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Developing a Scoring Credit Model Based on the Methodology of International Credit Rating Agencies

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Abstract

The purpose of this work is to examine the relationship of various financial and non-financial (qualitative) factors of performance of non-financial companies and their credit ratings.

We developed the scoring model which was based on the methodologies of international and Russian rating agencies. The modelled ratings of non-financial companies for 2018–2020 were compared with actual ratings assigned by the rating agencies and discrepancies were explained. The sample includes companies from retail, protein and agriculture, steel, oil and gas sectors from Russia, USA, Luxembourg, England, Canada, India, Ukraine and Brazil.

The paper proved that addition of business and environmental, social and governance factors improved the quality of scoring models in comparison to those including only financial metrics. There are strong patterns in the resulting ratings of companies for some industries. Retail industry companies are associated with high sales indicators, while steel industry companies have high interest expenses coverage ratios. Oil and gas industry companies mostly show high results in reserves coefficients.

The study developed a credit rating forecasting tool that emulates the work of analysts of rating agencies and therefore has a high predictive power. The developed model can be used by financial market practitioners to predict the credit ratings of Russian companies in the face of the refusal of international rating agencies to rate Russian issuers.

Keywords: credit default prediction, credit rating modelling, credit rating system, ESG rating

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Introduction

The paper examines the relationship between various financial and qualitative indicators and the credit ratings of non-financial companies based on publicly available information. The study assessed the creditworthiness of non-financial companies from the following sectors: retail; steel; agriculture; oil and gas. The research is dedicated to the development of a scoring model based on the methodology of international rating agencies for predicting credit risk and probability of default of international non-financial companies. Along with the financial position of the company, the scoring model allows to take into account support factors such as group and government support, environmental influence, and to consider social factors and management efficiency, as well as the company's key success factors.

The assessment is based on the methodologies of international rating agencies that are integrated into the developed model.

Relevance of research

First of all, the financial crisis of 2007–2008 demonstrated how important objective high-quality ratings are for the stability of the global economy. Erroneous ratings have led to the bankruptcy of a large number of firms [1]. A similar situation can emerge if the approach to companies' credit ratings is not thorough enough. Secondly, an independent credit rating methodology that unifies the existing models and adjustments is required to assess the creditworthiness of companies internationally, given the recent trends in the sphere of credit ratings and adjustments. Thirdly, large losses could be shifted to private investors, who may be driven by the incorrect ratings of the firms in which they invested. For instance, the Yutrade broker went bankrupt in 2008, and its clients lost all their investments [2]. Fourthly, corporate governance, and the environmental and social impact of a company on its creditworthiness score are now gaining popularity [3].

The objects of the research are the international non-financial companies from the retail, steel, protein and agriculture, and oil and gas industries for the period between 2018 and 2021. Therefore, the subject of research is the relationship between various financial and qualitative indicators and the credit ratings of non-financial companies.

The goals of the research are the selection and study of the scientific literature on the topic; choosing the most relevant methods and methodologies for building scoring models; collecting sample data for non-financial companies for 2018–2021; creating an Excel VBA-based interface to calculate financial and qualitative indicators; conducting a detailed analysis of model prediction accuracy; adding adjustments to improve prediction accuracy; building the scoring model suitable for rating distribution.

The scientific novelty of the research is underpinned by the limited number of studies on the topic of independent credit rating modelling for non-financial companies. In particular, the developed scoring model considers other important metrics in addition to financial data: government and group support factors, environmental influence with social and management efficiency and sovereign rating adjustment. Other novelty factors include: independent calculation of qualitative indicators without expert guidance; identification of patterns in the values of financial indicators and the resulting credit rating. Moreover, there is a lack of research that includes qualitative factors for non-financial companies, however, its importance is underpinned by several studies. For instance, the papers by G.M. Bodnar et al. [4], B. Lehmann [5] and J. Grunert et al. [6] conclude that accuracy is increased with the incorporation of several non-financial qualitative factors to analysis; however, these results are only valid for certain countries and only for financial companies, and thus could not be used for companies from other countries. ESG ratings could be used as an additional indicator of financial performance, as F. Kiesel and F. Lücke [7] mention in their paper, and hence it would also be reasonable to use the ESG rating when modelling credit ratings. Therefore, the creation of a model which incorporates qualitative factors seems practical in future research in related fields.

The practical relevance of the research is high. The present study developed a model ready for use and implementation, presenting an interface and data output that is understandable to all users. Such a tool is especially relevant, first and foremost, for assessing the creditworthiness of companies whose ratings have not been published by rating agencies. In this case, its application is the quickest and most plausible way to obtain a rating. Secondly, the open-source code allows the model to become a universal foundation for further improvement, implementation of third-party tools and connection to various resources.

Literature Review

The theoretical base of the paper comprises the studies of foreign and Russian researchers in the field of corporate finance and risk management. The works of the following Russian and foreign researchers were used: T.M. Zadorozhnaya, A.M. Karminsky, A.A. Polozov, B.H. Bergrem and others.

The literature review demonstrates that there is a limited number of studies on credit ratings and the development of models for assessing the credit risks of non-financial companies. In most cases, the significance of independent credit ratings and their impact on the financial system is provided. For instance, the paper by T.M. Zadorozhnaya [8] presents the basic definitions and objectives related to credit ratings and, most importantly, the tasks that the existence of ratings solves, i.e., information disclosure, setting limits on credit risk, forming an objective assessment of the borrower by the lender, promoting the diversification of funding sources, promoting the reduction of the cost of capital and directly regulating financial markets. Moreover, credit ratings are important in the financial performance assessment, as revealed in M. Singal's paper [9]. The author concludes that the changes in credit ratings are reflected in stock prices and the corresponding investors' reaction, and thus affect a company's financial performance.

An important part of the paper is related to qualitative factors. Several research studies agree that the incorporation of qualitative and non-financial variables in the model could improve the accuracy of credit rating prediction. The papers by B. Lehmann [5] and J. Grunert et al. [6] investigate the impact of qualitative factors on the credit rating assessment, therefore, this study accommodates for the non-financial qualitative factors to improve model accuracy.

Another important point is the distinction between developed and emerging countries. The paper by A.M. Karminsky entitled "Corporate rating models for emerging markets" [10] presents several financial, macroeconomic, and qualitative indicators and their effect on the credit rating of a company using econometric models that use these coefficients in different proportions. This study also examines the important question of how results differ for companies from emerging markets and what the key differences and specifics are in assessing their credit ratings. These findings have a key value in current research, and help to interpret results and make the correct conclusions for companies from emerging markets. Thus, companies from emerging countries are more exposed to macroeconomic factors, which are considered qualitative variables, or an adjustment for the sovereign rating.

In addition, most studies involve the use of different external factors and specific indicators for each non-financial industry to assess credit risks. A.M. Karminsky's paper "Credit ratings and their modelling" [11] completely covers the issues of credit quality assessment and their emergence. The study discusses the classification of ratings and conducts an analysis of existing methodologies and principles of credit rating formation used by the most recognised rating agencies. Moreover, B. H. Bergrem's paper "An empirical study of the relationship between credit ratings and financial ratios in the E&P industry" [12] examines the key indicators that are unusual for other methodologies, and are important in the E&P (Exploration and Production) sector of the oil and gas industry. The cost of discovery and development is one of the vital keys to understanding the operating efficiency of a company, and one of the fundamental indicators in assessing the scale of a company's unproven reserves. In this case, the stable replenishment of reserves, their volume and geographic diversification, unlike company revenue, can serve as the best indicator of long-term stability. Finally, A.I. Rybalka [13] demonstrates how different specific indicators of non-financial companies could affect the probability of default using logit regressions. The author determines the importance of including qualitative indicators and their effect on the results. The results reveal the difference when several corporate governance coefficients are included, and are also valuable for current research since the paper investigates companies' ESG ratings and specifically, their governance components. It has been established that governance factors affect the probability of default, which is lowered, for instance, when the CEO of a company is also its co-owner and increases when a company becomes a subsidiary. The second finding is significant for current research when the results are compared with an adjustment for being a part of a group, which traditionally has a positive effect on the credit rating. Therefore, using different variables to assess credit ratings for companies in different industries is theoretically reasonable.

Since not only the company itself affects its credit quality, a deep investigation into adjustments to its stand-alone creditworthiness assessment is required. Karminsky's paper [10] highlights the applicability of ratings and their distribution in today's financial world and shows the importance of using external support factors on a par with internal factors, both quantitative and qualitative, in evaluating a company's financial stability in one way or another. But it is important to mention the adjustment for the overall sovereign rating. The paper by A.M. Karminsky and A.A Polozov – "Handbook of ratings" [14] notes that a company's credit rating rarely exceeds the the sovereign rating. A company's stand-alone rating is measured in a "bubble", but there are macroeconomic risks that the company does not control: political stability, competitive environment, strength of invention protection. However, there are examples of companies that refute this rule. Such companies are assigned a rating higher than the sovereign rating because, due to certain circumstances, it is possible to exclude negative factors affecting credit quality from consideration (unlike in the calculation of the sovereign rating), or simply because other strongly positive features are present.

Reconciling the results obtained by using methodologies with different scales is important. The paper by N.F. Dyachkova "Comparison of rating scales of Russian and foreign agencies: industrial and financial companies" [15] reveals the importance of correct conversion of Russian rating scales to international ones. The study examines the relationships between rating scales used by different rating agencies, and it is mostly valuable for current purposes, since several companies have not been assigned a rating by Moody's. This paper presents a method of forming numeric rating scores. These scores are used in empirical models to study relationships between ratings and explanatory factors.

Highlighting the patterns for specific industries could be complicated due to various difficulties and a dissimilarity of the companies. However, there are research studies that draw almost the same conclusions about the most important factors for a specific industry. The scale-related factors generate many advantages for a retail company over its competitors, such as market power and price leadership. These advantages can lead to greater investor attractiveness compared to smaller companies. Such a strong effect of the scale is confirmed by several studies. For instance, A.B. Curtis et al. [16] argue that the revenue variable is the main component in the retail companies' financial performance forecast. As for the steel industry, profitability-related variables, particularly that of financial performance, are considered the most significant in assigning a credit rating, as confirmed by A. Banerjee [17]. The oil and gas industry functions in the long-term perspective, i.e., companies need to consider their reserves, which leads to higher values of these variables for such companies. Moreover, B.H. Bergrem [12] also underpins the relevance of the scale variables for the oil and gas companies, however, the monitoring of average daily oil and gas production as better representation of industry-specific factors that influence financial performance is also considered important.

The literature review demonstrates that research tasks are of primary importance for researchers and practitioners. The previous studies indicate that the results of credit risk assessment analysis differ when qualitative indicators from external databases vs. other factors are assessed.

Data

All financial data was obtained from official company reports, and qualitative factors are measured based on publicly available information. The financial data was retrieved from Bloomberg and Thomson Reuters terminals. The financial variables used are revenue, EBIT, interest expenses, retained cash flow, total debt, EBITDA, net debt, return on tangible assets, book capitalization, cash flow from operations, dividends. Specific variables for the oil and gas industry are also used: proven and developed reserves and average daily production. Therefore, the database is a sample of the five largest companies in each industry with previously published Moody's ratings and publicly available reports and forecasts. Additional qualitative data on 5 companies is obtained to test the ESG rating model. In most cases, since the majority of the companies in question publish IFRS statements, all their calculations are conducted in US dollars. But for representativeness we added two companies that use national currency for calculations, X5 Retail Group (Russian rubles) and Husky Inc. (Canadian dollars). The companies from eight countries are examined: Russia, USA, Luxembourg, England, Canada, India, Ukraine and Brazil. The average value 2018–2020 is calculated for each factor in the model. This is due to the fact that ratings are assigned through a cycle. With this approach, seasonal fluctuations in business activity are averaged. Since our model takes into account sovereign risks, the sample includes sovereign ratings for the studied countries with forecasts. This data was obtained from the Bloomberg system. However, a selection bias problem could be present due to the small number of observations in the dataset. Hence, the findings corresponding to the industry patterns are only relevant for similar situations.

Methodology

The methodological base of the paper was formed by the work of international rating agencies. The following methodologies were used: Moody's retail industry methodology [18]; Moody's steel industry methodology [19]; Moody's protein and agriculture industry methodology [20]; Moody's oil and gas (E&P) industry methodology [21]; ACRA government support methodology [22]; ACRA group belonging methodology [23]; Expert RA ESG rating methodology [24].

Moody's published methodologies used in the construction of the model do not completely reflect the procedure of companies' rating formation by Moody's. They only reflect the principles of assessment of the most common important indicators in a specific industry, which allow the authors of the model to use other relevant tools when compiling the rating calculator. The presented methodologies comprise a method of indicator evaluation on an 8–9 point scale, converting them from this scale to a quantitative scale according to Moody's rating evaluation formula and converting them into a final credit rating as demonstrated in Figure 1. A certain advantage of the selected methodologies over those of international competitors – Fitch and S&P – is the more expansive grading in the calculation of qualitative indicators, with more "binomial" parameters (value 0 or 1) in evaluation. The data for evaluation can only be found implicitly, by studying the companies' official presentations to investors or similar documents, in which they disclose information relevant for the study using the model.

Figure 1. The formula for the overall stand-alone credit rating

$$\sum_{i=1}^{n} x_i \cdot weight_i = X_s .$$

Note: x_i is a grade of a subfactor i and X_s is an overall stand-alone numerical credit rating.
Source: Moody's and authors' calculations.

The assessment is based on key indicators such as: scale, company's business profile, profitability and efficiency, leverage and coverage, and the financial policies pursued by the company. Generally, these indicators also contain sub-factors, which, when combined, will better reflect the value of the overall indicator itself. Each subfactor value is measured as a weighted year average: 2018 – 15%, 2019 – 25%, 2020 – 30% and 2021 – 30%.

Therefore, each factor and sub-factor is assessed and then transposed to the numerical value according to Table 1 to proceed to a calculation of the final rating using the weights specified in Tables A1–A4 depending on the industry.

Table 1. Rating scale

Credit rating	Aaa	Aa	A	Baa	Ba	B	Caa	Ca	C
Grade	1	3	6	9	12	15	18	20	21

Note: The rating grade is calculated for each sub-factor in the model.
Source: Moody's.

The created model will take the external influences into consideration; the result will not be a stand-alone rating. The model will allow to examine the influence of state support, group support, as well as to calculate the ESG rating. The selected methodologies are used to study, evaluate and take into account the influence of parent structures and the state on companies in the Russian Federation, but, since the model is designed to calculate the rating for companies around the world, these methodologies were taken only as the foundation and, as a result, the points relevant to the specifics of the Russian Federation were adapted to other countries. The estimates of the influence of state support and the of being a part of a group will be provided as corrections to the original stand-alone rating according to the specified methodologies, while the ESG rating was created as an independent rating, which could be included with the overall results of any company.

To account for external support from the state or shareholders, the joint default analysis approach was used. This approach includes assessment of two dimensions of support: (1) the strength of the links between the company and its shareholders; and (2) the probability of shareholders' support of the company (Table A5). The probability of support is assessed using the creditworthiness of the shareholder (SICA) with the following factors: presence of a legal relationship, presence of contingent liabilities (including sureties and guarantees), strategic importance and operational integration. Subsequently, the final adjustment value to stand-alone creditworthiness assessment (SCA) is calculated according to Table A5. The adjustment for state support requires an assessment of systemic importance and state influence levels as qualitative factors, and subsequent calculation of the adjustment value for the support from the shareholders (Table A6).

Moreover, the final credit rating is then compared with the stand-alone rating to avoid outliers and adjust for the specific country's macroeconomic risks. Therefore, the final quantitative credit rating is calculated as presented in Figure 2.

Figure 2. The formula for the final credit rating

$$\min(\text{sovereign rating},\ X_s + GOV + GROUP) = X_f\,.$$

Note: GOV and GROUP represent adjustment by state and group support, respectively.

Source: Authors' calculations.

Results

Baseline credit assessment results

The results of this model can be divided into two categories: company ratings compared to Moody's ratings and general patterns and trends identified based on the results of the model. To begin with, it should be noted that the model does not allow a company to possess a rating higher than the corresponding sovereign rating of its country. These results, presented by Moody's, were designated as outliers, and these companies' ratings were equated to the sovereign ratings.

The research results demonstrate that the resulting model is highly accurate, as the average deviation from the Moody's rating without adjustments is –0.75 points. With applied adjustments, model accuracy becomes –0.25 points, with an average ESG rating deviation of 0.5 points. This high accuracy value indicates that all the required coefficients were considered because, when the amount of data under consideration increases, the amount of discrepancies decreases, which also indicates that they should be considered when assessing credit quality.

The difference in the results may mainly indicate the existence of discrepancies in the data between potential users and rating agencies due to different years studied or different exchange rates of national currencies. The model mostly underestimates the ratings, which is caused by the presence of crisis years, when the main financial indicators are traditionally lower, in the sample.

Certain patterns emerged in the database, and the "Sales" coefficient for the retail industry is the most common successful result out of financial coefficients in terms of value added to the financial rating, not adjusted for coefficient weight for all the companies in the sample (Table 2). It could confirm that the key characteristic of the retail industry is that its sales generate the main profit, because it directly dictates the company's position in the market. On the other hand, 4 out of 5 companies demonstrate the least successful results in financial coefficients in terms of value added to financial rating, not adjusted for weight of debt-related coefficients (Table 2). It is important to note that the results obtained for X5 Retail Group, which are calculated in American dollars and rubles, do not differ from each other, which may indicate the correct accounting for the currency in which the reports are presented.

Table 2. Model ratings with adjustments of companies from the retail industry

Company	Agency rating	With adjustments	Best coefficient	Worst coefficient
X5 Retail Group (USD)	Ba1	Baa3	Sales	EBIT / Interest Expense
X5 Retail Group (RUB)	Ba1	Baa3	Sales	EBIT / Interest Expense
Costco	Aa3	Aa3	Sales	RCF / Net Debt
Walmart	Aa2	A2	Sales	RCF / Net Debt
Starbucks	Baa1	Baa1	Sales	RCF / Net Debt
Party City Holdco Inc.	Caa1	B3	Sales	Debt / EBITDA

Note: Best and worst coefficients are the most and least successful results among financial coefficients in terms of value added to financial rating, not adjusted for coefficient weight.
Source: Authors' calculations.

In addition, there is a clear pattern in the steel industry, with the "EBIT/Interest Expense" coefficient being the most successful for 4 out of 5 companies (Table 3). It can indicate a company's positive net profits and low interest expenses on short-term and long-term debts. While the worst indicators differ, 2 companies have almost the same deficiency in the CFO/Debt indicator (Table 3), which may indicate a small amount of free funds from operating activities. This indicator is important as it directly reflects the amount of cash that the company generates from its income. Also, 2 companies have an equally unsuccessful sales indicator (Table 3), which may be caused by the lack of demand for goods in the years under consideration or hint to at a weak position in the markets where the company carries out its activities.

Table 3. Model ratings with adjustments for companies in the steel industry

Company	Agency rating	With adjustments	Best coefficient	Worst coefficient
MMK	Baa2	Baa3	EBIT / Interest Expense	Sales
NLMK	Baa2	Baa3	EBIT / Interest Expense	CFO / Debt
Severstal	Baa2	Baa3	EBIT / Interest Expense	Sales
EVRAZ	Ba1	Baa3	EBIT / Interest Expense	CFO / Debt
ArcelorMittal	Ba1	Baa3	Sales	Debt / BookCap

Note: Best and worst coefficients are the most and least successful results in financial coefficients in terms of value added to financial rating, not adjusted for coefficient weight.

Source: Authors' calculations.

The oil and gas industry, especially the exploration and production sector, is directly related to the reserves and volumes of daily production. Therefore, the most successful results in this industry are revealed by the Debt / PD reserves indicator, and this is the case for each company (Table 4). Hence, it is possible to state that in this industry reserve indicators are important for companies and even despite the crisis years, the management board monitors and maintains this indicator at the proper level. The least successful indicator results for 4 out of 5 companies are reflected in RCF/Debt coefficient (Table 4), which may be due to the companies' high debt ratio or low retained cash flow. This would be a negative signal for investors, as this indicator is used to determine the company's ability to repay its debts from cash generated from operations, i.e., sales, after dividend payments. Notably, the only company with a different least successful indicator is Russneft, whose possible bankruptcy has been discussed in the news. It has the least successful results in the Average Daily Production coefficient that indicates poor sales estimates, which would negatively affect all financial results and, importantly, the company's lack of willingness to compete in the market and shows little impact on the development of the industry.

Table 4. Model ratings with adjustments of companies from the oil and gas (E&P sector) industry

Company	Agency rating	With adjustments	Best coefficient	Worst coefficient
Oil India	Baa3	Baa3	Debt / Reserves	RCF / Debt
Husky	A2	A3	Debt / Reserves	RCF / Debt
Russneft	Caa2	B2	Debt / Reserves	Avg Daily Prod
EOG resources	A3	Baa3	Debt / Reserves	RCF / Debt
Murphy Oil Corp	Ba3	Ba2	Debt / Reserves	RCF / Debt

Note: Best and worst coefficients are the most and least successful results in financial coefficients in terms of value added to financial rating, not adjusted for coefficient weight.

Source: Authors' calculations.

It is difficult to identify clear patterns for the most or least successful indicators in the protein and agriculture industry, which may be due to the sample of companies in the database: they are not similar to each other and may rank differently in sales and systemic importance within their markets. Only two companies have the same most successful metric, which is CFO/Debt (Table 5), and while it is equally positive, it does not have a very high rating. Because of high competition and low market power, the debt load is the key distinguishing factor between solvent and insolvent companies in this industry. The least successful performers differ even more, although the two companies have similarly lagged Debt/Book Capitalization (Table 5), suggesting that the metric that measures a company's total outstanding debt as a percentage of total company capitalization is lagging and requires work in the future.

Table 5. Model ratings with adjustments of companies from the protein and agriculture industry

Company	Agency rating	With adjustments	Best coefficient	Worst coefficient
Cherkizovo Group	B1	Ba3	Debt / EBITDA	EBIT / Interest Expense
Archer-Daniels-Midland Company	A2	Baa2	Sales	CFO / Debt
MHP SE	B2	B1	CFO / Debt	Debt / BookCap
Minerva S.A.	Ba3	B2	CFO / Debt	Debt / BookCap
Ingredion Inc	Baa1	Baa1	EBIT / Interest Expense	Sales

Note: Best and worst coefficients are the most and least successful results in financial coefficients in terms of value added to financial rating, not adjusted for coefficient weight.

Source: Authors' calculations.

The model's ability to predict and indicate weaknesses in companies, which can be adjusted by substituting different values, as well as to point out the line of effort, together with the resulting patterns in the relationship between the credit rating and the financial indicator values can help to identify a company's strengths and predict its level of credit risk.

ESG Rating results

The ESG rating is built into the model as an independent tool for calculating the rating of possible environmental and social damages, as well as corporate governance risks in the company. When calculating the main credit rating of a company, the potential user of the model can introduce corrections and proceed to the calculation of the ESG rating with the average variance between actual and modelled rating of about 0.5 notches.

The ratings obtained by the model and the rating agencies for PIK, AK BARS, GLAVSTROY, GTLK and TRINFICO apparently coincide (Table 6), since the Expert RA methodology was taken as the foundation when forming the ESG rating in the model, which is very similar to the NRA methodology for the majority of coefficients. However, in the case of X5, the obtained result is different: the rating calculated using the model is higher than the agency rating, which may be due to a different approach to evaluation and different views on environmental, social and corporate governance issues. The MSCI methodology is a guide to rating indicators on a broader scale. Each indicator is assessed on a scale of 0 to 10, adding more detail to the actions, while increasing the subjectivity of the assessment, as the user is given an opportunity in advance to assess the company's actions on a positive-negative spectrum, even though all the necessary data is publicly available, and it is easy to find relevant answers to all questions in each of the three areas.

Table 6. Model ESG ratings results

Company	Agency rating	Model rating
PIK GROUP	ESG-2 (Expert RA)	ESG-2
PJSC AK BARS BANK	ESG-3 (Expert RA)	ESG-3
GLAVSTROY	ESG-4 (Expert RA)	ESG-4
GTLK	ESG-3 (Expert RA)	ESG-3
TRINFICO	B1 (NRA)	ESG-3 (B1 NRA's scale)
X5 Retail Group	BB (MSCI)	ESG-3 (A-BBB MSCI's scale)

Source: Authors' calculations.

Conclusion, Contribution and Implication

An analysis of deviations from Moody's estimates was carried out; the obtained difference in the results can mainly indicate the presence of discrepancies in the data between potential users and rating agencies due to different years being analyzed or different exchange rates of national currencies. The model mostly underrates the results due to the presence of crisis years, when key financial indicators are traditionally lower, in the sample.

Differences in the results may also positively suggest an unbiased approach to assessing credit quality, that is, one without strong subjectivity. The approach to the assessment of qualitative indicators is different; accordingly, long-term ratings obtained by the rating agencies are not necessarily the only correct ones. The entire process of their formation is fully described in this paper, accordingly, the unbiased nature of the results obtained is an undeniable advantage.

From the analysis of the indicators, the most and least successful performances in each of the industries are identified and the reasons behind these patterns are demonstrated. The model's ability to predict and indicate weaknesses in companies' performance, which can be adjusted by substituting different values, as well as to point out line of effort, together with the resulting patterns in the relationship between the credit rating and the values of financial indicators can help to identify the strengths of a company and predict its level of credit risk.

Other positive aspects of the resulting model are its versatility, both in application and in its high adaptability to various new tasks. It can be modified in an uncomplicated way to study the credit quality of companies from other industries, a region's credit rating or the formation of sovereign ratings, depending on the interests of a potential customer.

The research has also provided detailed analyses of the information power (importance) of financial and nonfinancial factors within each credit rating scoring model.

The obtained tool can be updated, supplemented, and improved, and the example of the ESG rating shows how easy it is to build a variety of new solutions to tasks that will affect the final level of credit risk of the company. As this scoring model is a universal tool with a user-friendly interface and a ready database that can be updated for further development and expansion of various specific tasks, it can account for all possible necessary factors for the solution of risk assessment-related tasks. Therefore, such a model has great potential for development and practical application.

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Appendix 1

Table A1. Retail industry

Rating factors	*Weight, %*	x_i	*Weight$_i$, %*
Scale	10.00	Revenue	10.00
Business profile	30/00	Product stability	10.00
		Execution and Competitive Position	20.00
Leverage and coverage	45.00	EBIT / Interest Expense	15.00
		Retained Cash Flow / Net Debt	15.00
		Debt / EBITDA	15,00
Financial Policy	15.00	Financial Policy	15.00%
Total	**100.00**	**Total**	**100.00**

Source: Moody's and author's calculations.

Appendix 2

Table A2. Oil and Gas industry

Rating factors	*Weight, %*	x_i	*Weight$_i$, %*
Scale	20.00	Average Daily Production(Mboe/d)	10.00
		Proved Developed Reserves(MMboe)	10.00
Business profile	10.00	Business profile	10.00
Profitability and efficiency	25.00	Leveraged Full-Cycle Ratio (EBIT Margin)	25.00
Leverage and coverage	30.00	EBITDA / Interest Expense	7.50
		Debt / Average Daily Production	7.50
		Debt / PD Reserves boe	7.50
		RCF / Debt	7.50
Financial Policy	15.00	Financial Policy	15.00
Total	**100.00**	**Total**	**100.00**

Source: Moody's and author's calculations.

Appendix 3

Table A3. Steel industry

Rating factors	*Weight, %*	x_i	*Weight$_i$, %*
Scale	20.00	Revenue	20.00
Business profile	20.00	Business profile	20.00
Profitability and efficiency	15.00	EBIT Margin	10.00
		Return on Tangible Assets	5.00
Leverage and coverage	35.00	EBIT / Interest Expense	7.50
		Debt / Book Capitalization	5.00
		Debt / EBITDA	15.00
		(CFO-Dividends) / Debt	7.50
Financial Policy	10.00	Financial Policy	10.00
Total	**100.00**	**Total**	**100.00**

Source: Moody's and author's calculations.

Appendix 4

Table A4. Protein and agriculture industry

Rating factors	*Weight, %*	x_i	*Weight$_i$, %*
Scale	10.00	Revenue	10.00
Business profile	35.00	Geographic diversification	5.00
		Segment Diversification	5.00
		Market share	5.00
		Product Portfolio Profile	10.00
		Income stability	10/00
Leverage and coverage	40.00	Debt / EBITDA	10.00
		CFO / Debt	10.00
		Debt / Book Capitalization	10.00
		EBIT / Interest Expense	10.00
Financial policy	15.00	Financial policy	15.00
Total	**100.00**	**Total**	**100.00**

Source: Moody's and author's calculations.

Appendix 5

Table A5. Adjustment for support from the state or other shareholders

Supporting institution category	Degree of relationship: Very strong	Strong	Moderate	Weak	Very weak
Strong	Not higher than SICA*	Not higher than SCA + 4, but not higher than SICA* – 1	Not higher than SCA + 3, but not higher than SICA* – 2	Not higher than SCA + 2	SCA
Moderately strong	Not higher than SICA*	Not higher than SCA + 2	Not higher than SCA + 1	SCA	SCA
Neutral	SCA	SCA	SCA	SCA	SCA
Moderately weak	SICA*	Not higher than SICA* + 1	SCA	SCA	SCA
Weak	SICA*	Not higher than SICA* + 1	Not higher than SICA* + 2	SCA	SCA

* SICA or supporting institution's credit rating, if any.

Source: ACRA.

Appendix 6

Table A6. Adjustment for state and shareholder support

Level of state influence	Systemic importance level: Very high	High	Medium	Low
Very strong	Parity	Parity – [from 1 to 5 notches]	Not exceeding SCA + 3	Not exceeding SCA + 1
Strong	Parity – [from 1 to 3 notches]	Not exceeding SCA + 3	Not exceeding SCA + 2	Not exceeding SCA + 1
Moderate	Not exceeding SCA + 3	Not exceeding SCA + 2	Not exceeding SCA + 1	SCA
Weak	Not exceeding SCA + 1	Not exceeding SCA + 1	SCA	SCA

Source: ACRA.

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