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Evaluation of Impact of ESG Rating and Environmental Performance Factors on the Level of Credit Risk and Shareholder Expectations of Companies in Carbon-Intensive Industries from BRICS Countries

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Abstract

The objective of the study was to evaluate the impact of ESG ratings, environmental (E) pillar scores and environmental performance metrics of non-financial companies from BRICS countries on their credit risks (measured by credit rating) and shareholder expectations (measured by enterprise value (EV) to sales multiple). Environmental performance metrics included emission scores, water efficiency scores, environmental management team scores and the ability to cope with climate risks scores. The relevance of the study is underpinned by the limited number of research in the field for BRICS countries and contradictory conclusions in research about the strength and direction of the influence of ESG factors on the value and financial metrics of the companies. The ordered logit regression and OLS regression models were applied for credit ratings and EV/Sales multiple respectively. The sample included 206 companies from carbon-intensive industries from Brazil, China, India, South Africa and Russia for 2018-2021. Financial and ESG metrics were taken from Refinitiv while companies' credit ratings were taken from Moody's and S&P. The results showed that the improvements in ESG and E-scores as well as environmental performance metrics hurt companies' credit ratings. Conversely, the improvements in ESG, E-scores and environmental performance metrics had a positive impact on EV/Sales metrics. The latter confirms the TGMT (too-much-of-a-good-thing) effect of environmental performance as equity investors expect a positive effect from climate-related actions on equity performance in the long term.

Keywords: climate risk, credit rating, EV/Sales, ESG score

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Introduction

The consequences of climate change are exerting an ever greater impact on economies with every passing year. Global warming is raising risks for financial and non-financial companies. Indicators of company resistance to climate-related risks are now included in methodologies for the assessment of corporate financial sustainability. Sustainable development paths and ESG (environmental, social and governance) factors are growing in importance today. Investors are paying more attention to the non-financial reports of companies and their compliance with ESG requirements. The UN Climate Change Conference COP 26 [1] of November 2021 negotiated new settlements to keep the temperature increase below 1.5–2 ^{0}C in keeping with the Paris Agreement of 2015. This goal implies that all parties must respect the obligations of abandoning carbon fuels in a step-by-step manner, ending deforestation, shifting towards electric vehicles, and reducing methane emissions. The compliance with such requirements will inevitably influence the financial indicators of companies. In January 2022, the US Securities and Exchange Commission published a report which gave special consideration to the methods used by rating agencies to assess ESG indicators [2].

The purpose of the present study is to develop an econometric model for evaluating the impact of financial and climatic factors on cost (EV/Sales or Company Value/Sales) and financial sustainability indicators of companies from carbon-intensive industries of BRICS countries.

Our research objectives are as follows:

- Reviewing the literature to identify the impact of climatic factors on the cost and financial sustainability indicators of companies.
- Selecting explanatory variables for the model on the basis of economic rationale and the results of the literature review.
- Generating a database of indicators of companies from carbon-intensive industries of BRICS countries from 2018 to 2021.
- Constructing econometric models using the training sample and checking their quality.
- Forecasting cost and financial sustainability indicators on the basis of the test sample.
- Evaluating the forecast accuracy.

We advance the following hypotheses for verification:

- The growth of the ESG score has a positive impact on the corporate credit rating.
- The growth of the ESG score has a positive impact on the corporate market value.
- The improvement of a company's resistance to environmental risks has a positive impact on its corporate credit rating.
- The improvement of a company's resistance to environmental risks has a positive impact on its corporate market value.
- The improvement of a company's resistance to climate-related risks has a positive impact on its corporate credit rating.
- The improvement of a company's resistance to climate-related risks has a positive impact on its corporate market value.

We should note that investors have recently started to pay greater attention to the non-financial reports of companies and their compliance with ESG requirements. International rating agencies, especially after the COVID-19 pandemic, have begun to take ESG factors into consideration to evaluate the credit ratings of companies. In 2019–2020, some of them even purchased companies that compile ESG ratings [3]. In 2006, the UN promulgated the Principles for Responsible Investment (UNPRI) and later supplemented them with the Statement on ESG in Credit Risk and Ratings. The latter has been signed by 26 rating agencies, which thereby affirm their intention to include ESG factors in their methodology and to perform regular studies of these factors [4]. Russia and other emerging markets began to consider ESG factors at an even later stage. Green bonds appeared on the Moscow Stock Exchange only in 2018, and the first responsible investment funds were established in 2020. As for other BRICS countries, the first green bonds appeared in Brazil in 2015, in China in 2016, and in India and South Africa in 2018.

So far, only a few studies have examined the dependence of company financial performance on ESG indicators. Most of them consider developed countries (European and American companies). It should be said that emerging countries adhere to the principles of sustainable development and climate conservation only to a limited extent. This may have a stronger impact on the financial sustainability of companies from such countries in view of the increasing importance of environmental factors for investors. The present study will help to forecast the change of the cost and financial sustainability indicators of companies in the studied regions as a function of changes in their ESG indicators.

The object of the study is 800 companies from carbon-intensive industries of BRICS countries and their financial and environmental indicators.

The subject of the study is the financial sustainability and value of companies from carbon-intensive industries of BRICS countries.

The limitations of the study include the small number of countries in the sample, the limited set of independent variables, the probable inadequacy of the data, and the small size of some samples due to the insignificant amount of certain factors.

Literature Review

The TCFD (Task Force on Climate-Related Financial Disclosures) [5] divides climate risks into **physical** risks related to the damage caused by natural phenomena, catastrophes, and natural disasters and **transfer** risks related to the transfer to a low-carbon economy. The main transfer risks are regulatory, technological and behavioral risks. *Regulatory risks* arise when the government and regulatory authorities impose additional carbon dioxide taxes and establish information disclosure requirements and penalties for companies that do not respect sustainable development and ESG norms. Such novelties result in the growth of operating costs of non-financial companies, the premature retirement of assets and, as a consequence, the increase of capital costs. *Technological drivers* (implementation of environmentally cleaner manufacturing technologies) increase operating costs in the short term and capital costs in the long term. *Behavioral drivers* lead to a preference for "green" businesses among non-financial companies, which results in falling profits for brown companies, rising prices on raw materials, difficulties with fundraising, and the growth of borrowing costs.

Germanwatch [6] identifies countries with the highest climate risks using a climate risk index that shows the exposure of countries to extreme weather events. India has the highest index among BRICS countries, followed by Russia and China and then by Brazil and South Africa. This suggests that, in comparison to other countries, BRICS countries are quite seriously exposed to climate risks.

A high climate risk exposure may be confirmed by a high rate of carbon dioxide emissions against GDP. Over the period 1990–2018 (more recent data is not yet available from the World Bank), BRICS countries had greater emissions than developed countries. While all BRICS countries are reducing emissions, they remain high. As we have already mentioned, in view of the trend towards carbon neutrality and the compliance with the Paris Agreement, the countries with the largest emissions run the greatest risks for their economy.

The considerable growth potential of BRICS states, which are all emerging countries, explains our interest in them. As these economies grow, their companies will have to adapt to new environmental regulations established by developed countries. This will affect the financial standing of companies in BRICS countries. In this study, we will try to determine the nature of this influence.

In our literature review we identify several hypotheses that show the ambiguity of the relationship between environmental and financial indicators that may be verified using current data.

The *social impact theory* states that, if a company satisfies the interests of stakeholders and interested parties, it becomes more attractive and competitive on the market, which has a positive impact on financial indicators [7].

The *compromise hypothesis* states that companies which pay special attention to environmental friendliness and other socially significant aspects have worse financial performance than similar companies. Some researchers have pointed out that the market value of such companies decreases, because the profits from investments in environmental projects are lower than the expenditures [7].

The *managerial opportunism hypothesis* posits that company managers are first and foremost interested in the short-term growth of profits for getting the largest bonuses [7].

According to the natural-resource-based view (NRBV) developed by Stuart Hart in 1995 [8], the competitive advantage of a company on the market greatly depends on its relationship with the environment. Hart believes that production optimization leads to a reduction in the manufacturing time and in emissions and waste, which in turn results in lower operating expenditures. In his opinion, the transfer to sustainable development will contribute to improving the competitiveness of the company on the market in the long term, even if it lowers profits in the short term. This assertion suggests that the dependence between the financial and environmental indicators of a company is U-shaped.

The TMGT (Too-Much-of-a-Good-Thing) effect points to a U-shaped dependence between some indicators. The TMGT effect states that some factors have a minimal level of sufficiency. When this minimum is surpassed, the factor produces a positive impact on the dependent variable [9].

By the *law of diminishing marginal utility,* adding a new unit of the same factor gives a smaller result each time. In particular, this law applies to the dependence between expenditures on the environment and the financial indicators considered in the present study. According to this law, an *inverted U-shaped dependence* may apply. However, this hypothesis is more disputable than the hypothesis of the U-shaped dependence, because environmental expenditures must be repaid first.

As we noted above, there are few studies today about the influence of ESG factors. Moreover, existing studies make highly ambiguous conclusions. Some of them show that ESG factors have no impact on corporate financial indicators, while others point to the significance of ESG factors for evaluating the stability and value of companies. Some authors assert that the correlation between ESG factors and the credit rating is more evident in countries with high revenues and less obvious in countries with low revenues [4].

M. Nandy and S. Lodh [10] study the impact of a company's environmental friendliness on its attractiveness for bank lending. In their opinion, firms with a higher environmental impact estimate get more favorable lending terms.

Another study of the impact of ESG factors on corporate financial sustainability and, in particular, the impact of credit ratings was performed by P. Chodnicka-Jaworska [11], who showed that companies with *Fitch* ratings are more susceptible to ESG factors than firms with *Moody's* ratings. Power production and industrial and raw materials sectors are particularly sensitive to ESG factors.

D. Kouloukoui et al. [12] tried to identify the financial indicators that influence companies' perception of their exposure to climate risks. The authors reached the following conclusions: all independent variables, except for profitability, are insignificant in the model and are therefore not related to the number of implemented climate projects; the higher the profitability, the larger the number of implemented projects. The limitation of this study was its small sample.

A report by researchers from the University of Oxford [13] evaluates the potential losses of the financial sector from delays in the transfer to more environmentally friendly business measured as a change in the equity value and probability of default of firms. The authors establish that, if companies maintain the production rate according to their plans, the transfer to the sustainable development objectives and arrangements of the Paris Agreement would be possible only after 2026. To assess the financial losses from the transfer to new manufacturing procedures, the authors use the **market risk model** adjusted for climate and the **credit risk model** to evaluate changes in the corporate equity value and probability of default on credits and other loans. The authors assess the total losses at $4.16 trillion. The change in the equity value will amount to 23%. As for the increase in the probability of the default of companies, it would be the highest in the case of the delay in transfer to the sustainable development path in the carbon sector – up to 24% if the transfer is delayed for nine or more years. Thus, the authors of the study conclude that it is necessary to transfer to the sustainable development path as soon as possible.

In February 2022, *Fitch* declared that only 310 out of 10,500 issuers showed a positive impact of the ESG rating on the credit rating. The influence is mainly negative, especially in the corporate sector, where just 2% of issuers have experienced a positive influence [14].

C. Trumpp and T. Guenther [9] is the key study to prove the existence of a U-shaped relationship between environmental and financial indicators. The authors examined the type of interrelation between corporate environmental and financial performance. They managed to confirm their hypothesis of a U-shaped dependence between ROE and the P/E ratio for environmental factors in the processing industry. As for the services sector, the authors detected a significant influence of environmental factors only on company profitability, while the relation between environmental factors and the P/E ratio turned out to be insignificant. Thus, there is both a positive and a negative dependence between the environmental and financial performance of companies. In the present study, we seek to identify this dependence for BRICS countries.

Construction of an Econometric Model

To construct the econometric model, we used different regressions taken from the literature review and our own analysis. To determine the influence of factors on the corporate credit rating we used the **ordered logit model**, because credit ratings in the study are divided into seven groups according to their levels. This method has a high forecast power and classification accuracy:

$Y_i = \beta x'_i$,

where Y_i is the dependent variable with a value of 1 to 7 depending on the company's rating and x'_i is the explanatory variables vector.

A multiple linear LSM regression was used to determine the impact of factors on company value:

$Y^*_i = \beta x'_i + a$,

where Y^*_i is the quantitative dependent variable which characterizes the company's market value (*EV/ Sales*), and *a* is an intercept term.

After eliminating the outliers and checking the explanatory variables for multicollinearity, we divided the data into a training and a test sample. The training sample was used to develop models and analyze R^2, P-values and the signs of the coefficients of independent variables. Then the test sample was used to make forecasts for dependent variables, which were compared to the initial values to determine the predictive power of the model.

In the paper we use data by *Thomson Reuters* [2] for BRICS countries over the period 2018–2021. Three carbon-intensive industries are considered in the sample: raw materials, power production, and processing. They are the most carbon-intensive industries in the *Thomson Reuters* database.

The market value indicator – *EV/Sales* – is the dependent variable. The corporate credit rating serves as the financial sustainability indicator. Independent variables are presented in Table 1.

On the basis of the literature review and economic logic, we identified the directions of influence of the explanatory variables on the value and financial sustainability of companies. Non-financial variables were calculated according to the *Thomson Reuters* methodology and represent an aggregate of points on certain criteria – the more points the better.

Table 1. Independent variables

Variable		Description	Influence
Financial			
Profitability			
1	EBITDA Margin	Company profitability as the ratio of operational profit to revenue	+

Variable		Description	Influence
Earning power			
1	Asset turnover	Efficiency of the company use of assets	+
2	Natural log of assets	Value of corporate assets	+
Operating profit			
1	*Accounts payable turnover ratio*	How quickly the company repays debts to suppliers	–
2	*Accounts receivable turnover ratio*	How quickly the company accumulates buyer debts	–
Leverage			
1	*D/E*	Ratio of company liabilities to equity, the debt load	–
2	*D/EBITDA*	Similarly to D/E, it shows the company's ability to cover its debt using its operating profit	–
Operating			
3	*ROE*	The company's ability to generate profit using the invested capital	+
4	*ROA*	The company's ability to use assets efficiently and generate profits from them	+
5	*Interest Coverage Ratio*	The company's ability to serve interest-bearing debts using its income	+
Liquidity			
1	*Current ratio*	The company's ability to cover its short-term obligations using current assets	+
Non-financial (*ESG*)		**Calculated by *Thomson Reuters* according to its methodology**	
1	*ESG score*	The company's resistance to environmental, social and governance risks	+
2	*Environmental Pillar Score*	The company's resistance to environmental risks	+
3	*Emissions Score Grade*	The company's carbon dioxide emissions (rated in letters)	+
4	*Policy Water Efficiency*	Efficiency of the use of water (binary variable)	+
5	*Policy Energy Efficiency Score*	Optimality and efficiency of energy usage	+
6	*Estimated CO_2 Equivalents Emission Total*	Amount of CO_2 emissions in tons	–
7	*Corporate Governance Board Committee*	Existence of a corporate governance committee	+
8	*Environment Management Team*	Existence of a subdivision in the company which deals with environmental issues	+
9	*Climate Change Commercial Risks Opportunities Score*	The company's ability to cope with climate risks	+
Macroeconomic			
1	*Real GDP growth*	Growth of the gross domestic product in the country	+
2	*Inflation*	Inflation level	–

Source: Compiled by the author.

The descriptive statistics are given in Table 2.

Table 2. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Asset turnover	925	0.776	0.565	0.095	4.679
Accounts payable ratio	925	8.046	9.21	0.018	70.41
Accounts receivable ratio	925	16.536	25.056	0.941	196.094
ROE	925	11.556	13.012	–66.812	67.753
ROA	925	4.75	5.146	–19.198	31.354
Interest Coverage Ratio	925	10.429	18.363	–17.559	148.364
Gross margin	925	17.684	15.658	–15.443	74.474
Current ratio	925	1.214	0.42	0.215	2.235
EBITDA Margin	925	0.19	0.138	–0.015	0.985
Total Debt to Total Equity	925	1.089	1.413	0.001	14.312
Total Debt To EBITDA	925	5.163	6.744	0.007	69.787
Policy Energy Efficiency score	589	67.023	6.314	53.409	83.913
ESG Score	925	44.76	18.157	3.855	86.634
Environmental Pillar score	925	43.696	23.573	0.38	97.325
Emissions Score Grade	925	2.424	1.045	1	4
Policy Water Efficiency	925	0.737	0.44	0	1
Estimated CO_2 emissions	925	11 914 521	26 419 505	15.577	2.552e + 08
Corporate Governance team	925	0.108	0.311	0	1
Environment Management team	925	0.599	0.49	0	1
Real GDP growth	925	4.398	3.949	–7.3	9.5
Inflation	925	3.085	1.619	1.1	7.7
Climate Change risks	538	73.583	7.532	57.895	89.679
ln assets	925	22.862	1.328	18.963	26.54
EV/Sales	925	2.438	2.815	0.005	25.7

Source: The author's calculations.

Now we are going to verify the data for multicollinearity using the correlation matrix and the variance inflation factor $VIF = 1/ (1 - R^2))$ – the indicator which determines the amount of variance of the coefficient preceding the variable due to the correlation of regressors (Tables 3 and 4). The boxes where the correlation exceeds 55% are highlighted in pink: these variables cannot be used in the model simultaneously. As the general ESG score clearly correlates with its components, the models may be constructed separately for the general ESG score and for its components.

Table 3. Correlation matrix (%)

	A set turnover	Accounts payable turn over ratio	Accounts receivable turnover ratio	ROE	ROA	Interest Coverage Ratio	Cross margin	Current ratio	EBITDA Margin	Total Debt to Total Equity	Total Debt to EBITDA	Policy Energy Efficiency Score	ESG Score	Environmental Pillar Score	Emissions Score Grade	Policy Water Efficiency	Estimated CO2 Equivalents Emissions Total	Corporate Governance Board Committee	Environment Management Team	Real GDP Growth	Inflation	Climate Change Commercial Risks Opportunities Score	In assets
A set turnover	100																						
Accounts payable turnover ratio	56	100																					
Accounts receivable turnover ratio	3	5	100																				
ROE	5	1	0	100																			
ROA	16	11	-1	66	100																		
Interest Coverage Ratio	7	-3	0	1	1	100																	
Cross margin	-30	0	-4	21	20	-5	100																
Current ratio	13	-1	1	15	20	1	2	100															
EBITDA Margin	-16	-13	-2	23	27	-1	46	-4	100														
Total Debt to Total Equity	-6	0	0	-16	-14	-1	4	-7	0	100													
Total Debt to EBITDA	-8	3	-2	-18	-18	-2	-4	-18	-13	-18	100												
Policy Energy Efficiency Score	16	11	4	8	8	1	-17	5	-9	-10	-6	100											
ESG Score	4	-3											100										
Environmental Pillar Score	1	-3	3	-1	-4	-3	-16	10	15	0	-9	22	80	100									
Emissions Score Grade	-2	-2	-2	-3	2	0	12	-7	-15	0	10	-27	-76	-82	100								
Policy Water Efficiency	4	-1	3	-1	-3	-6	-6	3	12	4	-10	-1	55	53	-43	100							
Estimated CO2 Equivalents Emissions Total	-9	-8	-2	3	-1	-1	-7	-8	6	-2	-3	10	25	22	-21	16	100						
Corporate Governance Board Committee	8	0	0	-2	2	-2	0	10	9	-3	-6	12	31	19	-17	15	-1	100					
Environment Management Team	9	5	3	0	0	2	-4	-6	-4	-6	-1	18	32	33	-32	31	18	13	100				
Real GDP Growth	-8	-3	-10	-1	3	-2	1	-16	-7	2	8	-13	-24	-18	19	-19	-4	-17	-11	100			
Inflation	6	-5	2	0	0	4	-24	16	13	6	-10	7	48	39	-35	31	13	22	12	37	100		
Climate Change Commercial Risks Opportunities Score	-12	6	3	-6	13	7	15	16	16	-2	-7	8	11	14	-14	2	-15	9	-15	-30	-11	100	
In assets	-24	-18	-10	9	-5	-6	-7	-20	9	-2	2	27	27	28	-33	11	46	-1	17	6	0	-33	100

Source: The author's calculations.

The results of VIF analysis show that ROE, ROA, environmental pillar score and ESG score should not be used simultaneously because their VIF exceeds 4 [15] (conditional estimator, 5–6 may be used as the internal boundary value). The correlation matrix gives the same results: ROA correlates strongly with ROE, while the ESG score correlates strongly with the environmental pillar score.

Table 4. Variance inflation factor (VIF)

	VIF	1/*VIF*
ROE	6.31	0.158
Environmental Pillar	5.292	0.189
ROA	5.081	0.197
ESG Score	4.205	0.238
Total Debt to Total Equity	3.776	0.265
Ln assets	3.093	0.323
Asset turnover	2.749	0.364
Emissions Score Grade	2.646	0.378
Estimated CO2 Emission	2.269	0.441
Total Debt To EBITDA	2.257	0.443
EBITDA Margin	2.178	0.459
Policy Energy Efficiency score	2.063	0.485
Climate Change risks	1.882	0.531
Accounts payable turnover ratio	1.854	0.539
Interest Coverage Ratio	1.576	0.635
Gross margin	1.569	0.637
Corporate Governance committee	1.425	0.702
Environment Management team	1.412	0.708
Policy Water Efficiency	1.258	0.795
Real GDP growth	1.218	0.821
Current ratio	1.217	0.822
Inflation	1.14	0.877
Accounts receivable turnover ratio	1.096	0.913
Mean VIF	2.503	.

Source: The author's calculations.

Results of Modelling

We used an ordered logistic regression to construct a **model for the credit rating dependent variable** insofar as the rating is an ordered variable divided into several levels – for example, from *AAA* to *D* according to the *Fitch* methodology. We grouped the ratings into seven rating classes for the modelling [16] (Table 5).

Table 5. Seven categories of ratings

Credit rating	Category
AAA	1
AA+, AA, AA–	2
A+, A, A–	3
BBB+, BBB, BBB–	4
BB+, BB, BB–	5
B+, B, B–	6
C, D	7

Source: The author's calculations.

Ratings by the international agencies *Moody's* and *Fitch* are used in the sample. They are adjusted to a common scale according to the commonly accepted mapping [17]. The national ratings of BRICS countries are also used. Using the *S&P* mapping [18] for all countries except Russia, we adjusted the national ratings to the common scale of international ratings and subsequently put them into the corresponding category from 1 to 7. For Russia we applied the recommendations of the Bank of Russia [19].

In the present study, we also use other variables besides the credit rating for modelling. These variables allow us to make a rating according to the *Refinitiv* methodology. Such variables may be presented in numerical terms from 0 to 1 or in letters from *A* to *D*. In this paper, we use letter-based ratings, which we recategorize for modelling as categories from 1 to 4, where 1 is the highest rating and the best indicator, while 4 is the lowest rating and the worst indicator. The emission score grade is one such variable. The variables were recategorized according to Table 6.

Table 6. Four categories of ratings

Rating	Category
A+, A, A–	1
B+, B, B–	2
C+, C, C–	3
D+, D, D–	4

Source: The author's calculations.

The sample consists of 825 observations from five countries – Brazil, Russia, India, China, and South Africa – and the three aforementioned sectors in the proportions indicated in Table 7.

Table 7. Sector proportions in the country-related sample

	Sector			Total
Country	Raw materials	Power generation	Processing	
Brazil	31	16	38	**85**
China	199	76	279	**554**
India	36	40	21	**97**
Russia	41	26	3	**70**
South Africa	14	0	5	**19**
Total	321	158	346	825

Source: The author's calculations.

The distribution of ratings in the sample is presented in Table 8.

Table 8. Distribution of ratings in the sample

Credit rating	Rating category	Frequency	Frequency, %
AAA	1	330	40
AA+, AA, AA–	2	191	23.15
A+, A, A–	3	28	3.39
BBB+, BBB, BBB–	4	131	15.88
BB+, BB, BB–	5	103	12.48
B+, B, B–	6	33	4
C, D	7	9	1.09
	Total	825	100

Source: The author's calculations.

The default and pre-default levels are the rarest, because there is little data on them in the database. The general ESG score is taken in this model as the sustainable development factor, while individual factors – components of the ESG score – will be taken into consideration in the next model. The models are divided because the ESG score and its components should not be included in the model simultaneously, as this would result in multicollinearity.

Now we perform the heteroscedasticity test (Table 9).

Table 9. Heteroscedasticity test

White's test for Ho: homoskedasticity Ha: unrestricted heteroskedasticity Chi2(20) = 68.36 Prob>chi2 = 0,0000			
Source	Chi2	Df	p
Heteroskedasticity	68.36	20	0.0000
Skewness	12.56	5	0.0279
Kurtosis	2.63	1	0.1050

Source: The author's calculations.

It is apparent from Table 9 that the *p-value* = 0. Hence, the hypothesis on homoscedasticity is rejected at the 5% significance level, and one may assume that there is heteroscedasticity. To avoid heteroscedasticity, we will construct a model using robust errors.

In the **model with the general ESG score**, the sample was divided into training and test samples in the proportion of 80 to 20. The training sample consists of 468 observations. The regression results are given in Table 10.

Table 10. Regression results

Variable	Regression results		
	Coefficient	Standard error	*p-value*
Accounts payable turnover ratio	–0.025	0.009	0.004
D/E	0.166	0.066	0.012
ESG score	0.031	0.006	0.000
Inflation	1.188	0.095	0.000
Natural log of assets	–0.960	0.116	0.000
Number of observations	468		
Pseudo R^2	0.2613		
Prob > F	0.000		

Source: The author's calculations.

At the 5% significance level, the following variables turned out to be significant for this model: accounts payable turnover, leverage, ESG score, inflation and the natural log of assets. In this type of model, only the signs of independent variables may be evaluated. It is necessary to compute the marginal effects to calculate the probability of getting into a certain category. We do not strive to do this in the present paper, as we are primarily interested in the overall directions of influence of the factors. The signs of variables correspond to the following economic logic:

The higher the accounts payable turnover, i.e., the quicker the company makes payments to contractors, the lower its rating category and, according to Table 5, the higher its credit rating. This is logical because the company's ability to discharge its obligations characterizes it as a financially sustainable organization.

The higher the debt to total equity, the less sustainable the company from the financial point of view, the higher the rating category and the lower the company's rating.

The higher the ESG score, the lower the company's credit rating. This result confirms the hypothesis about an inverse dependence between environmental and financial indicators.

High inflation is basically an adverse factor for the economy, as it results in the growth of interest rates and decreases corporate creditworthiness

The higher the natural logarithm of corporate assets, the higher the company's rating. This is logical, because larger business is considered to be more financially sustainable in general.

We can use the chosen model and the test sample of 122 observations to forecast the rating categories into which observations from the test sample will get, i.e., we are able to evaluate the predictive power of the model (Table 11).

Table 11. Predictive power of the model

Credit rating	Category	Total number in the test sample	Percent share of correctly predicted values
AAA	1	47	79
AA+, AA, AA–	2	27	41
A+, A, A–	3	4	0
BBB+, BBB, BBB-	4	18	33
BB+, BB, BB–	5	18	50
B+, B, B–	6	5	20
C, D	7	3	0
Predictive power			52

Source: The author's calculations.

Table 11 shows that the model predicts ratings for companies with the *AAA* rating best of all. This is related to the fact that companies with this rating prevail in the sample.

Now let us calculate the predictive power of the model by letting it deviate from the predetermined rating category by one (Table 12).

Table 12. Predictive power of the model when there is a deviation from the predetermined rating category by one

Credit rating	Category	Total number in the test sample	Percent share of correctly predicted values
AAA	1 or 2	47	98
AA+, AA, AA–	1 or 2	27	96
A+, A, A–	2 or 4	4	75
BBB+, BBB, BBB–	4 or 5	18	56
BB+, BB, BB–	4, 5 or 6	18	78
B+, B, B–	5 or 6	5	60
C, D	7	3	0
Predictive power			84

Source: The author's calculations.

Thus, the predictive power of the model has grown significantly to 84%. The model predicts categories 1 and 2 best of all, followed by categories 3 and 5. In general, this is also related to the number of observations added to the sample. The greater the number of observations, the better the forecast. Summing up, we should note that the model has quite good predictive power. If we expand the general sample and make the values of rating categories more uniform, the model will have even higher predictive power.

The **environmental pillar score model** is built so as to ensure that the environmental pillar score, just as the general ESG score, is related negatively to the credit rating. This indicates the sign of the variable's coefficient (Table 13).

Table 13. Regression results

Variable	Regression results		
	Coefficient	Standard error	*p-value*
Accounts payable turnover ratio	–0.023	0.009	0.012
D/E	0.165	0.077	0.033
Environmental pillar Score	0.014	0.004	0.001
Inflation	1.231	0.092	0.000
Natural log of assets	–0.867	0.119	0.000
Number of observations	468		
Pseudo R^2	0.2513		
Prob > F	0.000		

Source: The author's calculations.

The **model with the factors included in the ESG score**, just as the previous model, is constructed using the training sample comprising 130 observations. Such a small number is explained by the fact that the model uses the factor of company's resistance to climate risks. It is a rather rare factor that has been calculated only for a small number of firms. The regression results are presented in Table 14.

Table 14. Regression results

Variable	Regression results		
	Coefficient	Standard error	*p-value*
Accounts receivables turnover ratio	–0.014	0.007	0.042
ROA	–0.103	0.032	0.001

Variable	Regression results		
	Coefficient	Standard error	*p-value*
Policy energy efficiency score	0.093	0.032	0.003
Inflation	1.064	0.142	0.000
Natural log of assets	–0.727	0.120	0.000
Climate change risks	0.092	0.027	0.001
Number of observations	130		
Pseudo R^2	0.2889		
Prob > F	0.000		

Source: The author's calculations.

It is clear from Table 14 that all variables in the model are significant at the 5% significance level. A positive coefficient is indicative of a credit rating downgrade, while a negative coefficient points to an improvement in the rating categories.

- As the accounts payable turnover grows, the corporate credit rating increases. This is logical, because a company that gets receivables quickly has less problems with liquidity, which is an important component of the credit rating score.
- The higher the return on assets, the higher the rating. This is logical because a growth in profitability is indicative of an improvement in the quality of assets management, which has a positive impact on the rating.
- The more efficiently a company spends energy, the lower its credit rating. This may be related to the fact that the procedure of optimization of resource utilization entails additional expenses. This reduces the financial performance of the company, which has a lot of significance for the credit rating score.
- A rise in inflation results in a lower rating, because high inflation leads to a sudden change in the market rates. This, in turn, results in problems with funding and the growth of past-due indebtedness, which reduces corporate financial performance (turnover, profitability).
- As the company's size grows, its credit rating increases. It is generally believed that larger business is more sustainable from the financial point of view.
- The more the company is concerned with climate risks, the lower its rating. This influence is explained in a similar way to the variable of energy usage efficiency. The elimination of climate risks requires additional expenses.

Now let us calculate the predictive power of the model using by letting the test sample (36 observations) deviate from the predetermined rating category by one (Table 15). Despite the small size of the test sample, the predictive power of the model is quite high.

Table 15. Predictive power of the model in the case of a deviation from the predetermined rating category by one

Credit rating	Category	Total number in the test sample	Percent share of correctly predicted values
AAA	1	5	40
AA+, AA, AA–	1 or 2	2	50
A+, A, A–	3 or 4	2	50
BBB+, BBB, BBB–	4 or 5	12	92
BB+, BB, BB–	4, 5 or 6	12	92
B+, B, B–	5 or 6	2	100
C, D	7	1	0
Predictive power			78

Source: The author's calculations.

Summing up the preliminary results, we may say that all models show a negative relation between sustainable development indicators and the credit rating. Thus, the hypothesis about a negative relation is not confirmed.

The distribution of the sample for the **model with the EV/Sales dependent variable** by countries and sectors is presented in Table 16.

Table 16. Proportions of sectors in the country-related sample

	Sector			Total
Country	**Raw materials**	**Power generation**	**Processing**	
Brazil	26	16	33	**75**
China	151	74	241	**466**
India	72	20	36	**128**
Russia	32	22	0	**54**
South Africa	62	5	25	**92**
Total	343	137	335	815

Source: The author's calculations.

This sample is also divided into training and test subsamples in the proportion of 80 to 20. We perform White's test for heteroscedasticity (Table 17).

Table 17. White's test for heteroscedasticity

White's test for Ho: homoskedasticity Ha: unrestricted heteroskedasticity			
Chi2(20) = 33.4			
Prob>chi2 = 0.0305			
Source	**Chi2**	**Df**	**p**
Heteroskedasticity	33.4	20	0.0305
Skewness	12.16	5	0.0327
Kurtosis	2.17	1	0.1409

Source: The author's calculations.

It is evident from Table 17 that the *p-value* = 3%. Thus, the hypothesis about homoscedasticity is rejected at the 5% significance level, and we may assume that heteroscedasticity is present. To avoid heteroscedasticity, we construct a model using robust errors.

The results of the regression of the **model using the general ESG score** are presented in Table 18.

Table 18. Regression results

		Regression results	
Variable	**Coefficient**	**Standard error**	***p-value***
Asset turnover	–1.263	0.180	0.000
ROA	0.052	0.020	0.008
EBITDA margin	5.248	0.810	0.000
ESG score	0.017	0.006	0.007
Inflation	–0.238	0.078	0.002
Real GDP growth	0.081	0.024	0.001
Natural log of assets	–0.737	0.084	0.000
Cons	18.674	1.992	0.000

Variable	Coefficient	Regression results Standard error	*p-value*
Number of observations		652	
R^2		31%	
Prob > F		0.000	

Source: The author's calculations.

The results of the **model using the environmental pillar score** are shown in Table 19.

Table 19. Regression results

Variable	Coefficient	Regression results Standard error	*p-value*
Asset turnover	–1.250	0.173	0.000
ROA	0.050	0.019	0.008
EBITDA margin	5.293	0.786	0.000
Environmental pillar score	0.012	0.005	0.025
Inflation	–0.217	0.075	0.004
Real GDP growth	0.079	0.024	0.001
Natural log of assets	–0.735	0.082	0.000
Cons	18.784	1.966	0.000
Number of observations		652	
R^2		31%	
Prob > F		0.000	

Source: The author's calculations.

In both models all variables are significant at the 5% significance level. As Table 19 shows, the values of the coefficients and their signs stay the same when the model is constructed using only the *E* component of the ESG score. The influence of the *S* and *G* components is insignificant or unidirectional with the *E* component. We should recall that a decrease in the EV/Sales multiplier indicates that the company's prospects deteriorate in the opinion of investors (Smart-lab), while an increase indicates that investors expect the company's income to rise. Let us check whether the signs of variables correspond to economic logic:

- An increase in the return on assets and the EBITDA margin is indicative of rising investor expectations about the company's growth.
- An increase in the ESG score and the environmental pillar score is indicative of rising investor expectations about the company's growth.
- An upturn in inflation is indicative of falling investor expectations about the company's growth, because high inflation is an unfavorable event for the economy.
- A growth in the GDP is indicative of rising investor expectations, as it is indicative of an upsurge in economic activity.
- Corporate assets growth, i.e., their increasing size, indicates a decline in economic activity.
- The assets turnover has a negative coefficient, which is contrary to economic logic. Nevertheless, the objective of the present study is to analyze the influence of environmental factors on company value. The sign of the coefficient may be explained as follows:

Assets turnover = Net sales/Average total assets

EV/Sales = (*Market capitalization + Debt – Cash*)/*Sales.*

Net sales are in the numerator of *Assets turnover* and *EV/Sales* – *Sales* are in the denominator. Thus, when *Net sales* grow and lead to the growth of *Assets turnover,* the denominator of *EV/Sales* increases, and *EV/Sales* decline.

The results of the regression of the **model with the factors included in the ESG score** are presented in Table 20.

Table 20. Regression results

Variable	Regression results		
	Coefficient	Standard errors	*p-value*
Assets turnover	–1.391	0.202	0.000
ROA	0.106	0.023	0.000
D/EBITDA	0.050	0.009	0.000
Real GDP growth	0.076	0.030	0.011
Climate change risks	0.037	0.017	0.032
Natural log of assets	–0.351	0.085	0.000
Cons	7.918	2.654	0.003
Number of observations	226		
R^2	31%		
Prob > F	0.000		

Source: The author's calculations.

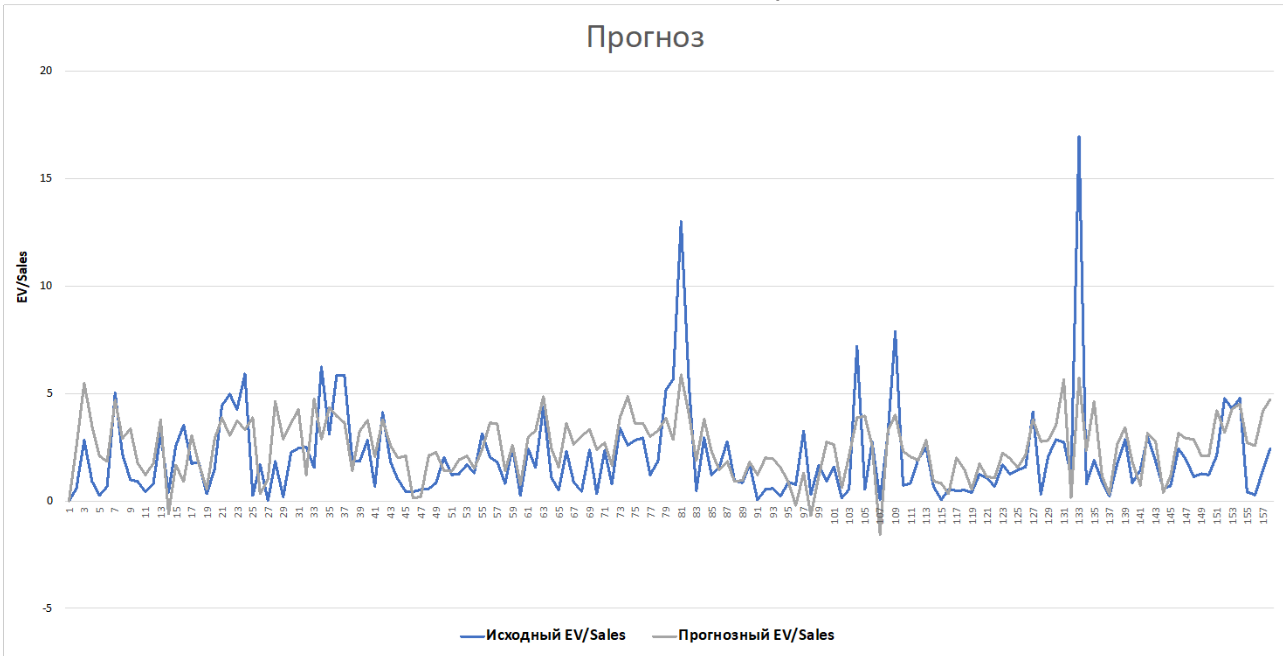
The independent variables are significant at the 5% significance level. The direction of influence of the financial variables is logical from the economic point of view and was described for the previous models, except for *D/EBITDA*. Now let us describe the influence of ESG factors.

The better a company manages climate risks, the higher the investors' expectations about its future growth

When the *EBITDA* debt grows, investors' expectations increase because the company gets more funds for investments in its development. Nevertheless, this is an inverted U-shaped dependence: when the borrowed funds begin to grow, investors' expectations are positive, yet, as the company debt increases, its burden grows and its non-payment risk increases, so the investors' expectations deteriorate.

Let now us forecast *EV/Sales* on the basis of the test sample for the model with the general ESG score (Figure 1).

Figure 1. *EV/Sales* on the basis of the test sample for the model with the general ESG score

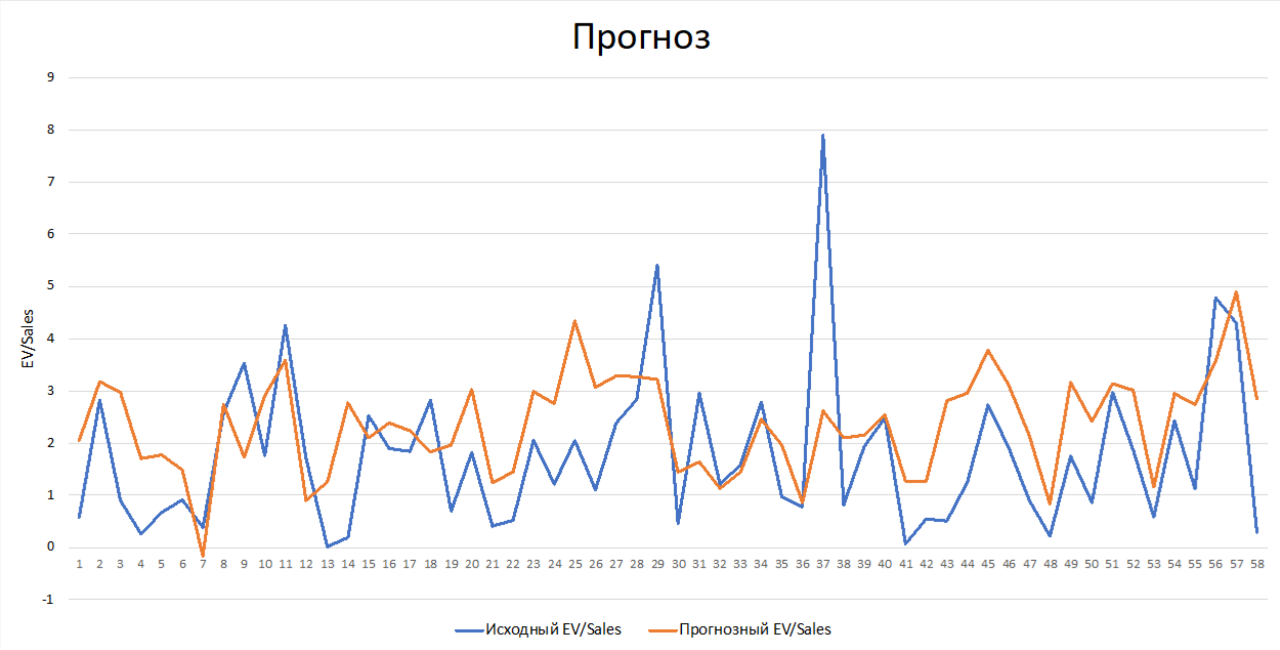


Source: The author's calculations.

It is evident from Figure 1 that the predicted value mirrors the initial value yet with a smaller amplitude. This indicates that the totality of factors in the model forecast the *EV/Sales* predicted value quite well.

Let us forecast *EV/Sales* on the basis of the test sample for the model with the factors included in the ESG score (Figure 2).

Figure 2. *EV/Sales* on the basis of the test sample for the model with the factors included in the ESG score



Source: The author's calculations.

Figure 2 shows that the predicted value mirrors the initial value yet not as well as in the previous model, because the test sample is small. Nevertheless, this figure also indicates the fairly high predictive power of the model for the *EV/Sales* indicator.

Interpretation of Results

- Let us now interpret the results on the basis of the initial hypotheses:
- An increase in the ESG score and the environmental pillar score has a negative impact on the corporate credit rating
- An increase in the ESG score and the environmental pillar score has a positive influence on the market value of the company
- An improvement in the quality of climate risks management has a negative impact on the credit rating
- An improvement in the quality of climate risks management has a positive impact on the market value

Thus, the hypotheses are confirmed for the indicator of cost yet disproven for the credit rating. This conclusion corroborates the hypothesis of a U-shaped relationship.

Conclusion

Global warming and growing environment pollution have led companies and investors to take a greater interest in climate risks. The development of strategies to mitigate these risks by companies may negatively affect their financial sustainability due to increasing expenses for environmental projects. However, in view of the growing regulatory, behavioral and technological risks, such companies will be more attractive for investors in the long run than companies that maintain and expand environmentally harmful production.

In the present paper, we have studied the influence of the environmental and climate risk sustainability factors of companies from carbon-intensive industries in BRICS countries on their credit rating and the *EV/Sales* indicator. The results of modelling showed a negative relationship between the environmental and climate risk sustainability factors of a company and its credit rating. As long as financial performance prevails in methodologies of rating agencies instead of ESG factors, the growth of ESG indicators will be negated by the deterioration of financial performance caused by the increase in environmental expenses, thus lowering the credit rating. On the contrary, strengthening corporate resistance to environmental and climate risks raises the company's value and has a positive impact on investors' expectations of the future growth of corporate income.

Our conclusions show that there is a U-shaped relationship between environmental and financial indicators. When the credit rating shows company creditworthiness in the short term (12–18 months), it is negatively related to environmental factors, because additional expenditures on the environment impede the financial performance of business in the short run. However, such investments are repaid in the long term, influencing business efficiency and optimization and improving financial indicators. Investors understand this, and *EV/Sales* show their increasing long-term expectations about company value. The modelling results demonstrate the significance of the climate risk factor for business. Its impact is similar to the influence of other environmental factors. Our results confirm the TMGT effect and some concepts described in the literature review. This shows that the present study is valid.

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References

1. United Nations Climate Change Conference (COP26). 2021. URL: https://ukcop26.org/ (accessed on 10.04.2022).
2. Thomson Reuters. URL: https://www.thomsonreuters.com/en.html (accessed on 10.04.2022).
3. Tillier N. ESG and credit rating agencies: The pressure accelerates. ING Bank N.V. Feb. 22, 2021. URL: https://think.ing.com/articles/esg-and-credit-ratings-the-pressure-has-accelerated/ (accessed on 10.04.2022).
4. DataBank. World development indicators. The World Bank Group. URL: https://databank.worldbank.org/reports.aspx?source=2&series=EN.ATM.CO2E.PP.GD&country (accessed on 11.04.2022).
5. Impact of climate risks and sustainable development of the financial sector of the Russian Federation: Report for public consultation. Moscow: Bank of Russia; 2020. 35 p. URL: https://cbr.ru/Content/Document/File/108263/Consultation_Paper_200608.pdf (accessed on 30.04.2022). (In Russ.).
6. Eckstein D., Künzel V., Schäfer L. Global climate risk index 2021: Who suffers most from extreme weather events? Weather-related loss events in 2019 and 2000-2019. Bonn: Germanwatch e.V.; 2021. 52 p. URL: https://www.germanwatch.org/sites/default/files/Global%20Climate%20Risk%20Index%202021_1.pdf (accessed on 10.04.2022).
7. Preston L.E., O'Bannon D.P. The corporate social-financial performance relationship: A typology and analysis. *Business & Society*. 1997:36(4):419-429. https://doi.org/10.1177/000765039703600406
8. Hart S.L. A natural-resource-based view of the firm. *The Academy of Management Review*. 1995:20(4):986-1014. DOI: 10.2307/258963
9. Trumpp C., Guenther T. Too little or too much? Exploring U-shaped relationships between corporate environmental performance and corporate financial performance. *Business Strategy and the Environment*. 2017:26(1):49-68. https://doi.org/10.1002/bse.1900
10. Nandy M., Lodh S. Do banks value the eco-friendliness of firms in their corporate lending decision? Some empirical evidence. *International Review of Financial Analysis*. 2012;25:83-93. https://doi.org/10.1016/j.irfa.2012.06.008
11. Chodnicka-Jaworska P. ESG as a measure of credit ratings. *Risks*. 2021;9(12):226. https://doi.org/10.3390/risks9120226
12. Kouloukoui D. et al. Factors influencing the perception of exposure to climate risks: Evidence from the world's largest carbon-intensive industries. *Journal of Cleaner Production*. 2021;306:127160. https://doi.org/10.1016/j.jclepro.2021.127160
13. Baer M., Kastl J., Kleinnijenhuis A., Thomae J., Caldecott B. The cost for the financial sector if firms delay climate action. Oxford: Oxford Sustainable Finance Group; 2021. 40 p. URL: https://www.smithschool.ox.ac.uk/sites/default/files/2022-02/The-Cost-for-the-Financial-Sector-if-Firms-Delay-Climate-Action.pdf (accessed on 10.04.2022).
14. ESG impact is rarely credit positive. FitchRatings. Feb. 07, 2022. URL: https://www.fitchratings.com/research/structured-finance/esg-impact-is-rarely-credit-positive-07-02-2022 (accessed on 10.04.2022).
15. Shitikov V., Mastitskii S. Modeling ordinal and counting variables. In: Shitikov V., Mastitskii S. Classification, regression and other data mining algorithms using R. 2017. URL: https://ranalytics.github.io/data-mining/081-Logit-for-Count.html (accessed on 30.04.2022). (In Russ.).
16. Karminskii A. Company ratings and their modeling. In: Proc. 10th Int. sci. conf. on the problems of development of the economy and society (in 3 books). Book 1. Moscow: SU-HSE; 2010:372-383. https://publications.hse.ru/pubs/share/folder/dmwt8m6g6k/78423642.pdf (In Russ.).
17. Long-term rating scales comparison. BIS. URL: https://www.bis.org/bcbs/qis/qisrating.htm (accessed on 10.04.2022).
18. General criteria: S&P global ratings' national and regional scale mapping tables. S&P Global Ratings. Aug. 14, 2017. URL: https://disclosure.spglobal.com/ratings/en/regulatory/article/-/view/sourceId/10194514 (accessed on 10.04.2022).
19. Information on the comparison of rating scales of Russian credit rating agencies. Bank of Russia. Dec. 30, 2021. URL: https://cbr.ru/press/pr/?file=30122021_101000PR2021-12-30T10_03_38.htm (accessed on 30.04.2022). (In Russ.).
20. ESG in credit ratings. S&P Global Ratings. URL: https://www.spglobal.com/ratings/en/research-insights/special-reports/esg-in-credit-ratings (accessed on 30.04.2022).

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