial data as predictors along with financial ratios.

The use of non-financial data to predict defaults is still not a prevailing approach, despite the findings of those researchers who have attempted to explore this area are promising. The previous studies show great increase in accuracy (expressed in accuracy or the area under ROC curve) (Altman et al., 2010; Grunert et al., 2005; Wilson et al., 2016).

However, there is still a limited number of studies, devoted to non-financial variables as defaults predictors (in Russia in particular), and this study aims to fill this gap.

Data description

The dataset I used for modelling consists of firms under 45.2 OKVED (NACE Class 45.2 - Maintenance and repair of motor vehicles). The dataset consists of 2 groups of firms: those, which faced a default, and "healthy" firms (hereinafter – healthy peers), which have not faced a default.

To form the "healthy" dataset it was decided to pair every default firm with a random healthy peer, using the value of total assets as the matching criterion. It was decided to lower the sampling error risk by creating 10 groups of healthy peers and fitting the model 10 times to check if the results are consistent across different samples.

The dependent variable is a binary one: 1 if the firm is in the default group, 0 – otherwise. The list of independent variables consists of two groups: financial and non-financial.

The financial data was collected from SPARK INTERFAX database for private firms. The set of financial ratios was chosen to cover 4 groups of financial ratios: profitability, liquidity, solvency, turnover.

The set of non-financial variables includes the number of legal claims filed against the firm and the sum of these legal claims (in rubles), the number of inspections, the number of violations, found during the inspections, the number of won tenders, the number of changes in management or shareholders, the number of changes of location during 1 year before the theoretical forecast date.

To be sure that the model can be applied in reality, I used two approaches to choose the time period, for which the values of independent variables should be calculated. The first approach was to model the default prediction one year before the date of default (the "Year-before-approach"). In this case I took the data certainly available 1 year before the default. The theoretical forecast date is, thus, exactly 1 year before the default date. The second approach was to take the most recent available financial reporting on the default date to calculate the financial variables, which means that the theoretical forecast date is the date, on which this financial report is becoming available (in Russia it is 01 April). I call the second approach the "Last-available-financial-report-approach".

In the end, the total number of observations appeared to be 2712 under the "Year-before-approach" and 2240 under the "Last-available-financial-report-approach" (includes 1 default sample and 10 healthy peer samples).

The datasets were split into training and testing samples (80%/20%) randomly.

Classification algorithm

I chose Random Forest Classification algorithm, described in (Breiman, 2001) for the purpose of modelling because of two reasons. Firstly, this algorithm has shown high predictive accuracy in previous studies by several researchers (Barboza et al., 2017; Brown and Mues, 2012), including my previous research (Afanasev, 2023). Secondly, it is one of the few algorithms, which has an option to assess the contribution of the independent variables in the explanation of the dependent variable, which is a necessary option if one aims to understand, whether non-financial factors improve the accuracy of default prediction.

Results

The results show that the accuracy of the default prediction for Russian auto repair firms is low if one uses only financial ratios to predict the default. This result holds for both the "Year-before-approach" and the "Last-available-financial-report-approach". The mean accuracy of classification on 10 test sets is 62% and 64% respectively. The sensitivity (the accuracy of default firms identification) is much higher than specificity (the accuracy of healthy peers identification) (70% and 68% sensitivity depending on the approach and 54% and 60% specificity).

However, if one adds non-financial data to the model, the mean accuracy of default prediction on 10 test sets goes up by around 10 percentage points (72% for the "Year-before-approach" and 73% for the "Last-available-financial-report-approach"). Also, the sensitivity and specificity are both around 70-73%, which indicates better "balance" of the classification algorithm. The table below shows the summary of the results (metrics obtained on the testing data).

Table 1. Mean prediction quality metrics obtained from the developed models

	"Year-before-approach"			*"Last-available-financial-report-approach"*		
Metric	*Financial data only*	*Financial and non-financial data*	*Non-financial data only*	*Financial data only*	*Financial and non-financial data*	*Non-financial data only*
Accuracy	62%	71%	66%	65%	72%	71%
Sensitivity	71%	69%	52%	68%	71%	63%
Specificity	53%	72%	81%	61%	73%	80%
AUC ROC	0.68	0.78	0.69	0.71	0.82	0.75

Prepared by the author

Thus, the results show that non-financial factors (mostly legal claims and inspections related data) can significantly improve the quality of default prediction. The findings of this study can be of interest for credit organizations and the counterparties of auto repair firms in Russia.

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