Российский журнал менеджмента
20 (3): 361–384 (2022)

Russian Management Journal
20 (3): 361–384 (2022)

IDENTIFICATION OF FACTORS FOR ASSESSING CREDIT RATING OF NON-FINANCIAL COMPANIES

G.S.POMORTSEV
Faculty of Economic Sciences, HSE University, Russia[a]

A.A.ASTAKHOVA
Joint Department with the Bank of Russia, HSE University, Russia[b]

Goal: an improvement of the quality and accuracy of credit rating estimation, to add non-financial companies' characteristics to the assessment, and to compare the importance of factors for different industries and countries. **Methodology:** the use of exploratory factor analysis and ordered logistic regression models. The study is based on publicly available data on non-financial companies from different industries and countries for the period from 2007 to 2021. **Findings:** a group of financial variables is the most significant in credit risk assessment for companies from developed countries, for emerging markets, macroeconomic variables mostly determine credit ratings instead. The nonfinancial variables have diverse effects, but as a group increase the accuracy of the credit rating assessment. **Originality and contribution of the authors:** there is limited research on the topic of credit rating assessment of non-financial companies with the inclusion of non-financial factors. In addition, the presented research contributes to the search for new relevant indicators that can be introduced instead of the qualitative variables used by international rating agencies and requiring expert assessment.

Keywords: credit default prediction, modelling of credit ratings, credit assessment of non-financial companies, credit rating system, ESG rating, women employees, emerging countries.

JEL: C51, C52, G24, G32, G33.

INTRODUCTION

The relevance of credit risk assessment could not be overestimated in the modern world. Financial markets, investing, and development of the international business, in general, are highly connected with the credit quality of firms related to the particular event. The decision-making process of the creditors is dependent on the opinion about the credit quality of the borrower. Relationships between the company-borrower and its

Postal addresses: [a, b] 11, Pokrovsky bul., Faculty of Economic Sciences, HSE University, Moscow, 109028, Russia.

https://doi.org/10.21638/spbu18.2022.303

creditors are fundamental in the financial fields specified above. Hence, assessment of the credit quality is crucial in terms of the discussion of whether some firms are more attractive to investors than others and therefore whether they are more successful or not because following authors [Amato, Furfine, 2004; Altman, Rijken, 2006] who pointed that credit ratings are designed to evaluate the long-term quality of governance.

Credit rating assessment measures and standardizes the credit quality of a particular firm. Drivers of the growth of credit rating are important to investors and firms who want to track changes and to know to which actions and news they need to pay attention more. It is common to consider that the global macroeconomic and financial performance factors affect credit ratings, but which factors exactly have a bigger or lower influence is not clear enough. Moreover, historical examples of incorrect credit rating assessments, which have taken part in leading to the financial crisis of 2008 according to [Zaidi, 2016], underpin the importance of the definition of relevant factors determining credit ratings.

As mentioned by [Low, Siesfeld, 1998] major investors' decisions are significantly affected by non-financial performance information. Thus, other non-financial and qualitative factors could also determine the credit quality, and hence measuring what has a positive or negative effect and comparative analysis are crucial for both investors, firms, and other interested parties.

The lack of attention to non-financial companies' characteristics in previous research indicates the problem of downgrading the significance of their inclusion. However, there is research on the same topic but there is no possibility to prove the external validity, thus J. Grunert, L. Norden, and M. Weber examine the role of such factors but for only a small and restrictive sample [Grunert, Norden, Weber, 2005]. Even though, they concluded an increase in the accuracy of the credit rating assessment by the inclusion of both financial (here and after the term — financial variables are used to describe variables that could be obtained from the companies' financial statements) and non-financial factors in the analysis.

Therefore, the topic is not investigated enough but is highly relevant, and hence additional research is needed to answer the main *research question* — what the interrelationships and trends are observed in the formation of credit ratings of non-financial companies in various industries in developed and developing countries also considering previously unused factors? Hence, the *main aim* of the paper is to investigate the comparative strength of the factors on credit rating. Moreover, the paper focuses on establishing the influence of the inclusion of various non-financial factors in the credit ratings' assessment on its prediction's strength. In order to answer the research question, it is needed to compare the results from the assessment using only traditional factors and including several other non-financial indicators thus different combinations of used indicators could change the findings. Therefore, the paper formulates five main hypotheses according to the theoretical base to evaluate the impact by changing the used set of indicators for different markets and their industries.

The paper examines and compares the influence of various financial and qualitative indicators on the credit ratings of non-financial companies based on publicly available information. The scientific novelty of the research is underpinned by limited research on the topic of credit rating assessment of non-financial companies with the inclusion of non-financial factors. In particular, the study presents the stand-alone role of other variables (here and after represents included in the research non-financial factors: non-financial companies' characteristics or industry-specific variables). A definition of the interaction between companies' non-financial characteristics and credit rating for different industries is presented. Extensive research on the impact of women employees' proportion on credit rating presents a new way to look at the effect of gender on some sides of financial performance. Finally, the study pays more focus on the company's market characteristics. Especially, it investigates whether the free float is a significant variable and how a high value could badly influence credit ratings.

The practical relevance of the research is high. The present study could be used to create or modify existing methodologies for the credit rating assessment. One of the goals of the study is to increase the accuracy of the credit rating assessment by finding new indicators that could be implemented instead of qualitative variables used by international rating agencies that require expert assessment [Moody's, 2021a]. New significant factors determining credit rating with the respect to an industry or market could be treated with more attention by any interested parties. The extensive nature of the dataset presents the possibility to implicate and extend results to other countries and industries but with the respect to the particular restrictions and the nature of chosen industry of the country.

The study provides a comparative analysis of factors affecting credit ratings of non-financial companies from both emerging and developed countries from the following sectors: (1) IT; (2) telecommunications; (3) steel; (4) oil and gas. The research is dedicated to the evaluation of the factors determining credit ratings by implementing different econometric models and the strength of the effects differentiated by the markets and industries.

A complete list of independent factors for this study was selected based on the methodology of rating agencies and prior research. In addition to the classical indicators a wide pool of qualitative indicators was applied, such as the share of women employees, free-float percentage, and production of crude oil.

This paper use ordered logistic regression models which differ in sets of data to investigate five hypotheses.

Moreover, following S. Yang and M. T. Islam confirmatory factor analysis approach is used to split variables into three groups: macroeconomic, financial, and other (which contains all other non-financial variables) [Yang, Islam, 2020]. Such separation is used to assess the impact of each group on the credit rating considering the corresponding industry and market. The study uses annual data from 170 oil and gas, steel, telecommunications, and IT companies from developed and emerging countries for the period between 2007 and 2020. The sample includes information on macroeconomic, financial, and other non-financial variables.

The rest of the paper is organized as follows. The literature review and formulation of the hypotheses of the study are outlined in Section 1. Section 2 explains the methodology used for the research. Data description is presented in Section 3. Section 4 discusses the results. The conclusion of the paper and further implications are outlined in Section 5.

LITERATURE REVIEW

The theoretical base and reasoning of the paper comprise the studies of foreign and Russian researchers in the field of corporate finance and risk management. To formulate the hypotheses and properly discuss the results, concepts and the implied experience from the previous research are needed.

The international credit rating agencies do not directly include macroeconomic factors in the assessment [Moody's, 2021a]. Moreover, it is underpinned by numerous research that the inclusion of macroeconomic variables is necessary as it gradually improves the accuracy of the model [Karmisnky, 2020]. However, it is stated in the methodologies of the credit rating assessment that corporate credit rating could not be higher than the sovereign one and thus it is possible to consider higher influence for companies from less developed countries with lower sovereign ratings. Thus, before the inclusion of additional non-financial factors it is possible to evaluate the impact of macroeconomic variables and to look deeper into trends and differences between developed and emerging markets by investigating the following hypothesis.

Hypothesis H1: a group of financial factors is the most valuable (the effect on the final rating from the same fluctuations in coefficients' values is bigger in terms of marginal effects) when determining the credit rating of a company. However, companies from emerging markets are more influenced by macroeconomic variables.

Literature review shows that there is a limited number of studies on the impact of non-financial factors on credit ratings and comparative analysis of non-financial differentiating by the industries and markets generally. The authors of the paper [Grunert, Norden, Weber, 2005] specify the role of non-financial factors in the internal credit rating assessment. However, they investigate the influence on the banks only. But the results support the idea about the improvement of the accuracy in the prediction of the credit ratings with the inclusion of non-financial factors in the assessment. Therefore, it is reasonable to expect an increase in the accuracy by adding variables corresponding to the non-financial companies' characteristics for the assessment of also non-financial companies' credit ratings.

The topic of gender differences and the impact of the presence of women in the top management and the share of female workers is popular in the research, thus such variables could be used for the inspection of the modern trends in companies' performance from different industries and markets. Numerous studies investigate the influence on the financial performance of a higher share of women in the company and the findings are usually contradictory and could vary across industries and markets. Hence, the effect is not clear enough as the results of the paper of [Salloum et al., 2016] indicate that the presence of a female is not positively correlated with financial performance. [Mohr, Schumacher, Kiefner, 2022] evaluate that the presence of a female in the top management of multinational companies helps achieve sustainable development goals and this is explained by the social role theory and theories about team decision-making. But the primary focus of the paper is on women employees and then women can be more likely to engage in social activities and if the social activities affect credit ratings, then it is possible to consider then also female employees are likely to influence corporate credit ratings.

The important fact is about difficulties for women working in male-occupied industries because of possible sexual harassment, higher stress, social expectations, and other factors [Catalyst (US), 2012)]. Therefore, hypothesis could be formulated as follows.

Hypothesis H2: a high proportion of women employees would positively and significantly affect the credit ratings of companies. The share of women employees has more impact on companies in pro-sustainable industries.

Environmental, social and corporate governance (ESG) as well as sustainable development is also a popular topic in the literature nowadays. Most of the research in the field of the impact of credit ratings is within the significance of the effect on the companies' credit ratings. However, the significance of the assessment for each of the industries and markets is questionable. The authors of paper of [Devalle, Fiandrino, Cantino, 2017] argues that there is only a significant effect from the social and governance scores (metrics related to social and governance). In the same paper, the effect of the environmental metrics is investigated and stated the necessity of additional research. Also, another research by [Jang et al., 2020] states the increasing impact of *E*-ratings (environmental metrics) but without binding results to a specific industry. In the meantime, the authors of study [Chodnicka-Jaworska, 2021] underpinned the importance of dividing research on the effect of the ESG rating into the industries analysis. Therefore, the question is about the effect of the ESG rating and its metrics on the credit rating with the respect to the industry and the market tested.

Moreover, a joint analysis of the ESG factors and a share of women employees could lead to interesting results. As women's presence in any collective increases the probability of participation in some social activities then it is important to check for the possible problems in the modeling: both statistical and logical. Hence, to answer the research question it is needed to investigate the following hypothesis.

Hypothesis H3: ESG rating positively and significantly affects credit ratings. G-score has a significant and positive effect on any industry, while the effects of the E-score and S-score vary.

Methodologies of an international rating agency Moody's consist of non-financial factors which are usually measured as qualitative variables with some scale. Thus, the methodology of a credit rating assessment of the companies from the steel industry [Moody's, 2021b] includes a business profile and financial stability sections which are qualitative.

A lifetime of a company could be used as a proxy for financial stability as all others keep constant, the more mature a company is then it is more stable. However, the high value of this variable could also indicate a higher probability of outdated technologies for a particular industry.

Moreover, qualitative indicators could be captured by other non-financial companies' characteristics and represent market stability by the free-float percent or level of internal dependence by the fact whether the chairman is an ex-CEO or not. There are contradictory results from the prior research on the impact of free-float percentage on the financial performance of the company. Authors of [Berle, Means, 1933; Morck, Shleifer, Vishny, 1988] argued that the impact is positive due to higher interconnection costs between main and smaller shareholders. However, in [Villalonga, Amit, 2006; Ozer, Ozen, 2018] authors conclude the negative and significant impact of more concentrated ownership on firm performance due to destroying the value of a firm by repulsion of potential shareholders' desire to buy shares. It is important to mention that there are studies that conclude insignificant influence from concentrated ownership. For instance, H. Demsetz and B. Villalonga concluded insignificance because of the endogeneity of shareholders' behaviour [Demsetz, Villalonga, 2001]. Therefore, the additional hypothesis is formulated as follows.

Hypothesis H4: free-float percentage, an indicator of whether the chairman is ex-CEO, and the company's lifespan have a significant impact on credit ratings.

The oil and gas industry methodologies of assessment of companies' credit ratings gradually differ from others. Moody's methodology for this industry includes variables related to oil and gas reserves and production [Moody's, 2021a]. Moody's underpins the importance of these variables as production is the main source of the cash flow while reserves could indicate a store of current and future extractable value. Moreover, B. H. Bergrem in the research about credit ratings in the oil and gas industry concluded the importance of the implication of these factors in the modeling [Bergrem, 2014]. Therefore, the companies from this industry could experience different impacts from the industry-specific factors and the following hypothesis is needed to be investigated.

Hypothesis H5: credit ratings of oil and gas companies are significantly and positively influenced by indicators of oil and gas production and reserves.

METHODOLOGY

The methodological base of the paper is constructed by investigating the most appropriate econometric model in terms of the least deviation of the predicted credit ratings from the actual ratings (explained below).

Concerning formulated hypotheses there two types of analysis are used: factor analysis and analysis through the model specification which results would be accurate and capable of interpretation.

Factor analysis helps to reduce a large number of variables into a latent variable by capturing the joint significance and this method could be implemented in the credit rating analysis [Yang, Islam, 2020]. *Hypotheses H1* and *H4* need a detailed factor analysis to calculate the merged factors and then assess the credit ratings by using them. Exploratory factor analysis (EFA) could be used to determine the factors, meaning that the goal is to choose only relevant factors among the variables in the study without prior conviction about the factors' structure. The following factor calculation formula is used:

$$y_{ij} = z_{i1}b_{1j} + z_{i2}b_{2j} + \cdots + z_{iq}b_{qj} + e_{ij},$$

where is the value of the ith observation on the jth variable, is the ith observation on the kth out of q common factor, is the set of q linear coefficients — factor loadings, and is the jth variable's unique factor. Right-hand-side is going to be estimated and thus there is an infinite number of solutions, but the method is constrained to an inspection of joint variance and hence estimates could be provided [Afifi et al., 2019].

For the modeling of credit ratings, it is important to determine and choose the appropriate method. As mentioned in [Karminsky, Burekhin, 2019] it is relevant to choose ordered logistic or probit models, but this result was obtained on different data and even types of company. The author used a dataset with financial companies, so it is reasonable to check it by inspecting the results of the fitted baseline model by three methods: (1) ordinary least squares (OLS); (2) ordered probit regression; (3) ordered logistic regression (OLR).

In the research different models for each of the hypotheses are constructed. However, all of those follow the same general assumption of constant impact over the period used in the model. Therefore, 10 different models with different sets of variables and samples to test the hypotheses are:

- baseline model.

  The baseline model is implemented to formulate a list of the control variables for the addition of the independent variables that are of primary interest due to certain hypotheses. The model should meet the requirements about the possibility of coefficient interpretation (significance) with reliable prediction power (prediction errors) to make a relevant conclusion on the hypotheses;
- *hypothesis H1*: EFA for comparative analysis.

  Model 1 is constructed as a regression using obtained factors from the EFA: macro, financial-1, and financial-2. Furthermore, the emerging dummy is added as an interaction term to capture moderating effects of the incorporation of a company in the developing country;
- *hypotheses H2, H3*: OLR with interaction terms as dummies for slope coefficients.

  Model 2 includes women employees as the main independent variable and the controls from the baseline model. Moreover, industry dummies are included to compare the effects for different industries.

  Models 3.1 and 3.2 include the ESG score and its divided *E*, *S*, and *G* scores respectively with the addition of the industry dummies and the controls from the baseline model.

  Models 2+3.1 and 2+3.2 are extended versions of the previously specified models when they are merged to see how the significance and the results are changed in the different specifications;
- *hypothesis H4*: EFA for comparative analysis with OLR for the overall model

  Model 4.1 is a model where all significant non-financial variables besides control variables at the maximum of 5% significance level are included.

  Model 4.2 has the same structure as the first model but with the inclusion of non-financial variables in the factor analysis, determining the fourth factor with the most explained variance by the non-financial variables. Moreover, interaction terms between non-financials and industry dummies are included in the hypothesis;

- *hypothesis H5*: OLR for oil and gas industry with interaction term as a dummy for slope coefficient.

  Model 5 is constructed for the oil and gas industry only as coefficients are unique and measured for the only corresponding industry. Controls and the oil and gas production and reserves are added to the model.

Therefore, the proposed methodology allows us to test hypotheses as well as assess the importance of including non-financial variables in the estimation by comparing the predictive power of the models.

DATA DESCRIPTION

The list of countries used in the study is Brazil, Russia, India, China, South Africa, the United States, Canada, the United Kingdom, and Germany. Therefore, the sample consists of both developed and developing countries according to the research question. The countries used in the study were classified according to [United Nations, 2014]. BRICS countries are used as representatives of the emerging countries with the most developed economies and thus the most balanced economies. However, these countries have their own specialization and comparative advantages following [Johansson, Olabería, 2014]. Thus, the oil and gas, steel and IT industries are chosen as mostly the export-oriented industries in the emerging markets. However, the classical industry is oriented on internal consumption — the telecommunications industry has its own specific due to lower dependence on macroeconomic fluctuations. Moreover, in order to compare developed countries are included with more developed economies to balance the sample. Four developed countries in the study are the richest (in terms of gross domestic product (GDP) ranking from [World bank, 2021]) which covers different levels of development of the industries and thus provides more information for the analysis.

The main dependent variable is the Numeric credit rating which is measured as a given credit rating by Moody's, S&P, or Fitch and rated by an ordered scale from 1 to 22 where 22 is the highest possible credit rating — "Aaa", and evenly decreasing — 1 is a lowest — "Ca" according to Moody's long-term rating scale [Moody's, 2022]. All data for modeling is retrieved from [Thomson Reuters Eikon, 2022]. Moody's, S&P, and Fitch reports are used where it is possible to fill in the missing observations.

Figure 1 (a — f) indicates that the dataset is balanced for each industry and market. It is possible to highlight those numeric ratings with scores of 13–14 (speculative categories) are the most frequent in the sample while other ratings are distributed waning from them on average. None of the industries and markets stands out and has much smaller observations thus the distribution of the credit ratings in the sample is well-diversified.

The classical financial and macroeconomic variables are chosen according to [Karminsky, 2015]. Table 1 presents all independent variables which are used in the study with an indication in which model they are included with the proposed sign. Moreover, there is no proposed sign for many variables because they are included in the factor analysis and are used to determine grouped variables thus the sign is not interesting in comparison with the variance of the variable.

All data on macroeconomic variables are from the [World bank, 2021] besides sovereign ratings whose historical values are acquired from the [Trading Economics, 2021]. Data on financial variables are obtained from the Thomson Reuters database for all firms from the specified industries and countries.

The group of non-financial variables is chosen to investigate proposed hypotheses and consists of 11 different variables and all data were obtained from the Thomson Reuters database. Variables of oil and gas production and reserves differ from others

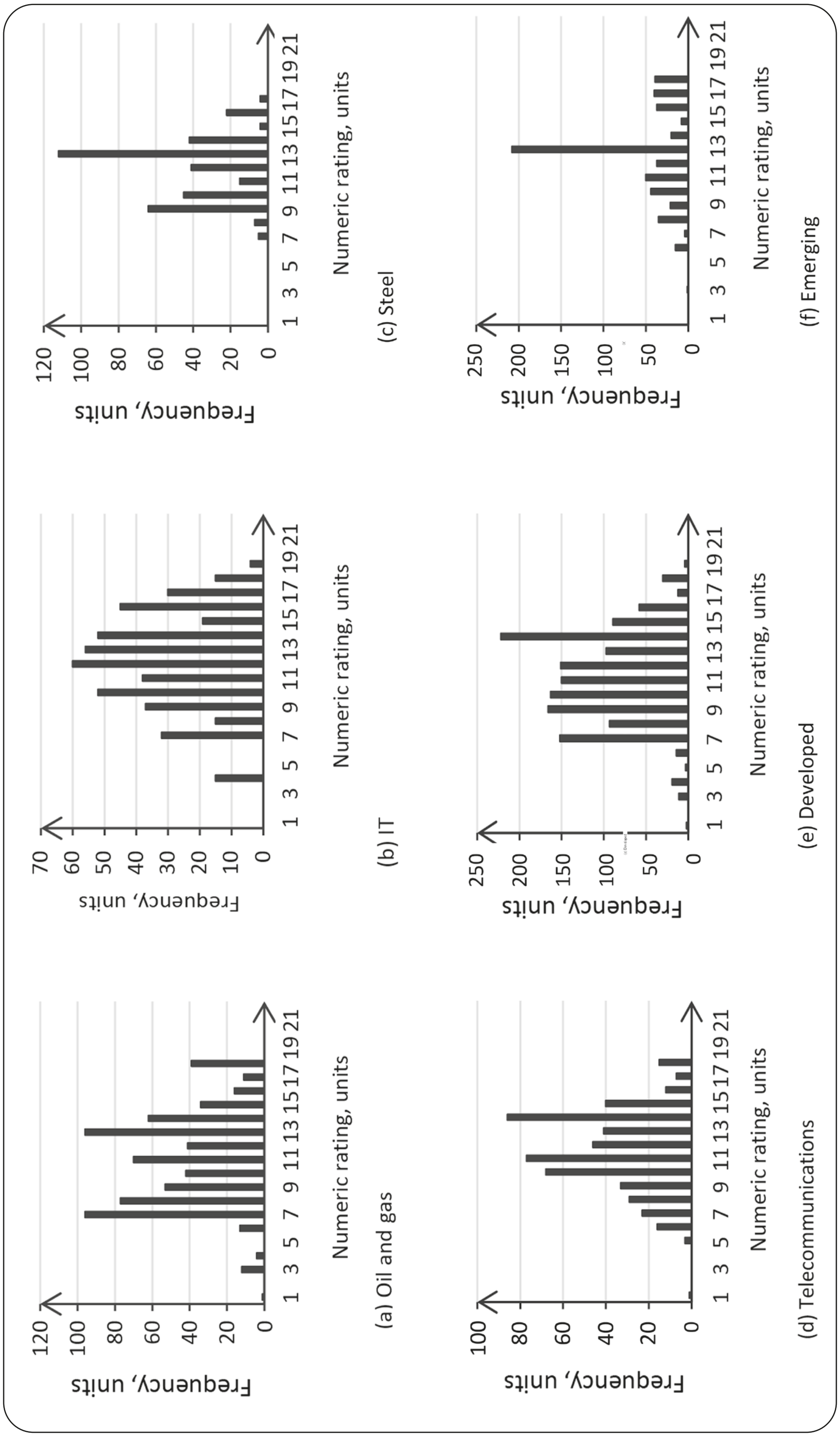

Fig. 1. Distribution of numeric ratings by industries and markets

Note: the y-axis corresponds to a number of observations corresponding to each value of Numeric ratings which are shown on the x-axis.

Table 1

The list of independent variables

Group of variables	Variable	Included in Model									Proposed sign
		1	2	3.1	2+3.1	3.2	2+3.2	4.1	4.2	5	
Macroeconomic	*GDP growth (%)*	+	+	+	+	+	+	+	+	+	+
	ln(GDP per capita)	+							+		+
	Gross savings to GDP	+							+		...
	Inflation	+							+		...
	Share of export to GDP	+	+	+	+	+	+	+	+	+	-
	Political stability	+							+		...
	Competitiveness index (GCI)	+							+		...
	Sovereign ratings	+	+	+	+	+	+	+	+	+	-
Financial	*ln(Total assets)*	+							+		...
	ln(Revenue)	+	+	+	+	+	+	+	+	+	+
	EBIT Margin (%)	+	+	+	+	+	+	+	+	+	+
	EBIT / Interest Expense	+	+	+	+	+	+	+	+	+	+
	Debt / Book capitalization	+	+	+	+	+	+	+	+	+	-
	RCF / Debt	+							+		...
	(RCF — CAPEX) / Debt	+							+		...
	Current ratio	+	+	+	+	+	+	+	+	+	+
	EBITDA margin (%)	+							+		...
	Pretax ROA (%)	+	+	+	+	+	+	+	+	+	+
	Dividends paid	+							+		...
	Quick ratio	+							+		...
Non-financial (Other)	*Crude oil — Production per day*								+	+	+
	Natural gas Reserves — Proved								+	+	+
	Oil & LNG reserves — Proved								+	+	+
	ESG score			+	+			+	+		+

Group of variables	Variable	Included in Model									Proposed sign
		1	2	3.1	2+3.1	3.2	2+3.2	4.1	4.2	5	
Non-financial (Other)	*Social pillar score*					+	+		+		+/−
	Governance pillar score					+	+		+		+
	Environmental pillar score					+	+		+		+/−
	Free float (%)							+	+		+/−
	Women employees		+		+		+	+	+		+/−
	Chairman is ex-CEO							+	+		+/−
	Days on the market							+	+		+/−

Notes: all independent variables used in the study besides dummy variables on industries and emerging markets are presented; "+" and blanks in columns 3–11 indicate an inclusion of a corresponding variable in a certain model; "+", "+/–" and "…" in the last column indicate proposed sign: "+" — positive sign, "+/–" — either positive or negative sign depending on industry and country and "…" — proposed sign is uncertain.

due to a small number of observations as they are measured for only the oil and gas industry. Moreover, the final sample is unbalanced with respect to the temporal dimension because of the relative contemporaneity of some variables, such as ESG ratings and its individual scores.

Correlation analysis shows that some macroeconomic variables are correlated with each other, for example, *GDP growth* and *ln(GDP per capita)* are highly correlated and therefore analysis of variance inflation factor (VIF) values after regressions is crucial to determine possible issues from the multicollinearity. The same could be applied to financial variables: *ln(Total assets)* and *ln(Revenue)* are highly correlated and variables measured by the same components as profit or debt are also highly correlated. But inclusion in the study is helpful to capture joint variance better in the factor analysis.

Important to mention the results from the correlation analysis of the non-financial variables. There are no highly correlated pairs in the sample besides oil and gas production and reserves variables and ESG factors and their factors with each other. Therefore, there could not be a problem of multicollinearity in terms of regression with these variables. However, for the factor analysis, it is a problem as it needs to capture joint variance.

RESULTS AND DISCUSSION

Appendix 1 shows that there are three significant factors determined with the respect to the eigenvalues more than 1 when including all macroeconomic and financial factors in the analysis. Moreover, Table 2 presents that these three factors could be renamed to macro, financial-1, and financial-2 respectively as factor loadings represent the nature of the factors.

Important to mention that factor loadings show that there are two factors related to financial variables. The first financial factor covers the total "size" of the company while the second represents the profitability of a company.

The estimated baseline models are reported in Appendix 2. The signs are the

Table 2

Factor loadings

Variable	Macro	Financial-1	Financial-2	Uniqueness*
ln(GDP per capita)	–0.8370	0.0391	0.0022	0.2979
Gross savings to GDP	0.6088	0.0873	–0.0342	0.6206
Inflation	0.7917	–0.1120	–0.0158	0.3604
Political stability	–0.9255	0.0361	0.0923	0.1336
Competitiveness index (GCI)	–0.9341	0.0644	0.0284	0.1224
Sovereign ratings	0.9474	–0.0693	–0.0742	0.0921
*Emerging***	0.9793	–0.0119	–0.0586	0.0374
ln(Total assets)	0.1228	0.9419	0.1163	0.0841
ln(Revenue)	0.1623	0.9487	–0.0156	0.0735
EBIT margin (%)	0.2961	–0.0420	0.7493	0.3491
EBITDA margin (%)	0.0507	–0.1843	0.8421	0.2542
Dividends paid	–0.0125	0.6949	0.1182	0.5030

Notes: * — uniqueness represents the share of unexplained variance by presented factors; ** — emerging is a dummy variable that is equal to 1 for companies from the emerging markets and 0 otherwise.

same as proposed and the same for each variable's coefficients from each model besides coefficient — *Current ratio* which sign is negative in the OLS model but is not significant and hence its sign could be determined incorrectly.

Inspection of VIF values obtained from the Baseline model estimation and reported in Appendix 3 indicates the absence of serious multicollinearity problems using a threshold of 10 [Fox, Monette, 1992].

Prediction errors of the models are reported in Table 3 and the highest accuracy is presented in the ordered logistic regression model. Therefore, as considered by the literature ordered logistic regression method would be used for fitting later models.

Figure 2 shows the structure assumed for the first hypothesis where the macro group and financials-1, 2 are treated as latent variables and there is moderating effect by the *Emerging* (dummy and equal 1 when the firm is from the emerging market and 0 otherwise). From Table 4 all three factors have positive signs and each coefficient is significant at a maximum of 1% significance level besides the interaction term between the financial-2 group and the *Emerging*. Therefore, it is possible to make conclusions. Model 1 indicates that when the company is from a developed country (*Emerging*=0) then the effect from the financial variables is higher.

However, when the company is from an emerging country (*Emerging* = 1) then

Table 3

Prediction errors of the Baseline Model

Model	Prediction error*, Δ (%)						
	−2	**−1**	**0**	**1**	**2**	**|Δ|≦1**	**|Δ|≦2**
OLS	13.30	19.18	21.48	15.35	8.95	56.01	78.26
Ordered logistic regression	10.49	26.34	18.67	17.65	11.00	62.66	84.15
Ordered probit regression	10.74	25.58	18.93	17.90	10.49	62.41	83.64

Note: prediction error is calculated as the rounded difference between predicted and actual numeric rating values from the test sample (30 %).

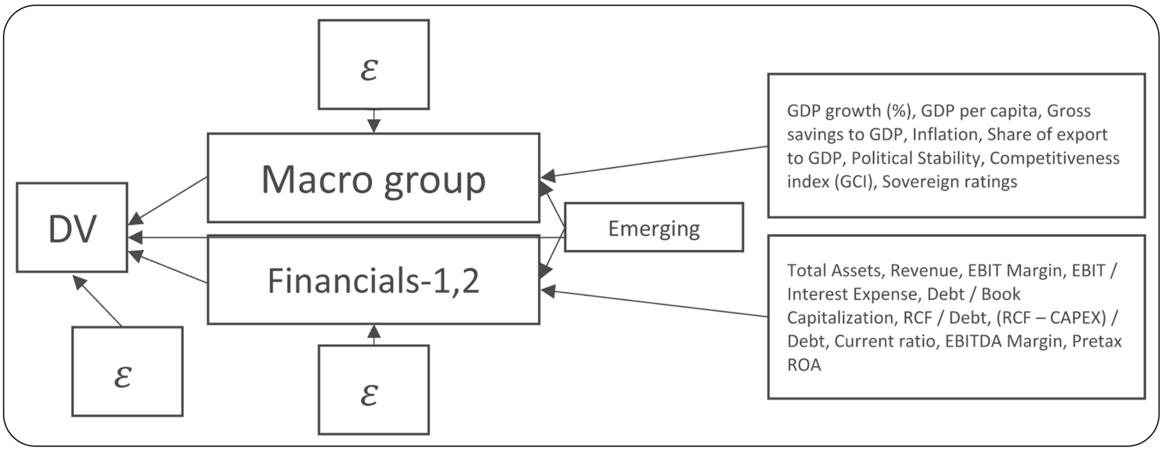

Fig. 2. Structure for Model 1

Note: the term “epsilon” corresponds to the error term of the dependent variables that are estimated.

a group of macro variables becomes more important as the overall calculated marginal effect on the probability is 1.3070424 approximately while from the first group of financials is 0.6222037 and the second group of financials have not signed and the comparatively small effect all other keeping constant (Table 4). These findings support the first hypothesis and evaluate that the macroeconomic group of variables become more important for companies from emerging countries. It does not confront the literature, and it could be explained by the methodologies of the international agencies which bind corporate credit ratings being not higher than the sovereign one. Moreover, firms from the emerging countries are likely to be influenced by government support and therefore they are more affected by changes in the global macroeconomic variables in the country.

It is important to mention that given the small value of the measure of goodness-of-fit — *Pseudo* (Table 4), it is possible to conclude small variance of the dependent

Table 4

Model 1

Variable	Model 1
Macro group	0.7078244* (0.5988917)
Financial-1 group	0.8634238*** (0.0765313)
Financial-2 group	0.0260839* (0.0169828)
Emerging (dummy)	–1.918259** (0.8625685)
Macro group X Emerging	0.599218* (0.4541115)
Financial-1 group X Emerging	–0.2412201** (0.0995998)
Financial-2 group X Emerging	0.08232 (0.1171604)
Number of observations	643
Pseudo	0.1036
Mean accuracy	2.294001

Notes: robust standard errors in parentheses reported under the regression coefficients; *** — $p<0.01$; ** — $p<0.05$; *— $p<0.1$; "*X*" in a variable name indicate multiplication sign.

variable is explained by the factors which could be driven by the absence of non-financial variables besides factor analysis method which decreases the amount of variance in the model by the definition.

To investigate *hypotheses H2* and *H3* models from 2 to 2+3.2 were assessed and results are reported in Tables 5 and 6. The share of women employees has a positive but partly significant effect (it is significant but not in each model: at the 5% significance level in Model 2 and not significant in model 2+3.1) on the credit rating in all models. Moreover, this effect is negatively moderated by including dummies. Consequently, the influence is positive for IT and telecommunications companies and negative otherwise, which is supported by the theory about the presence of women in male-dominated industries.

Overall ESG rating positively influences the credit ratings of the companies, but the influence is not significant for each industry. It is significant for the IT and steel industries (at the 1 and 0.1% significance level respectively) but not for the oil and gas and telecommunications industries. Important to mention the negative and highly significant impact on the credit ratings of steel companies. Furthermore, the highest positive effect is presented for the IT industry companies which need additional research on the effects of divided ESG scores to find an explanation.

The environmental score has a positive effect on each industry besides the steel industry. However, the effect is significant for IT and steel industries at the 5% significance level while effects for other industries are partly significant (at the 5% significance level in Model 2+3.2). The effect of the *E*-score on the credit rating of steel companies is not unambiguously defined. Moreover, it has also the highest influence on IT companies. The social score has a negative but partly significant impact on credit ratings for only the IT industry. The lowest negative effect is for the oil and gas industry, while the highest is for the IT industry. Therefore, it is crucial to pay attention to social factors for IT companies. Governance score positively and significantly (at a maximum of 5% significance level) influences credit ratings supporting findings from the prior research. Steel companies again expect a negative impact of high *G*-scores, while IT companies have the highest impact of this factor on their credit ratings. Thus, that is why the effect of ESG score is the highest for IT companies as each score's effect is the highest for the IT industry.

Due to highly correlated interaction terms in Model 3.2 and 2+3.2 (Table 6), there is no possibility to obtain high significance, but patterns in terms of significant variables for each industry are possible to present. To investigate *hypothesis H4* Models 4.1 and 4.2 from the Table 7 were implemented. Model 4.1 could serve as the "overall" model as it consists of all significant variables

Table 5

Models 2, 3.1 and 2+3.1

Variable	Model 2	Model 3.1	Model 2+3.1
Women employees	0.1476819* (0.1099546)		0.0892239 (0.1490001)
Women employees X Oil and gas	–0.2071688** (0.1124065)		–0.1495253 (0.1508403)
Women employees X Steel	–0.1568361* (0.1110815)		–0.1087956 (0.1486156)
Women employees X Telecommunications	–0.136467* (0.1000259)		–0.0796268 (0.1486213)
ESG score		0.0338874** (0.0114154)	0.0655294* (0.0282272)
ESG score X Oil and gas		–0.0099363 (0.012078)	–0.0406739 (0.0294779)
ESG score X Steel		–0.0518506*** (0.0130809)	–0.1143215*** (0.0333236)
ESG score X Telecommunications		–0.0177241 (0.0119207)	–0.0690059* (0.0324443)
Number of observations	459	835	459
Pseudo	0.2451	0.2313	0.258
Mean accuracy	1.368331	1.438271	1.386288

Notes: robust standard errors in parentheses reported under the regression coefficients; *** — $p<0.001$; ** — $p<0.01$; * — $p<0.05$; "X" in a variable name indicate multiplication sign. Blanks in certain cells indicate non-inclusion of a variable in a corresponding model; controls from the baseline model are included in the model but are suppressed in the report.

included in the research. From the outcome of this model, it is possible to evaluate that all estimates of non-financial characteristics are highly significant for the assessment of credit ratings (all coefficients are significant at the 0.1% significance level besides the *Free float percentage* that is significant at the 1% significance level). ESG score has a positive influence as mentioned earlier. The variables whether the chairman is an ex-CEO and days on the market also positively influence credit ratings keeping others constant (stand-alone). However, the share of free float has a significant and negative impact. A higher free float percentage means a less concentrated ownership structure and these findings suggest a negative impact from it and then contribute to the view of [Berle, Means, 1933], [Morck, Shleifer, Vishny, 1988] that presence of interconnection costs outweighs positive effects of liquidity and other.

For the Model 4.2 the "Other" group of variables was assumed as a latent variable and was obtained through the factor analysis (EFA), the structure is the same as for the Model 1, but with the addition of "Other" with moderating effects from the *Emerging* and industry dummies. The analysis points positive influence of the "Other" variables on the credit ratings for all industries besides IT. Moreover, the highest effect

Table 6

Models 3.2 and 2+3.2

Variable	Model 3.2	Model 2+3.2
Women employees		0.1310708* (0.1022683)
Women employees X *Oil and gas*		0.1972036** (0.1052819)
Women employees X *Steel*		0.1424535* (0.1030036)
Women employees X Telecommunications		–0.1115812 (0.1023074)
E-score	0.0280316* (0.0138114)	0.0947011* (0.0404526)
S-score	–0.0119395 (0.0181699)	–0.1155857* (0.0543047)
G-score	0.0168121* (0.0089333)	0.0595938*** (0.0117335)
E-score X *Oil and gas*	–0.0000943 (0.0162676)	–0.0690824* (0.0413012)
E-score X *Steel*	–0.0289951* (0.0152632)	–0.0609019* (0.0433725)
E-score X Telecommunications	–0.0162924 (0.0158376)	–0.0785989* (0.0421605)
S-score X *Oil and gas*	0.0027657 (0.0200156)	0.1064501* (0.0551431)
S-score X *Steel*	0.0062949 (0.0204517)	0.0764784 (0.0556863)
S-score X Telecommunications	0.0022019 (0.020484)	0.0753405 (0.054789)
G-score X *Oil and Gas*	–0.00839 (0.0103607)	–0.0496017*** (.0140379)
G-score X *Steel*	–0.0380402*** (0.0107736)	–0.0894153*** (0.0162445)
G-score X Telecommunications	0.0028509 (0.0114321)	–0.0320841* (0.0164283)
Number of observations	835	459
Pseudo	0.2376	0.2816
Mean accuracy	1.416594	1.354038

N o t e s: robust standard errors in parentheses reported under the regression coefficients; *** — $p<0.001$; ** — $p<0.01$; * — $p<0.05$; “X” in a variable name indicate multiplication sign. Blanks in certain cells indicate non-inclusion of a variable in a corresponding model; controls from the baseline model are included in the model but are suppressed in the report.

Table 7

Models 4.1 and 4.2

Variable	Model 4.1	Model 4.2
ESG score	0.0193484*** (0.0042718)	
Free float percentage	–1.002094** (0.3485048)	
Chairman is ex-CEO	0.5444386*** (0.1482851)	
ln(Days on the market)	0.3237659*** (0.0722943)	
Other group		–0.1099878 (0.1007416)
Other group X Oil and gas		0.2767409* (0.11656)
Other group X Steel		0.4995795*** (0.148774)
Other group X Telecommunications		0.4808628*** (0.1194703)
Other group X Sovereign rating		–0.0823592*** (0.0127892)
Number of observations	833	565
Pseudo	0.2325	0.1457
Mean accuracy	1.432525	2.08825

N o t e s: robust standard errors in parentheses reported under the regression coefficients; *** — $p<0.001$; ** — $p<0.01$; * — $p<0.05$; "X" in a variable name indicate multiplication sign. Blanks in certain cells indicate non-inclusion of a variable in a corresponding model; controls from the baseline are included in the model but suppressed in the report; macro and financial group variables, and direct effects from dummies are also suppressed from the report of Model 4.2. Blanks in certain cells indicate non-inclusion of a variable in a corresponding model.

is on the steel industry. Additionally, the effect is lower and even could be negative when the company is from an emerging country. However, the direct coefficient is not significant thus the results could be non-reliable.

Therefore, the effect of a company's non-financial characteristics differs for industries and markets. They have positive for oil and gas, steel and negative for tech industries due to composing marginal effects. Moreover, the implication of the non-financial factors positively affects the accuracy of prediction.

As was already mentioned before both models are the versions of the "overall" models for the credit rating assessment. Important to mention, that the addition of new variables does not reduce the explanatory power and significance of the model. Therefore, it is crucial to include an investigation of the "Other" variables in the research in the field of credit ratings.

For *hypothesis H5* Model 5 respectively from Table 8 was obtained. The volume of crude oil production per day negatively and insignificantly affects the credit ratings of

Table 8

Model 5

Variables	Model 5
ln(Crude oil production)	−0.1631692 (0.2410093)
ln(Natural gas reserves)	0.5060903* (0.2846547)
ln(Oil & LNG reserves)	0.4328863* (0.2394941)
ln(Crude oil production) X Sovereign ratings	0.1292643* (0.0699522)
ln(Natural gas reserves) X Sovereign ratings	−0.086843** (0.0302166)
ln(Oil & LNG reserves) X Sovereign ratings	−0.3263865*** (0.085379)
Number of observations	275
Pseudo	0.3929
Mean accuracy	1.025507

Notes: robust standard errors in parentheses reported under the regression coefficients; *** — $p<0.001$;** — $p<0.01$; * — $p<0.05$; "X" in a variable name indicate multiplication sign. Blanks in certain cells indicate non-inclusion of a variable in a corresponding model; controls from the baseline are included in the model but suppressed in the report.

oil and gas companies in the exploration and production sector.

Natural gas and oil proved developed reserves positively influence credit ratings. Moreover, the direct effects and moderating effects are both significant at a 5% significance level.

Since the variable sovereign rating is measured invertedly from 1 to 22, where 1 is "Aaa" and 22 is "Ca" (Moody's scale) and the signs of the moderating effects are negative, the findings show that the return on gas and oil proved developed reserves is lower for companies from emerging markets.

Therefore, the hypothesis is partly supported. Coefficients of proved developed oil and gas reserves and their production positively affect credit rating of companies from developed countries. However, this effect could be negative for emerging markets.

This hypothesis differs from others as it only measures effects for the companies from one industry — oil and gas. Thus, the sample size is small which decreases the overall significance of the model and individual t statistics and could lead to nonreliable results, but patterns in terms of significant variables for companies from emerging markets are possible to present.

From Table 9 it is possible to conclude the accuracy of the model by the same method as in the Methodology section. The analysis indicated that the least prediction error for predicting correctly within the −1 and 1 notch error range is in Model 5 (77%) which is high given the fact that there are 22 classes of the outcome variable in the study. However, the accuracy of Model 5 is questionable as it has the smallest test sample size (100 observations) because only oil and gas companies are in the model. As the distribution of the credit ratings in the oil and gas industry has shown that most of the observations are concentrated almost uniformly in the middle of the range then it increases the probability of random guessing of the actual numeric rating which then increases the accuracy. Every model which has no variables grouped by the factor analysis besides Model 3 has higher accuracy compared to the baseline model, which also indicates the significance of the additional variables.

An important point is that the overall models Model 4.1 and Model 4.2 have the highest accuracy in their groups (besides the Model 5).

Given the findings it is possible to state that given others constant an inclusion of more indicators and thus more information increase the accuracy for each industry. Moreover, the credit ratings of the companies from the emerging countries are less influenced by the company-specific characteristics due to the high role of the macroeconomic fluctuations. Political instability and market competition could also impact all emerging countries at the same time because of the trade unions. Higher international trade fees

Table 9

Prediction errors of Models 1–5

Model	Prediction error, Δ (%)		
	$\|\Delta\|=0$	$\|\Delta\|\leqq 1$	$\|\Delta\|\leqq 2$
Model 1	13.23	45.13	60.3
Model 2	21.11	65.83	85.94
Model 3.1	22.19	61.8	83.15
Model 2+3.1	24.12	62.82	84.43
Model 3.2	23.88	64.33	82.87
Model 2+3.2	26.63	64.82	87.94
Model 4.1 (Overall)	19.72	65.64	85.08
Model 4.2	19.33	52.95	71.44
Model 5 (Oil and gas)	29	77	92

Note: prediction error is calculated as a rounded difference between predicted and actual numeric rating values from the test sample (30%).

or sanctions for the developing countries are more significant due to less balanced economies and impossibility of replace the government earnings by other sources in the short-term period. Therefore, the results suggest still significant but less relevant influence.

CONCLUSION, CONTRIBUTION, AND IMPLICATION

All things considered, the relevance of the study and research question is explained. Due to a gap in academic literature related to the assessment of the impact of non-financial variables on credit ratings of non-financial companies this research is needed.

The study used macroeconomic, financial, and non-financial indicators obtained for oil and gas, steel, telecommunications, and IT companies from both developed and emerging markets to inspect five hypotheses by using OLR and EFA approaches.

The findings suggest that the first hypothesis is supported since a macroeconomic group of variables has a higher impact on the companies from the emerging countries. The second hypothesis is not supported because of changing the sign of the impact from the higher women employees share. The third hypothesis is partly supported as ESG rating does not have a significant and negative effect on each industry. Furthermore, its divided scores do not have a proposed impact due to lack of significance and not equally positive influence from the *G*-score. The fourth hypothesis is partly supported as included in Model 4.1 non-financial variables all have a significant effect on credit rating. However, not all coefficients from the Model 4.2 are significant. Moreover, it is established that the free-float percentage negatively influences credit ratings which confront the most recent studies on the topic of the impact of concentrated ownership. The fifth hypothesis is partly supported due to positive for only developed countries and significant effects from all oil and gas-related variables besides crude oil production. In addition, observed effects are even higher for companies from emerging markets.

Furthermore, the accuracy of credit rating prediction of non-financial companies increases with the addition of non-financial companies' characteristics and that is the main contribution. More specifically, the paper contributes to the existing literature by pointing out differences in the impact from industry to industry and from country to country. Thus, macroeconomic indicators can explain most of the emerging markets companies' credit ratings that could be used in future research of the emerging markets given that no matter how financially successful the company is, it could be not enough for investors if it operates in the unstable market. Moreover, the advantages of the expanding gender variety in the whole pool of workers could not outweigh the classical problems in male-dominated industries. ESG is a widely used indicator that gradually increases the prediction accuracy and thus is needed to be included in the credit rating assessment of presented industries for simplicity, but in order to evaluate true impact its components should be used. It is evaluated that a higher free-float percentage gets a negative impact on the firm's credit quality and thus buybacks and other actions supporting concentration are more attractive to potential creditors. Additionally, the oil and gas companies' credit ratings could not be assessed without the inclusion of the reserves and production indicators due to their significant impact.

In terms of differences in the effect on the different industries the results are obtained and there is no clear explanation of more or less impact from the other variables dividing industries by the export-oriented or by classifying by the specialization on the internal or external consumption what could drive the future research.

It is possible that some models could suffer from endogeneity through the omitted variable bias. For instance, the baseline model and model 1 do not include variables from the "Other" variables group which affect the credit ratings as presented in the later models. However, much of the "Other" variables are almost uncorrelated with the macroeconomic and financial variables as was shown in the data analysis section and as neither of the models includes constant. Therefore, the effect of omitting could be present but not significant to suffer.

However, there is a bridgehead for future research due to the insignificance of a few results and undetected sign of the impact. Hence, the impact of the high female presence in the company could be investigated further by splitting into workers and women in the top management as some other industries specific could add new factors into consideration.

To repeat once again, Models 3.2,2+3.2 and 5 are likely to suffer from the multicollinearity problem by the correlation on the regression sample due to the small sample size. Thus, to prevent such problems, it is relevant to increase the sample size and think about additional transformations of the variables.

Moreover, the models assume a constant effect of variables over time, and this assumption serves as a sacrifice to increase the sample size. However, the entire period from 2007 to 2021 is only included in the general models without contemporaneous variables such as ESG scores and their components, making the question of whether this assumption is satisfied less important. Moreover, the average patterns over the period are possible to obtain under the assumption. Nevertheless, this creates room for further research that could test the validity of this assumption.

"Financial" and "Other" variables have many missing observations which make the comparison difficult. Therefore, filling in the missing observations or adding new companies or countries to the sample is needed.

The study investigates both emerging and developed markets, hence this fact supports the external validity. However, only 4 different industries were included which makes it impossible to make conclusions on the credit rating of companies from absolutely any industry.

REFERENCES

Afifi A., May S., Donatello R., Clark V.A. 2019. *Practical Multivariate Analysis*. CRC Press.

Altman E.I., Rijken H.A. 2006. A point-in-time perspective on through-the-cycle ratings. *Financial Analysts Journal* **62** (1): 54–70.

Amato J.D., Furfine C.H. 2004. Are credit ratings procyclical? *Journal of Banking & Finance* **28** (11): 2641–2677.

Bergrem B.H. 2014. *The Determinants of Creditworthiness: An Empirical Study of the Relationship Between Credit Ratings and Financial Ratios in the E&P Industry*. Norwegian School of Economics.

Berle A.A., Means G.C. 1933. *The Modern Corporation and Private Property*, 1st Edition. Macmillan Publishers: N.Y.

Catalyst (US). 2012. *Women in Male-dominated Industries and Occupations in US and Canada*.

Chodnicka-Jaworska P. 2021. ESG as a Measure of Credit Ratings. *Risks* **9** (12): 226.

Demsetz H., Villalonga B. 2001. Ownership structure and corporate performance. *Journal of corporate finance* **7** (3): 209–233.

Devalle A., Fiandrino S., Cantino V. 2017. The linkage between ESG performance and credit ratings: A firm-level perspective analysis. *International Journal of Business and Management* **12** (9): 53–65.

Fox J., Monette G. 1992. Generalized collinearity diagnostics. *Journal of the American Statistical Association* **87**: 178–183.

Grunert J., Norden L., Weber M. 2005. The role of non-financial factors in internal credit ratings. *Journal of Banking & Finance* **29** (2): 509–531.

Jang G.Y., Kang H.G., Lee J.Y., Bae K. 2020. ESG scores and the credit market. *Sustainability* **12** (8): 3456.

Johansson E., Olaberria E. 2014. Global trade and specialisation patterns over the next 50 years. *Organisation for Economic Cooperation and Development*.

Low J., Siesfeld T. 1998. *Measures that Matter: Non-financial Performance*. Strategy & Leadership.

Karminsky A.M., Burekhin R.N. 2019. Comparative analysis of bankruptcy forecasting methods for Russian construction companies. *Business Informatics* **13** (3): 52–66.

Karminsky A.M. 2015. *Credit ratings and their modeling*. Moscow: Izdatelskii dom NRU HSE (In Russian).

Mohr A., Schumacher C., Kiefner V. 2022. Female executives and multinationals' support of the UN's sustainable development goals. *Journal of World Business* **57** (3): 101304.

Morck R., Shleifer A., Vishny R.W. 1988. Management ownership and market valuation: An empirical analysis. *Journal of Financial Economics* **20**: 293–315.

Moody's. 2021a. Independent exploration and production industry methodology. [Electronic resource]. https://ratings.moodys.com/api/rmc-documents/74836 (accessed: 03.02.2023).

Moody's. 2021b. Steel industry methodology. [Electronic resource]. http://www.moodys.com/ researchdocumentcontentpage.aspx?docid=PBC_1296098 (accessed: 03.02.2023).

Moody's. 2022. Rating symbols and definitions. [Electronic resource]. https://www.moodys.com/researchdocumentcontentpage.aspx?docid=pbc_79004 (accessed: 03.02.2023).

Ozer G., Ozen A.K. 2018. The effects of ownership structure on financial performance of enterprises in the light of accounting based performance indicators: a research on the firms traded on the BIST industrial index. *Journal of Economics, Finance and Accounting* **5** (2): 184–203

Salloum C., Azzi G., Mercier-Suissa C., Khalil S. 2016. The rise of women and their impact on firms' performance. *International Journal of Entrepreneurship and Small Business* **27** (2–3): 213–246.

Thomson Reuters Eikon. 2022. Non-financial companies, 2007–2021 [Data set]. https://eikon.thomsonreuters.com/index.html (accessed: 20.01.2022).

Trading Economics. 2021. *Credit Rating*. [Electronic resource]. https://tradingeconomics.com/country-list/rating (accessed: 29.03.2022).

United Nations. 2014. World economic situation and prospects 2014. *United Nations Publications*.

Villalonga B., Amit R. 2006. How do family ownership, control and management affect firm value? *Journal of Financial Economics* **80** (2): 385–417.

World bank. 2021. *World Bank Open Data*. [Electronic resource]. https://data.worldbank.org (accessed: 29.03.2022).

Yang S., Islam M.T. 2020. Principal component analysis and factor analysis for feature selection in credit rating. *arXiv preprint arXiv:2011.09137*.

Zaidi D. 2016. The indisputable role of credit ratings agencies in the 2008 collapse, and why nothing has changed. *Truthout*. [Electronic resource]. https://truthout.org/articles/the-indisputable-role-of-credit-ratings-agencies-in-the-2008-collapse-and-why-nothing-has-changed/ (accessed: 29.03.2022).

Initial Submission: May 25, 2022
Final Version Accepted: January 11, 2023

Определение факторов для оценки кредитного рейтинга нефинансовых компаний

Г.С. Поморцев

Факультет экономических наук, Национальный исследовательский университет «Высшая школа экономики», Россия

А.А. Астахова

Базовая кафедра Банка России, Национальный исследовательский университет «Высшая школа экономики», Россия

Цель исследования: повышение качества и точности оценки кредитного рейтинга, добавление характеристик нефинансовых компаний к оценке кредитоспособности, а также сравнение важности влияющих на нее факторов для различных отраслей и стран. **Методология исследования:** исследование включает использование исследовательского факторного анализа и моделей упорядоченной логистической регрессии. Исследование основано на общедоступных данных по нефинансовым компаниям из разных отраслей и стран за период с 2007 по 2021 г. **Результаты исследования:** группа финансовых переменных является наиболее значимой при оценке кредитного риска для компаний из развитых стран; для развивающихся рынков макроэкономические переменные в основном определяют кредитные рейтинги. Нефинансовые переменные имеют разностороннее влияние, но как группа повышают точность оценки кредитных рейтингов. **Оригинальность и вклад авторов:** существует ограниченность в исследованиях по теме оценки кредитных рейтингов нефинансовых компаний с включением нефинансовых факторов. Работа вносит вклад в поиск новых релевантных показателей, которые могут быть введены вместо качественных переменных, используемых международными рейтинговыми агентствами и требующих экспертной оценки.

Ключевые слова: прогнозирование кредитного дефолта, моделирование кредитных рейтингов, кредитная оценка нефинансовых компаний, система кредитных рейтингов, рейтинг ESG, женщины-работники, развивающиеся страны.

For citation: Pomortsev G.S., Astakhova A.A. 2022. Identification of factors for assessing credit rating of non-financial companies. *Russian Management Journal* **20** (3): 361–384. https://doi.org/10.21638/spbu18.2022.303

Для цитирования: Pomortsev G.S., Astakhova A.A. 2022. Identification of factors for assessing credit rating of non-financial companies. *Российский журнал менеджмента* **20** (3): 361–384. https://doi.org/10.21638/spbu18.2022.303

Статья поступила в редакцию 25 мая 2022 г.
Принята к публикации 11 января 2023 г.

Appendix

Appendix 1. Eigenvalues of factors

Factor	Eigenvalue
Macro	5.41725
Financial 1	2.37810
Financial 2	1.45535
Factor 4	0.40085
Factor 5	0.26005
Factor 6	0.15844
Factor 7	0.11205
Factor 8	0.04637
Factor 9	−0.00751
Factor 10	−0.01157
Factor 11	−0.06261
Factor 12	−0.07421
Factor 13	−0.10295

Appendix 2. Baseline model

Variable	OLS	Ordered logistic regression	Ordered probit regression
GDP growth	0.081412** (0.0233286)	0.0639563** (0.0214215)	0.0342906** (0.0117373)
Share of export to GDP	–	–	–
Sovereign ratings	−0.063901*** (0.0185981)	–	–
ln(Revenue)	0.553083*** (0.009163)	1.123559*** (0.0529644)	0.6163688*** (0.028215)
EBIT Margin	0.4083117 (0.3818671)	0.4698337 (0.3544888)	0.2976773 (0.1959264)
EBIT / Interest Expense	0.005565*** (0.0012893)	0.0050424*** (0.0013581)	0.003063*** (0.0007191)
Debt / Book Capitalization	–	–	–

The End of the Appendix 2

Variable	OLS	Ordered logistic regression	Ordered probit regression
CurrentRatio	-0.0324269 (0.0213709)	0.0257657* (0.0112726)	0.0165127** (0.006442)
Pretax ROA	5.83869*** (0.495945)	4.38067*** (0.4857905)	2.539062** (0.2599835)
Number of observations	927	927	927
R^2/*Pseudo* R^2	0.9723	0.2144	0.2048
Mean accuracy	1.671287	1.479998	1.478508

Note: robust standard errors in parentheses reported under the regression coefficients; *** — $p<0.001$; ** — $p<0.01$; * — $p<0.05$.

Appendix 3. VIF values obtained from Baseline Model

Variable	VIF
Log of revenue	7.63
Share of export to GDP	6.25
Sovereign ratings	2.15
EBIT Margin	1.71
GDP growth	1.48
CurrentRatio	1.38
Debt/Book Capitalization	1.37
Pretax ROA	1.3
EBIT/Interest Expense	1.24
Mean VIF	2.72