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Analyzing Insolvency Drivers and Developing Credit Rating System for Small and Medium-sized Enterprises in Russia

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Abstract. Small and medium-sized enterprises (SMEs) play a key role in the Russian economy. However, banks and investors are reluctant to provide debt financing to these firms. This is underpinned by SMEs' speculative credit quality and information asymmetry between borrowers and lenders. In this study, we aim to identify the insolvency drivers of Russian SMEs and compare them with those in other markets. The relevance of the study is underpinned by the scarcity of research in this field and the high demand for an accurate rating system for domestic SMEs. Logistic regression was selected as the modeling method. The sample contained 177 non-financial domestic SMEs over the period 2015–2019. The set of explanatory variables consisted of firm-specific financial, categorical, and macroeconomic factors. An accuracy ratio of >80% was achieved. We found that, unlike those in Asian emerging markets, financial factors explained around 70% of domestic SMEs' credit health. Significant financial factors included profitability, debt leverage, and coverage ratios and the term structure of debt. Non-financial drivers included ownership of the firm by large businesses (or group of companies), firm size, and territory of operation within Russia. Among macroeconomic drivers, the unemployment level was the most significant driver of SMEs' credit quality. In addition, we developed a rating system for domestic SMEs and determined the relative benchmarks from Expert RA and Moody's agencies. We found that the existing scales of rating agencies did not provide the granular assessment of SMEs' creditworthiness. This confirmed our hypothesis that distinct rating frameworks and methodologies for domestic SMEs in the Russian market are imperative. As shown in the literature, the greater the rating granularity and transparency, the more enhanced the debt market's appropriate risk-return tradeoff analysis.

Keywords: Credit rating agencies; Insolvency drivers; Probability of default; Risk management; Scoring model; Small and medium-sized enterprises

1. Introduction

Small and medium-sized enterprises (SMEs) play an important role in the Russian economy as they contribute to accelerating economic growth and increasing employment. However, their development is limited by restricted access to long-term funding. The recently organized security offering platform in Moscow Stock Exchange (MOEX)–Growth Sector (GS)–is aimed to provide SMEs access to the domestic debt capital market. This platform is aimed at breaking the monopoly of banks, channel government support, and enable access to unsecured and long-term funds. Nonetheless, the volume of bond issuance

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in GS remains low due to the high information asymmetry between borrowers and lenders.

The assignment of credit ratings (CRs) to SMEs can alleviate this problem. However, existing rating agencies lack the methodologies that address the specifics of SMEs. A literature review indicated that there are several analogs of GS in some emerging and developed markets (Anwar et al., 2018). In Italy, there is a "mini-bond" market where SMEs can issue public debt (Altman et al., 2020). In China, there are three types of bonds designed for SMEs. Analysis of study showed that the effective way to reduce information asymmetry between lenders and borrowers is to assign CR to firms' obligations (Anwar et al., 2018). As a result, the number of research in modeling defaults has been growing (Demeshev and Tikhonova, 2014).

The number of research on this topic, particularly devoted to SMEs, however, remains low. Nonetheless, few studies have stressed the importance of considering non-financial factors related to sales, operations, or governance, as well as macroeconomic drivers of default (Lyukevich et al., 2020; Koroleva et al., 2020; Hol and Van der Wijst, 2008). Anwar et al. (2018) studied the frameworks of rating agencies in assessing the creditworthinss of SMEs. For example, these institutions in Singapore and Malaysia are predominantly focused on financial data. This could be attributed to the mature governance and reporting in these countries, as well as the availability of a reliable database of SME data. Conversely, in Thailand, the Philippines, or Indonesia, where reporting and governance standards of SMEs are still emerging, the institutions focused on non-financial drivers of SME's insolvency (60%–70% of total assessment). From a practical standpoint, starting from 2021, Russia's MOEX requires that all issuers or issues in GS be rated by the domestic rating agencies. However, the existing methodologies of rating agencies are tailored for large businesses and do not consider specific risks of SMEs.

Among the modeling methods (MMs) of SME defaults, the most widespread are logistic and probit regressions (Demeshev and Tikhonova, 2014). They demonstrate good accuracy, including non-financial and macroeconomic variables, assume any form of explanatory factor distributions, and result in the interpreted scorings. Their disadvantages include susceptibility to multicollinearity and overfitting. However, in the most recent studies, artificial intelligence (AI) and hybrid methods have become widespread. Although these MMs have shown to have higher accuracy than that of regressions, they were often "black boxes" that reduced their application in practice. Fantazzini and Figini (2009) predicted SMEs' default probability in China using the random survival forests (RSF) method. RSF performed better than the logistic regression for the "in-sample"; however, for the "out-of-sample," performance evidence was the opposite. Demeshev and Tikhonova (2014) revisited differences in the predictive power of insolvency models for Russian SMEs and demonstrated that random forest outperformed logistic regression both "in-sample" and "out-of-sample." The addition of non-financial information to the model led to improved forecasts. In turn, hybrid models gave a better and stable performance (Zhu et al., 2017; Li et al., 2016).

To conclude, the literature review demonstrated that SME insolvency drivers vary significantly from country to country. The majority of the studies are focused on developed or emerging markets in Asia, and only a few, although outdated, studies covered Russia's SME. Therefore, this study aims to close these gaps by identifying the insolvency drivers of Russian SMEs. The novelty of this study is to identify the insolvency drivers that are particularly inherent to SMEs in Russia. We tested the non-financial (business, corporate governance, and macroeconomic) drivers that were not previously considered for Russian SMEs in the literature. We tested the hypothesis that the maturity of reporting and governance in the country directly affects the share of non-financial drivers in the SME scoring models. We tested the assumption that the existing methodologies and scales of rating agencies did not consider specific risks of SMEs. We compared identified insolvency drivers of domestic SMEs with those in other advanced and emerging markets. The results can be used by investment practitioners to assist in developing rating scales and methodologies for SMEs. They can also be interesting for researchers who are studying the differences in SME default drivers across various markets.

2. Methods

2.1. Dataset

The sample contained 177 SMEs over the period 2015–2019. This period covered 2 years before and after the launch of the GS platform. The criteria for SME selection were: (1) belonging to the non-financial industry; (2) revenue from RUB120 million to RUB10 billion; (3) >3 years old; and (4) average growth rate of revenue of at least 10%. The industry structure of the sample was trading (28%), production (17%), construction (9%), food processing (6%), transportation (6%), agriculture (5%), property management (4%), energy and mining (6%), and others (19%). The event of default is recognized as the starting of bankruptcy proceedings for the firm. The number of insolvent firms in the sample was 56 (32%). Financial and categorical variables were collected from the SPARK-Interfax database. Macroeconomic data have been obtained from the World Bank website. The final dataset included 885 observations. Initially, we selected 37 financial, 16 categorical, and 18 macroeconomic variables, which reflected the credit strength of SMEs, according to some studies (Demeshev and Tikhonova, 2014a; Altman et al., 2020). To reduce the data dimension, we used the weight of evidence method assuming calculation of the information value (IV) criterion (Eko et al., 2019). Based on the IV value, we removed financial and macro variables with insignificant and weak predictive power (IV < 0.1) and categorical variables with weak predictive power (IV < 0.02). To calculate the ratio, we used the formula below. For each variable, we split data into N = 20 bins and calculated the number of defaults (b_i) and non-defaults (g_i). Respectively, g and b were the total numbers of non-defaulted and defaulted firms.

$$IV = \sum_{i=1}^{N}\left(\left(\frac{g_i}{g} - \frac{b_i}{b}\right) * ln\left(\frac{g_i/g}{b_i/b}\right)\right) \tag{1}$$

To increase the predictive power of factors expressed by quantitative variables, we normalized such factors in the range of [0,10]. To lessen the effect of outliers, we capped the quantitative ratios at the 95% values and removed the lower 5% values. In addition, for qualitative metrics, we developed a scale ranging from [0,10]. To solve the multicollinearity problem, we estimated the correlation matrix and excluded variables with pairwise cross-factor correlations >0.5. For the remaining explanatory variables, we calculated the variance inflation factor (VIF) and excluded variables with a VIF of >5 (Senaviratna and Cooray, 2019). The final dataset was split into training and testing samples randomly in the ratio of 80%–20%. To select the specification of the model, we used (1) Gini coefficient; (2) accuracy and recall criteria; and (3) Kolmogorov-Smirnov (KS) criterion.

2.2. Model

We selected logistic regression as the modeling method due to its good default prediction ability, good interpretability of outcome, and the possibility of using weights from the model for further development of the rating system (Demeshev and Tikhonova, 2014). Conversely, as we discussed in the introduction section, AI methods and hybrid algorithms are "black boxes." Each prediction is not easily attributable to an individual variable. Because our aim was to identify the insolvency drivers of domestic SMEs, transparency and interpretability played a vital role in the model evaluation. Understanding the insolvency drivers and the sensitivity of model predictions to changes in the inputs in our case overweighted the benefits from the higher predictive power of AI and hybrid models.

$$PD = \frac{e^{\sum_{i=1}^{N} c + a_i x_i}}{1 + e^{\sum_{i=1}^{N} c + a_i x_i}} = \frac{1}{1 + e^{-\sum_{i=1}^{N} c + a_i x_i}} \tag{2}$$

where PD is the 1 year probability of SMEs' default (binary variable; 1: default, 0: non-default), x_i – independent variables (i = 1, N), a_i is the coefficients at independent variables, c is the constant. The maximum likelihood function is used to estimate coefficients.

In turn, the rating system translates the probability of defaults into the symbol system expressed with a cardinal scale (Karminsky et al., 2021). The level of each rating grade is determined by the scoring points (SP) assigned to each company.

$$SP = \sum_{i=1}^{N} \omega_i \, x_i = \sum_{i=1}^{N} \frac{a_i}{\sum_i a_i} x_i \tag{3}$$

where ω_i is the weight of the explanatory variable in the rating score.

2.3. Rating System and Bond Rating Equivalents

We applied cluster analysis to infer the number of rating classes and the range of SP for each rating class. We used the mean-shift (MS) algorithm (Liu et al., 2013). Its advantage is that it does not require a predetermined number of clusters at the input. Clustering of SP was carried out in two stages. Firstly, we determined the cluster centroids based on MS outcome separately for each year. The minimum and maximum values in each cluster were fixed by each year. Secondly, the ranges of rating classes were ordered in a way that ensured meeting the condition of the monotony of probability of default function (Mishchenko and Chizhova, 2008). After we estimated the number of rating classes, we distributed all observations by these classes and calculated observed PDs for each class ($\overline{PD}_{class,t}$) by years and across the sample:

$$\overline{PD}_{class,t} = {ND_t}/{M_t} \tag{4}$$

where ND_t is the number of defaults in the rating class in the year t, M_t is the number of firms in the rating class. Furthermore, for each rating class, we calculated the average theoretical probability of default across the whole sample using the inverse logistic function.

$$PD_j = \frac{1}{1 + e^{\alpha + \beta * SP_j}} \tag{5}$$

where α, β are regression coefficients, PD_j is the average probability of default in the rating class j, SP_j is the average scoring points in class j. Then, we ran Hosmer-Lemeshow and Spiegelhalter tests to assess if the system adequately assesses PDs. Finally, we determined the benchmark rating levels of Expert RA and Moody's agencies to each rating class in the system. We used the approach suggested in Altman et al.'s (2020) study and compared the theoretical PDs for each rating class with those in the most recent marginal probability of default matrices published by the rating agencies.

2.4. Summary of Method: Novelties

To summarize, firstly, we used the most recent data about Russian SMEs' performances (2015–2019). This is the period of upward credit trend of SMEs in the country in the last decade. In contrast, in the existing studies, the data from earlier periods were used. Secondly, we tested a large set of SME default drivers), which were not used in the previous studies. Thirdly, we developed the framework for building the rating classes and rating scale using cluster analysis. Fourthly, we applied the weight of evidence method for feature selection, which was also not used in the previous studies of Russia's SME defaults.

3. Results and Discussion

Table 1 presents the results of the estimation of the model (2). The model is specified correctly as the actual signs as almost all variables matched the expected signs, except at the unemployment level variable. An increase in employment level in the model decreased the probability of default.

Table 1 Results of the study and key drivers of insolvency of Russian SMEs

Explanatory variables	Value of coefficient	Expected sign	Actual sign	P > |Z|	Weights in the model (ω_i)
		Constant			
Constant	1.817	–	–	(0.000)	–
		Financial risks			
Gross profit margin	-0.356**	-	-	(0.000)	17%
Operating profit/interest expenses	-0.127**	-	-	(0.022)	7%
Return on equity	-0.170***	-	-	(0.000)	9%
Total equity/total liability	-0.186***	-	-	(0.001)	14%
Short-term debt/equity	0.093**	+	+	(0.044)	10%
Total debt/operating profit	0.188***	+	+	(0.000)	13%
		Business risks			
Ownership by the large company (group of companies) (1/0)	-0.047*	-	-	(0.051)	17%
Operations in the European part of Russia (1/0)	-0.125***	-	-	(0.000)	6%
Revenue <$10M	0.2395***	+	+	(0.000)	2%
		Macroeconomic factors			
Unemployment level (%)	-0.213**	+	-	(0.001)	5%
		Model characteristics			
Pseudo R^2 (%)	43%				
Log-likelihood	-248.9			(0.000)	
Share of non-financial factors	30%				

***, **, * - significance at 1%, 5%, and 10% respectively

In the Russian economy, with a historically very low unemployment rate and the dominance of state-owned companies, an increase in unemployment leads to the development of new SMEs. This increases the number of SME firms and reduces the likelihood of bankruptcy. The performance of the model coincided with that in Altman et al.'s study (2020). The weight of financial factors in the model is large: 70% vs 30% of non-financial and macroeconomic factors. This reflects the availability of well-organized databases on SMEs data in Russia, in line with Anwar et al.'s (2018) study. The most significant default drivers of Russian SMEs are gross profit margin and debt leverage metrics. Gross profit, which weighs 17% in total credit score, is the most important default metric as it reflects SMEs productivity, the competitive strength, as well as the ability to resist the power of suppliers and buyers. The reduction in gross profit results in cutbacks in the company's cash flows. The debt leverage, which weighs 14% in the score, shows the ability of shareholders' capital to cover the outstanding debt in the downturn. The high weight of these metrics is underpinned by: (1) the volatile nature of the Russian economy; and (2) elevated exposure of SMEs to business cycles due to their small size. The second group of significant default drivers of Russian SMEs is the debt servicing ratio, such as operating profit to interest expenses, total debt to operating profit, and short-term debt to equity. Their combined weight in the scoring model is 30%. These metrics are important leading indicators of defaults as they reveal how capable the firm is of paying its short-term debt, including interest, and other liabilities.

However, liquidity ratios, cash flow ratios, and working capital turnover ratios were insignificant for Russian SMEs. The latter contradicted the outcome of other studies (Altman et al., 2020; Anwar et al., 2018). The absence of liquidity ratio can be explained by the fact that the interest coverage ratio and short-term debt-to-equity ratio give a better picture of the prospective liquidity of SMEs than the current or quick ratio. Moreover, the latter ratios are retrospective in nature. The insignificance of working capital metrics could be attributed to the fact that domestic SMEs mostly perform service functions rather than be directly involved in production activities with heavy working capital usage. The insignificance of cash flow metrics is explained by the small share of accruals transactions in the accounting practices of domestic SMEs. Significant non-financial insolvency factors were: (1) ownership by a large group of companies (negative relationship); (2) operating in the European part of Russia (negative relationship); and (3) small revenue size (positive relationship). Indeed, an SME that is owned by a large company or large group of companies will have better access to the financial and other resources than an SME owned by private individuals, in line with the findings of Altman et al. (2010) for Italian "mini-bonds." The negative sign at the binary variable expressing the firm's business operations in the European part of Russia is explained by the higher level of economic development and high density of population in this territory. The features of these territories are: (1) high real disposable income of the population; (2) high proportion of the urban population; (3) concentration of large businesses that are customers of SME products; and (4) large number of benefits for SMEs. It is also due to the concentration of most SMEs in capital cities, Moscow and St. Petersburg, with significant managerial and entrepreneurial resources.

Conversely, the management aspects of SMEs were insignificant in the model. This contradicted the findings of Anwar et al. (2018), which showed that in Asian emerging markets the governance aspects took around 20%–40% of the rating scorecard. This could be attributed to the lack of complete information about the corporate governance and business practices of Russian SMEs in SPARK-Interfax databases. Testing of additional proxy factors related to governance aspects of domestic SMEs is, therefore, required. Interestingly, the factor of industry affiliation also turned out to be insignificant. This finding contradicted those in the study conducted by Altman et al. (2020). We attributed this to the dominance of trading and service SMEs in our sample. Further research is required for SMEs with manufacturing, construction, and real estate business models. Among macroeconomic factors, the only unemployment rate was significant. We explained this by high correlation among macro variables and between macro and financial variables. In addition, the impact of state support for SMEs was insignificant in the model. This may indicate that the support for domestic SMEs in Russia is significantly less in comparison to Asian emerging markets. However, additional study of this issue is required. To evaluate the quality of the model, we assessed its predictive and discriminative power (DP) using the testing sample. (Table 2).

The AR of the model was 84% and much above type I and type II errors. This indicates the excellent level of DP of the model. To assess the stability of the model's DP, we applied the five-step validation and estimated cross-validation estimation of AR (CV). The value of CV was close to AR, which proved the stability of the model. In addition, the quality of the model was evaluated by the calculation of the Gini coefficient. The Gini coefficient equals 64%, which also reflects the excellent predictive power of the model.

Table 2 Prediction and DP of the model

Metrics	Value
Accuracy ratio (AR), %	84%
Cross-validation estimation (CV), %	83%
Sensitivity (true positive rate), %	88%
Type I error (false positives), %	12%
Type II error (false negatives), %	25%
ROC/AUC, %	82%
Specificity, %	75%
Gini coefficient	64%
KS statistics	0.65

Lastly, the value of KS statistics is 0.65, which, in combination with p-value <0.01, rejects the hypothesis of equality of distributions of default and non-default cases. However, type II error is higher than type I error. This phenomenon is typical for the logistic regression; however, it somewhat reduces the quality of the model since investors most often commit type II errors (Zhu et al., 2017). Hence, additional study of the model specification is required to alleviate this issue.

Tables 3 and 4 present the grades in our rating system and the results of running statistical tests used to determine the quality of calibration of the system. The results of Hosmer-Lemeshow and Spiegelhalter tests indicate that there are no statistically significant deviations between the observed and theoretical PDs, which generally confirms the good quality of the rating system.

Table 3 Rating system for Russian SMEs

Rating notation	Range of rating scores	Theoretical 1-year PD
SME-1	(7,66;10]	0%
SME-2	(6,66;7,66]	6%
SME-3	(6,39;6,66]	18%
SME 4	(5,56;6,39]	20%
SME 5	(4,61;5,56]	24%
SME 6	(2,64;4,61]	26%
SME 7	(2,27;2,64]	29%
SME 8	(0;2,27]	79%

Table 4 Results of calibration tests for the rating system

Test	Test outcome	P-value	Test result (pass or fail)
Hosmer-Lemeshow statistics	10.04	0.044	Passed
Spiegelhalter Z-score	-2.24	0.010	Passed

Table 5 indicates benchmark rating equivalents (BRE) from the domestic rating agency (Expert RA) and international rating agency (Moody's) to rating grades in our system.

Table 5 shows that the MOEX's requirement for SMEs to obtain the credit rating will unlikely result in achieving the goal to reduce information asymmetry in the financial market and increase awareness and trust between borrowers and lenders. The rating scales of considered rating agencies do not provide sufficient granularity of rating classes for SMEs and give a very coarse assessment of SMEs' probabilities of default. This proved our hypothesis that distinct rating frameworks and methodologies for domestic SMEs are required.

Table 5 Benchmark rating levels for SME rating system[1]

Grades in the rating system	1 year PD	Expert RA		Moody's	
		BRE	1 year PD	BRE	1 year PD
SME-1	0%	ruBB-ruAAA	0%–3.66%	B-Aaa	0.00%–3.26%
SME-2	6%	ruB-ruBB	3.66%–7.96%	B-Caa	3.26%–9.84%
SME-3	18%	ruCCC-ruB	7.96%–21.54%	Caa-C	≤9.84%
SME-4	20%	ruCCC	21.54%		
SME-5	24%	ruCC-ruCCC	21.54%–40%		
SME-6	26%				
SME-7	29%				
SME-8	79%	ruC or below	>40%		

In turn, our findings may serve as the basis for the development of such frameworks. The results of benchmarking (Table 5) significantly correlate with those of the Italian "mini-bond" market (Altman et al., 2020). For the latter, the highest 1-year PD was 70%, whereas, in our rating system, it was 79%. However, around 90% of Russian SMEs would be assigned speculative grade level ratings (predominantly below B), whereas, in Italy, only around 70% of mini-bond issuers would be assigned these ratings (mainly in the B-BB spectrum). This confirms that Russia's SME market is still in an emerging stage, with above-average credit risk, and the question of the development of a rating framework is highly relevant.

4. Conclusions

This study aims to identify the insolvency drivers of SMEs in Russia. We compared our findings with those in other markets and found that, unlike those in Asian emerging markets, financial factors explained around 70% of domestic SMEs' credit health. Meaningful financial factors included gross profit margin, return on equity, debt leverage, and coverage ratios and the term structure of debt. Non-financial drivers included ownership of the firm by large businesses (or group of companies), firm size, and territory of operation within Russia. Among macroeconomic drivers, the unemployment level was the most significant driver of SMEs' credit quality. In addition, we developed a rating system for SMEs and determined the relative benchmarks from Expert RA and Moody's rating agencies. The benchmark indicated that the existing rating scales did not provide the granular assessment of SMEs' credit health and gave a very coarse evaluation of their default probabilities. This confirmed our hypothesis that distinct rating frameworks and methodologies for domestic SMEs in the Russian market are imperative. Future research concerning expanding the list of non-financial explanatory factors toward the business and corporate governance practices of entrepreneurs, a detailed analysis of the impact of government support on SMEs' credit quality, and comparing the ability of other empirical methods, including AI and hybrid models, to predict defaults of SMEs in various emerging markets is necessary.

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[1]Expert RA (https://www.raexpert.ru/docbank//312/45a/5cc/74bf6f3bdede355182d5d91.pdf); Moody's (https://www.moodys.com/research/Annual-default-study-Following-a-sharp-rise-in-2020-corporate--PBC_1263901

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