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M&A Prediction Model: Will Investors Benefit?

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Abstract

In this paper, we study the development of investment strategies by predicting M&A deals using a logistic model with the financial and non-financial indicators of public companies. A random sample of 1510 acquired and non-acquired companies in Germany, the United Kingdom, France, Sweden, and Russia over the period 2000-2021 was used to design an M&A logit prediction model with high predictive power. The use of interaction variables significantly improved the model's predictive power and allowed it to obtain more than 70% of correct out-of-sample predictions. Then the model's ability to generate abnormal returns was tested with the help of an event study using share price data over the period 2011-2021. We show that an M&A prediction model can also efficiently generate abnormal returns (up to 49% on average) for a portfolio of companies that are expected to be acquired. Moreover, we uncover evidence that reduction in false positive and negative predictions has a positive effect on abnormal returns due to the added model flexibility resulting from interaction terms. Our positive theoretical and empirical results can help both private and institutional investors to design investment strategies. In addition, there are indirect implications that support the practical importance of an efficient M&A prediction model.

Keywords: mergers & acquisitions, probability of acquisition, logit model, interaction terms, event study, investment strategies

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Introduction

Over the last two decades, the world economy has been damaged by several unique crises that affected all sectors. Investment opportunities shrank and became less attractive. Moreover, many investors became more cautious and reluctant to invest due to the difficulty of predicting future returns. In such times of uncertainty, unconventional investment opportunities have become more popular despite their risks. However, there still exist consistent sectors that investors can use to earn abnormal returns. One such field is M&A deals, which have not declined substantially even though companies have started to care more about cost reductions than growth. Statistics show that around 30 000 M&A deals were made every year in 2000-2010, and 50 006 deals totaling $3.4 trillion in 2019, which represents approximately a 60% increase in less than a decade. When the COVID-19 pandemic hit the global markets in 2020, the figures declined by only 12% with 84 deals totaling slightly over $5 billion, surpassing the record of the first decade according to a 2021 PWC report. Over 63 000 M&A deals were made in 2021. This happened because M&A deals retained the same goals for acquirers while becoming more attractive due to cheaper investment opportunities.

In the M&A field, consistency is not limited to statistics. There is a consistent pattern that is expressed in a core principle of such deals that is called "positive synergies." Positive synergies are among the main drivers of M&A deals. They also encourage acquirers to pay more for a business than it is valued, which can be seen in the premiums paid to the existing shareholders of the targeted company. This opens opportunities for investors to become shareholders before an acquisition to receive such premiums. The average premium ranges from 10% to 50% depending on the industry with a 90% probability that such a premium will be paid. On the other hand, information about any M&A deal is strictly confidential, and it is hard to tell whether a company will be acquired without a deeper analysis of public information, as private information trading is mostly prohibited. At the same time, one can try to design an accurate M&A prediction model that could be used by a management or consulting agency directly to generate investment opportunities or by a business as an indirect instrument to help it compete and grow more efficiently.

In this paper, we use the publicly available financial and non-financial indicators of public companies to develop an M&A prediction model that can be used for maximizing cumulative abnormal returns and designing efficient investment strategies. The novelty of this paper lies in its approach to increasing the significance of an M&A prediction model by incorporating interaction variables, making the model more flexible and adaptable to different economic environments. At the same time, we propose a better way of using effectively predicted acquisitions to earn highly positive abnormal returns through an efficient portfolio construction method based on predicted probabilities that can serve both profit generating and hedging goals.

This paper is structured as follows. Section 1 sets out the background of the study. Section 2 summarizes prior research in the field as found in the literature. Section 3 describes the data and processing methodology used for constructing the M&A prediction model and analyzing abnormal returns. In Section 4, we design the model and give the results of predictive power tests and insights into model performance. Section 5 traces the ability of different factors to generate abnormal returns for both individually acquired companies and portfolios of companies. Section 6 gives an overview of potential investment strategies. Section 7 summarizes the conclusions of the paper.

Literature Review

Approaches to M&A Prediction and Modelling

Several main methodologies are used for M&A predictions. They include multiple discriminant analysis for understanding the factors for differentiating targeted companies (Simkowitz and Monroe [1], Stevens [2], Barnes [3]), probit models for finding the characteristics of targeted companies (Harris, Stewart, Guilkey, and Carleton [4]), and logit models (Dietrich and Soerensen [5], Ohlson [6], De Jong and Fliers [7], Meghouar and Ibrahimi [8], Palepu [9]). Unlike the probit model, logit analysis can be used not only to identify characteristics but also to make conclusions about the probabilities of events. However, Palepu [9] criticized the methodology applied by previous empirical studies for forecasting takeovers and concludes that such predictions are unfeasible (especially for finding investment opportunities). After his critique, the number of empirical studies declined sharply. Palepu's work divided the whole field of research into "before and after." Palepu made a breakthrough by proposing an improved framework for measuring the likelihood of a takeover and outlining six hypotheses [9, p.11-12] for takeover forecasts and three main methodological errors [9, p. 3]. According to Palepu, companies should be ranked by their takeover probability and compared by cut-offs, which should be determined similarly for every company on the list. If a company is above the cut-off level, it is a targeted company; otherwise, it is non-targeted. Palepu defined the cut-off probability as the intersection of the PDFs (probability density functions) of takeover targets and non-targets [9, p. 14-15]. He used pre-specified variables, while other researchers have focused on statistically significant ones.

The share of tangible assets was found significant by Ambrose and Megginson [10]. They tested the importance of asset structuring, shareholdings, and the application of anti-takeover strategies. Institutional shareholdings turned out to be the only factor that had a significant impact on real data. The leverage factor has also been found significant [11], which has been linked to the low-level liquidity ratios of acquired companies [12]. A 2009 study of short-term factors by Brar, Giamouridis and Liodakis [12] yielded significant new results. It appears that the trading volume to market capitalization ratio and price momentum factors are significant in the short term yet insignificant over the long run. Each of the 13 hypotheses that had been formulated by 2009 posits between 1 and 17 factors as being relevant and significant for takeover forecasting.

Broader Perspective of the Application of M&A Prediction Models

There have been only a small number of significant studies of takeover predictions since 2009. However, they contributed to the field by focusing on the potential applications of M&A prediction models and conducting cross-topic analysis. Bhanot, Mansi, and Wald [13] studied how stock prices are related to returns and whether they can be used for estimating takeover risks. Cornett, Tanyeri and Tehranian [14] used the acquisition risks of targeted firms to measure market anticipation. Their results showed that market anticipation is correlated with returns for targeted companies and acquirers.

Danbolt, Siganos and Tunyi [15] advanced the claim that it is possible to create a profitable investment portfolio with predicted takeover targets. They showed that such a portfolio can be used to earn abnormal returns. However, the data must be sufficiently clean for the model to be correct. It is necessary to work with data accurately; otherwise, portfolio returns may be diluted due to errors such as inaccurate predicted targets, mistimed target selection and the inability to differentiate between potential targets and bankrupt firms. The latter problem was identified and described by Powell and Yawson [16] in 2007. However, such problems can be completely or partly removed by the use of an appropriate screening procedure during the data collection process to increase portfolio profitability. Another recent study by Tunyi [17] suggested reconsidering Palepu's results [9] insofar as his hypothesis lacks strategic rationale and reviewing the factors that act as motives for takeovers. It also called for improving existing models by testing them across time periods, regions, and contexts. This type of study was conducted in 2016 by Tunyi and Ntim [18] for the African region.

Formulation of Research Questions

The literature review led us to formulate two basic research questions:

1) Can the forecast power of an M&A prediction model be improved by using interaction variables?
2) Can an M&A prediction model be used to construct an efficient portfolio strategy?

Thus, our paper is divided into two parts: the construction of an M&A prediction model (Model 1) and the estimation of a portfolio of abnormal returns (Model 2) on its basis.

Model 1: M&A Prediction Model

Variables and Data Description (Model 1)

To answer the first research question, we construct a takeover probability model and analyze the main factors of influence. Four basic factors of influence on takeover probability were originally presented by Palepu [9], and two additional factors were later proposed by other authors to estimate company performance more accurately and make better takeover predictions. The selection of variables was based on statistical significance discovered in [9], [11] and [12] and on the availability of public data that assure a better data sample for empirical analysis.

Therefore, six main factors (with several variables chosen within each factor) are used in our model:

1) **Size factor:** The size of the firm is negatively correlated with its takeover probability, i.e., the bigger the firm, the less its chance of being acquired.
   - *Enterprise Value*, an alternative metric to market capitalization, is the sum of the market capitalization and the market value of net debt.
   - *Total Assets* is the book value in million USD of all the company's assets in its statement of financial position for the year before the acquisition.
2) **Undervaluation factor:** The P/E ratio [19] and the EV/B ratio [20] are negatively correlated with the takeover probability, i.e., the higher a company's EV/B ratio and P/E ratio, the less likely it is to be acquired.
   - *EV/B ratio* is the ratio of Enterprise Value to Total Assets.
   - *P/E ratio* is the ratio of Market Capitalization to Net Income.
3) **Leverage factor:** a company that borrows capital for quicker expansion is less likely to be acquired as its financial attractiveness for acquirers decreases.
   - *Debt/Equity ratio* is the ratio of the book value of company Debt to Equity.
4) **Liquidity factor:** if a company has a greater amount of liquid assets than capital assets, it is less likely to be acquired, which was found significant at the 1% significance level by Brar, Giamouridis and Liodakis [12].
   - *Current ratio* is the ratio of Current Assets to Short-Term Liabilities.
5) **Management inefficiency factor:** if management becomes more inefficient and underperforming, the company's chances of acquisition increase due to the possibility of using managerial synergies to generate extra value. This is the most widely used factors in papers.
   - *ROE* is the ratio of Net Income to Equity.
   - *EBITDA margin* is the ratio of Earnings before interest, taxes, depreciation, and amortization to Total Sales divided by Net Sales.
   - *Sales growth* is the ratio of a company's Total Sales in the current year to its Total Sales in the preceding year.
6) **Growth resource mismatch factor:** if a company's direction of growth does not correspond to its

resources, such a company is at risk to be targeted and acquired in the future, i.e., if a company has a lot of resources yet is growing slower than its resources allow, or vice versa, then it might be acquired.

- *Growth resource* is taken as the dummy variable with values 0 and 1. The *Growth resource* dummy variable is equal to 1 if the observed value of *EV/B ratio* and *Sales growth* is higher than the average for these variables and the *Current ratio* is less than its respective average value.

Information about expected signs, selection criteria and data sources for the listed variables is presented in *Appendix 1*.

We used two main samples of acquired and non-acquired companies for setting up and testing the M&A prediction model. Initially, public financial and non-financial data about 23 404 acquired and 66 400 non-acquired companies registered in Germany, the United Kingdom, France, Sweden, and Russia over the period 2000-2021 was collected from the Bloomberg Terminal and Thomson Reuters Eikon, respectively. The countries were selected on the basis of their M&A activity, e.g., Russia had the highest M&A activity in Eastern Europe at the time. The data was analyzed for selection biases, and the UK control was introduced into the model to avoid data skewness. Data selection was then conducted by removing observations with missing data from the sample and reducing the number of outlying observations so as to increase the accuracy of the model fitting process. Ultimately, 538 acquired and 972 non-acquired observations were included in the sample.

The filtered data was divided into two subsamples on a temporal basis: a training subsample (497 acquired and 800 non-acquired companies, 2000-2019) and a hold-out subsample (41 acquired and 172 non-acquired companies, 2020-2021). The training subsample was used for model fitting, and hold-out subsample for testing purposes. The latter was needed to avoid any possible bias during the predictive power test so as to obtain accurate valuation. It is also used for testing the ability of the model to predict M&A deals within unique economic environments such as the COVID-19 pandemic, which is crucial for understanding the usefulness of the model for potential users in real circumstances.

In addition, the set of variables was tested for multicollinearity. Results show that there is a multicollinearity problem present if both LNEV and LNTA variables are included. Therefore, only one of these variables can be used for model fitting. The final decision whether to use LNEV or LNTA should be based on the results of model fitting. The test for variable multicollinearity was made in STATA using the *collin* tool. Other tests such as heteroskedasticity, linearity, normality, autocorrelation, etc. are not required for the logistic regression used in our study (Figure 1).

Figure 1. Multicollinearity tests for the entire set of variables and for the set of variables without LNEV or LNTA, respectively

```
. collin ROE DE PE EVB LNTA UKD GRD EBITDAM LNEV
(obs=1,600)

  Collinearity Diagnostics

                        SQRT                   R-
  Variable      VIF     VIF    Tolerance    Squared
----------------------------------------------------
       ROE      1.17    1.08    0.8560      0.1440
        DE      1.05    1.03    0.9505      0.0495
        PE      1.11    1.05    0.9036      0.0964
       EVB      2.26    1.50    0.4428      0.5572
      LNTA     13.55    3.68    0.0738      0.9262
       UKD      1.02    1.01    0.9768      0.0232
       GRD      1.01    1.01    0.9892      0.0108
   EBITDAM      1.10    1.05    0.9061      0.0939
      LNEV     14.60    3.82    0.0685      0.9315
----------------------------------------------------
  Mean VIF      4.10
```

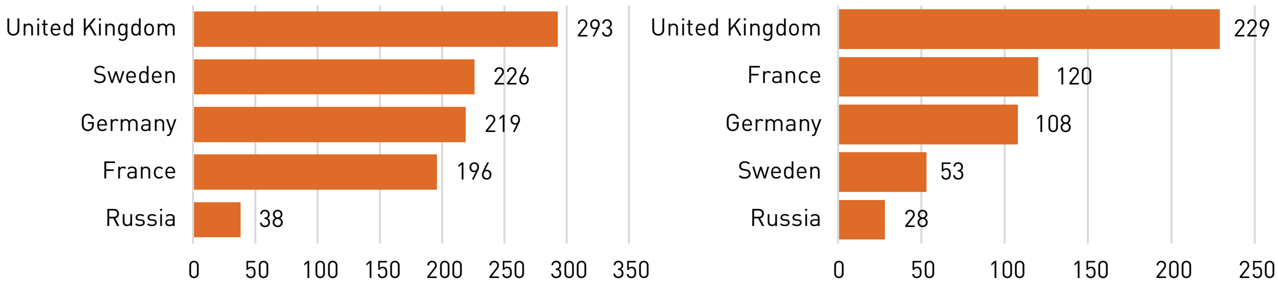
```
. collin ROE DE PE EVB UKD GRD EBITDAM LNEV
(obs=1,600)

  Collinearity Diagnostics

                        SQRT                   R-
  Variable      VIF     VIF    Tolerance    Squared
----------------------------------------------------
       ROE      1.17    1.08    0.8565      0.1435
        DE      1.02    1.01    0.9773      0.0227
        PE      1.09    1.04    0.9189      0.0811
       EVB      1.22    1.11    0.8184      0.1816
       UKD      1.02    1.01    0.9776      0.0224
       GRD      1.01    1.00    0.9947      0.0053
   EBITDAM      1.10    1.05    0.9104      0.0896
      LNEV      1.19    1.09    0.8433      0.1567
----------------------------------------------------
  Mean VIF      1.10
```

```
. collin ROE DE PE EVB LNTA UKD GRD EBITDAM
(obs=1,600)

  Collinearity Diagnostics

                        SQRT                   R-
  Variable      VIF     VIF    Tolerance    Squared
----------------------------------------------------
       ROE      1.17    1.08    0.8560      0.1440
        DE      1.04    1.02    0.9648      0.0352
        PE      1.08    1.04    0.9243      0.0757
       EVB      1.17    1.08    0.8528      0.1472
      LNTA      1.10    1.05    0.9090      0.0910
       UKD      1.02    1.01    0.9769      0.0231
       GRD      1.01    1.00    0.9920      0.0080
   EBITDAM      1.09    1.04    0.9166      0.0834
----------------------------------------------------
  Mean VIF      1.09
```

Source: Authors' analysis.

Moreover, a class imbalance problem exists, as acquired companies account for only 35.6% of the sample (38.3% of the training and 18% of the hold-out subsamples). It was mitigated by using SMOTE (Synthetic Minority Over-sampling Technique) in Python, which increases observations in a minority sample up to a majority level via generically created observations without affecting the sample characteristics. SMOTE was applied on the subsamples separately to retain the effect of the COVID-19 pandemic on M&A deals. As a result, the quantity of acquired companies increased to 800 in the training subsample and 172 in the hold-out subsample. The distribution by country of the over-sampled subsamples is presented in Figure 2.

Figure 2. Distribution of over-sampled subsamples by country



Source: Authors' analysis.

Figure 2 demonstrates that there is a large share of companies registered in the United Kingdom, which may create a bias toward UK observations. Therefore, the control binary variable "UK" was included in the model to avoid bias.

Methodology Description (Model 1)

We used the logit regression model in this paper. The maximum likelihood estimation method was chosen for model fitting, as it is more suitable for the logit regression and is better at estimating binary outputs in comparison to other classical methods.

The multivariable logit regression model is a modified version of the classical logistic regression model used for probability estimation:

$$P(y) = \frac{e^{\alpha+\beta x}}{1+e^{\alpha+\beta x}}$$, where

y is a dependent variable,

α is an intercept,

β is the coefficient of the independent variable X.

Modified form: $P(z,t) = \frac{1}{1+e^{-\beta x(z,t)}}$, where

(z, t) is a company acquired at time period t.

The logit model is enhanced with significant 2nd-order categorical-continuous interaction terms. An interaction does not require any additional data as it employs existing variables that have already been used to capture additional interaction effects. It increases model flexibility and adaptability to new data without creating the threat of multicollinearity. The logit model with interactions has the following general form:

$$log(y) = a + a_1X_1 + a_2X_2 + \ldots + a_nX_n + a_{n+1}X_1X_2 + \ldots + a_{n+k}X_nX_{n-1},$$

where

n is the number of main effects,

k is the number of interactions,

a_0, ..., a_{n+k} are the slope coefficients,

X_1, ..., X_n are the main variables,

X_1X_2, ..., X_nX_{n-1} are the interaction terms.

There are 10 main variables included in the constructed model: LN (Enterprise Value), LN (Total Assets), Price-to-Earnings ratio, EV-to-Book ratio, Debt-to-Equity, Current ratio, Return on Equity, EBITDA margin, Sales growth and Growth resource mismatch (the latter controls for over or under-performing companies among the sample).

Additionally, *AC* is introduced as a binary dependent variable for model estimation with the value 0 for non-acquired companies and 1 for acquired companies. Moreover, the independent binary variable *UK* is introduced to control for companies from the United Kingdom due to its major share in the dataset (33%). All these variables are used for the designing the model in Section 4. Descriptive statistics of variables are shown in Table 1.

Table 1. Descriptive statistics of main variables

Variable	Acquired (mean)	Non-Acquired (mean)	Acquired (st. dev.)	Non-Acquired (st. dev.)
LNEV	5.47	7.62	1.70	1.90
LNTA	5.52	7.50	1.63	2.05
P/E ratio	16.46	38.32	32.18	50.33
EV/B ratio	2.63	3.84	2.27	3.51
Debt/Equity	35.42	48.74	26.19	41.88
Current ratio	1.83	1.79	1.56	1.34
ROE	7.93	15.08	27.17	16.13

Variable	Acquired (mean)	Non-Acquired (mean)	Acquired (st. dev.)	Non-Acquired (st. dev.)
EBITDA margin	14.27	22.48	51.22	17.78
Sales growth	23.00	19.95	156.03	50.03
Growth resource	0.25	0.22	0.43	0.42

Source: Authors' analysis.

Modelling Results (Model 1)

In this section, we design a logit interaction model and train it on the training subsample to attain the goal of the paper. All the variables and potentially significant interaction terms described above are included in the model. A stepwise backward elimination procedure is applied to eliminate insignificant main and interaction terms to improve the model's performance. As a result, four multivariable logit regression models with interactions are obtained. Interaction Models 1 and 2 are used to see whether LNEV or LNTA with the respective interactions performs better. Interaction Models 3 and 4 are then built to maximize the performance of the model. The regression analysis is made in STATA; its results are aggregated in Table 2.

Interaction Models 1 and 2 show that the LNEV independent variable with its interactions makes the model perform better for pseudo R2, AIC and BIC indicators, which gives reason to prefer LNEV over LNTA for further model fitting. Next, Interaction Model 3 omits the EVB variable with its interactions, which are highly insignificant; it shows a better BIC result with AIC being the same as well as a decrease in pseudo R2 due to a reduction in the quantity of regressors. The final model is Interaction Model 4, which is improved by omitting insignificant interactions, making the main variables such as ROE and GRD significant and decreasing the AIC and BIC scores to 1557 and 1612, respectively. This is the best result in comparison with other possible interaction models for this set of factors. Pseudo R2 becomes slightly lower again due to a decrease in the quantity of regressors yet can nevertheless be considered a good fit. Indicators show that the model has good explanatory power.

Table 2. Representation of the logit interaction model selection procedure with results

	Int. Model 1 All interactions w/ LNTA	Int. Model 2 All interactions w/ LNEV	Int. Model 3 -EVB & interactions	Int. Model 4 -Insignificant interactions
CONST	3.824***	3.454***	3.418***	3.515***
	(0.35)	(0.33)	(0.33)	(0.31)
ROE	-0.006	-0.006	-0.007	-0.008*
	(0.00)	(0.00)	(0.00)	(0.00)
DE	-0.005	-0.006*	-0.005*	-0.006*
	(0.00)	(0.00)	(0.00)	(0.00)
PE	-0.016***	-0.015***	-0.016***	-0.019***
	(0.00)	(0.00)	(0.00)	(0.00)
LNEV	-	-0.423***	-0.431***	-0.432***
		(0.04)	(0.04)	(0.04)
EVB	-0.113***	-0.045	-	-
	(0.04)	(0.04)		
LNTA	-0.437***	-	-	-
	(0.04)			
GRD	0.972	1.066	1.074	0.922***
	(0.71)	(0.68)	(0.68)	(0.27)
UKD	3.521***	3.788***	3.790***	3.497***
	(0.71)	(0.69)	(0.68)	(0.65)

	Int. Model 1 All interactions w/ LNTA	Int. Model 2 All interactions w/ LNEV	Int. Model 3 -EVB & interactions	Int. Model 4 -Insignificant interactions
LNEV*UKD	-	-0.601*** (0.10)	-0.572*** (0.10)	-0.588*** (0.10)
PE*GRD	0.010* (0.00)	0.008 (0.00)	0.011* (0.00)	0.011** (0.00)
DE*GRD	-0.032*** (0.01)	-0.035*** (0.01)	-0.033*** (0.01)	-0.033*** (0.01)
DE*UKD	0.013* (0.01)	0.014** (0.00)	0.013** (0.00)	0.013** (0.00)
ROE*GRD	-0.000 (0.01)	0.002 (0.01)	0.005 (0.01)	-
PE*UKD	-0.018** (0.01)	-0.013** (0.01)	-0.010 (0.01)	-
ROE*UKD	-0.015 (0.01)	-0.014 (0.01)	-0.009 (0.01)	-
EVB*GRD	0.123* (0.06)	0.136* (0.06)	-	-
EVB*UKD	0.010 (0.06)	0.100 (0.06)	-	-
LNTA*UKD	-0.505*** (0.10)	-	-	-
Num of obs	1600	1600	1600	1600
Pseudo R2	0.3108	0.3139	0.3108	0.3081
AIC	1565	1558	1559	1557
BIC	1661	1655	1639	1612

* - p<0.5; ** - p<0.01; *** - p<0.001.

Source: Authors' analysis.

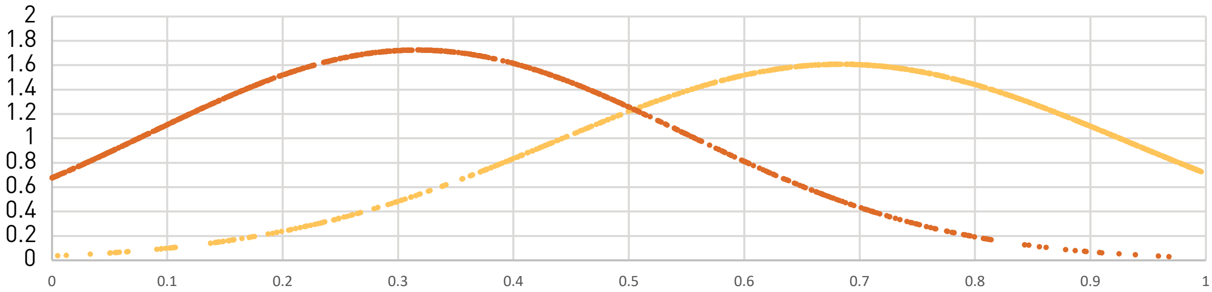
Out-of-Sample Predictive Power Test

In this section, an additional predictive power test is conducted on the hold-out subsample to see how Interaction Model 4 performs for data outside the training sample. This test is also important as the hold-out sample consists of deals made during the COVID-19 period, which impacted the global economy in a unique way. Therefore, it is also a test on the adaptability and flexibility of Interaction Model 4.

The predictive power test is also known as the classification test. It employs the following methodology. First, the observations from the hold-out sample are inserted into the model with the coefficients obtained during model fitting to calculate the model score and interpret it as the acquisition probability. Then, the probabilities are arranged in descending order and normalized for acquired and non-acquired companies separately to plot PDFs (Probability Density Functions), whose intersection is taken as the cut-off probability that is used as a benchmark to decide which observations are predicted to be acquired or non-acquired. Finally, the expected values are compared with real data to calculate the predictive power as percentages for the entire hold-out subsample and its restricted versions for a detailed analysis.

Here, the PDFs are plotted for the predicted probabilities of each subsample in the main sample (800 observations for the acquired sample and 800 observations for the non-acquired sample). The intersection is at 50.5%, which represents the cut-off probability for the main sample. Therefore, all the observations in the hold-out sample with probabilities higher than 50.5% can be described as expected targets in the combined hold-out sample. The resulting PDFs are presented below.

Figure 3. PDFs of probabilities predicted by Interaction Model



Source: Authors' analysis.

Table 3. Representation of predictive power test results

General information (Interaction Model 4)			Acquired Predictions			Non-Acquired Predictions			Results
№	Sample Description	Observations	Acquired	Expected	%	Non-Acquired	Expected	%	Predictive power
1	Hold-out sample	344	172	112	65.12	172	135	78.49	71.80
2	2021 hold-out sample	187	98	46	46.94	89	71	79.78	62.57
3	2020 hold-out sample	157	74	66	89.19	83	64	77.11	82.80
5	UK hold-out sample	97	37	31	83.78	60	48	80.00	81.44
6	Non-UK hold-out sample	247	135	81	60.00	112	87	77.68	68.02
	Total		**516**	**336**	**69.01**	**516**	**405**	**78.61**	**71.80**

Source: Authors' analysis.

The average predictive power for Interaction Model 4 across the combined sample and the four subsamples is equal to 71.8% and 70.64%, respectively, with the average percentage of correct acquisitions equal to 69.01%. The predictive power is lowest in 2021 due to the additional economic crisis caused by the prolonged COVID-19 pandemic, which influenced the strategies behind M&A deals. Earlier papers suggest that the accuracy of results can be improved by more precise cut-offs for subsamples. However, this is unnecessary in the case of an interaction model, as interactions make it possible to adjust estimation scores directly, rendering the results more accurate and the analysis easier to implement in practice. Therefore, Interaction Model 4 has good predictive power for both subsamples and can be used for abnormal returns analysis.

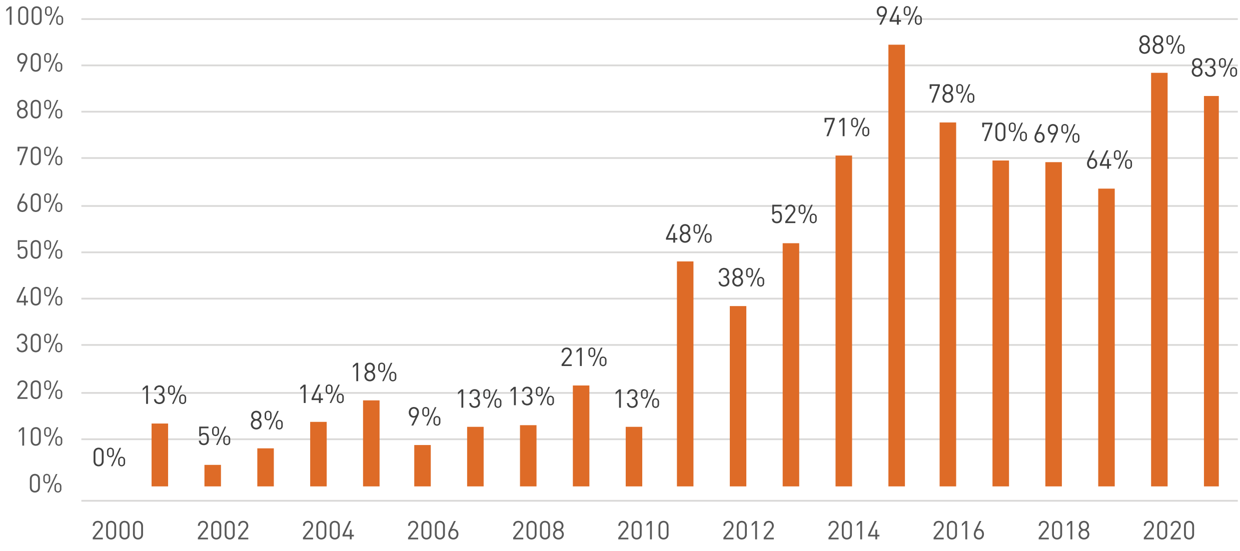
Model 2: Abnormal Portfolio Returns

To answer the second research question, the variables used in the model are tested for efficiency in generating abnormal returns. We analyze the influence of variables included in the final version of the prediction model on the abnormal returns of shareholders of the acquired company to see how the acquisition probability relates to abnormal returns with respect to a chosen factor. Our goal is to see whether acquired companies with the highest return and acquisition probability can be reliably identified. If the results of the first analysis are successful, we will design a portfolio that can be used for investment strategies and practical implications analysis.

Data Description (Model 2)

The second analytical part of this paper focuses on the analysis of abnormal returns using an event study based on acquired companies before over-sampling with 538 observations. Additional information about stock returns for 250 trading days before and 50 trading days after the acquisition date are collected from open sources (Yahoo. Finance, Google Finance, Investing.com and Euronext). As a result, 178 observations out of 538 are used for analysis. The reduction in observations can be explained by the limited availability of data for older transactions, as delisted companies have limited coverage: data availability clearly depends on the announcement date, the delisting date and the number of years between the date of research and the acquisition announcement. This can be seen from Figure 4, where the former figure shows the distribution of observations with available data by year and the latter figure depicts the percentage of observations that remain in comparison with the entire acquired subsample.

Figure 4. Percent of observations with share price data in the acquired subsample



Source: Authors' analysis.

There is a shortage of available data before 2011 both in absolute terms (19.4% of observations stem from 2000-2010) and in percentage terms – the ratio of remaining data to the entire sample is less than 21% for 2000-2010 acquisitions. Moreover, data on expected returns is collected to measure abnormal returns. The MSCI index by country (MSCI United Kingdom, MSCI France, MSCI Germany, MSCI Sweden and MSCI Russia) is used as a market returns benchmark for each acquired company individually based on its acquisition date. However, MSCI day-by-day index data is available only after 2008, which is another reason to restrict the observations by the year of acquisition. Therefore, there is good reason to exclude observations before 2011, leading to a total of 144 observations.

Moreover, 9 observations contain data only for the event window from -20 to 20 trading days and 1 observation from -10 to 10 trading days due to early delisting after acquisition. The descriptive statistics for the remaining observations are presented in Appendix C. Thus, the results are taken across two different groups with the maximum event windows [-50, 50] and [-20, 20] containing 134 and 143 observations, respectively.

Methodology Description (Model 2)

To attain the goal of this section, we conduct an analysis based on the event study concept, which we use to design event windows that include the acquisition date (set at t=0) and to derive their CAARs (Cumulative Average Abnormal Returns). A period from -250 to -50 trading days is used as the estimation window, while windows up to [-50, 50] trading days are used as event windows. They are separated to avoid the effects of pre-announcement returns on the market model, which were found to be insignificant two months prior to acquisition in previous empirical papers on this topic. While the estimation window length is unbounded as no significant evidence has been found in earlier papers, it is usually between 120 and 239 days.

ARs, AARs, CARs and CAARs

First, actual and expected returns are calculated to derive abnormal returns. Actual returns are obtained using collected data on trading day by trading day share prices by dividing the return by the return for the previous trading day. Expected returns are calculated using the singe-factor market model in the form

$E(R_{it}) = a_i + b_i{*}R_{mt} + e_i$, where

a_i is an intercept,

b_i is beta,

e_i is the company-specific shock,

R_{mt} is the market return.

Market returns are collected as MSCI country-specific day-by-day index. Intercept and beta values are derived for each acquired company and estimated using intercept and slope functions, respectively, in Excel based on actual and market returns within an estimation window.

Second, day-by-day abnormal returns for each acquired company are calculated using the actual and expected returns:

$AR_{it} = R_{it} - E(R_{it})$, where

R_{it} is the actual returns,

$E(R_{it})$ is the expected returns.

ARs are further used for calculating the AARs (Average Abnormal Returns) specifically for each trading day from -250 to 50 as a sum of ARs that belong to the same trading day across all observations divided by the quantity of observations. Moreover, AARs are defined for the entire, UK-only and non-UK subsamples. Furthermore, CARs (Cumulative Abnormal Returns) are calculated as the sum of ARs for each observation. Finally, CAARs (Cumulative Average Abnormal Returns) are calculated for each event window as the sum of AARs for each specific group and subsample.

t-tests for CAARs

Derived CAARs are tested for significance using the relevant t-test. To use it properly, the following hypotheses are made:

H0: $CAAR_i = 0$

H1: $CAAR_i \neq 0$.

Then, the t-statistics can be calculated:

$$t_{stat} = \frac{CAAR_i}{\sqrt{var(CAAR_i)}} = \frac{CAAR_i}{\sqrt{var\left(\sum AAR_i\right)}} =$$

$$= \frac{CAAR_i}{\sqrt{var(\frac{\sum AR_i}{N})}} = \frac{N * CAAR_i}{\sqrt{var\left(\sum AR_i\right)}},$$

where N is the length of the event window.

Finally, the resulting t-statistics are compared with the critical values of t, which are equal to 1.65, 1.96 and 2.58 for the 90%, 95% and 99% confidence levels, respectively. If t_{stat} is higher than the critical value, then there is significant statistical evidence to reject the null hypothesis.

Multivariable linear regression

CARs are used to fit a standard multivariable linear regression model to test the relationship between factors derived for Interaction Model 4 in Section 4 and the CARs calculated in this Section. The MLR has the following form:

$y=a_0+a_1X_1+a_2X_2+...+a_nX_n+u_i$, where

X_i are the independent variables derived previously

y is CAR_i

u_i are unobserved factors [21].

Model Results (Model 2)

CAARs

In this section, event windows ranging from [-1, 1] to [-50, 50] trading days are analyzed to capture both run-up returns before acquisition and returns generated by the acquisition deal itself. Moreover, additional event windows from [-50, -1] to [-5, -1] trading days are calculated to estimate run-up returns, and event windows from [1, 5] to [1, 50] are used to predict post-acquisition returns separately. The results are obtained for Group A (134 obs.) and Group B (143 obs.), which have maximum event windows of [-50, 50] and [-20, 20] days, respectively (see Table 4).

Table 4. CAARs for different data groups and subsamples with t-statistics

Group A (134 obs.)		All (134 obs.)			UK (36 obs.)			non-UK (98 obs.)		
Windows	Days	CAAR, %	SD	t-test	CAAR, %	SD	t-test	CAAR, %	SD	t-test
CAAR [-50 +50]	101	13.86	0.0025	282.07***	3.15	0.0054	43.26***	17.80	0.0026	353.25***
CAAR [-20 +20]	41	18.40	0.0025	151.99***	12.92	0.0054	71.92***	20.42	0.0026	164.51***
CAAR [-10 +10]	21	16.64	0.0025	70.38***	14.08	0.0054	40.17***	17.57	0.0026	72.52***
CAAR [-5 +5]	11	15.32	0.0025	33.95***	12.97	0.0054	19.38***	16.18	0.0026	34.98***
CAAR [-1 +1]	3	15.42	0.0025	9.32***	13.53	0.0054	5.51***	16.12	0.0026	9.50***
CAAR [-5 -1]	5	0.43	0.0025	0.44	1.58	0.0054	1.07	0.01	0.0026	0.01
CAAR [-10 -1]	10	1.91	0.0025	3.85***	3.14	0.0054	4.27***	1.46	0.0026	2.87***

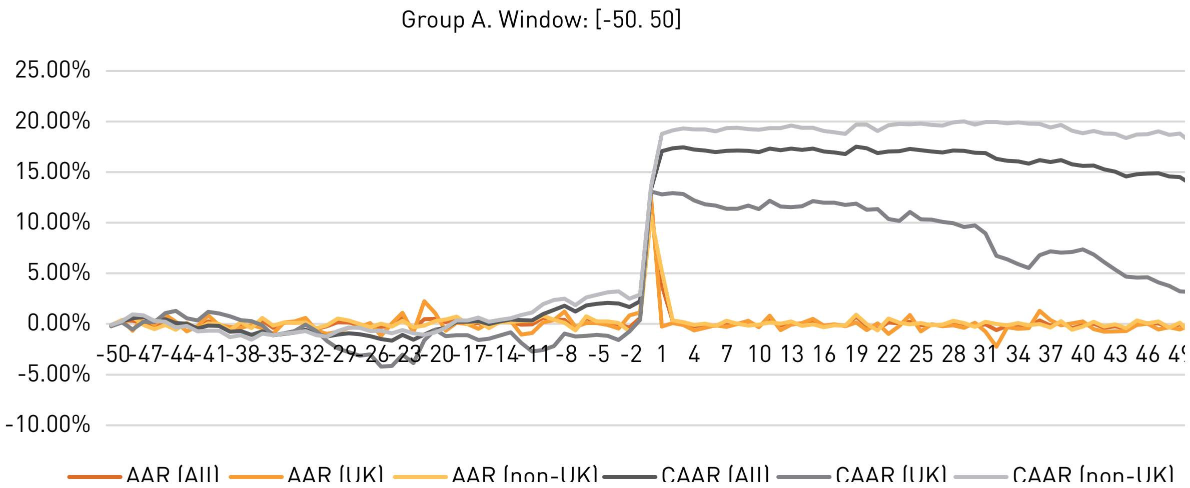
Group A (134 obs.)		All (134 obs.)			UK (36 obs.)			non-UK (98 obs.)		
CAAR [-20 -1]	20	3.31	0.0025	13.33***	2.05	0.0054	5.56***	3.77	0.0026	14.83***
CAAR [-50 -1]	50	2.25	0.0025	22.71***	0.42	0.0054	2.83***	2.93	0.0026	28.79***
CAAR [+1 +5]	5	3.88	0.0025	3.91***	-1.26	0.0054	-0.86	5.77	0.0026	5.67***
CAAR [+1 +10]	10	3.71	0.0025	7.48***	-1.72	0.0054	-2.33**	5.71	0.0026	11.22***
CAAR [+1 +20]	20	4.08	0.0025	16.45***	-1.79	0.0054	-4.86***	6.24	0.0026	24.52***
CAAR [+1 +50]	50	0.60	0.0025	6.02***	-9.92	0.0054	-67.38***	4.46	0.0026	43.85***
Group B (143 obs.)		**All (143 obs.)**			**UK (42 obs.)**			**non-UK (101 obs.)**		
Windows	Days	CAAR, %	SD	t-test	CAAR, %	SD	t-test	CAAR, %	SD	t-test
CAAR [-20 +20]	41	19.27	0.0025	159.16***	15.71	0.0054	87.48***	20.75	0.0026	167.19***
CAAR [-10 +10]	21	17.39	0.0025	73.56***	16.32	0.0054	46.55***	17.83	0.0026	73.59***
CAAR [-5 +5]	11	15.79	0.0025	34.98***	14.05	0.0054	21.00***	16.51	0.0026	35.68***
CAAR [-1 +1]	3	15.79	0.0025	9.54***	14.60	0.0054	5.95***	16.29	0.0026	9.60***
CAAR [-5 -1]	5	0.54	0.0025	0.55	1.24	0.0054	0.84	0.25	0.0026	0.25
CAAR [-10 -1]	10	2.29	0.0025	4.61***	3.84	0.0054	5.22***	1.64	0.0026	3.22***
CAAR [-20 -1]	20	3.83	0.0025	38.57***	3.28	0.0054	22.28***	4.06	0.0026	39.87***
CAAR [+1 +5]	5	3.61	0.0025	3.64***	-1.13	0.0054	-0.77	5.59	0.0026	5.49***
CAAR [+1 +10]	10	3.47	0.0025	6.99***	-1.47	0.0054	-1.99**	5.52	0.0026	10.85***
CAAR [+1 +20]	20	3.81	0.0025	15.36***	-1.51	0.0054	-4.11***	6.03	0.0026	23.68***

Source: Authors' analysis.

It is evident that all the main CAARs (which are symmetric around the acquisition date) have highly positive and highly significant (at more than 99%) cumulative returns from approx. 15% to 21%, depending on the group and the subsample used for their estimation. This is consistent with the empirical results and theoretical background provided by previous papers in the field.

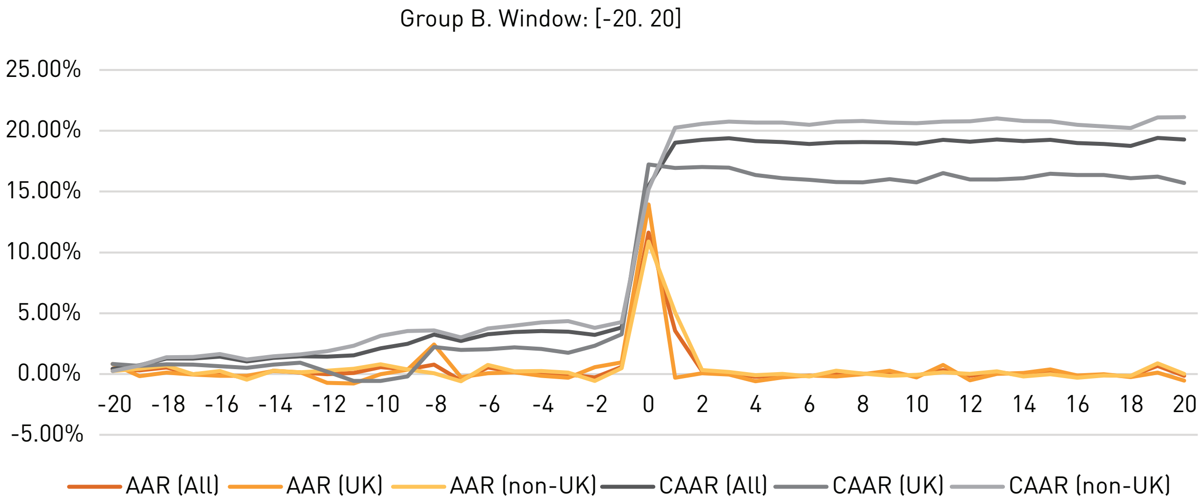
On the other hand, event windows from [-10, -1] to [-50, 1] show that run-up returns are significant at less than 4%, while run-up returns for the [-5, -1] window are insignificant across all groups and subsamples, which is 4-5 times lower than the main CAARs result. Thus, it can be considered as low, and the average level of trading based on private information is low, too. Moreover, event windows from [1, 5] to [1, 50] show that post-acquisition returns generally range from 3% to 4% for all countries. However, such returns are dramatically different between UK and non-UK observations: (-1%, -2%) with [1, 5] returns being insignificant for the UK subsample, and (4%, 6%) for the non-UK subsample. As the obtained results are easier to understand in graphical form, we drew a series of graphs for the [-50, 50] and [-20, 20] event windows for each subsample. The graphs show AARs and CAARs for each day of the event window (Figures 5 and 6).

Figure 5. AARs and CAARs for the event window [-50, 50] of Group A



Source: Authors' analysis.

Figure 6. AARs and CAARs for the event window [-20, 20] of Group B

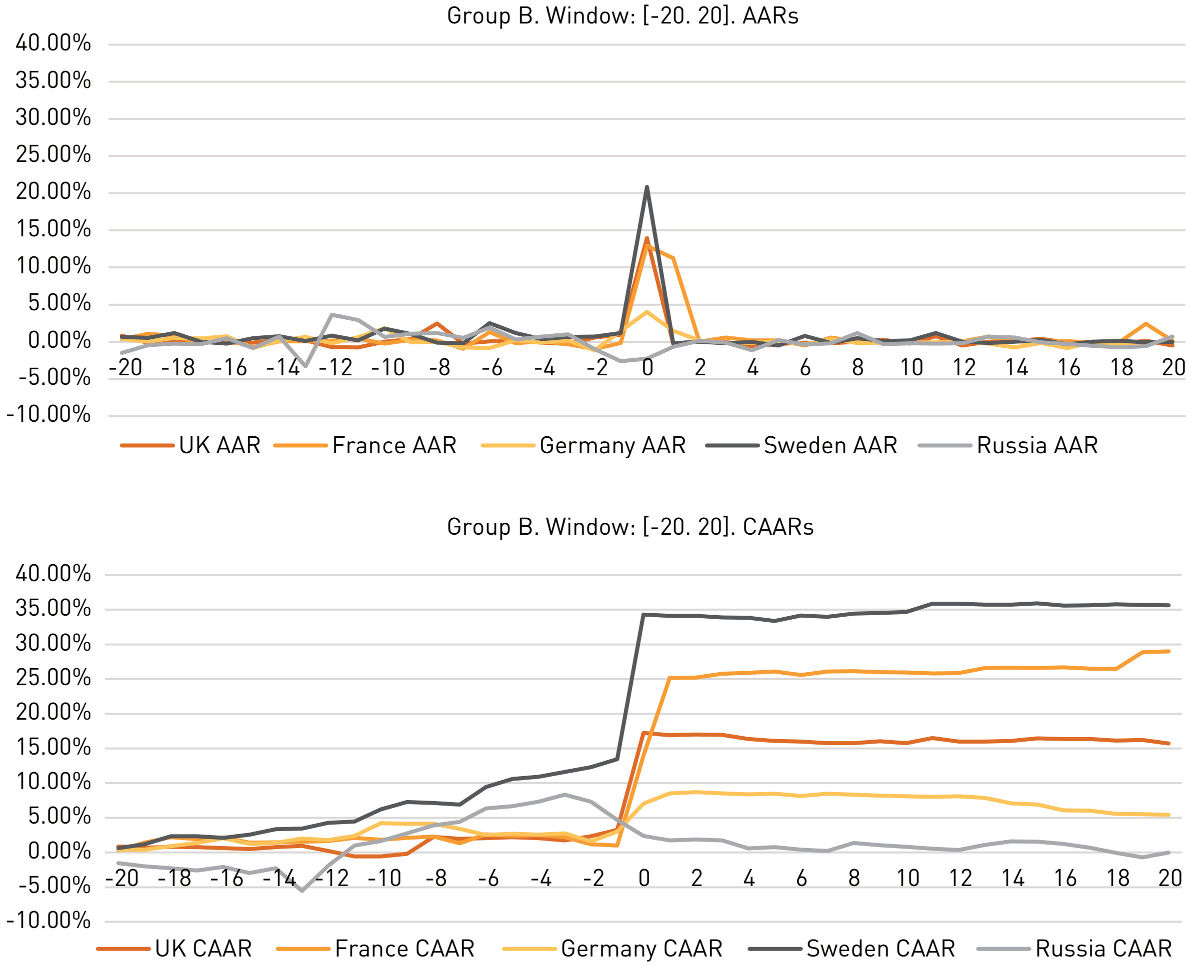


Source: Authors' analysis.

There is a definite peak for AARs (blue lines) at the acquisition date that decreases over the next 2 days, which positively affects CAARs (orange lines) that rise significantly until +2 trading days after the acquisition. Moreover, acquisitions in the UK tend to have a bigger impact than average on the acquisition returns followed by a gradual decrease after +20 trading days after the acquisition, while other acquisitions stay at a constant level. Run-up returns start to form between -20 and -10 days yet stay low in comparison with the abnormal returns on the day of acquisition as mentioned previously. To understand the dependence of CAARs on the country, we drew another graph that shows the distribution of CAARs by country using Group B data and includes all observations except for the [-20, 20] event window, which can be considered as the most representative for this dataset.

There are not enough observations on Russian companies to be able to interpret the results of CAAR and AAR estimation. Among the other countries, Sweden has the biggest CAAR for the entire estimation window, while Germany has the lowest result of the four countries. However, Sweden is the only country with distinctively high run-up returns, while other countries have returns below 5%, which may be a signal that the selected companies from Sweden show that insider trading or strong rumors have an influence on the market on average. In addition, Sweden has the highest returns on the acquisition date.

Figure 7. AARs and CAARs for the event window [-20, 20] of Group B



Source: Authors' analysis.

CARs and Variables

In this section, we test the influence of variables on CARs using OLS regression model estimation in STATA. Two new dependent variables (CAR50 and CAR20) are introduced to provide data about CARs for a particular observation. The independent variables and model structure are taken from Section 4. The results of model fitting are summarized in Table 5 below.

To test the CARs for the event windows [-50, 50] and [-20, 20] trading days from the acquisition, three different versions of the model are used. The first is Interaction Model 4, and the second is an adjusted Interaction Model 4 called Interaction Model 5. The IM5 takes advantage of interaction terms by altering them so as to increase the efficiency of Interaction Model 4 without changing the main variables.

Table 5. CAARs for different data groups and subsamples with t-statistics

	CAR50(IM4) Group A. I.Model 4	CAR50(IM5) Group A. I.Model 5	CAR20(IM4) Group B. I.Model 4	CAR20(IM5) Group A. I.Model 5
CONST	0.479*** (0.16)	0.422*** (0.15)	0.399*** (0.12)	0.389*** (0.11)
ROE	-0.003** (0.00)	-0.003*** (0.00)	-0.002* (0.00)	-0.002** (0.00)
DE	0.001 (0.00)	0.002 (0.00)	0.002 (0.00)	0.002* (0.00)
PE	-0.000 (0.00)	0.002** (0.00)	0.001 (0.00)	0.002*** (0.00)

	CAR50(IM4) Group A. I.Model 4	CAR50(IM5) Group A. I.Model 5	CAR20(IM4) Group B. I.Model 4	CAR20(IM5) Group A. I.Model 5
LNEV	-0.049** (0.02)	-0.054** (0.02)	-0.046*** (0.02)	-0.049*** (0.02)
GRD	-0.186 (0.14)	-0.026 (0.08)	-0.046 (0.10)	-0.016 (0.06)
UKD	-0.725*** (0.25)	-0.664*** (0.25)	-0.442** (0.19)	-0.443** (0.18)
LNEV*UKD	0.075* (0.04)	0.079* (0.04)	0.067** (0.03)	0.063** (0.04)
PE*GRD	0.005*** (0.00)	-	0.003** (0.00)	-
DE*GRD	0.001 (0.00)	-	0.000 (0.00)	-
DE*UKD	0.004 (0.00)	-	0.001 (0.00)	-
PE*UKD		0.005* (0.00)	-	0.003 (0.00)
Num of obs	134	134	143	143
p-value	0.00	0.00	0.00	0.00
AIC	137	141	69	69
BIC	169	167	102	96

* - p<0.1; ** - p<0.05; *** - p<0.01

Source: Authors' analysis.

ROE and LNEV are significant across all models and event windows. Interaction Model 4 has a low number of significant variables. In this case, the replacement of interaction terms gives a positive result in terms of the significance of the main variables. ROE becomes highly significant (higher by one "star" as shown in Table 6), PE becomes significant by more than 5% after being completely insignificant, while the significance of the other main variables does not decrease.

Table 6. Correlation of significant factors and acquisition probabilities with CARs

Group	Pearson's r Group A (134 obs.)			Group B (143 obs.)			
Two-tail a	0.1	0.05	0.01	0.1	0.05	0.01	
Crit. values	0.1466	0.1743	0.2278	0.1339	0.1592	0.2083	
Indication	*	**	***	*	**	***	
	Probability	**CAR50**	**CAR20**	**CAR10**	**CAR5**	**CAR2**	**CAR1**
Probability	1	0.0321	-0.0101	0.0422	0.0293	0.0357	0.0491
ROE	-0.3543***	-0.2411***	-0.1525*	-0.1466*	-0.1112	-0.1130	-0.1148
PE	-0.4272***	0.1922**	0.2903***	0.0760	0.0906	0.0777	0.0715
LNEV	-0.8204***	-0.1530*	-0.1635**	-0.1294	-0.1204	-0.1210	-0.1177
UKD	0.3354***	-0.1520*	-0.0710	-0.0241	-0.0407	-0.0121	-0.0278
DE	-0.3477***	0.1029	0.1191	0.0928	0.0673	0.0552	0.0267

Source: Authors' analysis.

Therefore, ROE, PE, LNEV and UKD can be considered as significant factors in terms of their influence on CARs, with DE being significant for shorter event windows. Moreover, the prediction probability for each observation obtained from Interaction Model 4 can be used to see how it correlates with CARs. CARs for shorter periods are collected to show the consistency of results and the overall direction of influence of significant factors. The correlation analysis is performed using the *corr* command in STATA. Stars are used to show the significance level, which is derived by comparing the correlation values with Pearson's r critical values. The results of correlation analysis are shown in Table 6.

It is evident that only a few correlation coefficients are significant. However, the significance of correlation coefficients strongly depends on the quantity of observations in the sample, which may make significance analysis less effective and representative in this case, as the number of observations is not too high.

There are no grounds or need to make any statements about either the true significance level or the values of correlation coefficients in this paper, which can be a subject for future research. However, there is a clear correlation trend between Probability, significant factors, and CARs across all event windows, which indicates that, even if the true values of correlation coefficients are different, they should not have the opposite sign from the obtained correlation coefficients. Therefore, conclusions about the direction of influence can still be made.

ROE and LNEV are negatively correlated with both Probability and CARs, while PE and DE are positively correlated and UKD is negatively correlated with CARs and have opposite signs from the correlation coefficients for Probability. Moreover, the UKD variable is excluded from this analysis, even if it is significant, as it is a country-specific dummy variable that influences CARs differences due to its nature to distinct UK and non-UK companies, while an effect of operating ratios may be hindered and results distorted due to a region-specific focus. Probability of acquisition is positively correlated with CARs for all event windows except for [-20, 20].

Overall, the influence of CARs on Probability can be considered as being positive. Therefore, it is better to maximize the predictive probabilities of observations and the overall predictive power of acquired companies to attain the goal of maximizing returns. These results confirm the hypothesis that, on the whole, markets are currently unable to accurately assess the probability of a company being acquired in the future, which would make it possible to earn significant abnormal returns.

Portfolio Returns

To build a portfolio with positive returns based on yearly returns data, we need to analyze average returns for acquired and non-acquired companies. Average returns are 34.65% for acquired companies and only 18.09% for non-acquired companies. Annual returns are 39% and 22.04% for 2021 and 28.62% and 13.94% for 2020 (for acquired and non-acquired companies, respectively). Thus, returns for acquired companies are about 2 times higher. The MSCI index value is 26.6% for 2021 and -3.1% for 2020, which means that the average market-adjusted returns of acquired companies are higher than 0 on average.

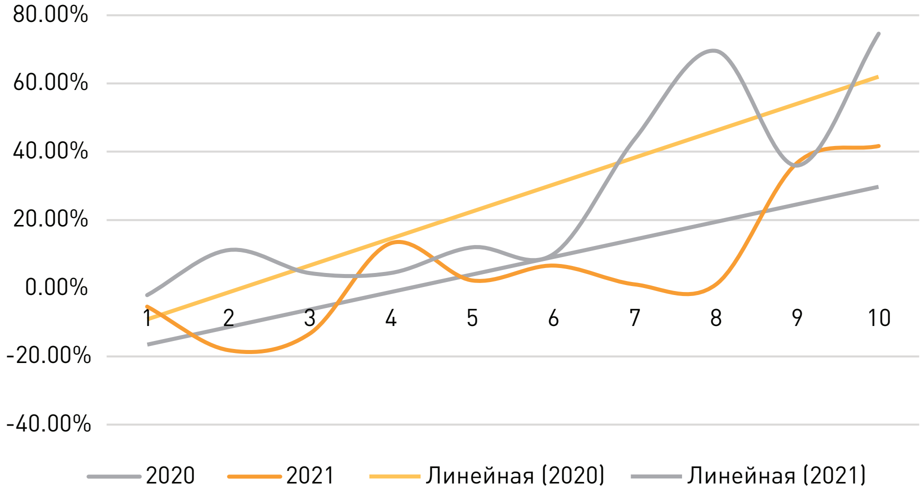
For further analysis, we divide the hold-out sample by 2 subsamples on a year-by-year basis. After that, subsamples are sorted in the order of descending probability. The 2021 subsample contains 24 acquired and 88 non-acquired companies, while the 2020 subsample contains 17 acquired and 84 non-acquired companies. We then create decile portfolios based on probabilities. The results of our analysis are summarized in Table 7 and Figure 8 below.

Table 7. Decile portfolios for a 2-year horizon hold-out sample

Deciles, %	2020 subsample					2021 subsample				
	# obs.	# Acq.	# n-Acq.	Ret. %	Adj. Ret. %	# obs.	# Acq.	# n-Acq.	Ret. %	Adj. Ret. %
100-90	3	3	0	74.59	77.69	2	2	0	68.29	41.69
89-80	6	3	3	35.96	39.06	6	4	2	63.41	36.81
79-70	4	2	2	69.53	72.63	10	3	7	27.73	1.13
69-60	11	3	8	43.77	46.87	5	2	3	27.71	1.11
59-50	9	3	6	10.05	13.15	7	1	6	33.24	6.64
49-40	15	2	13	12.02	15.12	15	2	13	28.88	2.28
39-30	6	0	6	4.50	7.60	18	3	15	39.81	13.21
29-20	19	0	19	4.46	7.56	15	3	12	13.27	-13.33
19-10	10	1	9	11.20	14.30	15	0	15	8.43	-18.17
9-0	18	0	0	-2.00	1.10	19	4	15	21.20	-5.40

Source: Authors' analysis.

Figure 8. Market-adjusted returns by probability deciles



Source: Authors' analysis.

The distribution of acquired observations among deciles is consistent with the results of predictive power analysis with 82% of acquired observations ranked in the 5th decile or higher in 2020 and 50% in 2021: the model is indeed expected to show significantly higher predictive power for acquired companies in 2020. On the other hand, 71.2% of non-acquired observations are ranked in the 6th decile or lower in 2020 and 79.5% in 2021: the model is indeed expected to show slightly higher predictive power for non-acquired companies in 2021.

Overall, the hold-out sample shows that there is a lot of potential for portfolio setup and investment strategy design, as there is a positive correlation between acquisition probabilities and stock returns, while abnormal returns are present for specific acquisition periods.

However, the hold-out sample produces only a 2-year horizon, which is somewhat too short to identify the actual trend over time. Therefore, an additional 5 years (2015-2019) are incorporated into the analysis. As a result, 423 new observations with 95 acquired and 328 non-acquired companies are added, increasing the total quantity of observations in the overall sample and the acquired/non-acquired subsamples by 3 times and the projection horizon to 7 years. For new observations, the same procedure of decile rankings is used. The resulting market-adjusted returns and quantitative observations for each decile are presented in Table 8 below.

Table 8. Decile portfolios for a 7-year horizon mixed sample

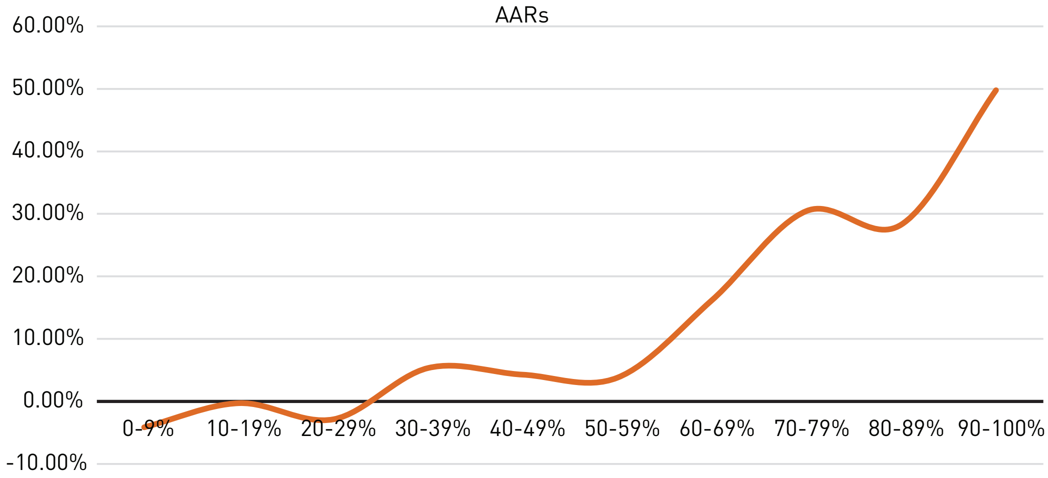
Deciles, %	2019		2018		2017		2016		2015	
	# obs.	Adj. Ret.%	# obs.	Adj. Ret.%	# obs.	Adj. Ret.%	# obs.	Adj. Ret.%	# obs.	Adj. Ret.%
100-90	2	34.68	1	47.02	4	27.44	5	57.17	3	67.73
89-80	5	15.27	3	16.60	10	24.76	1	52.85	4	27.10
79-70	7	-7.77	8	26.50	3	22.53	5	32.77	3	31.69
69-60	12	7.80	3	13.30	7	11.42	2	56.10	10	23.85
59-50	10	-7.11	3	7.52	13	4.53	8	23.58	9	-14.07
49-40	8	-27.91	6	12.17	10	-0.80	6	22.52	8	6.67
39-30	12	0.23	7	4.37	14	1.90	2	48.76	8	-1.92
29-20	6	-30.91	14	-3.04	8	-7.74	12	15.39	7	1.93
19-10	13	-19.36	15	-2.18	10	9.20	20	8.80	11	-3.87
9-0	11	-20.66	19	-2.17	15	-8.05	28	5.74	12	-16.60

Source: Authors' analysis.

The 7-year horizon analysis shows that the results obtained for the hold-out sample are consistent with longer horizons. Abnormal returns over 15% are generally generated between the 1st and 4th deciles, and negative returns between the 7th and 10th deciles, which allows for both long and short-term investment strategies. To find average results, decile-by-decile AARs are calculated. Moreover, annual CARs are obtained together with CAARs to see how cumulative returns are changing every additional year under a given strategy. AARs and CARs are calculated as the weighted average of ARs. CAARs are based on CARs instead of AARs to make the analysis more accurate. AARs are calculated first to decide on probable strategies; they are shown in Figure 9 below.

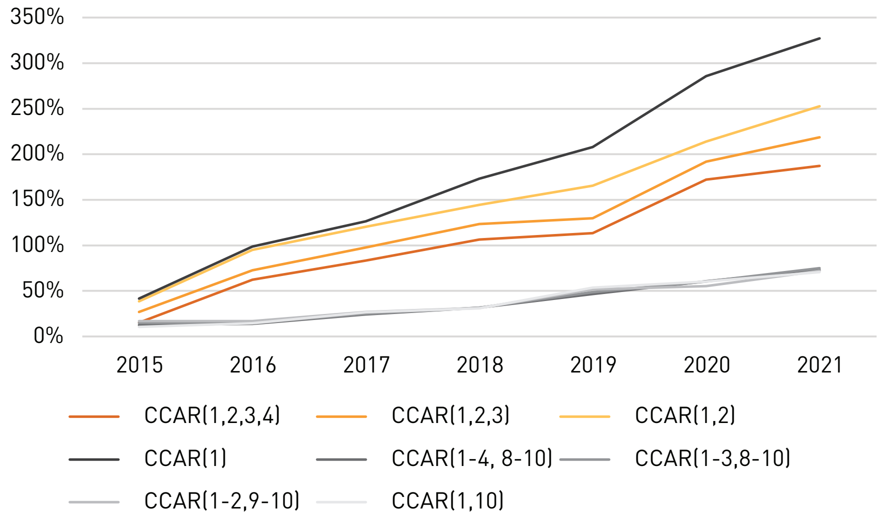
The distribution of the average number of observations by decile is skewed to a low probability due to the majority of non-acquired observations. AARs confirm that deciles 1 to 4 are the most profitable, while deciles 8 to 10 have negative abnormal returns. Next, CARs, CAARs and Cumulative CARs (the sum of CARs showing the cumulative abnormal returns that a strategy can generate year-by-year) are analyzed. Two main strategies are considered: long (buy to sell at a higher price) and long-short (long strategy + buy on loan, sell, buy back and return to the owner).

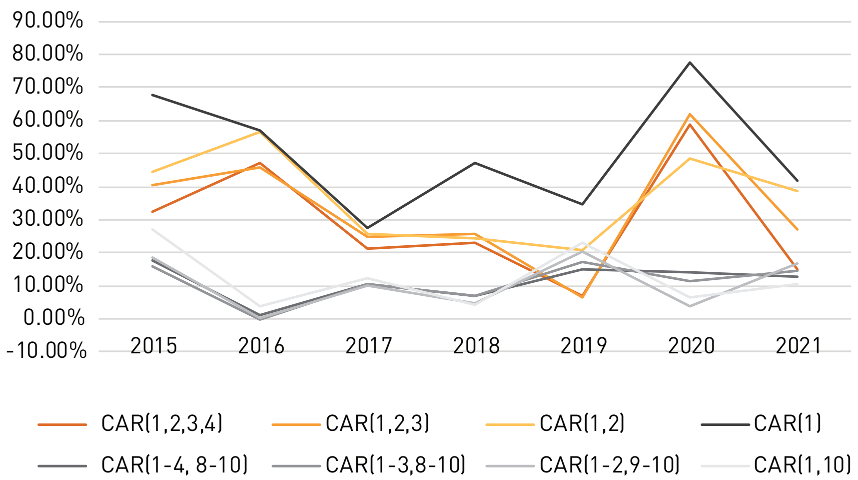
Figure 9. Average number of observations & AARs

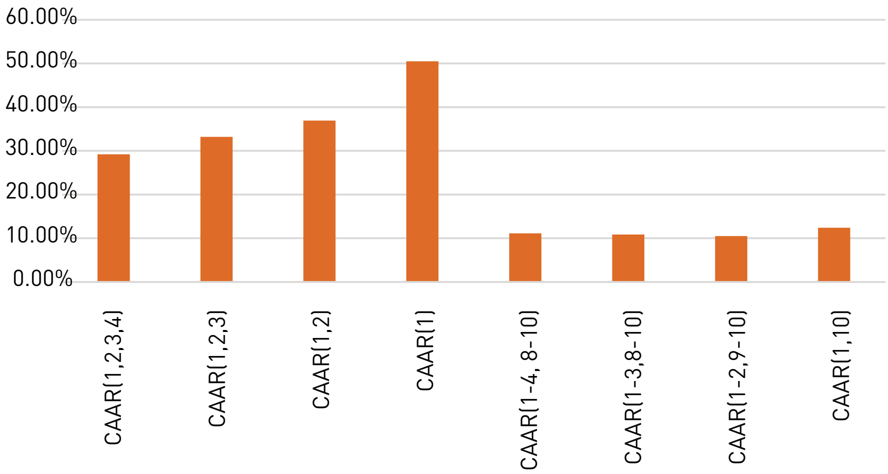


Source: Authors' analysis.

Figure 10. CARs, Cumulative CARs & CAARs







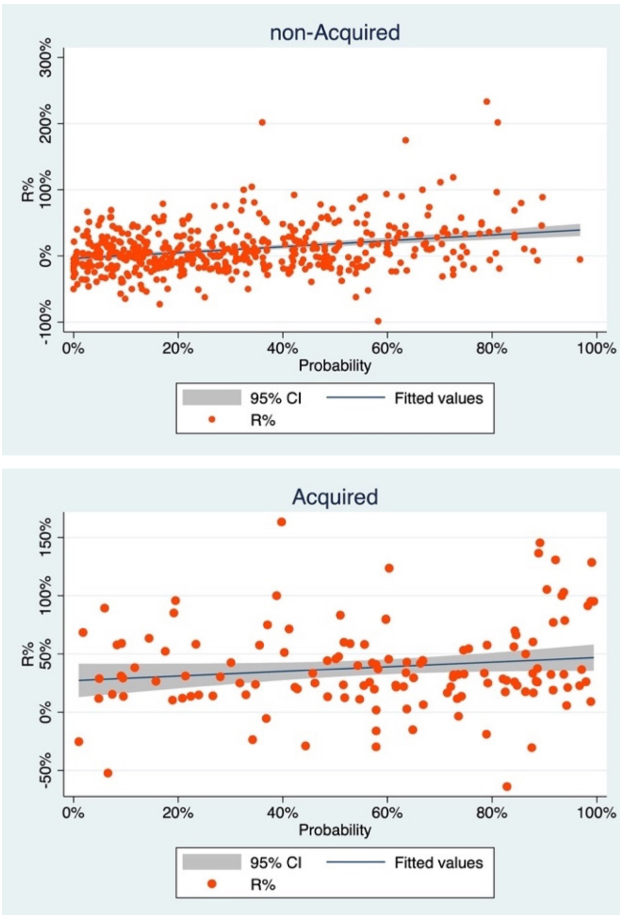
Source: Authors' analysis.

All the results are highly positive, which is consistent with the results for a hold-out sample with a 2-year horizon. The long-short strategy is less volatile from year to year due to the hedging "tail" that makes it possible to compensate for some losses with a short position if the market falls significantly yet may greatly reduce returns. For the 7-year horizon, it is more profitable to use a long strategy for the 1st decile only, which is an expected result as other long strategies with lower deciles only reduce abnormal returns while requiring greater initial investments as the quantity of observations increases between deciles 1 and 10. On the other hand, the long-short strategy is more consistent as the short part of this strategy is used as the hedging part for reducing the volatility of the MSCI index, which non-linearly decreases to -10.4% and grows to 26.8% over the 7-year horizon. Therefore, both types of strategies are profitable enough to be used yet serve very different purposes for investors, with the long (1st decile only) strategy being the most profitable and the long-short strategy with the 3 lowest deciles included being the least volatile and most hedged one.

The figures show that the model has good technical predictive power that can be easily interpreted and that there are more complex dependences in terms of abnormal returns as most of non-acquired companies with more than 70% acquisition probability generate highly positive abnormal returns. While the model does not have the highest predictive power among all the models found in literature, it is excellent at identifying abnormal returns. To understand which drivers are related to abnormal returns, we need to look at the dependence of abnormal returns on the acquisition probability for each acquired and non-acquired subsample. This is easier to visualize on graphs, which are obtained using a two-way scatter plot in STATA (Figure 11).

The graphs show no real signs of heteroscedasticity. However, abnormal returns for the non-acquired subsample with a 7-year horizon start from -10% at 0% acquisition probability and rise linearly to about 40% at 100% probability. The volatility of abnormal returns at low predictive probabilities can be due to a specific year or industry or other operational facts that influence share prices, while high probability results are more interesting in the sense that there are 69 observations higher than 60% probability with 41 having over 15% abnormal returns, which is around 8% of all non-acquired observations. These observations have significantly affected this analysis by increasing abnormal returns for higher probabilities and decreasing predictive power estimation results for acquired companies, which may explain the 10 p.p. difference between the predictive power of acquired and non-acquired companies.

Figure 11. Scatter plots of abnormal returns and probabilities by year



Source: Authors' analysis.

Still, this is unlikely to be an issue, as there exist several possible explanations for this phenomenon. First, rumors may well have circulated about the future acquisition of some of these firms, but an M&A deal fell through or there were no deal negotiations, generating price volatility of a targeted firm's stock and likely caused high run-up returns without any M&A deal further. One possible way to start such rumors is to get into the "Heard on the Street" column of *The Wall Street Journal* [22]. Secondly, data for 2021 may not be complete, as some M&A deals (12 observations in this analysis) might have been completed in 2022, which is out of the sample range but may have all properties to be labeled as "targeted" by the model Thirdly, a company might suffer similar effects to an M&A deal or experience another type of M&A that would omit it from the acquired sample of this study. Therefore, such observations may well be present in a variety of potential samples. However, they are not expected to have a significant adverse impact on abnormal returns estimation if the model is selected accurately.

Overall Results and Implications

Investment Strategies

Short position portfolio: the short position strategy is based on the investor's perception that stock prices will drop in the future, which leads him or her to create an arbitrage by borrowing stocks from a broker, selling them on the open market, waiting for the price to drop, buying the stocks back and returning them to a broker. This strategy can be applied to M&A predictions by looking for companies with the lowest probability of acquisitions. The results of abnormal returns analysis suggest that companies with probabilities from 0% to 29% are expected to generate negative abnormal returns on average. However, the annual results of companies with probabilities between 10% and 29% are highly inconsistent, mostly depending on overall market performance and ranging between -10.4% and 26.8%. However, investing even in the lowest decile companies is expected to generate fairly low returns. Therefore, it is not worth using short strategies on their own for the M&A prediction model, as there is too much risk for low abnormal returns.

Long position portfolio: the long position strategy is a common and popular strategy for all types of investing. Unlike the short one, it is based on the investor's belief that stock prices will rise over time, creating returns. Results suggest that a portfolio of companies with at least 60% acquisition can give quite high returns – from 29.22% to 40.39% a year on average depending on the chosen set of deciles. Empirical analysis suggests that the best strategy is to take only the 1st decile in consideration, as this maximizes abnormal returns without affecting volatility, which is consistent with the results obtained in earlier papers.

Mixed (long-short) portfolio: the long-short portfolio is a mix of a long and short positions, where long positions are usually abnormal return drivers, while short positions play more of a hedging role to minimize or offset market volatility, which tends to be high over a 7-year horizon. Results suggest that there is a significant reduction in abnormal return volatility over a 7-year horizon for the same set of deciles used in long portfolio analysis yet with the addition of a short component from the 8th to the 10th deciles, meaning that short positions can indeed be used for hedging for a set of companies without such high abnormal returns. CAARs are not really affected by the length of the decile window for the short component, while the year-by-year volatility is minimized by the addition of all suitable deciles.

Other investment strategies focus on changing the portfolio length yet not the core of the strategy. For example, decile portfolios are chosen on the basis of acquisition probability percentages in our study. At the same time, the most popular and widely used approach in the literature is to base such divisions on the quantity of observations in each portfolio. Alternative approaches are to use quartiles or quintiles instead of deciles or to make decisions on the basis of cut-off probabilities.

However, all these approaches only tend to increase the length of the portfolio, which usually affects abnormal returns negatively, as the inclusion of companies with lower returns dilutes average abnormal returns. A case in point is changing the quantity of deciles included in the portfolio returns estimation analysis in Section 6.5. Moreover, the number of companies to invest in will also grow, making it more difficult for a private investor to invest into the entire portfolio. This limits the applicability of these investment strategies, while the method used in our analysis makes the portfolio shorter with the potential of being extended, if needed, making the selection of portfolio length more flexible.

On the whole, the long and long-short strategies with a decile portfolio based on predictive probabilities turn out to be the most efficient in generating abnormal returns. The long investment strategy in companies with an acquisition probability higher than 90% can be considered as the most cost-efficient and abnormal return generating strategy, as empirical results suggest that only 5% of the sample can generate around 50% of the annual abnormal returns. However, one must search for companies to invest in each year (or custom period) anew, as no additional abnormal returns are expected to be generated after a few days following the announcement of an M&A deal. This strategy can be successfully used both by institutional investors (e.g., hedge or mutual funds) due to its consistency and potential ability to generate abnormal returns in a fairly short horizon and by private investors regardless of their budget and trading experience due to its cost-efficiency, availability of relevant data, and clarity.

On the other hand, the long-short strategy needs a lot more initial investments, which may limit its popularity among private investors and generate much lower abnormal returns. However, it can still be used by institutional investors thanks to its reduced volatility, making its abnormal return rate almost risk-free yet nevertheless quite high, which might be useful for hedging an existing portfolio.

Other Implications

Institutional investors can use acquisition predictions indirectly to manage the risks of existing short portfolios that can produce negative returns due to sudden M&A deals. Acquisition predictions may help one to avoid such deals or reduce losses from them. Moreover, the valuation analysis of targets for such a short portfolio may benefit from takeover predictions, making investment strategies more efficient.

Company managers may be interested in conducting acquisition analysis to see whether their company may be targeted and to adjust strategic and financial planning if the probability of acquisition is high. Moreover, such analysis can be used by company managers to monitor and assess competitors' strategies on the market. Consulting, advisory and investment banking companies can use it for making analytical reports for existing clients as well as for finding new clients by offering them the corresponding services.

Overall, the variety of indirect applications of our analysis can help to make M&A and financial markets more open and transparent. This may have a bigger structural impact on the global M&A market than the application of direct investment strategies, as the development of our analysis and its integration into common business processes may naturally make the M&A field more open and flexible and increase the market efficiency of M&A expectations. As a result, it would become much harder to attain the goal of outperforming natural market predictions to earn abnormal returns, making the prediction model less profitable to use.

Conclusion

In our paper, we developed a methodology for M&A predictions and an M&A prediction model based on the multivariable logit model with interactions. The model's high explanatory and predictive power and excellent flexibility makes it suitable for abnormal returns analysis based on event study. We showed that interactions between factors of influence on the designed M&A prediction model can generate a good level of abnormal returns, with Return-on-Equity, LN (Enterprise Value), Price-to-Earnings and Debt-to-Equity having a significant influence on the direction of abnormal returns. We then developed an efficient approach to designing a portfolio of predicted M&A targets and constructed such a portfolio.

Abnormal portfolio returns turned out to be highly positive for observations with a high probability of acquisition and slightly negative for observations with a low probability of acquisition. Such a distribution of returns makes it possible to apply several investment strategies that make the prediction of M&A deals applicable and useful for a wide range of potential users.

We showed that both long and short investment strategies can be used – either as a risky yet profitable investment strategy or a hedging instrument that can generate positive returns with very low volatility. Moreover, the efficiency of the M&A prediction model enhanced with acquisitions allow it to be used by consultants and managers of companies and hedge funds to attain a variety of goals.

The novelty of this paper is its discovery of new ways to increase the efficiency of the M&A prediction model by including basic factors that can describe any company from different perspectives and by adding interactions to make it more flexible and adaptable to different economic environments. This makes the model more attractive for different users without making the estimation process more dependent on data availability and different economic circumstances. Moreover, we present an improved way of using effectively predicted acquisitions to earn highly positive abnormal returns by outlining an efficient portfolio construction method based on predicted probabilities to serve either profit generating or hedging goals.

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Appendix

Appendix 1: Takeover probability explanatory variables

Table 9. Takeover probability explanatory variables. Source: [9], [11], [12] and the author's analysis

Variable	Code	Sign	Selection Criteria	Data Source
Enterprise Value	EV	-	>= $10 million	Bloomberg terminal & Thomson Reuters Eikon
Total Assets	TA	-	No	Bloomberg terminal & Thomson Reuters Eikon
P/E ratio	PE	-	Between -200 and 500	Bloomberg terminal & Thomson Reuters Eikon
EV/B ratio	EVB	-	Between 0 and 20	Bloomberg terminal & Thomson Reuters Eikon
Debt/Equity	DE	+	<= 100%	Bloomberg terminal & Thomson Reuters Eikon

Variable	Code	Sign	Selection Criteria	Data Source
Current ratio	CUR	-	<=20	Bloomberg terminal & Thomson Reuters Eikon
ROE	ROE	-	Between -500 and 1000	Bloomberg terminal & Thomson Reuters Eikon
EBITDA-margin	EBITDAM	-	Between -1500 and 500	Bloomberg terminal & Thomson Reuters Eikon
Sales growth	SGR	-	Between -80 and 5000	Bloomberg terminal & Thomson Reuters Eikon
Growth resource	GRD	+	No	Bloomberg terminal & Thomson Reuters Eikon

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Impact of Board of Directors on Funds Raising: Evidence for Green Bonds

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Abstract

The present paper attempts to reveal influence of characteristic features of the board of directors (BD) on fund raising using green bonds. The research involved a sample of 87 public companies which issued green bonds in 2021. We analyzed influence of such factors as the proportion of women and independent directors on the BD, CEO duality and the number of the BD members by the share of green bonds in the total debt of the company. The share of debt in the assets, the natural logarithm of total assets (company size) and return on equity (ROE) were used as control variables.

The logarithmic specification of the classical linear regression model was chosen as the optimal one. So, heteroscedasticity, autocorrelation and multicollinearity were not detected in the model with the dependent variable logarithm (the share of green bonds in the total debt). The least squares method (LSM) was applied to evaluate this model.

As long as the initial sample of companies which issued green bonds in 2021 comprises both financial and non-financial companies we verified the validity of the obtained results for two types of companies. Assessment of the optimal model for two subsamples of financial and non-financial companies yielded results somewhat different from the ones obtained from analysis of the total sample. Evaluation of the regression for financial and non-financial companies showed a reduction in significance of influence exerted by women's representation and the size of the BD. However, in case of non-financial companies the significance of such factor as presence of the sustainable development committee increases. According to the obtained results the companies with the CSR committee attract relatively larger financing using green bonds.

Keywords: sustainable development, board of directors, generalized method of moments, fixed effects panel model, least squares method, meta-analysis, panel data models, green bonds

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Introduction

Over the recent years, increasingly greater attention has been paid to global problems, thus, responsible business practices, assistance in sustainable development, preservation of the environment and minimization of human impact on it have become a priority for some large companies. However, these activities entail significant capital investments. This is precisely the reason for the creation of green bonds – a financial instrument with a fixed income. They are used to attract funds for the implementation of projects related to environment protection and mitigation of climate change consequences [1].

The green bond market has begun to develop rather recently. In November 2008, the World Bank was the first organization to issue green bonds in order to extend credits for climate change-related projects. According to the analysts of the *Climate Bonds Initiative*, the annual amount of green bonds' issue in 2023 may exceed $1 tln. [2].

The subject of the influence of the board of directors (BD) on fundraising using green bonds is relevant because it has not been studied in Russian or foreign literature.

The purpose of the present paper is to reveal the BD characteristics that have a significant stimulating or, on the contrary, restraining effect on fundraising using green bonds.

The research object is represented by companies that have issued green bonds and the research subject is the characteristics of the BD of such companies and their influence on fundraising using green bonds.

The information base comprises the data on the size of green bond issuance by public companies in 2021, and the share of females and independent directors on the BD, CEO duality, presence of a *CSR* committee in the company, the size of the BD, debt to assets ratio, total assets and return on equity. Some of the data was taken from *Bloomberg* and the other part was collected manually from annual company reports for 2021. Calculations were made using the *Gretl* statistical package and *Excel*.

The theoretical foundation comprises the articles dedicated to the study of the influence of BD composition on decision-making in regard to sustainable development, and an analysis of green bonds as the financing source (influence of green bond issuance on capital value). Almost all considered papers are empirical and apply econometric methods to test hypotheses and answer the research question.

Literature Review

The problem of the influence of the characteristic features of BD composition on corporate sustainable development was studied by multiple authors [3–14]. In the considered papers, the authors used a regression analysis of time series in an attempt to reveal the impact of BD composition on the efficiency of corporate sustainable development, including Corporate Social Responsibility (CSR), and environmental, social and corporate governance (*Environmental*, *Social and Governance*, or the *ESG*-rating). One of the considered studies [14] described the influence of BD composition on the amount of investments in environmental protection.

The method most frequently used for the evaluation of influence of BD composition on the efficiency of corporate sustainable development is the **generalized method of moments** (GMM). For example, it was used by V. Naciti [3] in his paper. His research sample contained 362 large companies from 46 countries and 26 industries, which were a part of the *Fortune Global 500 list*[1] at least once between 2013 and 2016. The author concluded that female representation, the share of foreign directors and the absence of CEO duality had a positive impact on sustainable development efficiency, while the share of independent directors had a negative impact.

A similar methodology was applied in the paper by S. Karim [5] to analyze the influence of the share of women occupying the positions of executive and independent directors on the interrelation between the CEO and executive directors' remuneration and *CSR* practices. A sample of 483 listed Malaysian companies in 2006-2017 was used for the research. As a result, the author concluded that the proportion of female executive directors has a significant influence on the mitigation of the dependence between remuneration size and CSR practices, while the proportion of female independent directors has an insignificant impact on the mitigation of this dependence.

The GMM was also used by C. Francoeur et al. [9]. In this paper, the authors studied the influence of female representation in the BD on various groups of stakeholders. The research was conducted based on a sample of only American companies from *Fortune 500,* whose social performance in 2007-2013 was evaluated by *Sustainalytics*. The authors arrived at the conclusion that female representation in the BD had a positive impact on weaker stakeholder groups (the environment, suppliers, the social one) and had no impact on employees or buyers.

A similar methodology was used by R. Beji et al. [10]. In this paper, the authors tried to reveal the influence of various BD characteristics on CSR in general and on its specific aspects. Such characteristics include BD size, share of foreign and independent directors, CEO duality, directors' sex, age diversity, education level, academic background, the fact of occupying several director's positions by the same person. A sample of all companies from the *SBF*120 index (France) from 2003 to 2016 was used for the research. The authors concluded that BD size, share of independent directors, age diversity, education level and the fact of occupying several director's positions by the same person produce a positive impact on the general CSR rating. Female representation has a positive influence only on governance quality and human rights. The share of foreign directors exerts a positive impact on the aspects related to the environment and society.

[1] Rating of companies based on the amount of revenue and published annually in *Fortune*.

Apart from the GMM, some papers we have considered applied the **fixed effects panel model**. The paper by M. Valls Martínez et al. [4] is an example. The authors tried to reveal the influence of gender diversity in the BD on CSR efficiency in the developed and emerging European markets. The sample comprised all European companies included in *MSCI Europe* (*MSCI*) and *MSCI Emerging Markets Europe* (*MSCI EM*) in 2010-2019. The authors arrived at the conclusion that female representation had a positive impact on CSR efficiency and that this impact is stronger in the developed markets than in emerging ones.

A similar fixed effects model was also applied in paper by A. Uyar et al. [11], where the authors tried to define the influence of BD composition on CSR efficiency. The research sample comprised all healthcare companies listed in the *Refinitiv Eikon* database in 2011-2018. The authors concluded that the presence of a CSR committee, female representation and a larger share of independent directors on the BD exert a positive influence on the efficiency of CSR practices, while CEO duality and a large BD – have a negative impact.

The paper by G. Birindelli et al. [13] was based on a similar methodology. It tried to detect characteristic features of BD composition that improve the efficiency of sustainable development in banking. The sample comprised data on 108 public European and American banks for 2011-2016. The researchers concluded that female representation on the BD, the presence of a CSR committee, a large BD size have a positive influence on ESG rating, while the share of independent directors – a negative one.

The next group of papers is based on applying the **least squares method** (LSM). It was used in paper by P. Prudêncio et al. [7], which is dedicated to revealing the influence of gender and age diversity on the BD and management of Brazilian companies. The sample comprised 317 companies listed on the *B3 S.A.* stock exchange in 2016-2017. As a result, the researchers concluded that a high female representation on the BD produced a positive influence on the CSR rating. BD size also has a positive influence on the CSR rating because a larger number of people provides more experience, knowledge and innovative solutions. The average age of BD members has no impact on the CSR rating, while age heterogeneity (age variation coefficient) influences the CSR rating negatively. The presence of women and age heterogeneity in management produce no influence on the CSR rating because management is focused more on achieving financial performance objectives.

LSM without taking into consideration the individual effects was also used in research by X. Jiang and A. Akbar [14], which was dedicated to the influence of female representation in management on investments in environmental protection. It used a sample of 359 Chinese public companies over the period of 2008-2016. Research results showed that women occupying the positions of the CEO and the chairman of the board, as well as the presence of women on the BD had a positive impact on investments in the environment due to the social responsibility characteristic that is unrelated to industry specifics.

A series of papers apply other data analysis methods. For instance, the paper by J. Endrikat et al. [6], which tried to detect the interrelation between BD characteristics and CSR efficiency used **meta-analysis** (random effects model). It was conducted using a sample of 82 empirical studies of the influence of BD characteristics on CSR in 1991-2019. The authors arrived at the conclusion that BD size, female representation, share of independent directors and presence of a CSR committee exert a positive impact on CSR efficiency.

The paper by S. Chen S et al. [8], which studies the influence of the number of directors with experience as directors of non-commercial organizations on CSR efficiency uses **panel data models** (Poisson regression and population-averaged linear regression). The research sample comprised all companies from *S&P 500* in 2009-2016. The results showed that directors with experience in non-commercial organizations produce a positive influence on CSR efficiency only in the three years following their assignment to the BD.

The paper by R. Jin et al. [12] used **propensity score matching** and the **Heckman two-stage model** to analyze the influence of independent female directors on the CSR strategy. The sample consisted of all public Chinese companies operating in real sectors and listed on the Shanghai and Shenzhen stock exchanges in 2008-2015. The authors concluded that independent female directors had a positive impact on the internal, but not the external CSR rating.

The paper by U.S. Bhutta et al. [15] classified the studies of **green bonds** and reviewed the factors related to development of the green bond market and their influence on the fundamental indicators of corporate performance. The authors analyzed 53 papers on this topic published between 2008 and 2020 in *Scopus* and *Web of Science* science citation databases. As a result, the authors concluded that the quality of information disclosure exerts a positive impact on the development of the green bond market. Regulators' support also has a positive influence on development of the green bond market. However, the authors failed to make unambiguous conclusions concerning the influence of green bond issuance on corporate financial performance. For this reason, we considered other papers on this topic.

All the papers we have discovered that discuss characteristics of green bonds as a financing source are empirical ones and indicate that green bond issuance decreases the cost of financing. For instance, in the paper by R. Zhang et al. [16], dedicated to the influence of green bond issuance to finance environmental protection initiatives on the cost of capital, the authors analyze a sample of 1,010 green bonds issued in China as at 31.12.2020 and conclude that green bond issuance reduces the cost of capital in three ways: decrease of information asymmetry, upsurge of corporate share liquidity, mitigation of anticipated risk.

Paper by F. Taghizadeh-Hesary et al. [17] analyzed economic and financial performance of the hydrogen power industry projects in China and defined an appropriate mechanism of green financing for those projects. The authors considered three hydrogen projects in China (hydrogen manufacture, hydrogen liquification and transportation, hydrogen filling stations). The authors conclude that in order to mitigate the risks of financing and cost of capital, the sources of hydrogen project funding in China should be diversified: loans should amount to about 56% in the capital structure, and green financing sources – to approximately 44%.

G. Gianfrate and M. Peri [18] also tried to answer the question regarding the reduction of funding cost when issuing green bonds. They analyzed a sample of 121 green bond issues (in euro) in 2007 - 2017. In order to compare the income from green and conventional bonds, the authors applied propensity score matching. As a result, they arrived at the conclusion that green bonds were more convenient financial instruments as compared to conventional ones because investors expected a relatively low income from them.

Another research study that confirms a decrease in the cost of financing in case of green bond use is the paper by Z. Li et al. [19], which describes the factors defining the interest expense of green bonds. The authors considered 114 green bonds issued by Chinese public companies from 2016 to 2018. They concluded that the issuer's type (financial or non-financial organization) has no impact on interest expenses, while green certification, a higher credit rating and CSR rating lead to lower spreads and, consequently, to interest expenses.

The hypothesis that green bond issuance helps to reduce the financing cost is also confirmed in the paper by B. Lin and T. Su [20], where the authors tried to find out which factors stimulate the issue of green and conventional bonds. In order to answer the posed question, they considered a sample of 9,255[2] bond issues in China in 2016-2021. The authors reached the conclusion that companies preferred to issue green bonds in order to decrease the cost of financing and conventional bonds – to attract more funds.

On the basis of the literature review, we may set forth the following hypotheses.

1. Other conditions being equal, a larger female representation on the BD has a positive influence on fundraising using green bonds.
2. Other conditions being equal, the presence of a CSR committee has a positive influence on fundraising using green bonds.
3. Other conditions being equal, the absence of CEO duality has a positive influence on fundraising using green bonds.
4. Other conditions being equal, a larger BD size has a positive influence on fundraising using green bonds.
5. Other conditions being equal, a share of independent directors on the BD has no significant influence on fundraising using green bonds.

Data Used in the Research

In order to verify the suggested hypotheses, we used data from the *Bloomberg* database on green bond issues in 2021. Apart from the volume of green bond issue, such company indicators as the share of independent directors and female representation on the BD, the total debt to total assets ratio and total assets were taken in absolute terms. The main and only criterion for adding a green bond issue to the sample was the availability of data for all the above indicators. Thus, the initial sample comprised 124 green bond issues of 2021.

Subsequently, the author collected such indicators as the presence of a CSR committee (or ESG committee/sustainable development committee), CEO duality, BD size, and return on equity (ROE) manually from the 2021 annual reports of the companies included in the initial sample. In view of geopolitical events, the final sample consisted of 87 companies that issued green bonds in 2021. It should be noted that the data used in this paper is of spatial nature (cross-sectional data).

The final list and a brief description of the variables used in the present research are presented in Table 1.

Table 1. Variables used in the research

Variables	Measurement unit	Description	Data source
Dependent variable			
GB_share_in_debt	%	Share of green bonds in the total debt	Author's calculation on the basis of *Bloomberg* data
Independent variables			
ind_on_board	%	Share of independent directors on the BD	*Bloomberg*
women_on_board	%	Women representation on the BD	*Bloomberg*

[2] The authors [20] eliminated from the sample non-public companies and bonds which had no potential for issue as green bonds (according to the intended purpose of raised funds), the exact number of green bonds issues analyzed in the paper is not stated.

Variables	Measurement unit	Description	Data source
CEO_duality	Binary variable (1 – no, 0 – yes)	CEO duality	Corporate annual reports
CSR_committee	Binary variable (1 – yes, 0 – no)	Presence of the CSR committee	Corporate annual reports
board_size	Person	BD size	Corporate annual reports
Control variables			
debt_to_assets	%	Share of debt in total assets	*Bloomberg*
ln_*total_assets*	–	Company size	Author's calculation on the basis of *Bloomberg* data
ROE	%	Return on equity	Corporate annual reports

Source: Compiled by the author.

It should be noted that the share of green bonds in total debt of each company was selected as the dependent variable instead of the absolute green bond issue volume because a relative indicator demonstrates the scope of fundraising using green bonds in a more unbiased way.

Independent and control variables were defined based on the literature review.

Choosing the Optimal Model

Since the data collected for the research is of spatial nature, the author considered it reasonable to apply LSM to analyze it. The following model was constructed on the basis of the collected data:

$$GB\_share\_in\_debt_i = \alpha + \beta_1 \cdot ind\_on\_board_i + \\ + \beta_2 \cdot women\_on\_board_i + \beta_3 \cdot CEO\_duality_i + \\ + \beta_4 \cdot CSR\_committee_i + \beta_5 \cdot board\_size_i + \\ + \beta_6 \cdot debt\_to\_assets_i + \beta_7 \cdot \ln\_total\_assets_i + \\ + \beta_8 \cdot ROE_i + \varepsilon_i ,$$

where $GB\_share\_in\_debt_i$ – the share of the green bond issue in 2021 in total debt expressed in %; α – the constant/permanent component of the model; $ind\_on\_board_i$ – the share of independent directors on the BD expressed in %; $women\_on\_board_i$ – female representation on the BD expressed in %; $CEO\_duality_i$ – the fact of the CEO also occupying the position of the chairman of the board, a binary variable (1 – no, 0 – yes); $CSR\_committee_i$ – the presence of a sustainable development committee in the company, a binary variable (1 – yes, 0 – no); $board\_size_i$ – number of BD members, persons; $debt\_to\_assets_i$ – the share of debt in total assets, expressed in %; $\ln\_total\_assets_i$ –company size, the natural logarithm of corporate total assets; ROE_i – return on equity, expressed in %; ε_i – model errors.

The results of evaluation of the initial model using LSM are presented in Table 2.

Table 2. Results of evaluation of the initial model using LSM

Variable	Coefficient	Standard error	*t*-statistics	*P*-value
const	0.79796	0.10526	7.581	6.07e–11***
ind_on_board	0.01755	0.05714	0.307	0.7595
women_on_board	–0.30746	0.10669	–2.882	0.0051***
CEO_duality	0.03514	0.03402	1.033	0.3047
CSR_committee	0.02385	0.02484	0.961	0.3398
board_size	–0.00496	0.00339	–1.460	0.1482
debt_to_assets	–0.21722	0.08274	–2.625	0.0104**
ln_*total_assets*	–0.04623	0.00530	–8.714	3.87e–13***

Variable	Coefficient	Standard error	*t*-statistics	*P*-value
ROE	0.04681	0.10919	0.429	0.6693
Mean value of dependent variables	0.091189			
Sum of squared errors	0.924892			
R-square	0.535260			
F (8,78)	11.22946			
Logarithmic likelihood	74.21574			
Schwarz criterion	−108.2383			
Standard deviation of dependent variables	0.152122			
Standard error of the model	0.108893			
Adjusted *R*-square	0.487594			
P-value (*F*)	1.97e–10			
Akaike criterion	−130.4315			
Hannan-Quinn criterion	−121.4950			

** Coefficients significant at the 10 and 5% significance levels.
*** Coefficients significant at all reasonable significance levels.
Source: Author's calculation performed in *Gretl*.

The *P*-value of *F*-statistics obtained as a result of evaluation of the initial model has the value of 1.97e–10, which is below any reasonable significance level. This factor demonstrated that the initial model is generally significant. However, it should be noted that the *R*-square of the model is rather low and amounts to 0.54 when rounded, i.e., this model explains only 54% of the sample.

As a result of the evaluation of the initial model, the constant (at any reasonable significance level), female representation on the BD (at any reasonable significance level), the share of debt in corporate total assets (at the 10 and 5% significance levels) and the natural logarithm of corporate total assets (at any reasonable significance level) turned out to be significant variables. All significant variables, except the constant, produce a negative influence on fundraising using green bonds.

Such variables as the share of independent directors on the BD, CEO duality, presence of the sustainable development committee, BD size and return on equity have no significant impact on fundraising using green bonds.

However, in order to understand whether we may trust the obtained LSM estimators, we have to make sure that the analyzed model meets a range of conditions. LSM estimators for the linear regression model are unbiassed, efficient and consistent (i.e., they are close to their true values) only when the prerequisites of the **classical linear regression model** (CLRM) or the Gauss-Markov conditions are fulfilled.

These prerequisites are as follows:

1) mathematical expectation of random error in any observation equals zero:

$M(\varepsilon_i) = 0$;

2) constant variability of random error for all observations:

$D(\varepsilon_i) = M\left(\varepsilon_i^2\right) = \sigma^2$;

3) no systematic relation between the random error values for any two observations:

$cov(\varepsilon_i, \varepsilon_j) = 0$;

4) independence of the random error from explanatory variables:

$cov(x_i, \varepsilon_j) = 0$;

5) normal distribution of random errors:

$\varepsilon_i \approx N\left(0, \sigma^2\right)$;

6) no correlation between dependent variables (no multicollinearity).

The first prerequisite in this case is fulfilled automatically because an intercept term is added to the model. Subsequently, the tests for the fulfillment of the first prerequisite have not been performed in the present paper. The second prerequisite implies that random error variance does not depend on the number of the observation and is called homoscedasticity (dependence of the random error variance on the number of the observation is called heteroscedasticity). If there is heteroscedasticity in the model, LSM estimators will be inefficient. The third prerequisite is usually not fulfilled when the data is represented by time series. If the precondition of random errors' uncorrelatedness is violated, there is autocorrelation in the model and LSM estimators also become inefficient. Since the data used in the research is of spatial nature, the tests for autocorrelation have not been conducted. In case of failure to fulfill the fourth prerequisite, LSM estimators become biased and inconsistent. The fifth prerequisite, which concerns the normal distribution of random errors, should be fulfilled to obtain an opportunity to test the hypotheses. The sixth prerequisite is also to be fulfilled in the considered case because the research study analyzes a multiple linear regression inasmuch as several characteristics of the BD composition influence fundraising using green bonds.

Thus, the above-described CLRM prerequisites were verified in the following order: verification of normality of distribution of the model's random errors; verification of absence of heteroscedasticity in the model; verification of absence of multicollinearity in the model.

The hypothesis regarding the normality of distribution of random errors in the initial model was verified by the Jarque-Bera test. The test results showed that the *P*-value amounted to 0.0000 bringing us to the conclusion that the hypothesis regarding normal distribution of the model residuals is rejected at any reasonable significance level.

The hypothesis of the absence of heteroscedasticity was verified using the White test. The test results showed that the *P*-value amounts to 0.0499. Consequently, the hypothesis about the absence of heteroscedasticity in the model is accepted only at the 1% significance level.

In order to detect multicollinearity in the initial model, we constructed a correlation matrix for all variables. The maximum correlation coefficient (–0.65) was revealed between the share of green bonds in financing sources (*GB_share_in_debt*) and the natural logarithm of total assets (ln_*total_assets*). The correlation between other variables is significantly lower (the correlation coefficients do not exceed 0.29). Subsequently, we may conclude that there is no multicollinearity in the initial model.

Thus, only one prerequisite regarding the normal distribution of random errors is not fulfilled in the initial model of dependence of the share of green bonds in total debt on BD characteristics. In order to solve this problem, the author decided to consider and analyze the model with a log-transformed dependent variable. All other variables underwent no changes.

The new model is as follows:

$$\begin{aligned}&\ln\_GB\_share\_in\_debt_i = \alpha + \beta_1 \cdot ind\_on\_board_i + \\ &+ \beta_2 \cdot women\_on\_board_i + \beta_3 \cdot CEO\_duality_i + \\ &+ \beta_4 \cdot CSR\_committee_i + \beta_5 \cdot board\_size_i + \\ &+ \beta_6 \cdot debt\_to\_assets_i + \beta_7 \cdot \ln\_total\_assets_i + \\ &+ \beta_8 \cdot ROE_i + \varepsilon_i,\end{aligned}$$

where ln_*GB_share_in_debt*$_i$ – the natural logarithm of the share of green bond issue in 2021 in total debt; α – the constant/permanent component of the model; *ind_on_board*$_i$ – the share of independent directors on the BD expressed in %; *women_on_board*$_i$ – female representation on the BD expressed in %; *CEO_duality*$_i$ – the fact of the CEO also occupying the position of the chairman of the board, a binary variable (1 – no, 0 – yes); *CSR_committee*$_i$ – presence of a sustainable development committee in the company, a binary variable (1 – yes, 0 – no); *board_size*$_i$ – number of BD members, persons; *debt_to_assets*$_i$ – the share of debt in total assets, expressed in %; ln_*total_assets*$_i$ –company size, the natural logarithm of corporate total assets; *ROE*$_i$ – return on equity, expressed in %; ε_i – model errors.

The random errors of this model were also verified for normality by the Jarque-Bera test. The *P*-value amounted to 0.0578, hence, the hypothesis regarding the normal distribution of random errors is accepted at the 1% and 5% significance levels.

The log-transformed model was also verified for heteroscedasticity using the White test. The *P*-value amounted to 0.6955. This brings us to the conclusion that the hypothesis about the absence of heteroscedasticity is accepted at any reasonable significance level.

Finally, the log-transformed model was verified for multicollinearity. A correlation matrix was built for all model variables. The highest correlation coefficient (0.93) was detected between the natural logarithm of the share of green bonds in total debt (ln_*GB_share_in_debt*) and the natural logarithm of total assets (ln_*total_assets*). In other cases, the correlation coefficients do not exceed 0.38, bringing us to the conclusion that there is no multicollinearity in the model.

Thus, the log-transformed specification of the model of dependence of green bonds in corporate total debt on characteristics of the BD composition is the optimal one.

Results of Use of the Optimal Model

Above we defined the optimal model for analyzing the influence of characteristic features of BD composition on fundraising using green bonds.

The specification of the optimal model is as follows:

$$\begin{aligned}&\ln\_GB\_share\_in\_debt_i = \alpha + \beta_1 \cdot ind\_on\_board_i + \\ &+ \beta_2 \cdot women\_on\_board_i + \beta_3 \cdot CEO\_duality_i + \\ &+ \beta_4 \cdot CSR\_committee_i + \beta_5 \cdot board\_size_i + \\ &+ \beta_6 \cdot debt\_to\_assets_i + \beta_7 \cdot \ln\_total\_assets_i + \\ &+ \beta_8 \cdot ROE_i + \varepsilon_i.\end{aligned}$$

The results of evaluation of this model are presented in Table 3.

Table 3. Results of evaluation of the optimal model using the LSM

Variable	Coefficient	Standard error	*t*-statistics	*P*-value
const	6.52295	0.50343	12.960	3.87e–21***
ind_on_board	0.19890	0.27327	0.728	0.4689
women_on_board	1.54601	0.51026	3.030	0.0033***
CEO_duality	–0.05708	0.16269	–0.351	0.7267
CSR_committee	0.08436	0.11878	0.710	0.4797
board_size	0.05213	0.01623	3.211	0.0019***
debt_to_assets	–3.42632	0.39572	–8.658	4.97e–13***
ln_*total_assets*	–0.92302	0.02537	–36.380	1.09e–50***
ROE	1.55170	0.52225	2.971	0.0039***
Mean value of dependent variables	–4.030957			
Sum of squared errors	21.15697			
R-square	0.956278			
F (8,78)	213.2503			
Logarithmic likelihood	–61.94132			
Schwarz criterion	164.0758			
Standard deviation of dependent variables	2.372072			
Standard error of the model	0.52081			
Adjusted *R*-square	0.951794			
P-value (F)	9.78e–50			
Akaike criterion	141.8826			
Hannan-Quinn criterion	150.8192			

*** Coefficients significant at all reasonable significance levels.
Source: Author's calculations performed in *Gretl*.

It may be deducted from Table 3 that the optimal model is statistically significant because the *P*-value of *F*-statistics amounts to 9.78e–50, which is below any reasonable significance level. The *R*-square of the log-transformed model (0.95) exceeds the *R*-square of the initial model (0.54), which is indicative of a higher quality of the regression. That is to say, the optimal model explains 95% of the sample.

Moreover, evaluation of the optimal model showed that along with the constant, female representation on the BD, debt to assets ratio and natural logarithm of corporate total assets, such variables as BD size and return on equity also turned out to be significant. It should be emphasized that all the above-mentioned variables are significant at any reasonable significance level.

According to the obtained results, a larger female representation on the BD, a bigger BD size and a higher return on equity lead to raising relatively larger funds using green bonds. The rest of the variables (the share of independent directors, CEO duality, presence of a sustainable development committee) produce no significant impact on fundraising using green bonds. The obtained results also indicate that companies with greater borrowed funds and large companies attract financing using green bonds in relatively smaller amounts.

The final results of verification of the hypotheses set forth at the beginning of the paper are stated in Table 4.

Table 4. Results of verification of hypotheses

Hypothesis	Confirmation
1. Other conditions being equal, a larger female representation on the BD has a positive influence on fundraising using green bonds.	Yes
2. Other conditions being equal, the presence of a CSR committee has a positive influence on fundraising using green bonds	No
3. Other conditions being equal, the absence of CEO duality has a positive influence on fundraising using green bonds	No
4. Other conditions being equal, a larger BD size has a positive influence on fundraising using green bonds	Yes
5. Other conditions being equal, the share of independent directors on the BD has no significant influence on fundraising using green bonds	Yes

Source: Compiled by the author.

The research results show that three of the five suggested hypotheses are correct.

Verification of Results

Inasmuch as the studied sample of green bond issue in 2021 comprises companies from various sectors, including financial and non-financial ones, it is reasonable to verify the results described in the previous section for reliability based on the type of company (financial/non-financial).

In order to verify the results using the LSM, we assessed the optimal log-transformed model for financial and non-financial companies separately. Financial companies comprise the firms from *financial* or *bank* sectors, and all other companies are considered to be non-financial. As a result of division, we obtained two similar samples of 43 financial companies and 44 non-financial ones. The results of evaluation of the optimal model for financial companies are presented in Table 5.

Table 5. Results of evaluation of the optimal model for financial companies using the LSM

Variable	Coefficient	Standard error	*t*-statistics	*P*-value
const	7.13506	0.68311	10.440	3.78e–12***
ind_on_board	0.09854	0.39443	0.250	0.8042
women_on_board	1.47310	0.76895	1.916	0.0638*
CEO_duality	0.14527	0.29652	0.490	0.6273
CSR_committee	–0.12301	0.18597	–0.662	0.5128
board_size	0.03997	0.02762	1.447	0.157
debt_to_assets	–3.87595	0.60657	–6.390	2.70e–07***
ln_*total_assets*	–0.93951	0.04225	–22.240	7.76e–22***
ROE	0.51900	1.11606	0.465	0.6449
Mean value of dependent variables	–4.428914			
Sum of squared errors	8.909481			
R-square	0.952379			
F (8,78)	84.99687			
Logarithmic likelihood	–27.17155			

Variable	Coefficient	Standard error	*t*-statistics	*P*-value
Schwarz criterion	88.1939			
Standard deviation of dependent variables	2.110589			
Standard error of the model	0.511902			
Adjusted *R*-square	0.941174			
P-value (*F*)	3.31e–20			
Akaike criterion	72.3431			
Hannan-Quinn criterion	78.1884			

* Coefficients significant at the 10% significance level.
** Coefficients significant at the 10 and 5% significance levels
*** Coefficients significant at all reasonable significance levels.
Source: Author's calculation performed in *Gretl*.

Based on the data in Table 5, we may conclude that the regression for financial companies is statistically significant (the *P*-value of *F*-statistics amounts to 3.31e–20, which is below any reasonable significance level). The *R*-square of the model is rather high and means that the model explains 95% of the sample.

However, the results of regression evaluation for financial companies in regard to BD characteristics that influence fundraising using green bonds differ from the results of evaluation of the general regression: the significance of influence of female representation on the BD decreases, and the significance of influence of the BD size is also lost.

The results of evaluation of the optimal model for non-financial companies are stated in Table 6.

Table 6. Results of evaluation of the optimal model for non-financial companies using the LSM

Variable	Coefficient	Standard error	*t*-statistics	*P*-value
const	6.06140	0.86644	6.996	3.87e–08***
ind_on_board	0.24377	0.43356	0.563	0.5773
women_on_board	1.76057	0.79147	2.224	0.0327**
CEO_duality	–0.17845	0.20676	–0.863	0.3940
CSR_committee	0.30789	0.16718	1.842	0.0740*
board_size	0.05037	0.02260	2.229	0.0323**
debt_to_assets	–3.06651	0.59100	–5.189	9.07e–06***
ln_*total_assets*	–0.91234	0.04035	–22.610	1.81e–22***
ROE	1.97713	0.67600	2.925	0.0060***
Mean value of dependent variables	–3.642044			
Sum of squared errors	9.909411			
R-square	0.965027			
F (8.78)	120.7199			
Logarithmic likelihood	–29.63779			
Schwarz criterion	93.33329			

Variable	Coefficient	Standard error	*t*-statistics	*P*-value
Standard deviation of dependent variables	2.566968			
Standard error of the model	0.532096			
Adjusted *R*-square	0.957033			
P-value (*F*)	3.65e–23			
Akaike criterion	77.27558			
Hannan-Quinn criterion	83.2306			

* Coefficients significant at the 10% significance level.
** Coefficients significant at the 10 and 5% significance levels
*** Coefficients significant at all reasonable significance levels.
Source: Author's calculation performed in *Gretl*.

Based on the data in Table 6, we may conclude that the regression for non-financial companies is also statistically significant (the *P*-value of *F*-statistics amounts to 3.65e–23, which is below any reasonable significance level). The *R*-square of the model is rather high and indicates that the model explains 96% of the sample.

The results of regression evaluation for financial companies in regard to BD characteristics that influence fundraising using green bonds differ from the results of evaluation of the general regression: the significance of influence of female representation on the BD and the significance of influence of the BD size are diminished. However, at the same time a factor as the presence of the sustainable development committee acquires significance. According to the obtained results, companies with a CSR committee attract relatively larger funds using green bonds.

Thus, the results obtained from the analysis of the general sample and subsamples for financial and non-financial companies differ. Subsequently, it is necessary to conduct further studies on the influence of BD characteristics on fundraising using green bonds in various industries.

Conclusion

The present paper is dedicated to revealing the influence of characteristic features of BD composition on fundraising using green bonds. In the research we used the sample of 87 public companies that issued green bonds in 2021. In this paper we analyzed the influence of such factors as female representation and share of independent directors on the BD, CEO duality and the BD size on the share of green bonds in corporate total debt. The following variables were used as control variables: the share of debt in assets, the natural logarithm of total assets (company size) and return on equity (ROE).

A log-transformed specification of the classical linear regression model was selected as the optimal model. As long as heteroscedasticity, autocorrelation and multicollinearity were not detected in the model with the dependent variable logarithm (share of green bonds in total debt) we used the LSM to evaluate it. The following results were obtained based on the evaluation of the optimal model:

- a larger female representation on the BD, a bigger BD size and a higher return on equity result in raising relatively larger financing using green bonds;
- such factors as the share of independent directors, CEO duality, presence of a sustainable development committee have no significant impact on fundraising using green bonds;
- companies with larger borrowed funds and larger companies attract financing using green bonds in relatively smaller amounts.

Since the initial sample of the companies that issued green bonds in 2021 comprises both financial and non-financial companies, we verified the reliability of the obtained results for these two types of companies. Evaluation of the optimal model for two subsamples of financial and non-financial companies yielded the results that are somewhat different from the ones obtained from the analysis of the general sample. An assessment of the regression for financial and non-financial companies showed a decrease in the significance of influence of female representation on the BD and BD size. However, in case of non-financial companies, the factor of the presence of a sustainable development committee becomes significant. The obtained results suggest that companies with a CSR committee attract relatively greater amounts of financing using green bonds.

Thus, it is necessary to conduct further research on the influence of characteristics of BD composition on fundraising using green bonds. For example, this dependence may be considered for various industries instead of just global groups, such as financial and non-financial companies. Also, this dependence may be considered from the point of view of the region where companies operate (for example, developed/emerging countries).

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Voluntary Delisting of Russian Companies at Different Stages of Corporate Life Cycle

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Abstract

Nowadays, the number of companies leaving the stock exchange is steadily increasing. Researchers and practitioners continue to actively discuss the reasons for voluntary delisting and explore the factors that influence the probability of it. However, the results of existing studies are heterogeneous and inconclusive, indicating the need for further research. This paper continues the line of research on the determinants of voluntary delisting by studying the delisting of Russian companies. Unlike previous studies, we identify and compare the factors that influence the decision to delist at different stages of the organization's life cycle. We argue that delisting factors, although specific to each company, should remain similar for firms at the same stage of development. The company-related factors that we test include investment expenditures, profitability, stock volatility and book-to-market ratio. The study is based on a sample of 162 public Russian companies traded on the Moscow Exchange, of which 75 delisted between 2011 and 2019. The Bloomberg database was used to generate the sample of companies. Using the panel probit regression model, we found that firms with greater investment expenditures are less likely to delist at the Introduction and more likely at the Maturity and Decline stages. The results of our research also show that firm stock volatility had a positive effect on the delisting probability of Russian firms at all stages of their life cycle, except for the Introduction stage. Finally, we demonstrate that companies at the Introduction and Growth stages are more likely to leave the stock exchange if they have a greater book-to-market ratio. The results of our study can be used by financial analysts and academics to analyze the probability of delisting of public companies at different life cycle stages.

Keywords: delisting probability, delisting factors, Russian market

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Introduction

Delisting is the termination of the listing of a public company's shares on a stock exchange. This phenomenon has become both a popular topic on the academic agenda and a frequent financial practice. Delistings are now more common than initial public offerings: between 2010 and 2020, for every IPO, there were 2.5 delistings in the EU and 1.4 in the US. Large global corporations such as Dell, Hilton, Burger King are also resorting to this solution.

Leaving the stock exchange leads to significant changes in the life of a company. It simplifies the requirements for the composition of the board of directors and corporate governance, facilitates internal control, and reduces or eliminates the influence of minority shareholders on decision-making. Companies tend to change their capital structure, adopt new payment policies and simplify their accounting. The reaction of a company's customers to a delisting usually results in changes in sales and market share. Typically, this decision is made to either save financially distressed companies or to eliminate restrictions and costs for the firms which do not obtain the expected benefits from being public. In times of recession and economic decline, the idea of cutting costs through delisting is of significant interest to large companies.

The topic of delisting is currently gaining popularity on the academic agenda, as to this day no recognized theory describing the reasons why companies tend to make this decision has been developed. Delisting is usually studied by assessing the influence of different factors on the probability of leaving the stock exchange. Usually, the authors identify these factors using logistic regression and separately examine firm-level financial factors [1], industry and geographic factors [2; 3], and external factors, such as the adoption of new laws, SOX, etc. [4–6]. Despite the large number of papers on the determinants of firm delisting, there is a strong heterogeneity in the obtained results, which suggests their volatility and inability of observing similar effects for identical markets and timelines.

The aim of this paper is to investigate the factors affecting the probability of voluntary delisting of companies in Russia. Currently, there are very few publications devoted to the topic of delisting that use Russian data. Russian authors P. Andrukovich [7], E. Rogova and M. Belousova [8], E. Dreving and L. Khrustova [9], S. Klyev and A. Sorokina [10] mainly discuss such delisting-related questions as the reasons for delisting, the dynamics of stock prices during delisting, the reaction of the stock market to delisting announcements and questions about the delisting of companies in the technology sector, but do not touch upon the issue of factors affecting the probability of company delisting. Thus, we expand the discussion of this topic and provide a deeper understanding of it in the Russian market, which is characterized by a specific market, institutional and legal environment.

We also contribute to the existing literature by revealing the determinants of company delisting at different corporate life cycle stages. We presume that while every delisting is unique, companies sharing a similar life cycle stage should have common reasons to delist that can be explained by their changing needs in sources of finance and economic nature. Additionally, we are using the objective advantage of logistic analysis – the ability to define the determinants for compared samples.

The results of our study can be used by financial analysts and academics to analyze the probability of delisting of public companies at different life cycle stages.

Literature Review and Hypotheses Development

Voluntary Delisting

J. Macey et al. [11] first identified two types of delisting: voluntary (when company leaves stock exchange by its own decision) and forced (caused by financial distress). H. DeAngelo et al. [12] and K. Lehn and A. Poulsen [13] note that the key motive for delisting is the desire to reduce costs of being public. These include exchange service fees and regulatory payments (direct costs) and the price of standardized disclosure (indirect costs). The authors show that companies with low operating performance and low growth rates relative to the industry as a whole may decide to delist in order to reduce costs. W.S. Kim and E.O. Lyn [14], P. Halpern et al. [15] point out a negative relationship between company size and the likelihood of exiting the exchange: large businesses are less sensitive to fixed listing costs and also often benefit from it.

R.J. Maupin et al. [16] found that companies that do not remain public tend to be undervalued, while the management of such firms is a major shareholder. The positive impact of firm undervaluation on delisting probability is explained by the owners' desire to obtain additional benefits.

It seems objective that one of the key motives for delisting may be the owner's awareness of low public status efficiency, expressed in illiquidity of shares, high stock price volatility and excessive required rate of return. For example, A.K. Achleitner et al. [17] note that low stock liquidity increases the likelihood of delisting, while W.S. Kim and E.O. Lyn [14] and I. Martinez and S. Serve [18] show that owners often prefer to keep the company private when they think that market sets the risk premium unfairly. C.I. Lee et al. [19] note that there is a positive relationship between a company's chance of delisting and poor coverage of financial analysts.

The listing costs factor, which is expressed in the cost of regulatory requirements execution for corporate governance and accounting standards is also considered significant. B. Becker and J.M. Pollet [20], I. Martinez and S. Serve [18] note the impact of regulatory bills (SOX and FSL respectively) on companies' delisting decisions, while G. Pownall and M. Wieczynska [6] explains the delisting decisions of some European companies in 2005 by the adoption of mandatory IFRS standards.

The study by E.K. Pour and M. Lasfer [21] examines the financial position of UK companies from 1995 to 2009 from

IPO to delisting: they show that these companies did not aim to raise capital for growth, but went public to change their capital structure. However, as the cost of equity capital increased, these companies only destroyed their value and left the stock exchange. The authors conclude that the delisting was caused by the initial wrong purpose of the share offering.

Another study by G. Hu et al. [4] demonstrates the delisting of companies listed on foreign exchanges as a method of returning to home jurisdiction, using the example of Chinese companies. The key factor discovered is the changing political and social environment, which leads to an increase in listing costs. The study of H. Agyei-Boapeah et al. [3] shows that firms with a large amount of intangible assets are more likely to delist – the author justifies this by the industry specifics of IT companies, which are believed to prefer retained earnings as the main source of capital for development. As shown in the study by M. Kokoreva et al. [22], such policies can be caused, among other, by additional financing limitations set for these firms and by the motive of management entrenchment. As these factors are based on the nature of high-tech firms' governance and asset structure (and ergo applies not only to debt financing), we assume that it can also be a sufficient factor in causing them to delist.

We summarize main motives for companies to delist in Table 1.

Table 1. Delisting Motives Presented in the Literature

Delisting motive	Description	Articles
Cost reduction by low-performing companies	Companies with lower operating performance seek to eliminate listing costs	Lehn and Polusen, 1989 [13]; Kim and Lyn, 1991 [14]; Weir, Laing, 2006 [30]; Thomsen, Vinten, 2014 [32]
Undervalued companies	Owners of such companies want to obtain additional benefits	Maupin et al., 1984 [16]; Weir et al., 2006 [30]; Bharat and Ditmar, 2010 [31]
Low effectiveness of public status	Companies with an excessive required return abolish expensive public capital	Martinez and Serve, 2011 [18]
Application of new compliance requirements	Companies delist due to higher listing costs caused by new standards	Pownall, Wieczynska, 2018 [6]
Agency hypothesis	Increasing debt reduces free cash flow, which motivates management to reject projects with a negative NPV	Halpern et al., 1999 [15]
Change of jurisdiction	Companies of certain countries can leave foreign exchanges in case of conflicts	Agyei-Boapeah et al., 2019 [3]

Source: Authors' review.

To identify factors that affect the probability of companies to delist, researchers mainly use logistic regressions and test three groups of hypotheses, concerning (1) company-related factors; (2) industry, geographic and other local factors, and (3) external factors. We present the examples of these hypotheses in Table A1 in the Appendix.

The results obtained by researchers when testing these hypotheses are characterised by significant heterogeneity. In order to demonstrate this effect, we provide the results of the main papers that examine company related factors in explaining the probability of a firm delisting in Table 2.

Table 2. Test Results for Internal Factors Hypothesis

Article	Sample	Operating performance	Undervaluation	Efficiency of public status	Agency costs
Weir et al., 2006 [30]	354 UK delistings, 1998–2000	Low growth rate increases the likelihood	Undervaluation increases the likelihood	Factors are not significant	Hypothesis rejected
Bharat and Ditmar, 2010 [31]	1023 US delistings, 1980–2004	Delisting companies are financially distressed	Undervaluation increases the likelihood	High debt and poor financial coverage increase the likelihood	Concentration of ownership reduces the likelihood
Thomsen and Vinten, 2014 [32]	3577 delistings in 21 European countries, 1995–2005	Poor operating performance increases the likelihood	Factors are not significant	Factors are not significant	Concentration of ownership increases the likelihood
Pour, Lasfer, 2013 [21]	380 UK delistings, 1995–2009	Poor operating performance increases the likelihood	Factors are not significant	High debt and poor financial coverage increase the likelihood	Factors are not significant
Balios et al., 2015 [1]	239 companies of the Athens Stock Exchange (Greece), 2002–2012	Delisting companies are financially distressed	Factors are not significant	High debt and poor financial coverage increase the likelihood	Factors are not significant
Bortolon and Junior, 2015 [33]	227 delistings from 2001 to 2015 in Brazil	Factors are not significant	Factors are not significant	Low liquidity of stocks increases the likelihood	Concentration of ownership increases the likelihood

Source: Authors' review.

As can be observed from Table 2, even for samples with comparable geography (1 and 3), study period (5 and 6) and type of the market (2 and 4 for developed, 6 and 7 for developing), the results of hypotheses testing are often incoherent and even oppositely directed. For example, for studies 2 and 4, which review the delisting of companies in developed markets, only the positive impact of high level of debt coincides. In papers 3 and 5, which study European markets, none of the observed effects are similar. All these point to the contradictory results, which does not allow us to draw unambiguous conclusions about the reasons for the delisting of companies (I. Martínez and S. Serve [18]). Analyzing the papers presented in Table 2, we can also notice that almost all the papers are based on the assumption that companies delist in order to reduce their public costs (both direct and indirect), which is not always true, since the company may be more motivated by increasing cash inflows than by reducing cash outflows. In addition, the previous papers do not assess the consequences of delisting in any way and can be used only for a theoretical analysis of the reasons for a given decision, demonstrating consistent results only when evaluating the distinctive determinants of delisting in the analysis of samples in comparison.

Life Cycle and Delisting

In this paper, we identify the determinants of the company's delisting at different stages of the life cycle. The life cycle concept is based on the notion that a company goes through several stages in its development, each of which has its own distinctive features, including the peculiarities of the choice of the company's capital structure. Although the influence of the life cycle on the delisting phenomenon is not well understood, the capital structure theories and organization's life cycle concept suggest that the capital structure of a company depends on the stage of the life cycle, as the financing needs may change depending on the company's changing circumstances.

According to V. Goyal and M. Frank [23] companies tend to use internal funds first when choosing sources of capital, while larger and more mature firms preferring higher financial leverage and follow the concept of Pecking order of financing, but this is not confirmed for small companies.

As shown in Diamond's study [24], a firm's financing policy depends on age and public reputation. Companies accumulate credit history at early life cycle stages and utilise this resource later on, adjusting their capital structure. A.N. Berger and G.F. Udell [25] demonstrate that it is common for small firms with a short history to attract venture capital financing and use internal funds. The authors note that debt financing becomes more efficient and affordable with an increase in asset volume, since the latter can act as collateral.

The study by J. Blomquist and S. Waldo [26] shows that firms are most active in raising debt in the *Growth* and *Maturity* stages, which motivates them to pursue credit ratings, while in the *Decline* stage the level of financial coverage by analysts for the firm often decreases and credit rating becomes less relevant. The authors conclude that management is more interested in actively managing the financing policy at the *Growth* and *Maturity* stages than at the other stages.

The study by M. La Rocca et al. [27], in particular, shows that the pattern of the financial cycle of small and medium-sized firms is homogeneous over time and very similar for different institutional settings and industries, i.e., firms from different industries and institutional context behave similarly at the same stage of the life cycle in terms of capital structure choices.

In this study, we introduce the life cycle of an organization when studying delisting. Since delisting affects the choice of sources of capital raising and the capital structure itself is affected by the company's life cycle, it seems appropriate to examine the determinants of firm delisting at different stages of their life cycle. Despite the individual firm specificity, we expect that at each stage of the life cycle, the factors influencing delisting should be similar, as the principles of behavior within a single stage remain largely unchanged. Using the V. Dickinson [28] approach, we will consider the following stages: *Introduction, Growth, Maturity and Decline*.

Hypotheses Development

Based on capital structure theories, an organization's life cycle concept and previous empirical findings outlined above, we intend to test four hypotheses about the influence of company-related factors on delisting probability on the sample of Russian firms. The factors chosen were investment expenditures, stock volatility, profitability, and book-to-market value ratio, which are among the most discussed determinants of delisting in the empirical literature. Unlike previous authors, we compared the effects of these factors on the probability of delisting at different stages of a company's life cycle.

H1. Capital expenditures decrease the probability of delisting at all stages of the life cycle

Companies characterized by more substantial investment volumes expect to receive additional economic benefits from the assets being formed, for which they attract all available sources of financing [21]. We assume that companies with high level of investment expenditures are less likely to leave the stock exchange, as it seems logical to expand the list of sources of financing rather than reduce it.

H2. Stock volatility increases the probability of delisting at all stages of the life cycle

Share price volatility is one of the key factors in the delisting decision. According to E.K. Poor and M. Lasfer [21], firms with high stock volatility and low stock turnover will have low financial visibility and investor recognition, and hence a higher probability of delisting. Such firms often face an overestimation of their risk level by investors, leading to a higher required rate of return and eventually forcing them to leave the stock exchange and turn to debt financing. We assume that companies with more volatile shares are more likely to leave the stock exchange on the Russian market as well.

H3. Profitability decreases the probability of delisting at the Maturity and Decline stages of the life cycle

This hypothesis is traditional for delisting studies [18], as it is based on the classical assumption that firms leave the stock exchange in order to eliminate listing costs. It is generally believed that firms with low net profit will delist more frequently because the listing burden is more tangible for them. Unlike firms at other stages, the low profitability of firms at the *Maturity* and *Decline* stages has a longer-term effect because their operations are stable, the core assets and markets are already established, and their growth is intensive rather than extensive - that is, these firms are focused on maintaining profits by optimizing processes rather than by increasing revenues [29]. We suggest that such firms may view leaving the exchange as an opportunity to reduce listing costs and improve profitability, as public equity capital does not represent a source of additional growth for them.

H4. *Book-to-market ratio increases the likelihood of delisting at Growth and Introduction stages of the life cycle*

According to C. Weir et al. [30], S. Bharat and A. Ditmar [31], companies may delist from the stock exchange if their owners believe that the market undervalues such firms. The motivation to delist is to extract additional value by buying back the shares from minority shareholders at a lower price. *Introduction* and *Growth* stage firms are, in our view, the most susceptible to delist for this reason, as their value is largely based on expectations of future cash flows rather than on the book value of disposable assets, and thus the difference between 'expectations' for such companies will be objectively higher than for companies in other stages. Therefore, we believe that the higher the book-to-market ratio, the higher the likelihood of a company leaving the stock exchange.

Methodology

Our empirical analysis includes two steps. The first step is the identification of companies' life cycle stages. We used the V. Dickinson [28] methodology because unlike other instruments, it does not compare firms in the sample with each other and ergo does not provide relative estimates. This approach assumes that all companies' important activities are captured in three different types of cash flows – operating, investing and financing. Thus, a company's lifecycle stage is identified based on the signs of its cash flows in correspondence with Table 3. The number of stages was reduced to four: *Introduction, Growth, Maturity, Decline,* as also shown in Table 3. *Transition* stage companies were assigned to *Maturity* and *Decline* according to the operating cash flow sign.

Table 3. Cash Flow Signs Used to Define Life Cycle Stages

	Introduction	Growth	Maturity	Decline
Operating cash flow	–	+	+	–
Investing cash flow	–	–	–	+
Financing cash flow	+	+	–	+/–

Source: [28].

Table 4. Variable Descriptions (the values of all variables) are considered for the calendar year)

Name	Description	Source
CapEx	Capital Expenditures to Sales Ratio	Pour and Lasfer, 2013 [21]
Volatility	Average Share Price Volatility	
Profitability	Net Income to Book Value of Total Assets Ratio (ROA)	Pour and Lasfer, 2013 [21]
BM	Book value over market value of equity	Pour and Lasfer, 2013 [21]
Liquidity	Current Assets to Current Liabilities Ratio *(control variable)*	Martinez and Serve, 2011 [18]
Listing Years	Number of Full Years Since IPO *(control variable)*	Agyei-Boapeah et al., 2019 [3]
Leverage	Total Debt/Total Assets *(control variable)*	Pour and Lasfer, 2013 [21]

Source: Authors' review.

At the second step, similarly to previous studies (e.g. E.K. Pour and M. Lasfer [21], H. Agyei-Boapeah [3]), we use panel probit regression with population averaged effect and the probability of firm delisting as dependent variable:

$$Delisting = \begin{cases} 1, Y^*_{i,t} \geq 0 \\ 0, Y^*_{i,t} < 0 \end{cases}, \quad (1)$$

$$P\left(Delisting = 1\right) = P\left(Y^*_{i,t} \geq 0\right), \quad (2)$$

In this case, the latent variable is as follows:

$$Y^*_{i,t} = \beta_1 + \beta_2 CapEx_{i,t} + \beta_3 Volatility_{i,t} + \\ + \beta_4 Profitability_{i,t} + \beta_5 BM_{i,t} + \beta_7 Liquidity_{i,t} + \\ + \beta_8 ListingYears_{i,t} + \beta_8 Leverage_{i,t} + \varepsilon_i.(3)$$

The description of our independent and control variables is presented in Table 4[1].

Data

Our sample contains 162 Russian companies, including 75 that delisted between 2011 and 2019 calendar years. The total number of firm-and-year observations is 1458.

The distribution of companies by industry is presented in Figure 1.

We generated our sample by collecting available data on all Russian listed and voluntarily delisted public firms in the described period of time. No additional filters were set because the number of such firms is initially very small, and otherwise there would not be enough observations in our sample for meaningful analysis.

We exclude the companies from financial and utilities sectors from our sample. As can be seen from Figure 1, the majority of companies in our sample belong to industrials and materials sectors according to Bloomberg classification system. 44% of the companies belong to high-tech industries according to OECD classification.

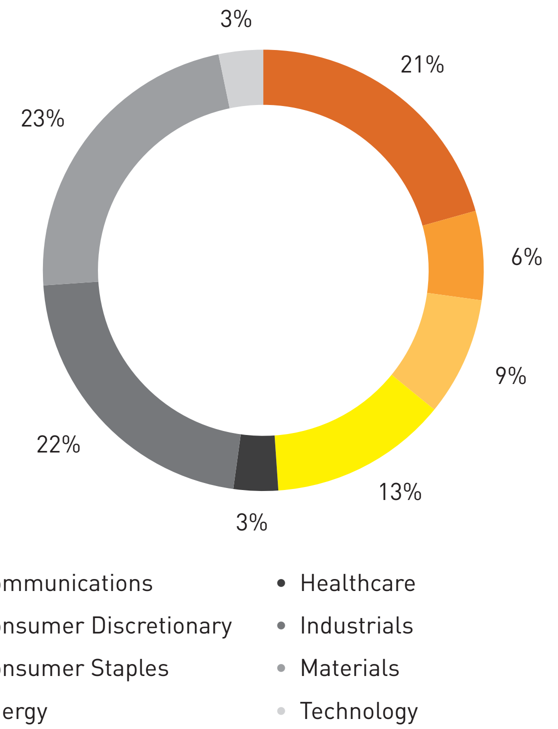
[1] Before testing our hypotheses, we checked our model for multicollinearity. The correlation between the variables does not exceed the critical value for any pairs of variables, from which we can conclude that there is no problem of multicollinearity in our model.

Table 5. Identification of Life Cycle Stages

Year	Introduction	Growth	Maturity	Decline
2011	15	48	50	13
2012	24	49	73	18
2013	25	38	73	19
2014	10	57	72	17
2015	15	48	76	21
2016	8	28	45	82
2017	8	24	51	82
2018	7	26	48	84
2019	8	23	50	82

Source: Authors' calculations.

Figure 1. Distribution of Companies by Industry



Source: Authors' calculations.

Applying the Dickinson [28] methodology, we have categorized the companies in our sample by life cycle stages and present this distribution in Table 5.

As Table 6 shows, there is a rather small number of companies at *Introduction* stage. This result seems understandable, as such firms are rarely listed. Another interesting observation is the one-stage forward "shift" observed for a large number of companies in 2015–2016. Since reporting data is presented at the beginning of calendar year, the effect of the 2015 crisis in Russia is reflected in observations for 2016. We suggest that this effect is mainly caused by the 2014–2015 economic crisis in Russia.

Results

In Table 6, we present the results for each stage of the life cycle respectively. The marginal effects shown demonstrate the local effect of each financial factor on delisting probability [21]. For example, at *Maturity* stage a unit growth in profitability increases delisting likelihood by 0.337%. For each model, we also indicated our results for hit ratio tests and calculated pseudo R2 (or McFadden's R2), which are considered standard for such probit regressions [3]. Pseudo R2 of 0.15 and above is considered a good fit.

Table 6. Test Results

Variables	Introduction	Growth	Maturity	Decline
Observations	**120**	**341**	**574**	**457**
CapEx	–2.231***	–0.153	0.689*	1.057**
	(0.569)	(0.293)	(0.402)	(0.435)
Volatility	0.000419	0.00246***	0.000571*	0.000611**
	(0.000345)	(0.000400)	(0.000302)	(0.000241)

Variables	Introduction	Growth	Maturity	Decline
Profitability	–0.0298	0.230	0.337**	0.219***
	(0.532)	(0.209)	(0.162)	(0.0848)
BM	0.0787 *	0.0287**	–0.0480	0.0310
	(0.0516)	(0.0122)	(0.0328)	(0.0216)
Liquidity	–0.476***	0.160***	0.110***	0.00390 *
	(0.137)	(0.0405)	(0.0329)	(0.0249)
Listing Years	0.0550***	0.00136	0.00388	–0.00733
	(0.0100)	(0.00597)	(0.00487)	(0.00449)
Leverage	–0.139*	0.153***	-0.0157	–0.0246
	(0.0843)	(0.0252)	(0.0426)	(0.0269)
Pseudo R^2	0.155	0.201	0.215	0.182
Hit Ratio, %	95	78	80	82

Robust standard errors in parentheses. *** p< 0.01, ** p<0.05, * p<0.1.

Source: Authors' calculations.

As can be observed, a unit increase in CapEx reduces the probability of delisting by 2.231% for the *Introduction* stage and has a positive impact of 0.689% for *Maturity* and 1.057% for *Decline*, while the variable is not significant for *Growth* stage. Thus, we cannot reject hypothesis H1 at 1% level of significance only for *Introduction*. For the rest of the stages, the hypothesis is rejected.

The negative impact of investment on delisting at *Introduction*, in our view, is observed due to the fact that companies at this stage are just forming their assets and are financially immature, thus public status is atypical for them and represents a very significant burden due to listing costs. Accordingly, when funds that form the main sources of future revenues decrease, such firms will seek to drastically reduce costs that are not critical, including listing costs. This way, the observed effect, although it has the same sign as formulated in hypothesis H1, still has a different cause than we initially hypothesized.

Looking at the other stages, we believe that the observed positive effect from CapEx is due to the fact that quite a large number of firms in our sample delisted due to their participation in M&As, which means they tried to reflect higher CapEx values before delisting in order to increase their attractiveness as a target.

Share price volatility is significant for all stages except *Introduction*, increases the probability of delisting and has the largest modulus for companies in the *Growth* stage. However, despite this, the value of the average marginal effect itself is very small, indicating in fact that this factor has no influence on the probability of delisting. We believe that one of the possible reasons for this effect is that we did not additionally filter companies by the liquidity of their shares, since there was initially a small number of companies on the Russian market. If the sample had been larger and was additionally filtered by this principle, we assume that the results of testing this hypothesis would have been more significant.

A unit increase in firm profitability increases the probability of delisting by 0.377% for *Maturity* and 0.219% for *Decline*. This effect is opposite to the one we formulated in hypothesis H3, this is why we reject it. The motive of "delist to cut costs if profitability is low" is not observed in this case, which we can probably also explain by the presence of companies that participated in M&A transactions and delisted after the transaction – being the target of a merger, they were also likely to reflect higher profitability in their reports.

A 1% increase in book-to-market increases the probability of delisting at *Introduction* and *Growth* stages by 0.0787% and 0.0287%, respectively. Thus, hypothesis H4 is not rejected at a 10% significance level for *Introduction* and 5% for *Growth*, indicating that firms at these stages are more likely to delist, as they are able to extract additional value by buying back shares from minority shareholders at a lower price when the market undervalues them.

Conclusion

In our research we focus mainly on revealing the factors influencing delisting probability for Russian companies. Unlike previous research, we decided to adjust the widely used probit regression model by introducing the corporate life cycle. This allows us to analyze samples in comparison, and to point out stage-specific financial determinants of delisting likelihood based on the premise that the firms belonging to the same life cycle stage delist due to similar factors.

Based on the sample of 162 Russian companies, including 75 delisted firms, over 2011–2019 and using the panel probit regression model we found that in the *Introduction* and *Growth* stages, the main financial factor affecting the probability of delisting is the undervaluation of the business. In the early stages, companies are very attentive to the market's valuation of their business when deciding whether to delist and when looking for alternative sources of financing. At the *Maturity* and *Decline* stages, companies no longer react to this indicator, as in order to be competitive and continue their long-term market presence, they need to implement other strategies, such as diversification, M&A transactions, etc. Therefore, at the *Maturity* and *Decline* stages, the main indicators affecting the probability of delisting are high operating efficiency and investment expenditures necessary for the realization of future strategy. The obtained results can be used to predict the relative probability of delisting depending on the stage of a company's life cycle.

One limitation of our study is that we did not account for delistings resulting from M&As as a separate phenomenon; however, our results suggest that such delistings have a significant impact on the observed effects, indicating the need to account for these transactions in further research. Another limitation is that the observed effects can only be assessed "in comparison" - this means that we cannot draw independent conclusions about the factors that led to the delisting of a firm, but can only analyze the situation in the market as a whole. In addition, due to the small number of delisted firms, we did not set the filters for size, value, stock liquidity and other characteristics for the firms in our sample, which may have resulted in some distortion of the results.

Each delisting decision is unique, and the approach used to study delisting produces very simplified and averaged results that can only provide a general idea of the overall relationships that occur in a particular sample. In addition, this approach tends to assume that the delisting of a firm is due to some factors or events that have occurred previously, while the delisting may represent some prediction of the firm's future development, its strategy, justifying the decision to delist. We believe that the future of the study of the delisting phenomenon lies in finding ways to assess what happens to firms after this decision is made, and the answer to this research question could help to understand why firms do it in the first place.

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Appendix

Table A1. Hypothesis Classification on Delisting

Hypothesis type	Examples of hypotheses	Articles
Hypotheses testing the impact of company-related factors	Delisted companies have low operating performance Delisted companies are undervalued Delisted companies have a high stock price volatility Delisted companies have a poor analytical coverage Delisting is done by companies with higher FCF Delisted companies have a higher level of financial leverage	Pour, Lasfer, 2013 [21] Thomsen et al., 2014 [32] Martinez and Serve, 2011 [18]; Bharat and Ditmar, 2010 [31]; Balios et al., 2015 [1]
Hypotheses testing the influence of industrial, geographical and other local factors	High-tech companies delist more often than low-tech companies The volume of investment affects the likelihood of delisting construction companies (compared to real estate)	Agyei-Boapeah et al., 2019 [3] Konno and Itoh, 2018 [2]
Hypotheses testing the impact of changing external realities	Introduction of SOX influenced the growth in the number of delistings Adoption of IFRS increases the likelihood of delisting Industry deregulation increases the likelihood of delisting The economic conflict between China and the United States has affected the growth in the number of delistings of Chinese companies	Pownall and Wieczynska, 2012 [6] Loveland et al., 2021 [5]

Source: Authors' review.

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The Impact of Sanctions on the Capitalization of Russian Companies: The Sectoral Aspect[1]

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Abstract

The research purpose is to evaluate influence of sanctions on the Russian economy taking into consideration the sectoral aspect (oil and gas, telecommunications and consumer sector). The research methodology comprises econometric modeling (elastic net and GARCH modeling) and text analysis. In the paper we developed author's sanction indices based on the text analysis. We used the EcSentiThemeLex dictionary to assess the news' positivity and negativity.

The empiric research base consists of news publications of the lenta.ru portal for the period from 01.01.2014 to 31.03.2023 represented by the thematic sections "economy" and "science and technology". The research results are as follows. On the basis of GARCH modeling we revealed that sanctions have a negative impact on capitalization of the largest companies in oil and gas, the consumer sector and telecommunications. The news tonality influences companies' capitalization. We have developed sanctions indices (a minimal index, an expanded index, a maximally expanded index) which allow to assess the extent of sanctions pressure. On the basis of elastic net method we made the conclusion of priority of sentiment variables over the control ones, i.e. information on sanctions and its tonality influences the stock market more than the oil prices, rouble exchange rate and interbank rate in the short term. Sanctions influence is not industry specific.

However, the study does entail certain limitations: 1. reliance on publications from a single source; 2. the use of a single dictionary for evaluating news sentiment; 3. the sanctions index does not allow the incorporation of new terms when fresh sanctions are imposed. We intend to address these issues in future research.

Keywords: stock market, sanctions, sanctions index, text analysis

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Introduction

After its inception in 2014, the conflict between Russia and Ukraine provoked a geopolitical crisis in the USA, EU and other Western states. Since 2014, many countries have introduced different multilateral sanctions targeted at the most important industries of the Russian economy, including power generating companies, the banking sector and the defense industry.

After Russia began to experience the pressure of heavy sanctions, a lot of IT companies left the country and denied their services to Russian citizens, including users of license-based enterprise software. Some Chinese companies such as Huawei stopped delivering data storage systems. A lot of Russian telecommunications manufacturers were added to the SDN list (Specially Designated Nationals): Baikal Electronics, MCST, Elvees RnD Center, MultiClet, Angstrem and others. This influenced the capitalization of the telecommunications industry. Car manufacturers such as Audi, BMW, and Ford and consumer good brands withdrew from the Russian market. Problems arose with deliveries of vital equipment for the functioning of major domestic companies. Research questions arise about the influence of the imposed sanctions on the capitalization of domestic companies. The purpose of our study is to evaluate the impact of sanctions on the capitalization of domestic companies, taking sectoral specifics into account.

While numerous Russian and foreign authors have assessed the influence of sanctions on the Russian economy, our study differs in the following aspects. First, as this topic is relevant for the Russian market, several studies [1–5] have considered the influence of sanctions on different aspects of the national economy; we consider the influence of sanctions on the financial market, taking sectoral specifics into account. Secondly, we take the major Russian news portal lenta.ru as our source[1]. Over the period January 2014 – March 2023, over 16 200 publications appeared in the rubrics “Economics” and “Science and Technology”. Thirdly, we use text analysis methods to obtain sanctions indices, including analyses of frequency and correlations and topic analysis using the BERT neural network.

The paper consists of an introduction, four main sections, a conclusion and references. The first section is dedicated to the literature review and the formulation of the research hypotheses. The second section describes the research methodology. The third section reviews the data and calculates descriptive statistics. The fourth section models the influence of sanctions on industry-related stock indices and discusses the results.

Theoretical Review of the Impact of Sanctions on the National Economy

Since 2014, the impact of sanctions has been a highly relevant research topic. As of today, Russia has a record number of sanctions imposed on it, and forecasts of their effects differ. It is difficult to predict the influence of sanctions, as there are always a lot of unintended side effects, which, interestingly enough, vary over time. The economic literature offers some indicators for measuring the impact of sanctions and their unanticipated effects. The direct consequences of sanctions usually include a decrease in international trade in goods and services. When researchers evaluate the impact of sanctions, they usually focus on certain fields or sanction effects to study the dynamics of indicators and compare the ultimate overall effects of sanctions in different countries.

For example, M. Crozet and J. Hinz [1] studied the impact on exporters that had been slapped with sanctions using Iran and Russia as examples. They revealed that the number of exporters in certain industries decreased by 39 and 23%, respectively. J. Sonnenfeld et al. [2] have shown the significant influence of sanctions on the economy. For example, sanctions and anti-Russian prejudice led over 1000 international companies to leave Russia in 2022, impairing its access to international supply chains and technologies. Some authors trace the impact of sanctions on the employment level, especially in industries that are highly dependent on equipment imports [3].

Still, the most important effect of sanctions is a slowdown in the growth of the GDP [4–5]. On the basis of general equilibrium modeling, the GDP is forecast to decrease by 14 as a result of trade embargoes [6]. Sanctions have also had an impact on the countries that imposed sanctions: their GDP fell by 0.1 to 1.6%. So, sanctions work both ways: they influence the countries which impose them and the countries that they target.

Moreover, the effect of sanctions is ambiguous because they cause structural changes in international integration: the market reorientation of the national economy, the reconfiguration of global value chains, and the localization of production facilities [7]. These restructuring processes diminish the negative macroeconomic impact of sanctions. In addition, the impact of sanctions wanes as time passes: the country loosens its dependence on external supplies and imported technologies, and national resistance stiffens due to the localization of supply chains and the diversification of trade models. Consequently, the longer sanctions work, the less economically destructive they are, because economic actors develop alternative ways of doing business [8].

In some sanctioned countries such as Iraq, South Africa and Yugoslavia, domestic products replaced imported ones [7]. Studies of Iranian exporters show that, although foreign countries redirected to “non-sanctioned” exporters, Iranian export volumes actually grew while their rates of return decreased [9]. Similarly, after sanctions were imposed in 2014, Russian consumers switched to local products or products imported from non-Western countries [10]. As for the financial market, researchers point to the increase in the volatility of Russian stocks during the

[1] https://lenta.ru/

sanctions period [11]. Western sanctions caused a rapid outflow of direct foreign investments and a decline in the profitability of the Russian market [12].

Russian and foreign literature considers the impact of sanctions not just on the economy in general but also on specific elements such as industrial sectors targeted by sanctions. Indeed, total imports and exports decline unevenly: according to a study by E. Gurvich and I. Prilepskiy [13], the greatest damage was caused to the output of oil and agricultural products. Some researchers emphasize the impact of sanctions on the fuel and energy sector in both Iran [14] and Russia [15], focusing on the change of the output volume as well as hydrocarbon imports and exports. Changes in oil prices due to the embargo and ruble exchange rate fluctuations influence both the country's industry in general and the domestic oil market in particular, raising gasoline prices [16]. Some sanctions are directed at limiting technology transfer such as the sale of semiconductors and other high-technology products [17]. Sanctions may also create long-term consequences for some industrial sectors. For example, a study by A. Demarais [18] notes that the US share in the global space market was 75% in 1998 yet declined in ten years to less than 50% after the USA adopted the International Traffic in Arms Regulation (ITAR) with a set of export control measures intended to protect the know-how of the American aerospace sector.

The impact of sanctions on stock indices is also a frequently studied topic. It has been analyzed by means of event study (the fact of imposed sanctions), which has confirmed the negative influence of sanctions on prices. Moreover, US sanctions are more significant than those of the EU [19]. A similar methodology is applied to analyze the influence of corporate reports on corporate stock values [20]. The Russian researcher A.D. Aganin [21] has studied the influence of Brent oil price volatility and sanctions on the RTS Index over a long research period including several crisis periods (2007–2018).

The influence of news tonality (in particular, during sanction periods) on economic indicators has also been confirmed by academic research. The overall sentiment of news exerts an impact on the currency market [22], and there is also an interrelation between the Economic Policy Uncertainty (EPU) Index and sectoral indices [23]. The EPU index is also calculated on the basis of news publication, i.e., one can say that economic policy uncertainty (monitored by means of text analysis) influences financial markets.

We have confirmed the negative impact of sanctions on the economy through our literature review, and we also agree that sanctions influence the Russian financial market negatively. At the same time, we conjecture that the impact of sanctions has sectoral specifics.

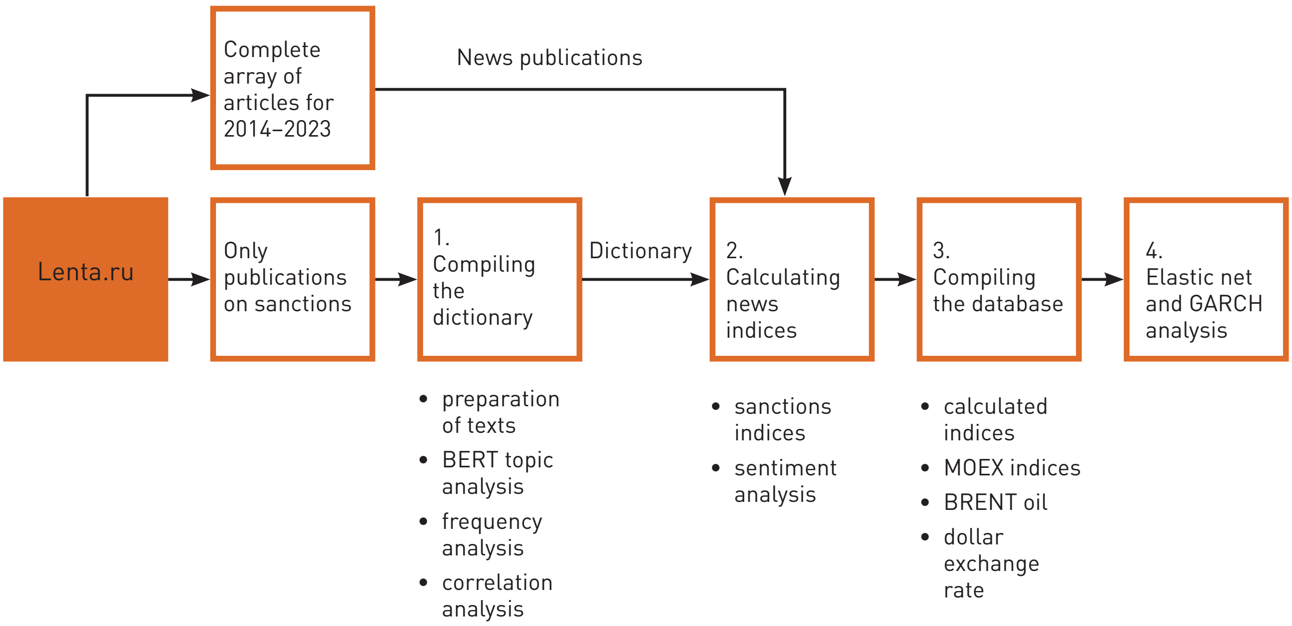
We present our research methodology below.

Research Methodology

Research Map

Our research map is presented in Figure 1. During the first stage, we create the empiric base of the study, download the news dataset from lenta.ru for the period between January 2014 and March 2023, select only the news articles about sanctions, and analyze them using different machine methods. Then we employ text analysis to create original sanctions indices and assess their influence on the capitalization of domestic companies in the oil and gas, telecommunications, and consumer sectors with the help of the elastic net method and GARCH modeling.

Figure 1. Research map



The research map calls for gathering and processing an empiric research base, making a dictionary of sanctions indices and collecting supplementary data. The obtained database is then used directly to define the influence of the sanctions index in news on sectoral independent indices.

Elastic Net Method and GARCH Modeling

To study the significance of variables in linear models, we applied elastic nets – a specific type of regression model that allows setting additional regularization parameters. For the classic linear model given in Formula (1), the selection of indicators x_t^k with the elastic net consists in evaluating the model parameters by minimizing function (2):

$$y_t = b_0 + \sum_k b_k x_t^k + \varepsilon_t; \quad (1)$$

$$\min_{b_0, b} \left\{ \frac{1}{T} \sum_{t=1} \left(y_t - b_0 - \sum_k b_k x_t \right)^2 + \right.$$
$$\left. + \lambda \left(\alpha \left[b_0 + \sum_k b_k \right] + (1-\alpha) \left[b_0^2 + \sum_k b_k^2 \right] \right) \right\}, \quad (2)$$

where T is the number of observations; t is the sequence number of the observation; k is the sequence number of the input parameter of the dataset; y_t is the predicted regression value; b_k is the parameter coefficient; x_t^k is the input parameter of observation t; λ, α are regularization parameters; and b_0 is the absolute term of the regression equation used to define the displacement.

In Formula (2), the first term is the loss function of linear regression, and the addend is the means of regularization, which imposes a penalty for the number of variables introduced into the model. The regularization parameter λ determines the overall penalty coefficient. If it is equal to zero, the model is reduced to a simple linear regression; if it grows, all the coefficients of the model diminish. By manipulating this parameter one can select only potentially significant parameters. The elastic net simultaneously includes two regularization methods that are characteristic of regression methods defined by Ridge [24] and Lasso [25]. The α (alpha) parameter determines the balance between these two types of regularization. If this parameter is set at 0, the elastic net assumes the shape of an ordinary Ridge regression, and, if it is equal to 1, the net assumes the shape of an ordinary Lasso regression. Thus, this parameter can be used to make a mixture of these two regression methods by differently accounting for the two regularization methods in the loss function.

In our study, we varied both parameters (λ and α) using ten intermediate values within the interval of 0 to 1. Thus, we tried 100 different parameter combinations, selecting the best one on the basis of the RMSE value. We then used the glmnet package to derive the significance of the variables.

We constructed models of the impact of sanctions on Russian industrial sectors using the results of the preliminary analysis of the temporal series obtained above. We used the GARCH model for analysis. Due to the limited number of news articles about sanctions (in periods when the pressure of sanctions decreased, the number of news reports was very low) and in order to trace the impact at the macrolevel, we averaged the data by months for constructing the model. We also used the following control variables: Brent oil futures price, USD-RUB exchange rate and the RUONIA benchmark interest rate [22; 26]. The formula used for analysis is the same for all three sectors:

$$Log(y_t) = a_1 BRENT_t + a_2 USD_{RUB_t} + a_3 RUONIA_t +$$
$$+ a_4 NegativeSent_t + a_5 PositiveSent_t +$$
$$+ a_6 SAN0_t + a_7 SAN1_t + a_8 SAN2_t, \quad (3)$$

where $LOG(y_t)$ is the MOEX index increment logarithm for the oil and gas, telecommunications and consumer sectors; $BRENT_t$ is the logarithmic profitability of the Brent oil price; USD_RUB_t is the logarithmic profitability of the ruble exchange rate; $RUONIA_t$ is the increment of the benchmark interest rate; $NegativeSent_t$ is the mean level of negative news sentiment for the period; $PositiveSent_t$ is the mean level of positive news sentiment for the period; and $SAN0$, $SAN1$, $SAN2$ are the derived sanctions indices. Note that we have taken the absolute value of negative calculated values to make it more convenient to interpret the results. The index of sanctions coverage in a text is calculated as the ratio of the total word count in the dictionary to the total word count in the text.

We will evaluate the impact of the sentiment and sanctions indices, which are strongly correlated with each other, by constructing several individual models using only one of the indices.

Compilation of Sanctions Indices

Sentiment analysis emerged at the end of the 20th century with the formation of the principal approaches and applications of this line of research [27]. In modern systems, it is often associated with text tonality analysis (defining positive/negative sentiment), which makes use of lexicon-based methods. This method views words as markers that are correlated with a certain sentiment scale to identify the general tonality of the text.

In addition to measuring the overall tonality, researchers have compiled dictionaries to evaluate the extent of coverage of a certain topic in the text and obtain an estimation index applicable to the question under study (for example, the level of morality, the uncertainty of economic policy, or the main focus of corporate economic strategy). There are several principal approaches to compiling the text index, which usually consists of a set of words united by a certain topic.

The first approach is to choose such words through questionaries or computer analysis (selecting words for the index by using machine text analysis); such indices can also be constructed by experts. The MFD (Moral Foundations Dictionary) [28] is an example of an index compiled through a questionary.

The second approach uses computer-aided modeling to single out words and collocations for the index. This method is called content analysis and can be used to make contextual conclusions [29]. Examples of dictionaries created through the computer-aided analysis of dictionaries include Sustainability Orientation, made from letters to stockholders [30], and Debt/Equity Focus, compiled using 10-k corporate reporting forms to determine the principal focus of corporate strategy [31]. These indices were made in similar ways by analyzing a corpus of texts and singling out the most frequent words and collocations occurring in the corpus as a whole. The analysis of large data objects is one of the main advantages of the method [32–33].

An example of the third approach is EPU – an index constructed using the expert method [34]. This index measures the uncertainty of economic policy. The initial index was created by a group of experts using the time-consuming procedure of manually analyzing news publications. Crisis and sanctions indices were constructed in the same way in paper by E.A. Fedorova et al. [35]: an expert in linguistics manually analyzed a large text corpus, singling out evaluative words pertaining to the respective semantic field.

The methods may be combined to obtain more reliable results. The method of computer-aided analysis has a range of advantages for research: minimizing the researcher's influence, increasing the stability and reliability of results, and being applicable to both qualitative and quantitative studies [32; 36]. This is the method we use to compile the sanctions index.

Table 1. Frequency of words and collocations

Word	Frequency	Word	Frequency
sanction	2770	sanction package	76
ban	795	import ban	68
limitation	749	delivery block	64
embargo	292	economic sanction	61
anti-russian	172	export ban	42
impose sanction	169	european union sanction	41
anti-russian sanction	153	ruble devaluation	40
limiting	142	sanction pressure	35
new sanction	137	import bar	35
restrictive measure	108	Retaliation	29
imposing sanction	102	severe sanction	28
sanction list	97	punitive sanction	24
western sanction	90	Barrier	22
block	84	washington sanction	13
american sanction	76	Blockage	8

A number of authors have created sanctions using the cumulative sum of sanctions packages for each month. A. Omelchenko and E. Khrustalev [37] proposed calculating a sanctions index using the share of sanctioned banks in the assets of the banking system, the share of assets of sanctioned countries in the GDP, the share of the currency of the sanctioning country in the portfolio of banks' external debt, and similar factors. Such sanctions indices have also been constructed for the Russian economy by other authors. For the first time, such an index was proposed in C. Dreger et al. [38]. In our paper, we construct a sanctions index that we use as a benchmark[2].

Our methodology of compiling a sanctions index dictionary is based on the first approach and consists of several stages:

Creating the empiric research database. To compile the dictionary, we select articles from the lenta.ru news portal which include the word "sanction" or "ban". The texts are cleaned and lemmatized. For the period from January 2014

[2] We call it the "cumulative index of the number of sanctions" (NSAN) below.

to March 2023, we downloaded over 16 200 publications in the rubrics "Economy" and "Science and Technology". We selected only texts containing the words "sanction" or "ban", obtaining 1960 publications (approximately 1,700 of them pertain to the Economy rubric).

Evaluating word and collocations frequency. Here, we identified the most frequent elements for the index.

Analyzing the correlation of words in the text corpus with the word "sanction" (the correlation level of each individual word standing next to the word "sanction," as many different words are used together with the word "sanction"). This analysis of interconnected words allowed us to identify the most important collocations for the index.

Selecting topics by means of topic analysis using the BERT artificial neural network [39–40]. This method allowed us to single out the key words of sanction-related topics and determine the context in which mass media usually speak about sanctions.

Conducting a final expert analysis of the resulting lists of words and topics in order to single out the most important words and collocations for the index. We included not only high-frequency words but also words that occur rarely but are specific to the field and important for constructing the index.

Using this methodology, we created a dictionary for our index. This approach is typical for compiling dictionaries [41]. The words related to our measured construction in one particular context may have different meanings in other contexts. For this reason, we followed the approach of A.F. McKenny et al. [42] to analyze manually the contextual use of certain words and phrases so as to mitigate potential errors. The index dictionary was stored in simple text format just as many other dictionaries based on the expert approach that consist of a list of words with some attributes or a set of several lists [41].

Now we passed to the analysis of the text corpus according to our methodology. First, we analyzed the frequency of words and collocations. The resulting tables were carefully reviewed to single out the units relating to sanctions and often pertaining to a single semantic field. The results are presented in Table 1.

We selected the main collocations relating to sanctions, bans and the main effects of sanctions, eliminating words with an overly broad meaning. During the next stage, we analyzed correlations with the word "sanction" to make a list of words closely related to sanctions. Table 2 presents the correlations table, from which we eliminated unrelated and overly general words.

Table 2. Analysis of word correlations with the word "sanction"

Word	Corr. coef.	Word	Corr. coef.
against	0.886859	Introduce	0.62727
relation	0.831773	American	0.625276
impose	0.811745	european union	0.622889
limitation	0.807373	Embargo	0.596917
imposing	0.746288	Threat	0.580081
anti-russian	0.708944	Ban	0.563605
party	0.701746	Government	0.530223
new	0.69573	Package	0.522207
measure	0.68424	Penalty	0.495037
restrictive	0.661153	Retaliatory	0.489354
retaliation	0.649114	European	0.445831
washington	0.644006	Economic	0.418316

As we see from Table 2, news outlets focus on the source of sanctions, their nature, and synonyms. A lot of words correlate with the frequency list; the analysis of correlations shows the significance of these words for the topic.

At the final stage of the keyword selection, we analyzed the text corpus using the BERT neural network. BERT singles out topics in the text corpus automatically; in addition, the number of topics, unlike in LDA, is defined automatically, and textual semantics are better analyzed. In particular, the BERTopic applied algorithm is the most advanced method for topic modeling today. It takes the semantic relations of words into account and uses a flexible model for distributing words into clusters, allowing one to delineate topics with a lot of accuracy [43].

The topic modeling led us to single out 30 topic keywords, as shown in Table 3.

Table 3. Topic analysis using BERTopic

Topic 1	Topic 2	Topic 3
russia	space	Huawei
russian	missile	Company
which	airplane	Chinese
sanction	which	smartphone
country	russian	China
percentage	russia	Apple
company	military	American
bank	engine	Google
ruble	apparatus	Which
dollar	american	installation
also	roscosmos	User
oil	one	Trading
market	time	Become
such	satellite	manufacturer
become	company	application
billion	first	New
economy	robot	Iphone
new	such	Trump
whole	system	Reuters
this	missile-related	Screen
declare	also	Market
one	carrier	telephone
time	flight	Samsung
news	other	Ban
economic	country	Sale
if	become	Duty
growth	whole	However
word	however	Other
ukraine	this	Service
more	center	Goods

This analysis mainly focused on what is described in news publications in relation to sanctions. As we see, the most important topics were banks and finance, oil, different hi-tech sectors (planes, missiles, satellites, etc.) as well as hi-tech microelectronics and the operations of IT giants.

After the expert analysis of the obtained word and collocation sets, we developed several versions of the sanctions coverage index, from a maximally condensed index to a more expanded one with a greater number of words and collocations. We indicate their initial word forms.

SAN0 – a minimal index that analyzes the number of mentions of sanctions as such. It consists of the following words: sanction, economic sanction.

SAN1 – an expanded index which considers some of the closest words to sanctions. It consists of the following words: sanction, economic sanction, restriction, ban, block, import ban, export ban.

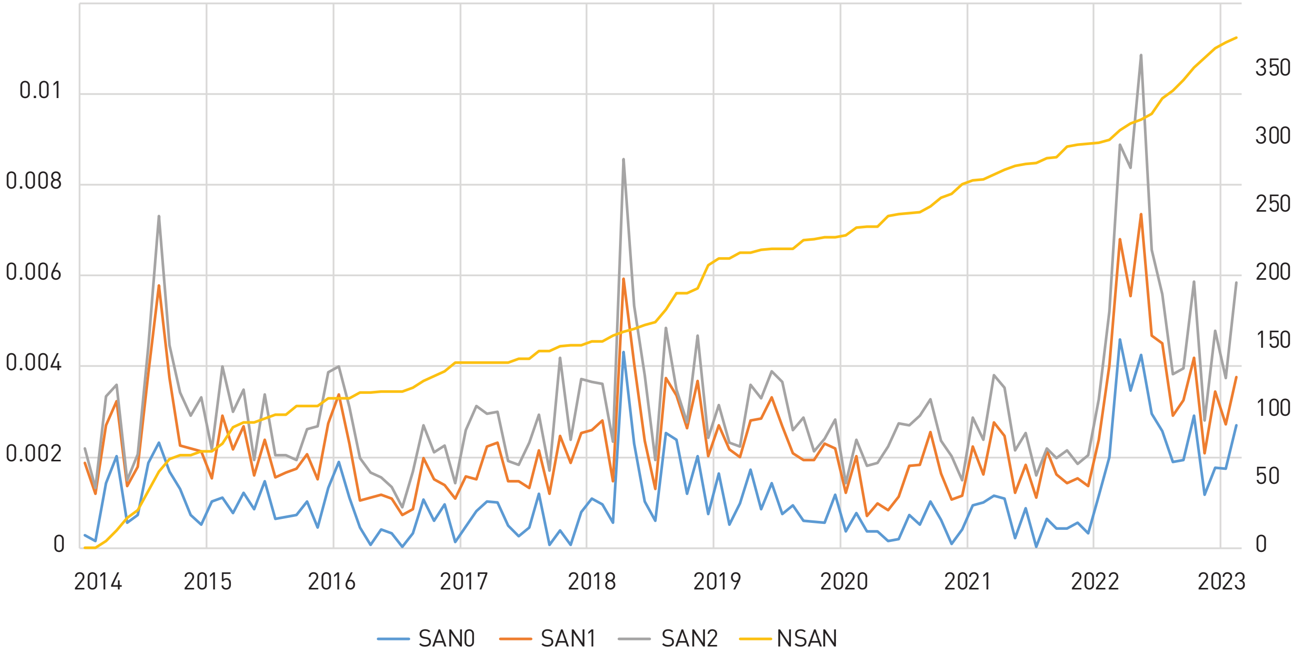
SAN2 – a maximally expanded index which includes rare words and collocations as well as words whose meaning may change significantly according to the context. Some of the words are taken twice. It consists of the following words: sanction, economic sanction, restriction, ban, blockage, block, barrier, import ban, export ban, severe sanction, punitive sanction, restrictive, embargo, retaliation, anti-russian, west sanction, imposing sanction, european union sanction, washington response, western sanction, sanction package, sanction list, new sanction, ruble devaluation, delivery block, sanction pressure, import bar.

Note that that the SAN0 index is similar to the index compiled in [44], while SAN1 is partially similar. The reason is that the indices are constructed with comparable methodologies and are related to the same field. Nevertheless, [44] uses mainly expert evaluation, while our index is based on text analysis methods that are widely used in academic research to compile indices. In addition, we apply the BERTopic algorithm to justify the obtained dictionaries. We also compile a significantly expanded SAN2 index which may provide better results.

For testing, the dictionary was used to obtain the sanctions index of news articles from the lenta.ru portal in the rubrics "Economy" and "Science and Technology". All news publications were taken into consideration, which made it possible to trace the share of this topic in the total news and to calculate the sanctions coverage index of news outlets. As our objective was to determine the general level of concern about sanctions in the mass media, we analyzed the whole news corpus for the period from January 2014 to March 2023. Using the index dictionary, we summed up all the occurrences of words from the index in the expurgated text. The index was then calculated as the ratio of the number of found words and collocations to the total number of words in the text.

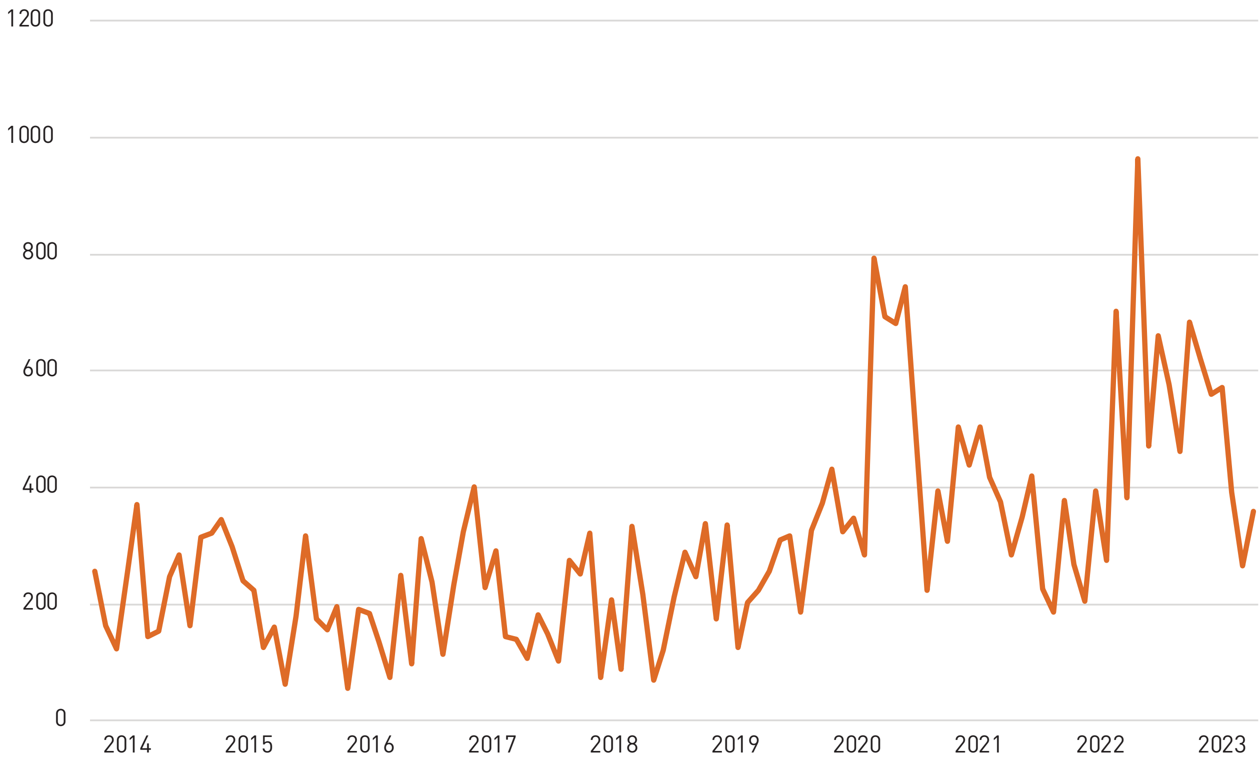
Figure 2 shows the values of the sanctions index calculated by means of text analysis and the NSAN cumulative index of imposed sanctions (or their packages) plotted against a second axis.

Figure 2. Sanctions index for news on the lenta.ru portal in 2014–2023



As we see, the main peaks of sanctions coverage occurred in 2018 and 2022. In 2018, Skripal was poisoned, for which the USA blamed Russia. This justified the second large sanctions package. This was also the year when the European Union imposed sanctions on the company that built the Crimean Bridge. In 2022, the special military operation in Ukraine was launched, triggering new packages of sanctions against Russia. For the sake of comparison, Figure 3 shows the dynamics of the EPU index for Russia for 2014–2023. This index has proved effective in explaining different econometric and financial indicators of the economy as a whole and of individual corporations [33].

Figure 3. Russian EPU index in 2014–2023



Let us now consider the fluctuations of the economic policy uncertainty (EPU) index presented in Figure 3.

The EPU and our compiled indices move in the same direction. Uncertainty remained stable even at the beginning of sanctions and during the introduction of subsequent sanctions packages (in particular, in 2016). However, the COVID-19 pandemic and its lockdowns, whose main impact occurred in 2020, and the events of 2022 increased the uncertainty level manyfold.

On the whole, the compiled sanctions indices appear to coincide with the periods of sanctions. The most complete index SAN2 is more sensitive and responds better to world events than other indices. Appendix A shows the correlation matrix for the sensitive variables of text analysis.

Creation of the Dataset and Descriptive Statistics

To test the index and attain our research objective, we compiled an empiric database including the sectoral indices MOEXOG (oil and gas), MOEXCN (consumer sector) and MOEXTL (telecommunications). They were chosen as the sectors that were the most affected by sanctions and whose index was calculated for the whole period in question (in contrast, the information technology index only began to be calculated in December 2020).

To verify the influence of the general sentiment on the sectoral indices, we evaluated the tonality of news reports that mention the words "sanctions" or "ban". To this end, we used the rulexicon library which offers a dictionary of tones of the Russian language for economic texts [45]. This dictionary allowed us to assess the positivity or negativity of news to obtain the overall tonality (negative or positive) for each day on the basis of the number of positive and negative words in a news article. If several news items were published in one day, they were considered as one text for calculating tonality.

Table 4 shows the descriptive statistics for the compiled empiric database. Over this period, Moscow Exchange indices fluctuated significantly (especially for the oil and gas sector) with up to threefold differences between minimal and maximum indicators. Changes in the Brent oil prices showed a 14-fold difference. As for text analysis, the absolute value of the negative tonality (–0.62) is almost twice as high as that of the positive tonality (0.33), which is quite expected insofar as sanctions were mainly covered in the news from a negative point of view. At the same time, the average tonality did not vary much: –0.13 for the negative tonality versus 0.098 for the positive one.

Table 4. Descriptive statistics

	mean	std	min	max	kurtosis	skewness
MOEXOG	6003.77	1669.57	3066.65	10024.82	–0.89	0.22
MOEXCN	6522.76	1072.31	4499.87	9596.56	0.83	1.28
MOEXTL	1887.59	249.07	1261.74	2434.21	–0.73	0.46
Brent	66.33	21.98	9.12	129.20	–0.17	0.59
RUONIA	8.31	2.85	3.28	28.65	3.50	1.30
Usd-rub	62.91	10.90	33.00	105.27	1.19	–1.09
Negative sent	–0.14	0.08	–0.62	0.00	4.16	–0.17
Positive sent	0.10	0.05	0.00	0.34	1.88	0.54
SAN0	0.00113	0.00482	0	0.06316	40.73	5.82
SAN1	0.00243	0.00713	0	0.09184	21.95	4.23
SAN2	0.00327	0.00938	0	0.10309	23.65	4.38

Figure 4 shows the dynamics of the sentiment (positive or negative) of the coverage of sanctions in 2014–2023. For the sake of convenience, the values are averaged by year, and negativity is presented as minus values. The level of positive sentiment in news articles was roughly the same over the whole period. However, the negative sentiment varied somewhat, with the most negative news reports occurring in 2018 after the introduction of a new package of sanctions. The events of 2022 also led negative sentiments to rise steeply in the news after their decrease in preceding years despite the pandemic.

Figure 4. Sentiment of the coverage of sanctions on the lenta.ru portal in 2014–2023

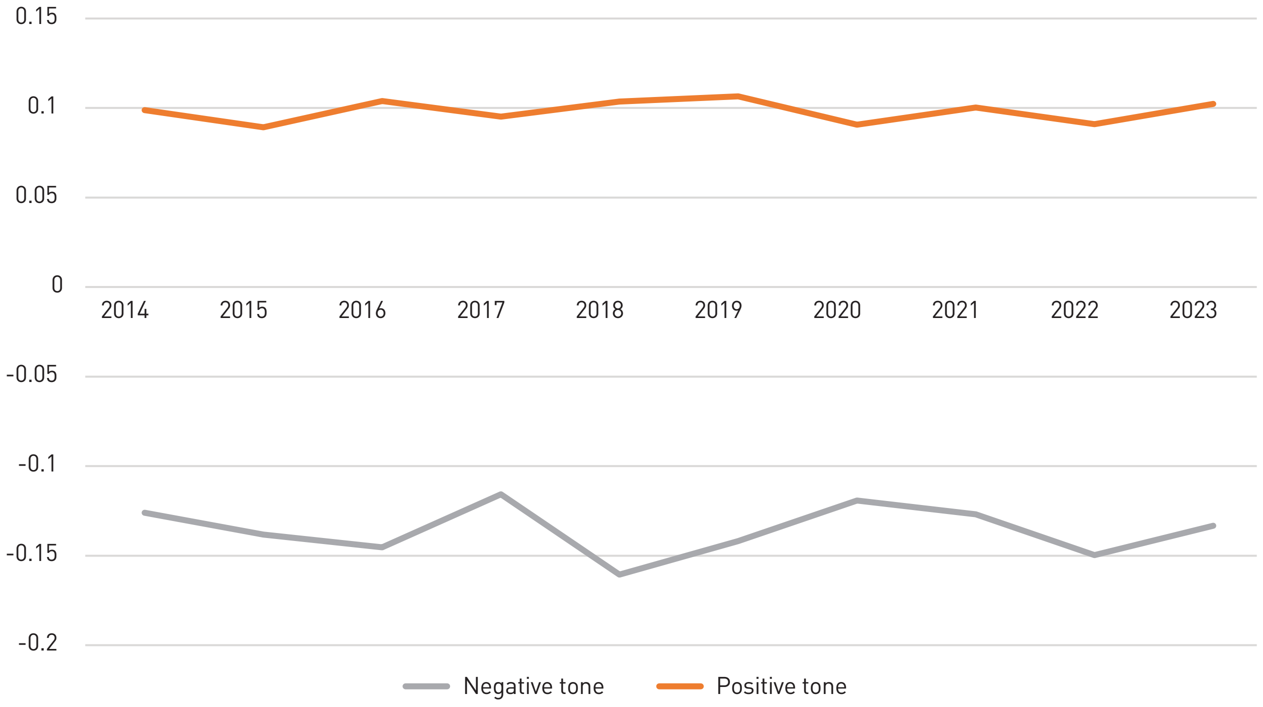


Figure 5. Fundamental economic indicators in 2014–2023 (the Brent oil price and the USD-RUB exchange rate are plotted on the left axis and the RUONIA rate on the right axis)

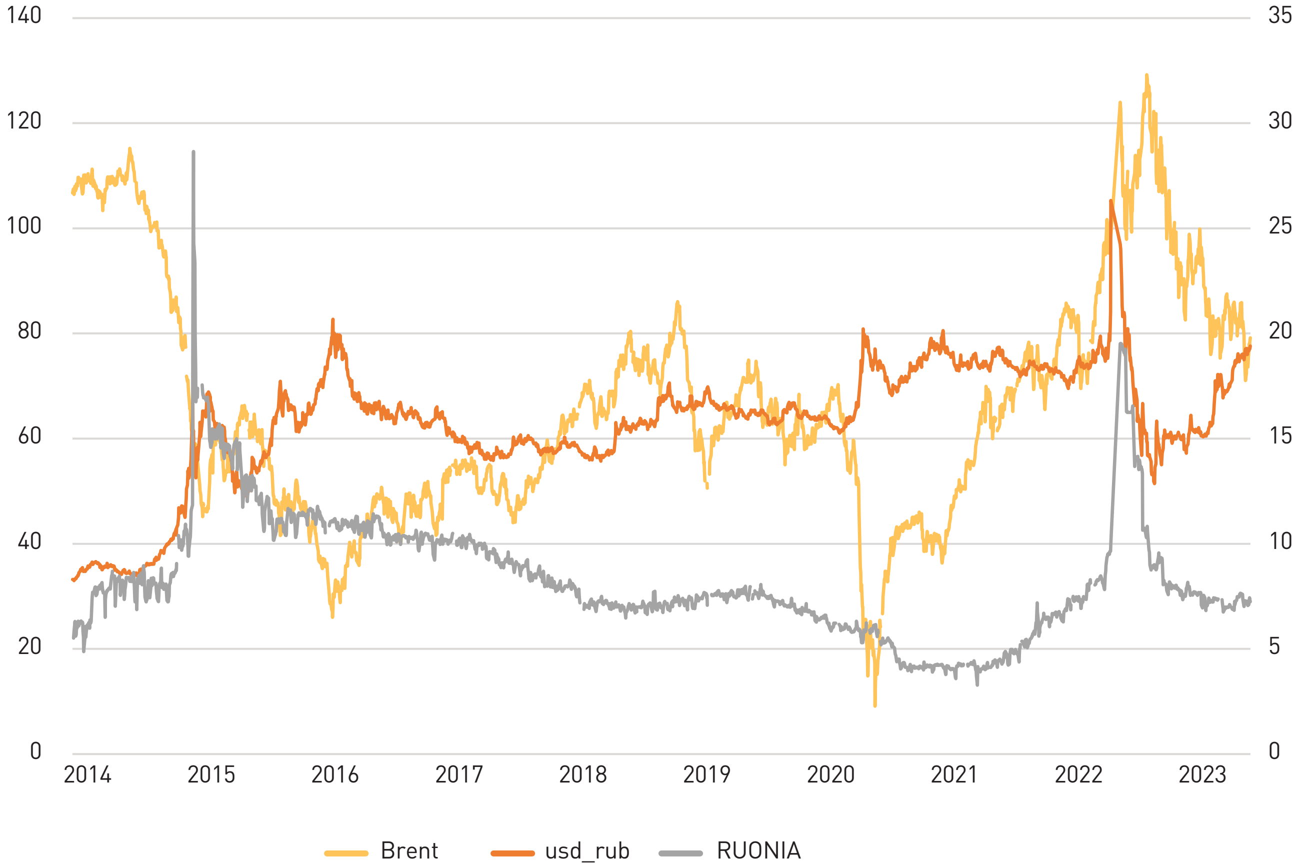


Figure 5 shows the dynamics of the fundamental economic indicators. As we see, the indicators fluctuated significantly during this period and so have to be checked for stationarity.

The statistical test ADF showed that all of the variables are non-stationary (Table 5). As a result, we transformed them as follows: we used the logarithmic profitability of the dollar-ruble exchange rate and of the Brent oil price (the first logarithms of difference) and the increment of the RUONIA rate and the sectoral indices.

Table 5. Testing the stationarity of time series for economic indicators and MOEX sectoral indices

Time series	statistics	p-value	lag
	Initial data in levels		
USD-RUB	−2.826	0.057	2
Brent	−2.578	0.10	1
RUONIA	−2.463	0.127	0
MOEXOG	−1.66	0.44	0
MOEXCN	−2.10	0.24	1
MOEXTL	−2.49	0.12	0
	Transformed data		
USD-RUB (log profitability)	−7.456	0.0	1
Brent (log profitability)	−8.013	0.0	1
RUONIA (increment)	−8.704	0.0	0
MOEXOG (increment)	−9.058	0.0	0
MOEXCN (increment)	−7.695	0.0	0
MOEXTL (increment)	−10.447	0.0	0

Note. The zero hypothesis of the ADF test posits the presence of at least one unit root in the model with a constant and trend.

The calculated values of the indices and the sentiment variables of news pass the ADF test and so require no further processing.

We also checked for the autocorrelation of sectoral MOEX indices. To this end, we calculated the autocorrelation function and performed the Ljung-Box Q-test with one lag (for evaluating the influence of the exchange rates of the preceding month). The analysis showed that autocorrelation effects were statistically insignificant at the 5% level and that the hypothesis of the absence of autocorrelation is not rejected by the Q-test at the 5% level (p-value = 0.447). As a result, we did not incorporate any lags of the explained variable into the model.

Research Results

We began by considering the significance of variables singled out by the elastic net. The results are shown in Table 6. As we calculated the monthly values of indicators, the number of observations amounts to 111.

Table 6. Results of the analysis of variable significance using an elastic net

MOEXOG (oil and gas)		MOEXCN (consumer sector)		MOEXTL (telecommunications)	
variable	significance	variable	significance	variable	significance
SAN1	100.00000	SAN2	100.0000	SAN2	100.000
SAN2	71.71046	SAN1	30.9043	SAN1	62.806

MOEXOG (oil and gas)		MOEXCN (consumer sector)		MOEXTL (telecommunications)	
variable	significance	variable	significance	variable	significance
SAN0	61.98518	SAN0	15.6118	SAN0	54.046
Positive sent	5.65517	Positive sent	2.8241	Positive sent	4.338
Negative sent	1.51969	Negative sent	1.224	Negative sent	2.379
brent	0.78532	usd_rub	0.8300	usd_rub	2.252
usd_rub	0.22304	brent	0.4879	brent	1.337
RUONIA	0.08529	RUONIA	0.1283	RUONIA	0.9790
NSAN	0.00000	NSAN	0.0000	NSAN	0.0000

As we see, the sanctions indices and sentiment variables have major significance for the sectoral indices. SAN1 and SAN2 are the most significant indices, while the reduced index SAN1 (comprising only a limited number of words) is highly significant only for the oil and gas sector. As to the complete index, it turns out to be extremely significant for the two other sectors, i.e., any mention of sanctions had an impact on the capitalization of the biggest Russian companies for a month.

Note that the cumulative index NSAN shows zero significance in all models. This is not surprising, because the cumulative sum over the number of imposed sanctions cannot be used efficiently to determine the impact on the rapidly changing real values of the MOEX indices. As this indicator has no explanatory value, it would be unreasonable to add it to the GARCH model for further analysis.

To understand the direction of the impact of sanctions indices and the sentiment of the coverage of sanctions, we built the following models shown in Tables 7–9.

Table 7. Results of modeling the impact of the sanctions index on the MOEXOG (oil and gas) index over the period from 01.01.2014 to 03.31.2023

Parameter	Sanctions indices				
	SAN0	SAN1	SAN2	Negative sent	Positive sent
Control economic variables					
Brent (log profitability)	0.321717 (1.048927)	0.363534 (0.521085)	0.705498 (0.511827)	0.358703 (0.605524)	0.873253 (0.300509)***
USD-RUB (log profitability)	1.358921 (3.780938)	1.243317 (1.745461)	2.196666 (1.573944)	0.433786 (1.374903)	0.773282 (1.473289)
RUONIA (increment)	−0.041242 (0.075004)	−0.010045 (0.054400)	−0.027271 (0.046395)	−0.052850 (0.051667)	−0.018690 (0.070417)
News sentiment estimates					
Negative sent				−2.885422 (0.001363)***	
Positive sent					−3.604029 (0.021829)***
Sanctions indices					
SAN0	−1.175633 (0.021410)***				
SAN1		−1.387106 (0.011191)***			
SAN2			−1.466230 (0.012035)***		
Coefficients of the GARCH component					
C	0.371383 (0.470055)	0.261707 (0.238229)	0.127017 (0.068760)*	0.002223 (0.005077)	0.240305 (0.144030)*
RESID(-1)^2	0.142498 (0.169610)	0.418951 (0.307221)	0.363700 (0.206557)*	−0.076586 (0.054096)	0.450856 (0.280734)*
GARCH(-1)	0.599553 (0.441043)	0.052154 (0.565459)	0.354714 (0.201906)*	1.103563 (0.068865)***	-0.134693 (0.393064)
Model parameters					
LL	−771.1096	−769.7807	−770.0755	−769.2572	−767.9493
AIC	3.285606	2.169224	2.047076	1.794354	2.149633
R-square	0.139063	0.135204	0.135271	0.142757	0.166369

Notes. Levels of statistical significance: *** – 1%, ** – 5%, * – 10%. The standard errors of the model coefficients are enclosed in brackets. LL is the value of the log-likelihood function, and AIC the value of the Akaike information criterion.

As we see, the indices as well as the sentiment of sanctions news are of high statistical significance. At the same time, both positive and negative tonalities have a reverse influence on the index. A negative news sentiment yields a positive value, which is in line with the logic that the more negative the sanctions, the lower the MOEX sectoral index. The reverse influence of positivity may stem from the fact that any mention of sanctions leads to a decrease in these indices.

All the variations of the sanctions index in this case are also significant at the 1% level, confirming the applicability of the constructed sanctions indices.

Now let us examine the MOEXCN (consumer sector) index. The results of modeling its impact are presented in Table 8.

Table 8. Results of modeling the impact of the sanctions index on the MOEXCN (consumer sector) index over the period from 01.01.2014 to 03.31.2023

Parameter	Sanctions indices				
	SAN0	SAN1	SAN2	Negative sent	Positive sent
Control economic variables					
Brent (log profitability)	–0.279697 (0.918740)	0.462660 (0.409400)	0.689196 (0.380670)*	0.367903 (0.297978)	0.939620 (0.356013)***
USD-RUB (log profitability)	2.363858 (3.127183)	0.803080 (1.313489)	3.013663 (1.347928)**	–0.059828 (0.971369)	0.916568 (1.213518)
RUONIA (increment)	–0.036942 (0.064378)	–0.010180 (0.042351)	–0.023763 (0.037848)	–0.042894 (0.035780)	–0.008270 (0.041514)
News sentiment estimates					
Negative sent				–2.998344 (0.021295)***	
Positive sent					–3.622533 (0.018068)***
Sanctions indices					
SAN0	–1.194857 (0.019679)***				
SAN1		–1.410501 (0.009624)***			
SAN2			–1.483773 (0.009335)***		
Coefficients of the GARCH component					
C	0.477527 (1.231639)	0.154908 (0.126259)	0.266242 (0.108291)***	0.022803 (0.031335)	0.131772 (0.060102)**
RESID(-1)^2	0.055852 (0.141834)	0.404597 (0.245154)*	0.461795 (0.199361)*	0.227799 (0.177775)	0.538583 (0.264177)**
GARCH(-1)	0.569588 (1.045114)	0.213034 (0.393130)	–0.179058 (0.257863)	0.735967 (0.185655)***	–0.062262 (0.259481)
Model parameters					
LL	–758.5163	–759.1463	–759.0475	–759.4788	–759.4937
AIC	3.211908	1.925365	1.830697	1.826759	1.369222
R-square	0.153742	0.135963	0.140032	0.116473	0.110886

Notes. Levels of statistical significance: *** – 1%, ** – 5%, * – 10%. The standard errors of the model coefficients are enclosed in brackets. LL is the value of the log-likelihood function, and AIC the value of the Akaike information criterion.

Thus, the results for the index of the consumer sector are quite similar. The sanctions indices as well as the news sentiment have a reverse impact on the value of the MOEX index.

Finally, let us examine the MOEXTL (telecommunications) index. Its dependence on the sanctions indices and sentiment variables is shown in Table 9.

Table 9. Results of modeling the impact of the sanctions index on the MOEXTL (telecommunications) index over the period from 01.01.2014 to 03.31.2023

Parameter	Sanctions indices				
	SAN0	SAN1	SAN2	Negative sent	Positive sent
Control economic variables					
Brent (log profitability)	–0.351165 (0.888679)	0.311104 (0.370737)	0.550950 (0.307118)*	0.287411 (0.283218)	0.357670 (0.549980)
USD-RUB (log profitability)	1.775249 (2.561000)	1.056256 (1.180407)	3.867352 (0.903373)***	0.120831 (0.950268)	0.097597 (1.252678)
RUONIA (increment)	–0.035998 (0.056155)	–0.000798 (0.035394)	–0.023445 (0.029423)	–0.020671 (0.027127)	–0.017101 (0.036578)
News sentiment estimates					
Negative sent				–2.601789 (0.020021)***	
Positive sent					–3.114236 (0.000396)***
Sanctions indices					
SAN0	–1.027443 (0.016183)***				
SAN1		–1.209497 (0.008396)***			
SAN2			–1.258919 (3.30E-10)***		
Coefficients of the GARCH component					
C	0.365459 (2.331351)	0.159012 (0.144144)	0.274344 (0.068583)***	0.033462 (0.037276)	–0.001170 (0.005845)
RESID(-1)^2	0.020320 (0.124020)	0.385468 (0.235487)*	0.503533 (0.148344)***	0.203760 (0.179722)	–0.063577 (0.051764)
GARCH(-1)	0.595496 (2.530895)	0.080459 (0.558507)	–0.499789 (0.164898)***	0.689558 (0.232495)***	1.077361 (0.081332) ***
Model parameters					
LL	–634.2666	–634.5457	-634.3412	-634.7566	–634.8776
AIC	2.921234	1.660978	1.459595	1.598906	1.076629
R-square	0.340179	0.336184	0.338311	0.333536	0.332249

Notes. Levels of statistical significance: *** – 1%, ** – 5%, * – 10%. The standard errors of the model coefficients are enclosed in brackets. LL is the value of the log-likelihood function, and AIC the value of the Akaike information criterion.

The telecommunications sector gives the same results. We can therefore make the following conclusions: (a) sanctions have a significant impact on different sectors of the Russian economy and (b) the rise in sanctions pressure after the introduction of new sanctions can be traced through the text analysis of news publications. All sanctions and news of sanctions have a negative impact on the MOEX indices. We also tested models with lags of sanctions indices and sentiment variables; they were statistically insignificant, however. This shows that news of sanctions has an impact on sectoral stock exchange quotations for a month yet no long-term effects.

Conclusion

First, our research has confirmed previous studies [1–2; 4–6; 11]. Sanctions do influence the capitalization of Russian companies. All our models show a reverse dependence, i.e., sanctions produce a negative impact on the capitalization of the largest companies in the oil and gas, consumer, and telecommunications sectors.

Secondly, the impact of sanctions on stock indices manifests itself in the short run – for a month after the publication of news.

Thirdly, employing a combination of computer-aided analysis (frequency of words and collocations, correlation and BERT topic analysis) and expert analysis, we developed a bag of words which we used to create tools for evaluating sanctions intensity: the SAN0, SAN1 and SAN2 indices. These indices turned out to be significant and may have practical applications for forecasting the capitalization of Russian companies.

Fourthly, we used the elastic net method to show the priority of sentiment variables over control variables, i.e., information about sanctions and its tonality produce a greater impact on the financial market than oil prices, the ruble exchange rate or the interbank rate.

The limitations of our research include the choice of news source. We selected lenta.ru, because it provided the opportunity of parsing news in the long term (in contrast, we were unable to obtain such news from RBC). We decided not to include the rubric "Russia" in the paper insofar as its publications tend to be of a general character and are usually not related to the economy or the impact of sanctions (which is significant for the technique). In the future it may also be interesting to evaluate the impact of sanctions not just on companies but also on the financial market – for example, on the currency exchange rates of friendly and unfriendly countries.

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Appendix

Appendix A

Table A1. Correlation matrix of sensitive variables and sanctions indices

	Negative sent	Positive sent	SAN0	SAN1	SAN2
Negative sent	1				
Positive sent	0.026041	1			
SAN0	−0.58052	−0.10657	1		
SAN1	−0.53066	−0.10429	0.939516	1	
SAN2	−0.563	−0.10368	0.922317	0.96557	1

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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	Regression results		
	Coefficient	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	Regression results		
	Coefficient	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	Coefficient	Regression results 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.

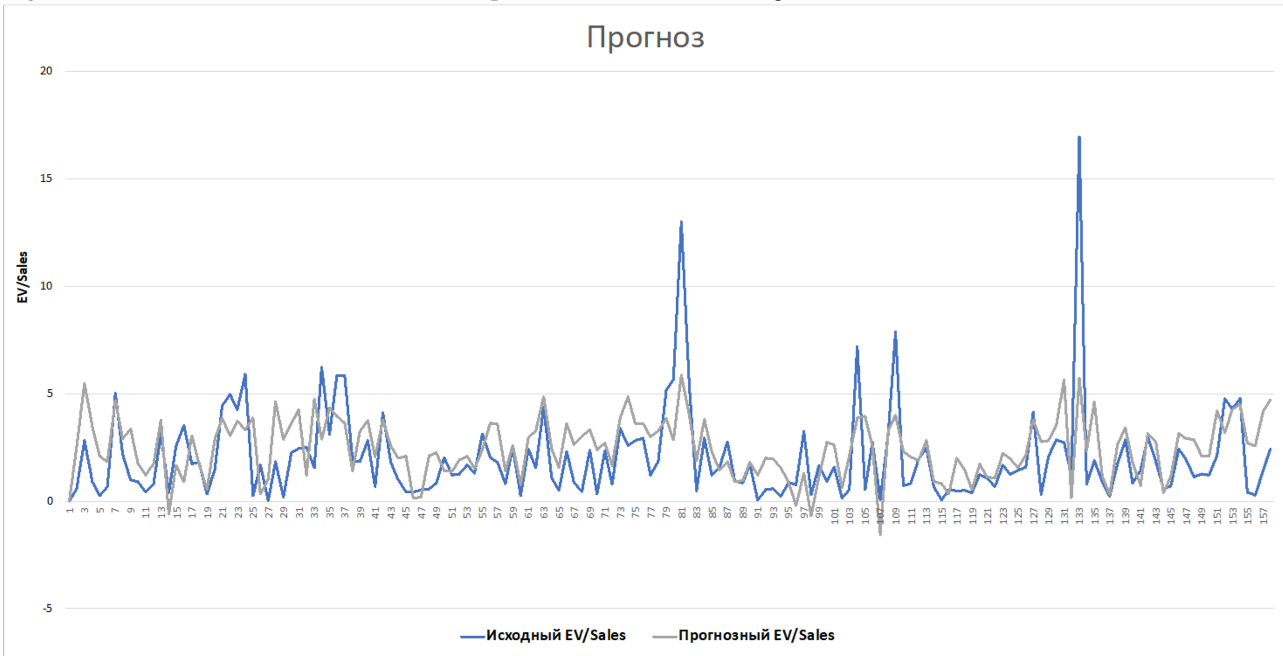
The independent variables are significant at the 5% significance level. The direction of influence of the financial variables is logical from the economic point of view and was described for the previous models, except for *D/EBITDA*. Now let us describe the influence of ESG factors.

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

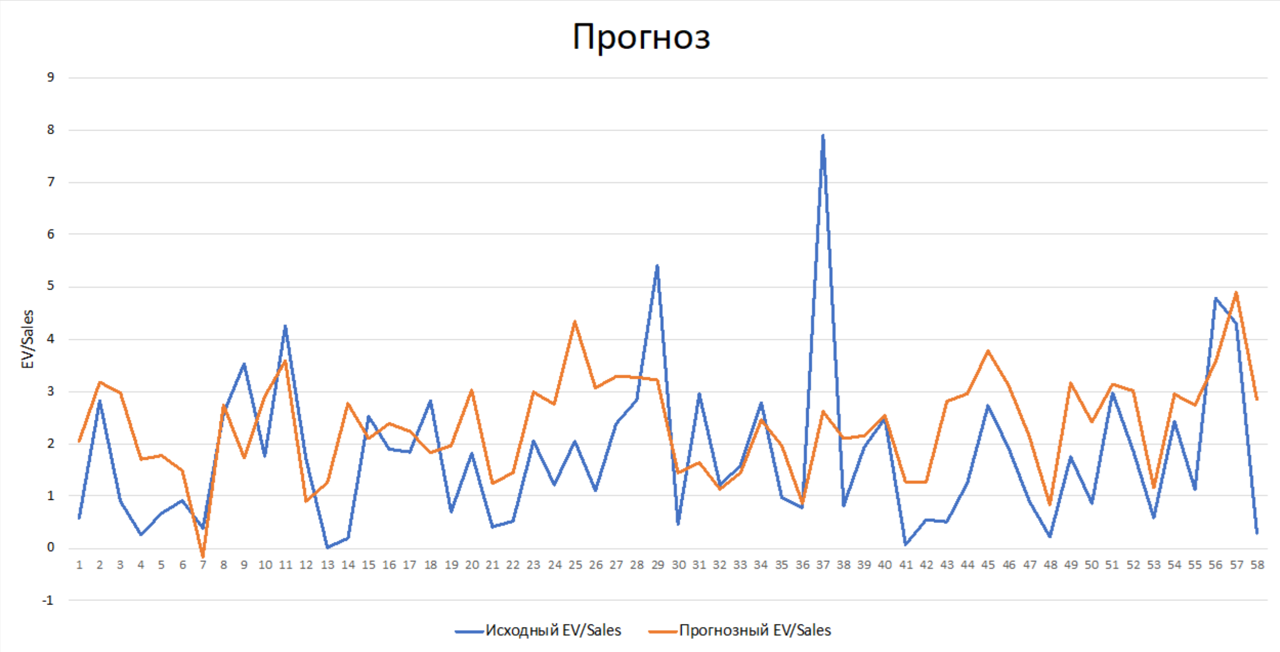


Source: The author's calculations.

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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Dynamic Maintenance of Solvency of the Russian Insurance Companies: the Evidence from Russian Insurers

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Abstract

The Russian economy is facing sanctions pressure, resulting in weakening business relations with foreign insurers. Medium-sized insurance companies, targeting regional economic entities, play a crucial role in the insurance market. To improve the efficiency of Russian insurance, the number of medium-sized companies operating in regional markets must increase. To regulate their capitalization, special conditions must be developed, focusing on capital adequacy requirements and financial stability parameters. While earlier research has examined what factors might impact profitability growth, the investment income factor in maintaining corporate financial stability has been underexplored. This paper aims to explore conditions for improving insurers' financial soundness through growth of a company's internal capitalization. Medium-sized insurance companies often struggle to meet regulators' minimum capital requirements (a core variable linked with companies' capitalization) leading to potential market shrinkage. Our hypothesis is that it possible to create a financial reserve that meets the regulator's increasing equity requirements without raising additional external investments. This study examined the factors which impacted the growth of medium-sized insurance companies operating in the emerging markets. Operating results of seven randomly selected medium-sized insurance companies in 2014–2022 were used for the analysis. The paper suggests that institutionalization of insurance companies' capitalization is crucial to minimize the risk of capital inadequacy. The study contributes to our understanding of how medium-sized insurance companies can be governed and suggests a way to increase their capitalization.

Keywords: financial stability, proportional regulation, dynamic increase of capitalization, equity holding structure of an insurance company

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Introduction

With the sanctions pressure affecting the Russian economy, the business relations of Russian companies with foreign insurers are weakening or severed due to tightening of the foreign exchange legislation and the withdrawal of international brokers, which have provided insurance coverage for owners of multiple property risks, from the system of interaction with insurers. For this reason, the operation of medium-sized insurance companies, which often target their services to the insurance needs of regional economic entities, assumes special importance in the insurance market. Conditions favourable for the development of such insurers will diversify insurance services in the regions and encourage the growth of the insurance sector.

In the author's opinion, a precondition for the improvement of popularity and efficiency of Russian insurance is the increase in the number of medium-sized insurance companies operating in the regional markets as well. For this purpose, it is necessary to develop special conditions to regulate their capitalization. In order to preserve the segment of medium-sized insurance companies, which develop mainly due to internal sources, it is necessary to apply a proportional approach to the regulation of their operations from the viewpoint of capital adequacy requirements and financial stability parameters.

A regular toughening of requirements of the Central Bank of the Russian Federation for minimum equity (according to the terminology of the European Standard Solvency II MCR (Minimum Capital Requirements)) is caused by the expected implementation of Solvency II into the Russian legislation. It is common knowledge that the main goal and at the same time the requirement of Solvency II is to ensure a company's 99.5% reliability within a one-year horizon. Amid the growing inflation, which increases the cost of insurable risks, i.e., the insurer's financial obligations, this makes it necessary to toughen equity requirements in order to provide a sufficient solvency margin.

Besides, the reason for the strengthening of equity requirements is the growth of the insurance portfolio. Risks associated with the insurance portfolio quality, insurance rate adequacy, reinsurance coverage reliability are managed by a mandatory amount of equity called SCR (Solvency Capital Requirement – the capital necessary to ensure solvency) according to the terminology of Solvency II.

However, in order to enter the insurance market without a portfolio, according to Solvency II, the insurer's equity should equal or exceed the established amount or MCR. Presumably, this amount guarantees a company's solvency for the next year with a probability of 85%. This is the limit value of guarantee reliability, and the company's license is cancelled if its unobligated equity is less than the MCR amount established by the regulator.

Essentially, the requirements for the minimum capital amount imply its proportional value assessment in comparison to the quality and value of the existing portfolio. However, in the Russian Federation these requirements are the same for all insurance companies irrespective of the amount of the risks for which insurance coverage is provided.

Increasingly toughening requirements for the MCR amount may be met by attracting additional shareholder investments or by means of a company's internal growth stemming from its high profitability.

A lot of research papers are dedicated to the analysis of possible factors of insurance operations' profitability growth. However, they do not consider the investment income a factor in maintaining corporate financial stability. We failed to find the papers that describe provision of institutional conditions for improvement of insurers' financial soundness by means of growth of a company's internal capitalization. The present research attempts to fill this gap.

As we have mentioned before, the role of MCR consists, first, in ensuring the solvency of a company when it starts its business and has not yet accumulated sufficient insurance reserves to distribute the risk to insurance population; and second, in being a "cash cushion" in case of insolvency caused by business risks coming to fruition, thus producing an unexpected negative effect on the insurance company's financial soundness. This is why the amount of corporate equity cannot be less than the minimal amount established by the regulator.

The value of insurable risks actually grows with time; besides, as the insurance portfolio expands, it increases the need to raise the minimal capital amount, which guarantees company solvency in case of decrease in replenishment of insurance reserves. Due to the fact that the established amount of minimal capital loses its guaranteeing power, it gradually becomes possible for the minimal capital requirements to be officially met, while the guaranteeing power is partially lost due to practical reasons. However, often insurers of medium-sized companies are unable to adhere to the regulator's minimal capital requirements. This may force medium-sized companies out of the market and cause abrupt market shrinkage in spite of a significant potential of these companies to develop the sector of economy in which they operate [1].

The above reasons make highly relevant the institutionalization of insurance companies' capitalization, which minimizes the risk of their capital inadequacy caused by the tightening of requirements for the capital amount.

Literature Review

The author adheres to the view that the basis for the development of the non-life insurance market in Russia is the growth of specifically medium-sized insurance companies, which often operate in the regions and have a high potential. The factors that positively and negatively affect the development of this sector were the subject of special research [2; 3].

The potential for development of medium-sized insurance companies is related to the following factors. First, it is the median amount of equity as the basis for calculation of profitability and, second, it is the understanding of the insured and their insurance needs, which allows to create a well-balanced insurance portfolio of small homogeneous risks that may be accepted for insurance, taking the existing equity into consideration [4]. Such homogeneous portfolios of medium-sized insurers do not actually require a significant equity. Moreover, the MCR regulatory capital requirements are excessive for them when they are seeking their consumer demand niche.

It seems justified to be premised on the study of emerging markets in Asia, Africa, Latin America when analyzing the growth factors of medium-sized insurance companies. The comparison of these countries' national markets with the Russian market seems appropriate due to the similarity of the development level, insurance culture, size of insurance companies, their capitalization and other financial and economic indicators.

As long as the primary objective of an insurance company as a business entity consists in earning profit for its shareholders, the author considers profitability to be the main indicator of insurance business performance. A medium-sized company as a business entity concerned with the growth of its market share may finance its developing projects through internal growth due to a rise in profitability of insurance operations. Such profitability is a reliable way to meet the regulator's requirements to accrue the insurer's internal funds. For this reason, the methods of its increase are studied by insurance professionals in various national markets.

Studies of operations of Turkish insurers show that such variables as debt-to-equity ratio, premium retention ratio, listing status and growth of total assets significantly influence business performance (ROA) as a result of the company's use of capital, including credits. The factors defining the profitability of foreign insurers in the Turkish market are company size, debt-to-equity ratio, underwriting risk, premium retention ratio, listing status and company age, respectively [5]. In addition, the technical profitability ratio and the return on sales ratio of Turkish companies depend greatly on such variables as company size and age, the loss ratio, current ratio and premium growth ratio [6].

In the Canadian insurance market, such variables as size, liquidity, capital proportion, industry-related concentration, share market profitability and GDP growth have a considerable impact on ROA and ROE [7].

An analysis of Serbian insurance companies showed that ROA depends greatly on such variables as income growth, equity ratio, operating costs, premium growth, underwriting risk and the size of the market share [8].

Study of insurance markets of the four Central and Eastern Europe countries (Croatia, Slovenia, Hungary and Poland) revealed that an increase in such variables as company age and gross domestic product (GDP) has a major influence on ROA and ROE in these markets [9].

The main tools for maintaining financial stability of insurance companies in the emerging markets of various countries were analyzed by the authors using a wide range of its indicators. The results of such research may serve as a basis for decision-making regarding the management of insurance efficiency, and first and foremost, improvement of insurance profitability. The emphasis is placed on revealing its growth factors. Such growth satisfies the interests of all company stakeholders and increases the wealth of shareholders by means of raising company value and guaranteeing insurance protection using internal funds in the interests of the insured. In particular, I.Abdeljawad et al. point out that high profitability strengthens company solvency, which is very important for risk counteraction and fulfillment of obligations to the insured and, consequently, for achieving the insurance objectives [10]. Besides, the insurer obtains more opportunities to raise payments to human capital serving the interests of employees and more weight in the reinsurance market.

Consequently, it is quite clear why researchers are so interested in the tools that allow to manage the insurer's profitability and in the factors that have both a positive and negative impact on it.

The research study by L.Tsvetkova et al. found that ROA had a positive relationship with the company size, ROE, the liquidity ratio and the claim ratio. According to these authors, inflation and premium growth rates have a negative relationship with ROA [11].

In order to be unbiassed, we should note that few researchers share this view. For instance, according to analytics of Saudi Arabia's insurance market, the liquidity ratio and the company size have no significant influence on ROA, i.e., in compliance with the model selected by such authors, company profitability depends mainly on the premium growth rate, leverage, loss ratio and company age, rather than the insurance company size [12].

Papers of the abovementioned authors are of practical interest for managers of insurance companies who seek to solve not just the problem of satisfying shareholders' interests by means of raising insurance profitability, but also that of an equity increase in order to meet the regulator's equity requirements . This may be done by way of choosing an efficient business model for company management.

M.Lament and S.Bukowski prove a specific influence of the business model on the efficiency of insurance companies, in particular, on ROE, ROA, customer retention rate (RR) and the combined ratio (CR) [13]. A. Al-Mutairi et al. confirmed the influence of the company profitability on its value in their studies [14].

M. Balytska discovered the general sources of financial stability and the most important source among them. This author believes that capital adequacy is secured not so much by the financial flow volume as by its constancy in the continuously changing environment [15]. In her opinion, state regulation of insurance is of particular importance.

A paper by L.Ben Dhiab is dedicated to the study of profitability factors as the source of an insurance company's growth. Analyzing the insurance market of Saudi Arabia, the author concludes that there is a recursive link between the rise in company capitalization and the increase in its profitability, which means that a regular capitalization of the gained profit is necessary [12].

The paper by S.V. Mkrtychev et al. examines the creation of an efficient operating activity contour, that increases the payoff from expenses and the profit, which, in its turn, ensures capitalization growth, as an instrument for the increase of the insurer's capitalization [16].

As far back as 1996, R. Kopcke pointed out the significance of profit, which, while intended to ensure shareholders' interests, mostly provides for the financial stability of the insurer in the interests of the insured. This author emphasized: "Shareholders' income is, first of all, a financial shock-absorber which protects interests of the insured" [17].

It is interesting that R. Kopcke indicated the relationship between the capitalization amount and frequency of regulator's control of its amount, which forces the company to continuously use the earned profit for equity replenishment. At the same time, the insurer has to make a decision on further capitalization based on the self-control of the capital inadequacy risk. This provision was stated later in the principle of management of financial stability of an insurance company, taking into consideration the risk that underlies the Solvency II standard. The abovementioned author indicates that shareholders are obliged to participate in the creation of the "cash cushion" using undistributed profit, which is of special importance for a steady growth of medium-sized insurance companies relying on internal capital sources.

Using the profits earned by conducting insurance operations in order to accumulate equity may be opposed by shareholders who, according to the Gordon model, are determined to get regular dividend payments. Apart from that, the regulator's requirements for equity investment tools decrease the prospective investment income, thus impairing the effectiveness of investments for shareholders. Hence, it is necessary to find a way to meet the tightening requirements for the minimal capital amount and solvency margin that would give the maximum consideration to shareholders' interests and ensure continuity of business.

A regular strengthening of requirements for the minimal equity amount in Russia was accompanied by a massive withdrawal from the market of medium-sized insurers, who were unable to attract extra funding from their shareholders or to find new investors. Equity buildup through the business model based on the internal growth could assist in a gradual equity increment, i.e., ensure the correspondence of the actual equity amount to the required amount. This will improve the company's financial stability and its market share due to an enhanced ability to accept more insurance risks for insurance. As a result, corporate assets and value will grow and interests of shareholders will be respected.

Acknowledging the significance of the internal growth strategy for medium-sized insurers, the researchers emphasize the success of this strategy depending on the equity structure as an aggregate of the minimally required (MCR) and additional (SCR) capital. J.Rudden considers, in particular, the minimum capital requirement (MCR) ratio in Europe as a characteristic feature of this structure. He concluded that this ratio depends on the development level of the national insurance market, which manifests itself in the volume of operations [18]. In the opinion of this author, establishing the correlation between the MCR and SCR value (provided for in the Solvency II standard) that is optimal for the market, should be used to make the decision regarding the necessity of tightening the minimum capital requirements. At the same time, this correlation is established fairly depending on the volume of performed insurance operations.

A researcher of the emerging insurance market of India N. Mor in his paper The Prudence of Lower Minimum Capital Requirements for Insurers introduces the same idea. In particular, this paper indicates that there is a high impoverishment rate among Indian households, and the range of risks they are able to insure is very narrow. Consequently, the assets which secure the assumed obligations will also be small. This also predetermines a slackening of the requirements both for the total and minimal capital [19].

Some authors indicate a negative influence of inflation on corporate solvency [11], however, the majority of studies do not detect such an influence. For example, the papers that analyze solvency factors do not indicate inflation as a factor that influences financial performance in the insurance sector [20].

Nevertheless, inflation is precisely the reason for the regulator's tightening of the requirements for minimum capital, the amount of which defines a company's right to start and conduct insurance operations. Hence, in order to obtain this right, the insurer has to ensure dynamic capitalization growth, which will prevent a decrease of equity below the required level when the regulator strengthens the requirements for such insurers.

An abrupt tightening of the minimum capital requirements has a "stunning" effect on the market. It is a variation of shock, and as a response, insurance offers shrink both in terms of the amount (because a lot of insurance companies exit the market) and diversity (because medium-sized companies merge with each other or with large companies, so the merged companies offer a single set of insurance products). Meeting the capitalization requirement by way of attracting additional shareholders' capital or new shareholders is unattractive because if the market share is preserved, ROE will be reduced, thus lowering the shareholder satisfaction level. As for mergers, they will decrease market competitiveness [21].

To resolve the situation which occurs when minimum capital growth requirements are fulfilled, a the system of capital growth management that does not significantly lower the shareholders' satisfaction can be implemented. In order to state the basic provisions of this system, we offer a specific point of view concerning the functions of the minimum capital amount.

The main hypothesis

The author's main hypothesis comprises the following provisions.

1) The minimum required capital of an insurance company may be considered analogous to corporate fixed capital because when it is insufficient or absent, the company is unable to render insurance services and cannot be considered an insurer.
2) The amount of such capital is designated to maintain the solvency of the insurance company in case of insufficiency of its assets created by using the funds obtained from the insured both at the start of insurance business and in case of a sudden decrease in the current asset flow gained from the sale of insurance services to them.
3) If we stick to the suggested hypothesis on the fundamental nature of the minimum capital, it seems necessary to take measures aimed at the preservation of its value by way of "quasi-depreciation deductions" in order to compensate for the reduction in its "guaranteeing capability" caused by inflation and the increase in the offer of insurance services. These deductions will provide a gain of the depreciating capital and compliance of MCR with new requirements.

The following grounding is offered to prove the suggested hypothesis.

The strengthening of requirements for the minimum capital amount is caused by inflation, which decreases its actual guaranteeing capability due to increase in the value of insurable risks. A company's failure to meet these requirements deprives it of the opportunity to offer insurance services. In this respect, it appears necessary to mitigate the risk of such a situation as inflation grows. If we consider inflation the reason for capital depreciation and its required amount - the precondition for starting to render insurance services, we may substantiate the role of minimum capital as fixed capital.

This point of view is presented in the paper by L.I. Tsvetkova Fixed and Working Capital of the Insurance Company. The author's reasoning is based on the traditional capital structure, namely, its division into fixed and working capital. These structural units differ in the intensity of value "transfer" to the manufactured product or created service. The key distinctive feature of fixed capital (as compared to working capital) is the gradual "transfer" of its value to the manufactured product [22].

It is commonly known that in order to obtain an insurance license, i.e., to be able to start an insurance business, the legislation established a minimal amount of authorized capital that the insurer must have at the start of its business. It is precisely because this capital amount provides the actual opportunity for an insurance services provider to operate, it is logical to consider it the fixed capital of an insurance organization. Since in the course of time and due to inflation the value of the property interests offered for insurance increases and requirements for the guaranteeing capital tighten, a corresponding growth of minimum capital is necessary.

The above reasoning allows to use the notion of "depreciation" when describing the amount of the minimum capital requirements due to a decrease in its sufficiency. This specific relative "depreciation" of the minimum capital amount is at least at the inflation level.

As long as the value of individual property interests offered for insurance grows along with inflation and the regulator's requirements to allocation of the assets that secure the investment income are rather strict, it is necessary to reduce the insurer's taxation basis by the amount of such investment income, which offsets inflation. This income should be transferred to a "depreciation reserve" with a strict intended purpose. If the income from the allocation of fixed capital exceeds the official inflation rate, only the exceedance amount may be subject to taxation.

This dynamically growing guaranteeing reserve solves the problem of bringing internal funds into compliance with the requirements, including the strengthening requirements for the minimum capital amount.

Each insurance company should have the right but not be obligated to build up such a reserve guaranteeing the improvement of solvency (or the "depreciation reserve"). The company may choose not to accumulate the investment income in such reserve designated for capitalization as a way to compensate for the depreciation of fixed capital, however, it is perfectly natural that in this case the reserve may be utilized by shareholders and is subject to taxation.

Methods

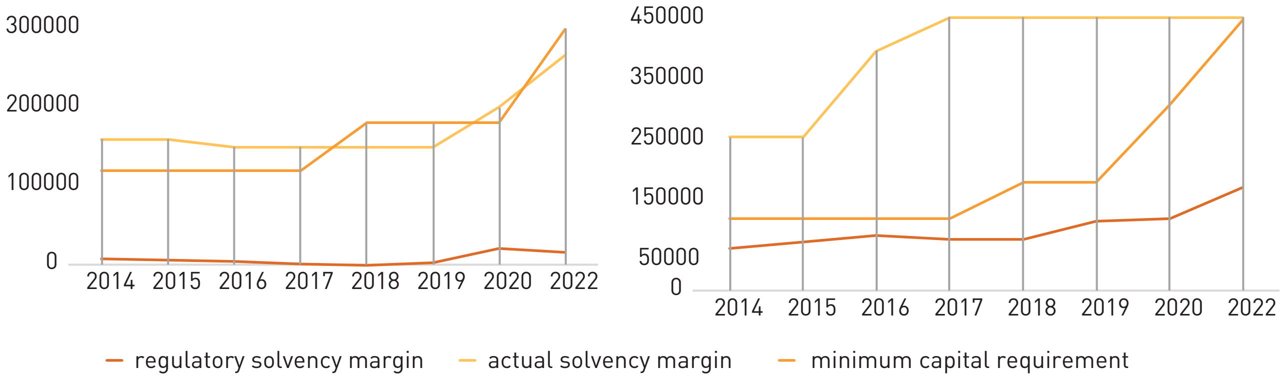
An analysis of dynamics of insurance companies' solvency at the time of strengthening of requirements for its permissible limits is a method for verifying the advanced hypothesis regarding the efficiency of maintaining insurance companies' solvency at the level established by the regulator. This analysis implies the creation of an additional solvency reserve by means of capitalization of the income from allocation of the minimum capital amount when such income is exempt from taxation.

The analysis was conducted in two stages and used the operating results of seven randomly selected medium-sized insurance companies in 2014–2022 (Figures 1–4).

At the first stage, we considered the relationship between the dynamics of minimum capital requirements and the amount of the actual margin of companies' solvency and the one established by regulations. Figures 1–4 present the dynamics of change in these indicators. The amounts of the regulatory and actual solvency margin are calculated according to the requirements of Directive of the Central Bank of the Russian Federation of 28.07.2015 No. 3743-U[1].

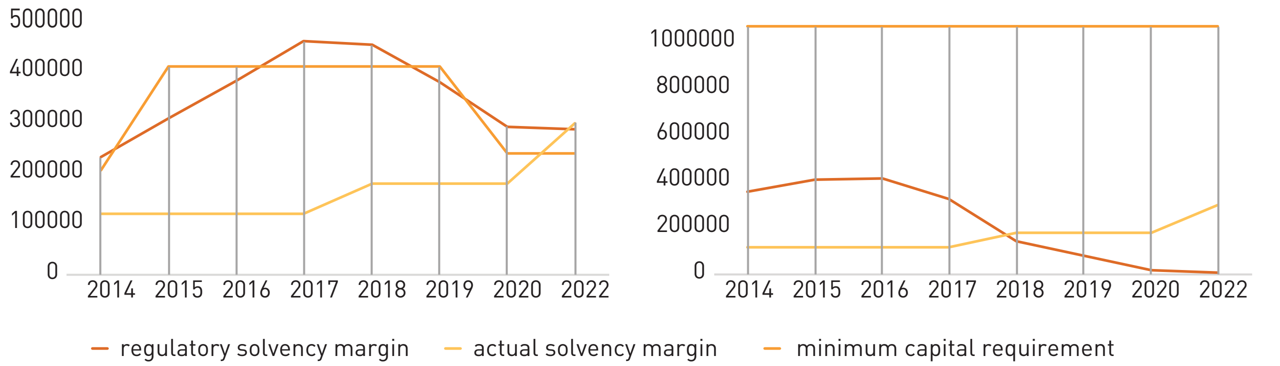
[1] 2021 is excluded from analysis as an uncharacteristic year due to the pandemic.

Figure 1. The dynamics of solvency when changing the requirements for the minimum capital of the Prestige Policy and Kolymskaya insurance companies



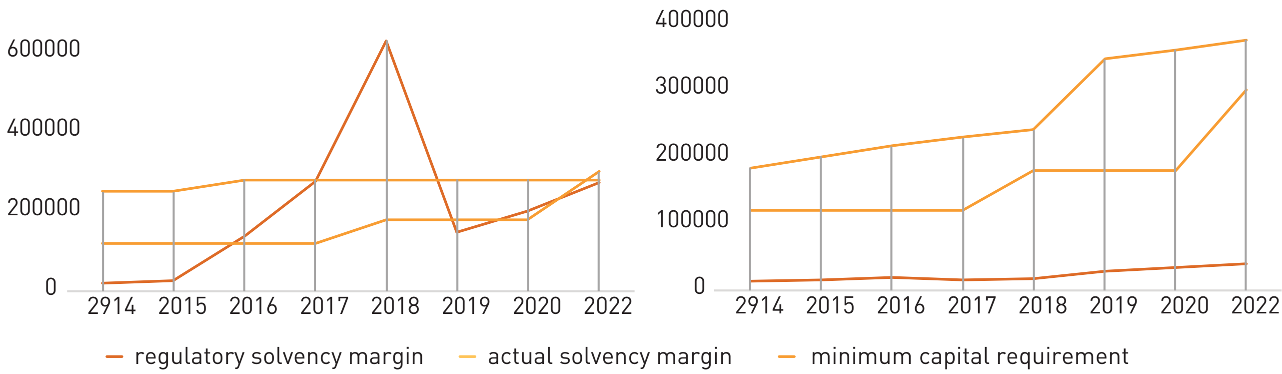
Source: Calculated by the author on the basis of reports of individual insurers. URL: https://cbr.ru/statistics/insurance/report_individual_ins/

Figure 2. The dynamics of solvency when changing the requirements for the minimum capital of the Nadezhda and Bin Insurance insurance companies



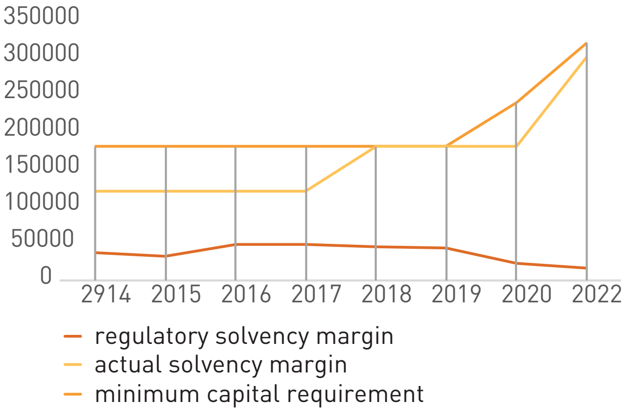
Source: Calculated by the author on the basis of reports of individual insurers. URL: https://cbr.ru/statistics/insurance/report_individual_ins/

Figure 3. The dynamics of solvency when changing the requirements for the minimum capital of the Verna and Ingvar insurance companies



Source: Calculated by the author on the basis of reports of individual insurers. URL: ht tps://cbr.ru/statistics/insurance/report_individual_ins/

Figure 4. The dynamics of solvency when changing the requirements for the minimum capital of the Dal-Jaso insurance company



Source: Calculated by the author on the basis of reports of individual insurers. URL: https://cbr.ru/statistics/insurance/report_individual_ins/

As we see from schedules in Figures 1–4, the following companies experienced difficulties with solvency within the analyzed period:

- IC Prestige Policy;
- IC Nadezhda;
- IC Verna;
- IC Dal-Jaso.

In 2017–2018 all companies showed a significant excess of MCR over the regulatory solvency margin, or these requirements exceeded the actual solvency margin.

While the first group of problems, essentially refers to the fact that requirements for capitalization of these companies are excessive, the second group is indicative of a high insolvency and bankruptcy risk or an insolvency that has already occurred.

Both groups are quite dangerous, and the differences between them imply different approaches to solving the associated problems.

1) Excess capitalization affects the interests of shareholders and should cause capital outflow because it reduces profitability. Hence, it is logical to lower the minimum capital requirements for these companies.
2) If the actual margin is below MCR, it is unacceptable from the regulator's point of view, it affects the interests of the insured, and the company's ability to fulfill its obligations to the insured becomes problematic.
3) If the regulatory margin exceeds the actual margin, it is a sign of insolvency.

As we know, corporate undercapitalization becomes apparent on the date of submitting the financial statements, when it is too late to take any measures. The loss of solvency takes place gradually during the whole reporting period due to excessive accepted risks. Of course, a decrease of excessiveness of insurance commitments is achieved by an efficient reinsurance strategy. However, in order to raise ROA, medium-sized companies try to accumulate working capital which is why is it not used for the necessary reinsurance protection.

It follows herefrom that during the period of accumulation of the insurance portfolio, it is reasonable to take measures for a dynamic increase of insurance companies' solvency, which, in its turn, will ensure their readiness to comply with tightened regulator's requirements for the MCR level.

If we consider the capital amount at the MCR level fixed capital, the loss of its value caused by inflation - "depreciation", and the income from its investment – "depreciation deductions," a regular capitalization of profit from its allocation equaling inflation may be added to the strategy of capital management of an insurance company.

The results of maintenance of insurance companies' solvency when applying the offered strategy were verified by analyzing the dynamics of the estimated theoretical solvency margin of insurance companies selected for analysis.

The algorithm of calculation of the theoretical solvency margin introduced to the analysis comprises the following:

- calculation of income from allocation of minimum capital amounting to the key rate of the Central Bank of Russia valid in the period in question (another calendar year);
- accumulation of the depreciation reserve through an incoming annual transfer of the investment income from the minimum required equity;
- increase of the actual solvency margin calculated on the basis of the standard algorithm by the amount of the depreciation reserve made up of the investment income accumulated by the end of another year.

The hypothesis of efficiency of the reserve that compensates for depreciation was considered confirmed if the insurer had enough capital to meet regulator's tightened requirements for the MCR amount as of the time of their tightening.

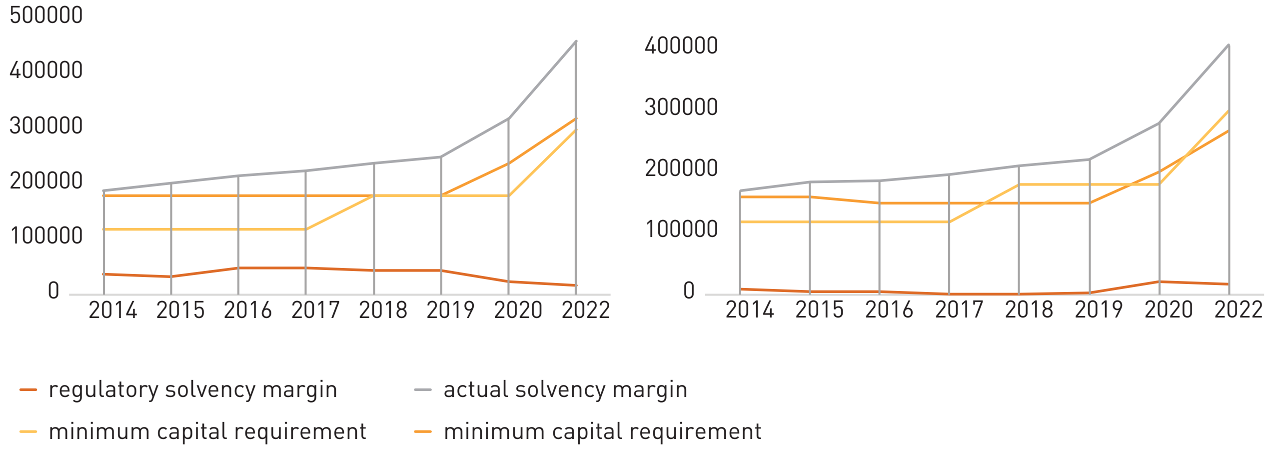
Results

The results of calculations on the efficiency of the offered approach are presented in Figures 5 and 6, which demonstrate the dynamics of the theoretical solvency margin.

The actual solvency margin of the first two companies – Dal-Jaso and Prestige Policy – exceeded the regulatory requirement for the whole period of analysis, but there was an insufficiency of equity necessary to meet the minimum capital requirements (Figure 5).

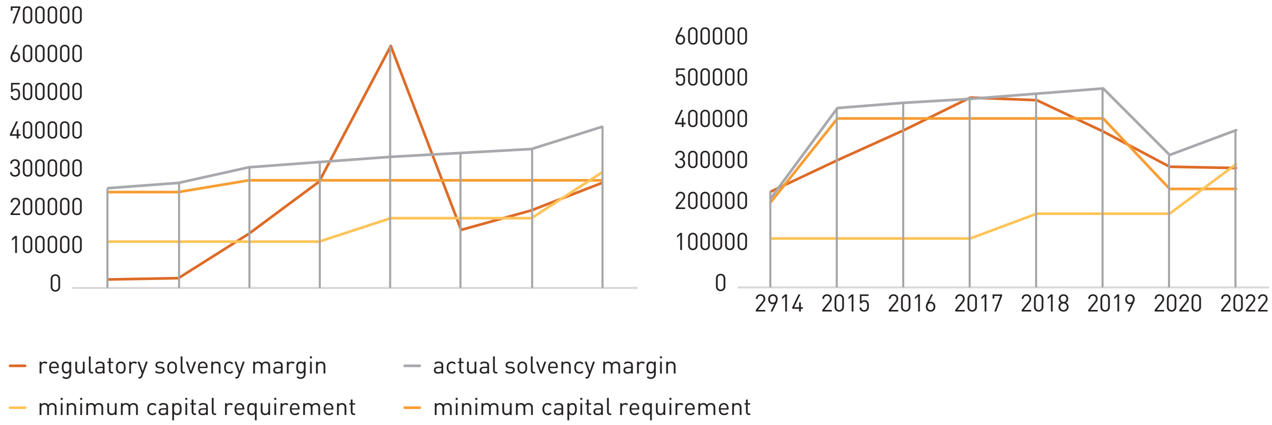
Regular tax-free deductions of the investment income to the "depreciation reserve" could increase the actual solvency margin and ensure the companies' compliance with the requirements for the new amount of minimum required capital in all periods of strengthening of these requirements by the regulator.

Figure 5. Dynamics of maintaining the solvency of the Dal-Jaso and Prestige Policy insurance companies by creating a depreciation reserve



Source: Compiled by the author.

Figure 6. Dynamics of maintaining the solvency of the Verna and Nadezhda insurance companies by creating a depreciation reserve



Source: Compiled by the author.

It follows from the figure that the depreciation reserve could ensure compliance with the tightened requirements for the minimum capital amount without additional lump-sum large-scale investments.

As for the Verna insurance company, the risk of equity deficiency in 2017–2019 was critical. Creating a reserve based on the investment income from allocation of the minimum capital amount still would not solve this problem. However, the solvency problems of the Nadezhda company were solved using such a reserve (Figure 6).

Discussion

The main course of the discussion about the sources of ensuring by insurance companies of conformity to the regulator's requirements on financial stability in the emerging market concerns use of their external and internal nature.

For example, when comparing the ways to increase insurers' capitalization, N.G. Chernova places a priority on M&A (merger and acquisition) as an external growth tool [23]. However, the author agrees that this approach is not always appropriate for small companies, and it often results in their liquidation in case of a takeover by a large federal company. According to N.G. Chernova, small insurance companies may have a rather stable insurance portfolio, and as long as they produce a positive impact on upturn in insurance demand, they should have a right to cost benefits.

In her dissertation, I.V. Grigorenko presents the idea of reasonableness of making additional issues of shares or increasing the value of corporate property in order to meet the requirements for the capitalization of an insurance company. Besides, a decision on the issue should be based on the correlation between the regulatory and actual solvency margin [24].

In the paper by J.D. Cummins et al., capitalization growth is associated with an increase in corporate market value, which serves as shareholders' remuneration [25]. Nevertheless, the paper points out that this rule is not always applicable to emerging markets such as, for example, the Asian insurance market.

M. Eling and R. Jia support the idea of internal growth as a tool for securing the necessary amount of equity. A significant number of studied insurance companies allows these authors to assert that the influence of insurance companies' performance on their profitability and the potential for creation of their equity decrease at some point because high performance requires a raise in the remuneration to the bearers of human capital whose knowledge and competence is related to its growth [26].

Following these authors, P. Zweifel, R. Eisen and D. Eckles also assert that new technology in all sectors of insurance product creation should become the source of corporate capitalization growth. This also implies investment in the quality of human capital and corporate expertise level [27].

Studies of the Tunisian rising market conducted by A.M.-S. Derbali and A. Lamouchi are also dedicated to the analysis of the principal capitalization growth factors of insurance companies from emerging markets. These authors consider efficient management to be one of such factors, along with human capital contribution [28].

Croatian researchers D. Učkar and D. Petrović analyzed the influence of M&A strategies on the development of the national insurance market. The purpose of their research was to define whether large insurers emerging as a result of this process were more efficient than medium-sized and small ones. They concluded that, as a rule, small insurance companies are no less efficient than large ones, while the results of medium-sized insurance companies vary greatly. At the same time, the average efficiency of insurance companies in the market within the observed period of multiple mergers and acquisitions improved, while the gap between the large, medium-sized and small insurers increased further [29].

Conclusion

The technique offered in the present research for the maintenance of compliance with the requirements for medium-sized insurance companies in terms of the MCR amount and general solvency is based on the approach to the nature of minimum capital as fixed capital which loses its guaranteeing capability as a result of inflation.

This assumption allows to speak of the possibility of tax exemptions for the part of the investment income when allocating MCR capital which does not exceed inflation.

This income may be accrued, increasing the actual solvency margin and enabling the company to satisfy the regulator's requirements regarding a regular increase of the minimum amount of the insurer's equity.

At present, the issue of efficiency of the sources of increasing insurance companies' capitalization cannot be considered solved, although the advantage of the internal growth strategy implemented by means of a variety of factors in emerging markets is apparent. In this case the investment income is not typically considered as a separate source or factor of the insurer's capital growth because in a generalized sense it is recognized as the shareholders' property. However, the offered method may maintain the solvency of medium-sized insurance companies provided there are corresponding institutional changes in place to regulate taxation of medium-sized companies implementing the internal growth strategy.

Due to the incomprehensive and incomplete nature of the conducted analysis, the offered research results may be considered to be the first step in the process of its extension to the entire medium-sized insurance business in Russia.

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JEL classification: G30, G40, G41

Determinants of CEO Investment Horizon. A Literature Review

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Abstract

This paper conducts a comprehensive literature review of the factors influencing the emergence of the CEO investment horizon problem – a preference for short-term investments over long-term ones. The root cause of this CEO issue, as indicated in existing literature, is often attributed to the CEO's personal risk attitude, shaped by factors like age, tenure, and cultural background.

Numerous sources contributing to the short-term investment problem in public companies are described in the current academic literature. Prominent among these determinants are the challenges of quarterly reporting, the association of corporate performance with short-term metrics, market pressures, and the company's specific risk profile. A study by McKinsey & Company, focused on the short horizon problem, demonstrates that companies inclined toward short-term investments exhibit weaker fundamentals and performance. The consulting firm Ernst & Young has introduced the Long-term Orientation Index, offering a basis for cross-country comparison of decision horizons. In 2010, Antia and colleagues introduced a metric for measuring CEO decision horizons, which relies on CEO personal characteristics. Despite these efforts, a comprehensive literature review addressing the specificity of the CEO investment horizon problem and its distinctions from the broader corporate investment horizon problem has been absent.

This paper not only investigates the initial empirical exploration of the short investment horizon problem but also raises questions about its cross-country manifestations, its potential correlation with economic crises, and the relevant personal traits of CEOs for its study. Finally, the paper proposes various strategies to mitigate the CEO investment horizon problem within companies.

Keywords: CEO investment horizon, corporate short-termism, CEO horizon problem, CEO behavioral characteristics, behavioral corporate finance

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Anybody can manage short. Anybody can manage long.
Balancing those two things is what management is.

Jack Welch, CEO of General Electric

Introduction

Balance between short-term and long-term planning is an integral part of growth of a public company's market value [1]. Jack Welch quoted in the epigraph to the present paper may have understood it like no other because in the 20 years of his CEO tenure at General Electric his company's capitalization increased by over 2,800%[1].

Some decisions we make provide instant results, but there are decisions that take months and sometimes years to show an observable advantageous effect. Modelling of the decision-making process gets more complicated when actions that result in long-term benefits force managers to disregard short-term results [2]. The converse statement is also true. However, it is more natural for a human to neglect a long-term perspective for the sake of an instant benefit. This is the way decision-making works: due to a fundamental aversion to excessive risk by the cognitive part of our mind we are afraid of a high degree of uncertainty and focus on short-term planning horizons more often than on long-term ones [3].

CEOs may be considered economic operators whose decision-taking enables companies to exist in the market environment, provide capitalization growth as well as maintain and improve their competitive advantages [4]. Therefore, in corporate finance when we consider CEOs in particular, choosing of short-term investment decisions was called, apart from short-termism, the CEO investment horizon problem [5]. Examples of manifestation of the CEO horizon problem are as follows: pursuit of short-term quarterly performance (quarterly reporting problem) [6], especially EPS; distribution of profit to shareholders for dividend payout to the detriment of long-term projects; full or partial abandonment of R&D investments [7] and indisposition to follow innovation trends due to a high degree of their uncertainty [8].

Up to a point one may believe that the CEO horizon problem is a specific problem of several companies, and to solve it one merely has to refrain from interfering and let the invisible hand of the market do its job [9]. However, it is not true. The horizon problem pertains not just to CEOs of companies and shareholders [10]. It affects the interests of all stakeholders [11]. When the investment horizon problem arises in one large company, it subsequently manifests itself in the capital market and, which is even more destructive, at the macroeconomic level – the level of the government. In particular, the pursuit of short-term benefit by the largest banks in 2007 and the global crisis which followed it manifested obvious features of short-termism, and the CEO investment horizon problem is rooted in it. This once again emphasizes the relevance of the issue considered in the present paper.

The paper is a review of the CEO investment horizon problem, based on an analysis of a range of academic sources and business literature. It answers the following questions: where does the study of the CEO investment horizon problem start; how is the insufficiently explored CEO investment horizon problem related to the well-known short-termism problem; how is the CEO investment horizon formed, measured and how can it influence decision-taking in companies; how is culture, through the example of countries, able to influence CEO investment horizons; and finally, what are the ways of solving the horizon problem?

Origin: What Do We Know About the Short-Term Planning Problem in the World?

To ensure the successful growth and improvement in corporate performance, a company needs a steady balance between short-term and long-term investments. However, nowadays the amount of evidence that companies disregard long-term projects is increasing because companies focus a lot on short-term goals. This phenomenon was called "short-termism" across the world. Academic research and study of the largest public companies showed that short-termism results in deterioration of companies' competitivity, an increase in their systemic risk and a decrease in the potential of the whole economy [12]. For example, the study of the short-termism problem conducted by the McKinsey Global Institute showed that companies with strategies focused on a long-term growth in 14 years (since 2001 to 2015) outperformed their competitors in terms of profit by 36%, in terms of revenue – by 47%, market capitalization – by $7 bln. and economic profit growth – by 81%[2].

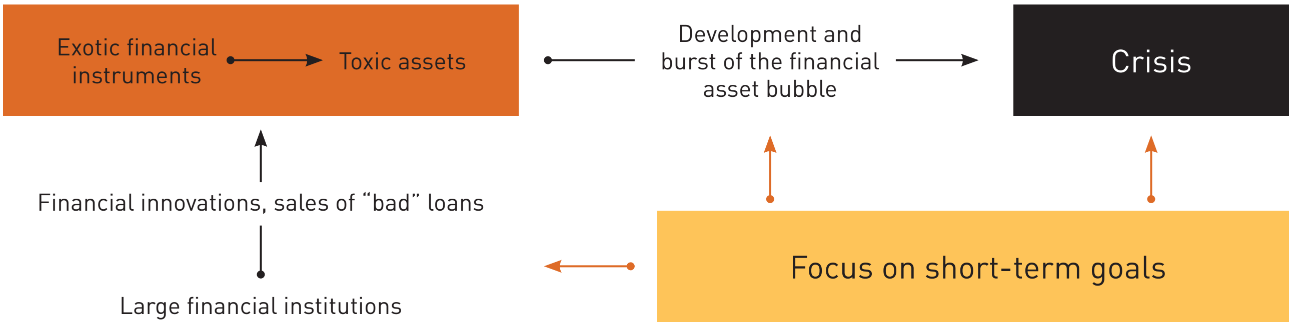
K. Laverty in the paper Managerial Myopia or Systemic Short-Termism? [13] points out the difference between the terms "managerial myopia" and "corporate short-termism," which is of great importance for understanding the approaches to the study of the problem under consideration. For Laverty *corporate short-termism* is a systemic characteristic of an organization that overestimates short-term benefits and underestimates long-term consequences, while *managerial myopia* is a characteristic of the adopted decision when short-term benefits are overestimated and long-term consequences – underestimated. Cultural characteristics, organizational and routine procedures taking place in the company may be factors of short-termism, while the scientist speaking of the market pressure on managers and erratic investment strategies are myopia-related factors. Thus, the optimal temporary decisions for managers become suboptimal for the company.

It is remarkable that English scientists have been discussing the short-termism problem since the late XIX – early XX centuries, since the time of domination of political economics.

[1] GE (2014). Past Leaders, John F. Welch, Jr., Chairman & CEO 1981–2001. URL: http://www.ge.com/about-us/leadership/profiles/john-f-welch-jr

[2] URL: https://www.mckinsey.com/~/media/mckinsey/featured%20insights/long%20term%20capitalism/where%20companies%20with%20a%20long%20term%20view%20outperform%20their%20peers/mgi-measuring-the-economic-impact-of-short-termism.ashx

Figure 1. Short-termism and financial crisis



Source: Study by EY.

W. Jevons wrote: "The untutored savage, like the child, is wholly occupied with the pleasures and the troubles of the moment; the morrow is dimly felt; the limit of his horizon is but a few days off" [14]. A Marshall believed that economic operators act "like the children who pick the plums out of their pudding to eat them at once" [15]. A.C. Pigou asserted that "our telescopic faculty is defective, and we see future pleasures on a diminished scale" [16]. J.M. Keynes when performing his own speculations pointed out that excessive short-term strategies are "antisocial, destructive of confidence, and incompatible with the working of the economic system" [17]. A little later in the post-war period, B. Graham, a teacher of W. Buffett and supporter of value investing [18], was not the only one in America to criticize short-termism. Buffett himself, the investment guru, was of the same opinion. In his 1987 letter to shareholders he quoted B. Graham: "In the short run, the market is a voting machine but in the long run, it is a weighing machine" [3].

Nevertheless, empirical evidence of the short-termism problem was found only in 1964. P. Neild [19] who published his research later in the scientific journal of the University of Cambridge, was the first in the world to compile a questionnaire intended to verify the short-termism hypothesis. The researcher managed to show that the firms, typically expect a return on their investment as quickly as three-five years, while the lifetime of the equipment that provides this return on investment is on average 10 times longer. Soon, using the example of American and British capital markets, which are considered to be the most developed capital markets in the world. evidence was found. It stated that managers were short-sighted in terms of investments, especially those related to advanced technologies, which may pay off only in the long term [20]. It is customary to emphasize in literature a combination of factors that results in managerial short-termism when decisions are made [21]. Different sources distinguish the following factors: commitment of popular managerial methods to short-termism [22], managers' eagerness to build their reputation as soon as possible [23], peculiarities of the national [24] and corporate culture [25].

In order to prove that short-sighted managerial decisions have a negative impact on companies, one may define the following string of factors. First, in 1982 T.K. Lee indicated that horizon of managerial decisions decreased, and investments of companies in R&D were also reduced [26]. Second, in 1985 M.C. Jensen and C.W. Smith reached the conclusion that managers' decision horizons were shorter than those of investors [27]. Third, after the study of managerial myopia in his model, J.C. Stein reveals that managers are always more concerned with stock value at a certain moment [28]. Fourth, it was shown that commitment of corporate managers was limited to their tenure in the company, which started decreasing at the beginning of 2000s [29]. Finally, fifth, M. Antia et al. showed that in the companies with the CEOs who prefer short decision horizons agency costs were higher, the assets' market value was lower and information risk was higher [30].

Finally, the short-termism problem played a key role in causing the global financial crisis of 2007 (Figure 1). Everything started when large US financial institutions aimed to sell as many loans as possible as fast as feasible [12]. The idea was that banks could issue mortgage loans even to those unable to repay them. So called NINJA ("no income, no job and no assets") loans appeared in the banking market. Low interest was established for the issued loans and the loans themselves were gathered in a rather complex financial instrument intended to distribute risk between the financial market participants. The participants were interested in the number of issued loans rather than their quality because the number influenced the resulting bonuses. Therefore, a strong demand for mortgage loans was created, and a bubble formed as a result of a rise in prices of real estate, which, it seemed, would never stop. And then the consequences of short-termism in decision-making became apparent: exotic financial instruments fell short of expectations and were recognized as "toxic assets". A need for an urgent order in banks' balance-sheets, where "toxic assets" prevailed, produced a negative impact on non-financial companies because the majority of them failed to get financial support to continue operations. As a consequence, the crisis spread beyond the boundaries of the USA and affected the whole world.

[3] To the Shareholders of Berkshire Hathaway Inc. URL: https://www.berkshirehathaway.com/letters/1987.html

From Short-Termism in Companies to CEO Investment Decision Horizon

As stated before, people's preference for shorter investment periods manifested itself in economics and finance simultaneously with the beginning of study of the behavioral component of decision-making – since the times of political economics. Nevertheless, there is a key difference between the short-termism problem and the investment horizon problem, which should be discussed here. The studies in this field put an emphasis on the factors that cause short-termism without showing how it influences performance indicators and company's operations [30]. For example, M.E. Porter [31] provides evidence that short-termism is characteristic of the companies that invest little in capital expenditures. R. Henderson [32] indicates insufficient investments in new technology, while R.E. Hoskisson et al. [33] shows that the same happens in case of insufficient investments in R&D. However, the investment horizon problem seems understudied against this background. It happened because of the absence of an organized source of summary information or a unified database containing the cases of public companies, whose analog is presented by Bloomberg for financial data or by CapitalIQ for the data on CEO and boards of directors. While in the existing literature sufficient attention is put on short-termism and the degree of exploration excludes any doubt of its importance, the investment horizon problem, no less the CEO investment horizon problem, is just becoming the subject of frequent discussions, which makes it interesting to consider in the present paper.

First, we are going to give the definition of investment horizon provided by modern academic papers. Nowadays *investment horizon* is understood as the forecast period limited in length, within which it is possible to plan investments in the projects implemented by the company [20]. Investment horizon is the key component of the strategy of any company, which constitutes daily behavioral procedures of decision-making. It should be noted that in particular these decisions allow companies to augment income and competitiveness [34].

Second, we distinguish the CEO investment horizon problem as a special case of the investment horizon problem. According to the upper echelons theory, all decisions made by companies may be reduced to decisions made by the CEO. Putting the CEO at the forefront, we are going to define the role of the human factor in CEO's decision-making to subsequently consider the problem from the viewpoint of CEO's personal traits. In order to solve this problem, we identify two features: personal traits and the cultural background.

Third, we point out the prerequisites of modern scientific theories from the sphere of behavioral corporate finance, which explain the nature of CEOs' decision-making. These prerequisites are as follows: some prerequisites from the theories preceding behavioral economics; prerequisites of the prospect theory; and prerequisites of the behavioral agency theory.

The *agency model* of interaction between managers (agents) and company owners (principals) offered by the Nobel prize winners M. Jensen and W. Meckling [35] is the classical theory which is the first in the study of corporate finance. In the agency theory the key problem is that of opportunistic behavior of managers who are better informed about the state of things in the company than shareholders. This problem is solved by means of incentive mechanisms for managers offered by the owners, which make the managers' preference for short-term and private benefits disadvantageous [36].

The second theory that approximates to behavioral models in corporate finance is the prospect theory of Kahneman and Tversky. In this theory decision-making is considered as a choice made by an economic operator in an uncertain environment, and it affects the economic operator's personal wealth or the expected value growth. The prospect theory provides us with the loss aversion concept, whose extent is individual for each operator and depends on his view of wealth: for some people, loss of $ 1,000 has a serious impact on their wealth, while others won't even notice such an amount.

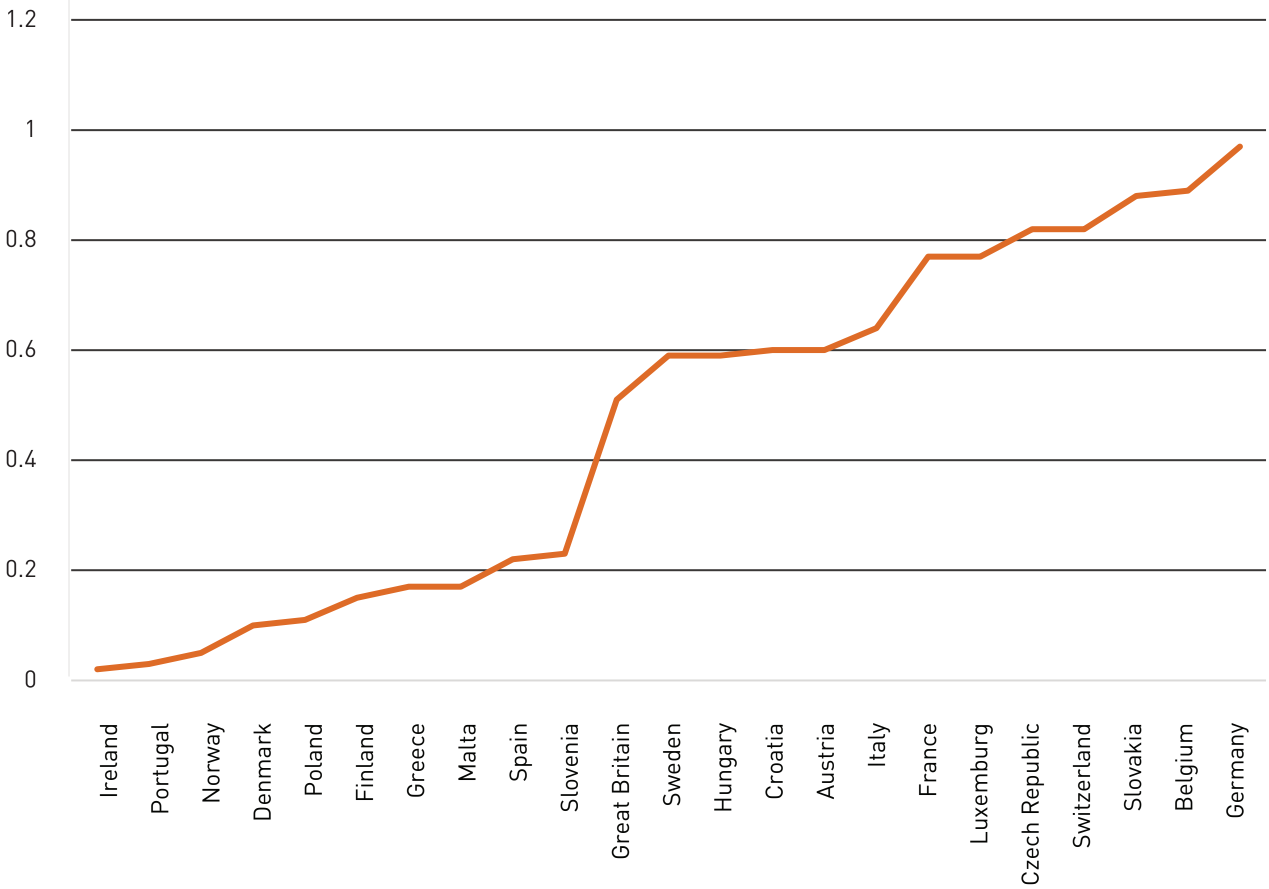
The third theory that determines the behavioral principles of CEO's decision-making is the concept of behavioral agency model. The behavioral agency theory differs from the traditional agency theory in three main aspects, which arise from the prerequisites presented in Table 1.

Table 1. Prerequisites of CEO's behavior within the traditional agency model and behavioral agency model

Prerequisite	CEO in the traditional agency model	CEO in the behavioral agency model
Shareholders' attitude to risk	Shareholders are risk-neutral	Shareholders are risk-neutral or inclined to assume excess risks
CEO's utility function	CEO's utility depends positively on monetary incentive and depends negatively on made efforts	CEO's utility depends positively on monetary incentive and depends negatively on made efforts but with limitations related to rationality, motivation, losses, risk, uncertainty and time preferences

Prerequisite	CEO in the traditional agency model	CEO in the behavioral agency model
CEO rationality	CEOs make rational investment and strategic decisions	CEOs are limited by the obtained information, thus they are rational to a limited extent in their decisions
CEO motivation	Any motivation unrelated to material benefit is absent	The motivation is intrinsic and extrinsic. The two motivation types are not additive and not independent of each other.
CEO's attitude to risk	CEOs demonstrate risk aversion	CEOs demonstrate loss aversion
CEO's attitude to time	The function of CEO time preferences is calculated on the basis of the exponential discount factor	The function of CEO time preferences is calculated on the basis of the hyperbolic discount factor

Figure 2. Empirical function of cumulative distribution of the long-term orientation index



Source: Calculations of EY based on the data by SPIQ, Thomson Reuters and Hofstede (2010).

The behavioral agency theory asserts that the model of the CEO who makes decisions within the traditional agency theory is oversimplified and needs rethinking; the development of a new model that implies limited rationality (instead of complete rationality) acknowledges the importance of human capital of agents (considering human capital as the function of abilities and work motivation). Prerequisites of this theory indicate that when managers are driven by the incentives that relate them to corporate equity, they start using heuristics in strategic decision-making. As a result of use of such heuristics of a completely psychological nature, managers try to change their own wealth by means of influence on corporate business processes.

Thus, the shift from the classical agency model to the behavioral one is contingent on a chain of the following three prerequisites: 1) agents make decisions in an uncertain environment and their choice may have both a positive and negative impact on their own wealth; 2) agents evaluate the expected consequences of their decisions in different ways;

3) agents are short-sighted in their preferences related to loss aversion [37]. Hence, we may say that now we have a set of prerequisites that allows to analyze various CEO investment decisions depending on the personal traits of such CEOs and their cultural background.

Cultural Specifics of CEO Decision-Making

Using the example of Long-Term Orientation Index of Hofstede. which was compiled using the sample of European countries, it is possible to observe how planning depends on culture. As we see in the cumulative distribution schedule (Figure 2) constructed by experts from Ernst and Young, the longest terms are characteristic of Germany, Switzerland, the Netherlands and France, while the shortest ones (short-termism in decision-making) are intrinsic to Ireland, Portugal, Greece, Finland and Poland. Consequently, we may conclude that decision horizons may differ more than tenfold even in geographically close countries.

Nowadays studies in finance examine with increasing frequency the fact that culture is capable of explaining the differences in economic operators' decision-making [38]. However, first, we have to define what is currently understood by culture. For example, G. Hofstede, one of the most prominent researchers in this field, understands culture as "the collective programming of the mind that distinguishes the members of one group or category of people from others" [39, p. 25]. The economist L. Guiso, in his turn, defines culture as "those customary beliefs and values that ethnic, religious, and social groups transmit fairly unchanged from generation to generation" [40]. Professor of the University of Chicago L. Zingales [40] subsequently notes that cultural constructs represented as beliefs and values may, while transforming into individual preferences, be used in behavioral models. Hence, considering the role of cultural specifics in CEO decision-making within the horizon problem may produce results significant for the research [41]. Nevertheless, when considering the CEO horizon problem, it is also highly important to distinguish between national and corporate culture [42–43]. The idea is that national culture is a broader concept based on the nation's values, while corporate culture is based on organizational values of companies formed when they implement certain organizational practices.

Any long-term planning or long-term decision horizon turns out to be risk-bearing. Therefore, we start considering the reasons for the differences between cultural specifics in decision-making in behavioral finance from the research results of M. Statman. Statman titled the principal part of his with comparing people's behavior in the USA and Estonia; then he confessed that "one voice in me said that people are the same all over the world, similar not only in physical features but also in cognition and emotions" [44]. However, this myth was dispelled after he heard two men on a train talking. One of them (from Israel) told the other that he was not planning to support his daughter after the college. Statman was astonished because he knew that in that country it was the other way around, and parents supported children long after they graduated from educational institutions and, probably, that astonishment led him to the empirical results described in his paper. Polls of over 4,000 respondents from 22 countries showed that Americans were ready to risk and switch their current job for a similar one in order to increase their life income (the probability was previously established at 50%) only if the amount of the annual income increase exceeded the amount for which the income could decrease 5 times. It is also remarkable that Chinese and Vietnamese turned out to be most prone to risk. They were ready to change employment if the expected life income was only 3 times more than the possible loss. Even more remarkable is the fact that people from Switzerland and Germany turned out to be the least inclined to risk. In the research presented at the beginning of this section and conducted by Ernst and Young they were long-termists, hence, most risk-prone. These contradictions are quite natural and depend on the methodology applied in the research.

Let us consider and compare management approaches in Russia and China. Russian management practices are often different from the western ones. As noted by Manfred F. Kets de Vries, professor of the business school INSEAD, "an autocratic managerial style is characteristic of Russian managers, they try to impose total control, overreact to uncertainty and have their own way in coping with contemporary challenges"[4]. Ichak Adizes[5] says almost the same about Russian management, adding that the autocratic style stems from Russian culture and history where a manager, leader, seeks and will fight whoever challenges their authority, otherwise their power will be reduced. As a consequence, in such a cultural environment a CEO will be less inclined to take risks and implement changes in the company. It is natural for Russian CEOs to appreciate stability a lot and prefer short-term prospects. Managing director & senior partner at BCG Vladislav Boutenko says the same about the Russian society in general: "According to OECD.stat in Russia life insurance, which is an indicator of planning horizon, is obtained 3.5–5.5 times less than in the OECD countries and China. It means that Russians live right here, right now"[6].

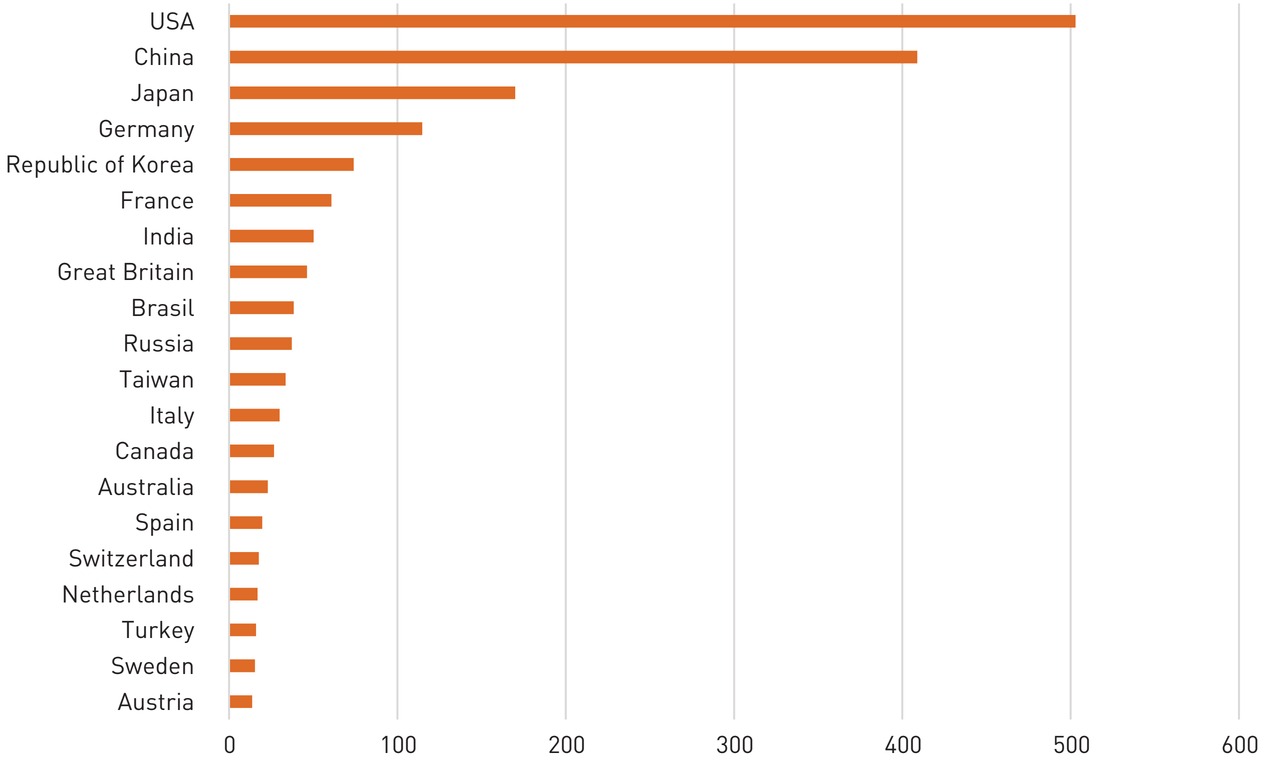
As for China, management practices there differ from both western and Russian practices. Nowadays in China, they take it for granted that the future lies in innovations. After adopting technology from across the globe Chinese managed to get rid of poverty and develop their own world-class technology innovations.

[4] URL: https://hbr-russia.ru/management/upravlenie-personalom/792111/

[5] URL: https://hbr-russia.ru/management/upravlenie-personalom/a11479/

[6] URL: https://hbr-russia.ru/management/strategiya/a24991

Figure 3. List of leading countries in terms of internal research and development costs ($ bln, calculated with regard for the purchasing power parity of national currencies)



Today CEOs of Chinese companies are the leaders who operate in the sphere of artificial intelligence, biotechnology and space exploration; they created Alibaba and Tencent. At the same time, R. Mitter, professor of history and politics of modern China at the University of Oxford, says that authoritarianism still prevails in Chinese culture, but this does not change the fact of innovations[7]. Moreover, the Chinese approach to decision-making and risk perception has little in common with the western perspective. A high volatility of the capital market made Chinese top managers disregard the long-term perspective, therefore, the farther their decision horizon, the more apprehensive they are about risks (another contradiction: but this time it contradicts the results of M. Statman's research about risk proneness). It manifests itself in the investment style. According to E. Johnson, a senior lecturer at the MIT School of Management, 81% of Chinese managers reduce the long-term value of their companies by investing and adjusting blocks of stocks[8]. This indicator is higher not just in comparison to any western country (in the USA it equals 53%), but also in comparison to the neighbouring Hong Kong, whose population is made up of the same nationality. Such conclusions on the influence of culture on investment preferences and horizons are frequently true for CEOs as well.

Thus, in spite of similarity in CEO authoritarianism, CEO attitude to risk, aversion to long-term investment horizons and disposition towards living for today, Russia and China differ rather considerably from each other if we compare these countries from the cultural component perspective. The amount of investment of various countries in research and development may be traced in the same way [45]. Based on the findings of the research conducted in the NRU HSE,[9] in 2016 Russia is the 10th among leaders in this indicator. Russia is behind the USA, which occupy the first position ($ 502.9 bln), almost by a factor of 13 and behind China (the 2nd, $ 408.8 bln) – by a factor of 11 (Figure 3).

In conclusion we would like to state an intriguing difference between CEO remuneration across the globe[10]. According to data for 2014, the lowest remuneration is in Israel, and constitutes the equivalent of 44 salaries of a worker, in Great Britain a CEO earns on average 84 times more; in Australia – 93 times; in Germany – 147 times; finally, in the USA – 354 times. There may be numerous determinants of this difference, from economic to political ones, but, in our opinion, cultural determinants have an important share in this case.

[7] URL: https://hbr-russia.ru/biznes-i-obshchestvo/ekonomika/870324/

[8] URL: https://hbr-russia.ru/biznes-i-obshchestvo/ekonomika/870324/

[9] URL: https://iq.hse.ru/news/209276310.html

[10] URL: https://hbr-russia.ru/biznes-i-obshchestvo/fenomeny/p17835/

Age, Tenure and CEO Investment Horizon

Today one of the principal problems faced by researchers studying CEO decision-making is the unavailability of a sufficient amount of data regarding personal traits to describe a stable sample when the results are transferred to the parent population [46]. D. Hambrik, the author of the upper echelons theory, asserts that it is very difficult to obtain such data because "it is necessary to talk to a lot of directors who, as a rule, are too busy to participate in a poll, experiment or in-depth interview" [47, p. 337]. For this reason, it is determined by history that since it is impossible to measure CEO personal traits (overconfidence, leadership, narcissism etc.) directly, researchers rely on measuring the demographic characteristics [48], which are more easily available. It may comprise age, CEO tenure, professional experience and education, although this list is not exhaustive. In this way, one of the few current indicators measuring the CEO decision-making investment horizon emerged. It consists of two indicators: age and tenure, and was introduced for the first time in 2010 [27]. More on this below. At the same time, we should point out that the above-described approach of financial experts to opening the "black box" of the organization is called in question by psychologists and sociologists who are more experienced in personality evaluation [49].

CEO retirement is one of the most commonly analyzed milestones in his careerv. For example, the research by D. Kahneman and D. Lovallo [50] demonstrates that individuals are inclined to avoid risk more when the expected irreversibility of the consequences of such decision is closer in time. Risk-generating decisions may jeopardize a company's operations and CEO reputation, especially in the last years of tenure. The burden of failure turns out to be very heavy for a CEO because the most of the blame rests with him. Thus, the research by B. Eckbo and K. Thorburn showed that 32% of liquidated trusts blamed CEO's incompetence. Besides, CEOs value their reputation because after retirement some of them continue their career as directors of other companies. J. Brickley, J. Linck and J. Coles [52] revealed that 8% of CEOs continue to cooperate with their firm for two or three years after retirement. Since degradation of corporate performance indicators may damage the reputation that CEO values so much and lessen the likelihood of CEO's getting on the board of directors after retirement, we may assume that CEO investment horizon shortens because the CEO tries to minimize risks when making decisions, guarding his reputation, and thus choosing not to invest in long-term projects [53].

Apparent and unapparent, explored and unexplored personality factors define the formation of CEO investment horizon. The apparent and explored factors are age and tenure, unapparent and unexplored – CEO power. Education, professional experience, narcissism, optimism, reputation and CEO success are also unexplored factors. In the present paper we discuss the first group of factors – apparent and well-explored – because they allow to quantitatively demonstrate how CEO investment horizon influences corporate performance indicators on the basis of statistics and econometric research.

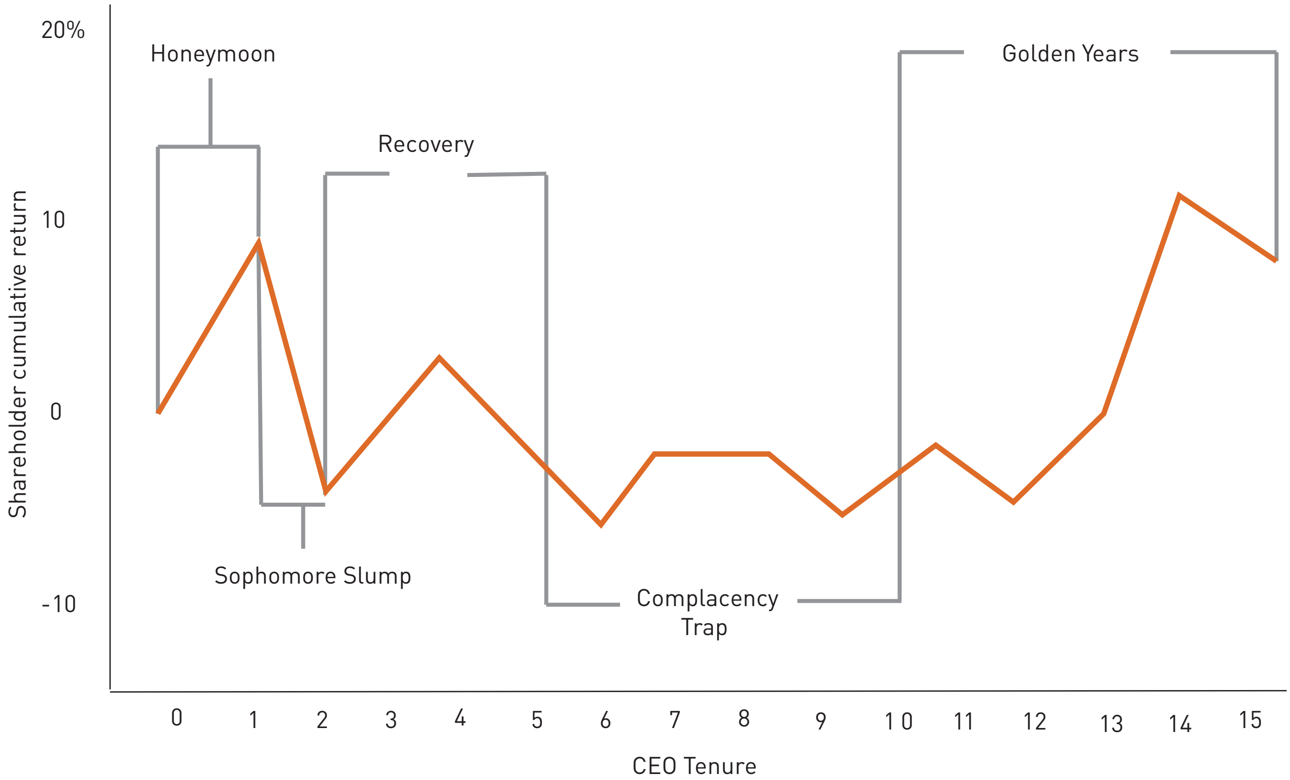
The first considered feature is age. Over the past 20 years, researchers have said a lot about the way in which CEO age may influence their investment preferences [54]. In particular, age (along with tenure) is one of character features that replace or approximate cognitive specific features of decision-making that are difficult to measure. When measuring horizon of this variable the effect of CEO "youth", in fact, is assessed as well as the effect of the number of years left to CEO's retirement. It should be noted that for the first time the term "horizon problem" was used in relation to CEO age and was considered within the context of career horizon [55, p. 198]. While younger CEOs are inclined to implement risk-bearing strategies, older CEOs are less prone to risk due to only this factor. If we add to this assumption the fact that CEO age approximates the retirement age (irrespective of tenure), we may point out with a high degree of confidence that the older the CEO, the shorter their decision horizon should be. Moreover, the CEO will agree to assume additional risks if he expects to get investment pay-off before he retires. In most cases these actions are related to the amount of corporate investments in R&D [56], capital expenditures [56] or international transactions of company acquisition [57].

CEO tenure is the second considered characteristic feature. In 2019 Harvard Business Review compiled a rating of the most efficient CEOs in the world[11]. It is remarkable that on average CEOs from this list have been running their companies for 15 years, which is twice as long as the average tenure of CEOs from S&P 500 (7.2 years). It is also remarkable that on average companies of efficient CEOs adhere to a more aggressive investment policy and riskier strategies. A term "CEO life cycle" was introduced for such directors. It demonstrates rather clearly that even the most successful CEOs suffer setbacks at some point in their career. In order to construct the diagram presented in Figure 4, the researchers studied the results of work of 747 CEOs and conducted 41 in-depth interviews with CEOs and members of the board of directors. The researchers determined three parameters to measure CEO efficiency: total shareholder return adjusted for the country; total shareholder return adjusted for the industry; change of market capitalization in US dollars corrected for inflation. Another interesting result of the research conducted by HBR is the fact that according to the poll "CEOs and members of the board of directors are of different opinion on ideal tenure"[12] CEOs believe that the ideal tenure should be seven years, while the members of the board of directors think that it is 9.5 years. After that period, corporate performance indicators stop growing. However, neither group could indicate the factors on which their opinions are based.

[11] URL: https://hbr-russia.ru/liderstvo/lidery/815146/

[12] URL: https://hbr-russia.ru/liderstvo/lidery/815146/

Figure 4. Five stages of CEO life cycle



Source: J. Citrin, C. Hildebrand, R. Stark (2019) The CEO Life Cycle // Big Ideas. URL: https://big-i.ru/liderstvo/lidery/815146/

If we appeal to empirical scientific research, we may single out the following range of detected factors that are related to CEO tenure. First, this indicator has diminished in the American market from the average value of eight years to four years over the past few years [58]. Second, after analysis of a sample of 1,024 European companies, we may conclude that in Europe this value is lower than in the USA and amounts on average to 3.5 years. Third, according to the most recent data for China, this indicator is almost the same as in Europe and amounts to 3.48 years [3]. Besides, CEOs with little time left until retirement will not invest in long-term assets that do not generate short-term profit [6]. It is common knowledge that the less time the CEO has until retirement, the less the volatility of the market stock value of the company.

Since a lot of attention was given to age and tenure in the past decade, these two indicators became the principal ones for measuring CEO investment horizon. In 2010 M. Antia et al. [29] created a CEO decision horizon indicator and applied it to a sample of companies from S&P 1500. The research began with the assumption that the expected decision horizon of the CEO in question depends on age and expected CEO tenure, which he compares to the same indicators of other CEOs who operate in the same industry. As a result, the researchers derived the following formula:

$$Horizon_{i,t} = (CEOAge_{i,t} - CEOAge_{average} + (CEOTenure_{i,t} - CEOTenure_{average}), \quad (1)$$

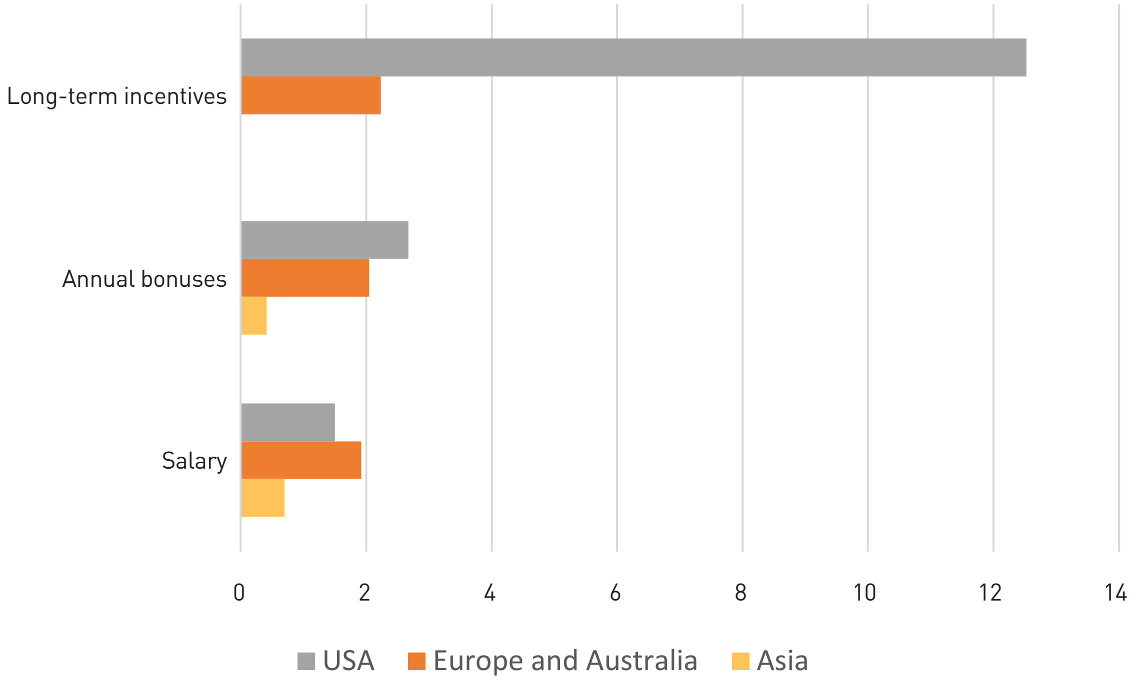
where $CEOTenure_{i,t}$ – CEO tenure in company i in year t; $CEOTenure_{average}$ – industry average value; $CEO\ Age_{i,t}$ – CEO age in company i in year t; $CEO\ Age_{average}$ – industry average value.

On the basis of the study results, researchers arrived at the conclusion that the span of the decision horizon is related positively to financial indicators' growth and depends negatively on information risk and agency costs [59]. Thus, companies with longer investment horizons will have a higher market value and make a good impression on investors. It should be noted that the indicator used in the paper also suits to measure investment horizon. The only difference is the choice of the dependent variable in the economic model: R&D expenses, capital expenditures (*CapEx*) or any other indicator of long-term investment, which manifests growth prospects both for the company's market value and its long-term performance indicators.

Can we Solve the Problem of CEO Short-Term Investment Horizon?

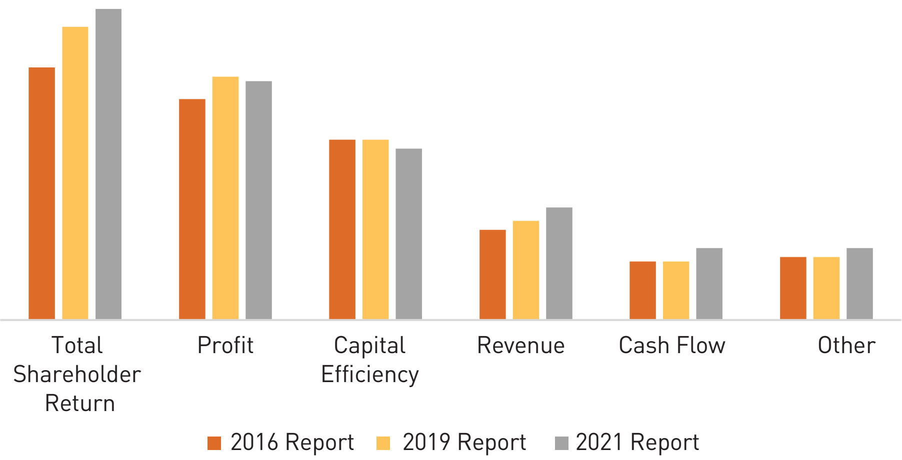
The following quotation from the book Bezonomics by B. Dumaine is dedicated to Jeff Bezos, Amazon founder, who had been its CEO up to 2021: "If everything is to work in two or three years your action spectrum is limited. But if one is ready to wait for seven years one gets a lot more opportunities" [60].

Figure 5. Median amount of total remuneration to CEOs according to regions



Source: B. Groysberg et al. (2021) A New Approach to Calculation of Top Managers' Compensation // Big Ideas. URL: https://big-i.ru/management/operatsionnoe-upravlenie/858464/

Figure 6. Criteria of corporate performance efficiency



Source: FW Cook 2021 Top 250 Report. URL: https://www.fwcook.com/Publications-Events/Research/2021-Top-250-Report/

Who would have thought that Bezos' decision in 2003 to work on a long-term project of creating a cloud environment would make Amazon the owner of the largest cloud platform in the world in 2018? One may assert various things about the CEO investment horizon problem, but at the same time one has to think of the actions to be taken by companies in order to solve this problem. Even more interesting is the question that arises: is it possible to solve this problem at all?

The first and currently most effective way of solving the short-term CEO investment horizon problem involves long-term incentives [61–62]. Examples of such incentives are restricted stock, stock options, stock-appreciation rights, performance shares and phantom equity.[13] In 2018 the American corporate governance consulting company FW Cook together with the British FIT Remuneration Consultants and Hong Kong Pretium Partners Asia Limited carried out global research on compensations for top managers from 250 largest companies. Research results demonstrate that long-term incentives are uncharacteristic of Asian companies at all (mainly because companies are owned and controlled by the government), in Europe

[13] URL: https://hbr.org/2021/01/compensation-packages-that-actually-drive-performance

and Australia long-term incentives amount to 36% of compensation, and the USA holds a record of 75%. The Asian countries also have the lowest median CEO compensation[14] (Figure 5).

The report by FW Cook of 2021 provides examples of other financial and corporate performance indicators to which CEO incentive contracts may be tied[15]. They are: total shareholders' return, EBIT, EBITDA, operating profit, ROE, ROA, ROIC, free cash flows (FCFF) and an individual KPI. Data by FW Cook divides these indicators into five categories represented in Figure 6.

Thus, we may conclude that over the past five years the use of financial metrics still prevails. Shareholders' return is still one of the most frequently used metrics, which was used by 69% of companies (4% more than in 2019 and 13% more than in 2016) in 2021. As a rule, this indicator is used together with other financial and strategic indicators (80% of companies draw a plan for the CEO, which comprises several indicators). Profitability and capital efficiency indicators are the next in popularity. They are applied by 53 and 38% of companies, respectively. It should be noted that one of the advantages of such an incentive system is that companies may adjust long-term indicators depending on the market and economic situation. For example, in 2020 due to the COVID-19 pandemic many companies decided not to take into consideration all the planned indicators in full. The bright side of the crisis consisted in the companies' need to add to their plans the indicators that take into account stakeholder interests to a greater extent than those of shareholders, which is another way of solving the short-term CEO investment horizon problem and which will be described below.

The second possible way to solve the short-term investment horizon problem was offered as a result of a round-table meeting of Business Roundtable in 2019. The association of CEOs of America's leading companies organized another round table, which adopted the Statement on the Purpose of a Corporation. It was signed by over 200 executive officers including the CEOs of Apple, GM, Walmart and BlackRock. The Statement proposes that managers depart from the goal of profit maximization and change the focus to value maximization for stakeholders, i.e., company employees, consumers, suppliers and other parties interested in the company business.

After the adoption of this Statement, Kellogg School of Management immediately convened a round table, where five professors of finance (C. Frydman, R. Jagannathan, R. Korajczyk, J. Maria Liberti and A. Yoon) discussed its possible consequences[16]. The main conclusion made at that meeting that deserves attention from the perspective of the CEO investment horizon problem is that neither the executive officer, nor the board of directors are obliged to maximize shareholder value or company profit, because the current corporations law does not set it as the CEO's top priority objective, especially to the detriment of all other aspects. A CEO's objective is currently long-term value maximization, and to achieve it, first, it is necessary to abandon the pursuit of short-term performance results. Abandoning of this pursuit is presented in the report of non-commercial organization FCLTGlobal published in October 2017[17]: the share of companies from S&P500 that use the long-term value of the company in implementation of their strategy and then publish quarterly reports decreased from 36% in 2010 to 27% in 2016. Moreover, in 2016 only one in three companies (31.4%) provided guidelines for short-term reports. Thus, we may conclude that at present an active transfer is performed from the traditional model of CEO-shareholder interrelation within the classical agency theory to the model of CEO-stakeholders interrelation that fits into the behavioral agency theory. An important reason to study the CEO investment horizon problem within the behavioral agency theory is the fact that it is consistent with the upper echelons theory, which states that top management teams produce a significant influence on corporate performance indicators. The behavioral agency theory makes us pay attention to personal traits and CEO motivation when they make investment and strategic decisions and to creating proper incentives, which enable the parties interested in the company's efficiency to influence CEO's motivation.

The third possible way of solving the CEO investment horizon problem is the implementation of ESG practices in corporate governance and in creation of company value. Indeed, calculation and comparison of ESG ratings and comparison of the influence of each component – E, S and G – on company performance is usual practice today. However, 10–20 years ago the situation was different because this methodology was subjected to experts' serious criticism and skepticism [63].

Getting back to the CEO horizon problem, we may point out that the addition of new indicators for evaluation of CEO efficiency is discussed rather often nowadays. Thus, for example, in the Harvard Law School Forum there are the CFA Institute's recommendations for companies to prevent short-termism[18]. Among other things, emphasis is laid on implementation of ESG practices when making CEO compensation packages. And as we noted, in the majority of cases CEO compensation, along with ESG indicators, is an incentive for long-term activity. The environmental component is centered around CEO

[14] URL: https://hbr-russia.ru/management/operatsionnoe-upravlenie/858464/

[15] URL: https://www.fwcook.com/Publications-Events/Research/2021-Top-250-Report/

[16] URL: https://insight.kellogg.northwestern.edu/article/shareholder-value-purpose-corporation

[17] Moving Beyond Quarterly Guidance: A Relic of the Past (FCLTGlobal, October 2017). URL: https://fcltglobal.org/wp-content/uploads/Moving-Beyond-Quarterly-Guidance-A-Relic-of-the-Past.pdf

[18] URL: https://corpgov.law.harvard.edu/2020/10/11/short-termism-revisited/

decisions and actions related to energy utilization by the company, non-pollution of the environment and natural resource conservation. The social component comprises the conduct of business principles and maintenance of relationships with stakeholders: taking into consideration their values and expectations. Finally, the governance component takes into account decision-making regarding shareholders and other internal control mechanisms. In spite of the fact that the offered method is still at the emerging stage a study by PricewaterhouseCoopers of 2018[19] showed that 29% of the board members in the USA considered the institutional investors' behavior excessive in relation to the discussion of ESG issues. This is indicative of a serious concern with this issue. At minimum the following organizations may be indicated as an example of companies comprising the very "multitude" that creates, standardizes and publishes ESG indicators: Carbon Disclosure Project (CDP), G20-based Financial Stability Board, Sustainability Accounting Standards Board (SASB), Global Reporting Initiative (GRI), International Integrated Reporting Council (IIRC) and the UN-led Principles for Responsible Investment[20]. At the same time, the existence of a large number of ESG sustainability metrics and a limited time range of their implementation still has not allowed to conduct a satisfactory analysis of sustainability. The latter would have allowed to make the conclusion on inalienability of these indicators for the analysis of each CEO's horizons or at least of investment decisions of the CEO of each major company.

Thus, we come to the conclusion that today the solution of the CEO investment horizon problem exists not just in the form of plans and theory, but also as attempts of practical implementation by companies.

Discussion

The difference between the outstanding and just good is that the outstanding is always the result of a marathon rather than a single successful breakthrough. It is proven by economy of countries, annual corporate reports, decisions made by economic operators and people's actions based on their preferences. It is not good when the investment horizon is too short (companies face short-termism), but it is also not good when companies try to look too far ahead (with high uncertainty and a risk of being unable to accomplish even one project successfully and improve efficiency). In order to improve efficiency, a company has to define the balance between short-term and long-term planning of investment beforehand and try to maintain both horizons in the optimal correlation.

In the present paper we managed to show how corporate short-termism in one of its highest degrees is able to bring economy to a global crisis; how and why it became necessary to single out a new problem in corporate finance – that of CEO investment horizon; how 12 years ago a synthetic metric to measure CEO horizon was discovered; why the most efficient CEOs in the world occupy their positions at least for 15 years, while the tenure of an average CEO does not exceed four years; how the cultural component of a CEO's life may be related to the length of his investment horizon; and finally, that today there are at least three possible ways to solve the problem of short-term CEO investment horizon.

All of the above provides a lot of clues concerning the actions to be taken by companies to improve their performance. At the same time, there are a lot of unanswered questions.

Which factors, apart from age and tenure may be added to the CEO investment horizon indicator? It has already been established that the degree of risk assumption by chief executive officers depends on demographic indicators, such as education and professional experience, personal traits such as narcissism, optimism and CEO power. However, in terms of the horizon problem researchers still have neither theoretical, nor empirical models.

Which of the cultural metrics of investment decision-making is suitable for use in the same model with an investment horizon indicator? Moreover, is there a unified metric applicable to different groups of countries: for example, for Eastern Europe, Western Europe, Asia etc.? Nowadays there are just separate assumptions concerning the relations between CEO decision horizon and the cultural aspect when a person makes decisions, however, as of today there is no empirical evidence of this fact.

Which way of solving the problem of short-term CEO investment horizon is the most efficient one: long-term incentive contracts, dependence of CEO compensation on long-term indicators or implementation of ESG metrics? As long as the number of observations is insufficient, except for certain companies, the researchers have no unambiguous answers to this question.

Today it is possible to presume with a high degree of confidence that human factor and personal traits in CEO investment decision-making will play a leading role in economics and finance research, and an understanding of the influence of the CEO investment horizon on corporate operations will help practical specialists improve corporate performance indicators. CEO investment decisions are proportionate to personal traits, cultural values and setup of the environment where decisions are made while corporate performance, in its turn, is proportional to CEO investment decisions. In the near future we are likely to see how CEO portraits are made for companies in order to forecast their optimal investment horizons .

[19] "ESG in the Boardroom: What Directors Need to Know," Governance Insights Center (February 2019). URL: https://www.pwc.com/us/en/services/assets/pwc-esg-directors-boardroom.pdf.

[20] URL: https://www.integratedreporting.org/resource/sp-global-long-termism-versus-short-termism-time-for-the-pendulum-to-shift/

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