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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.

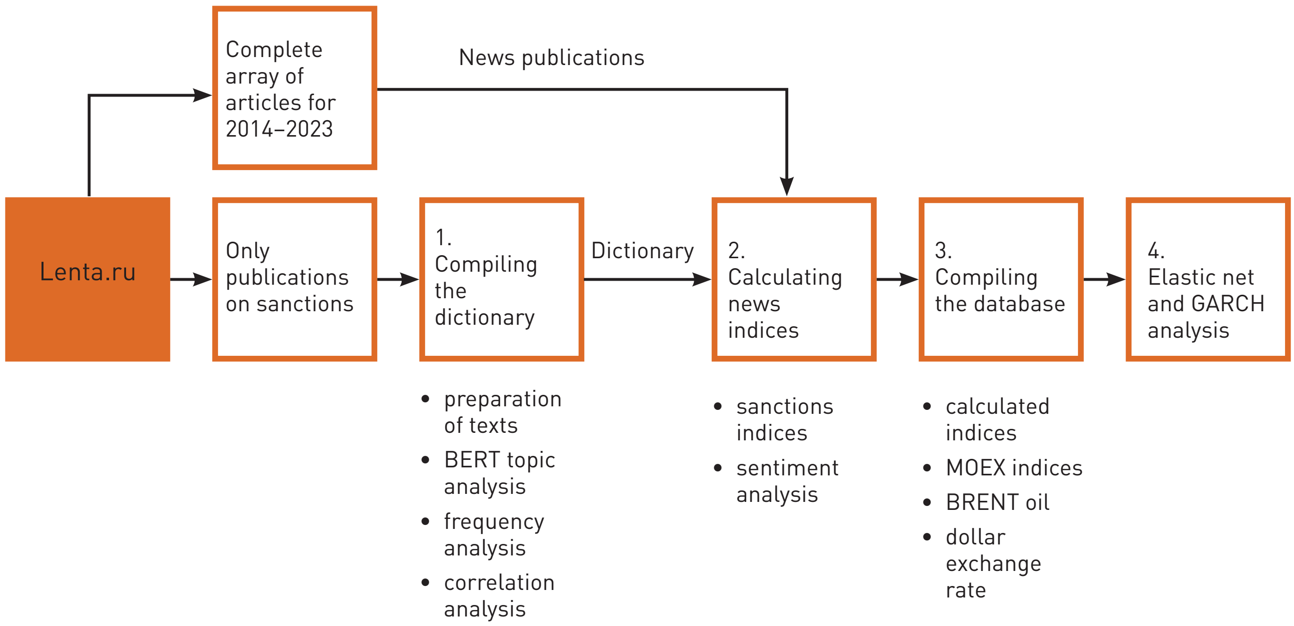
We present our research methodology below.

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.

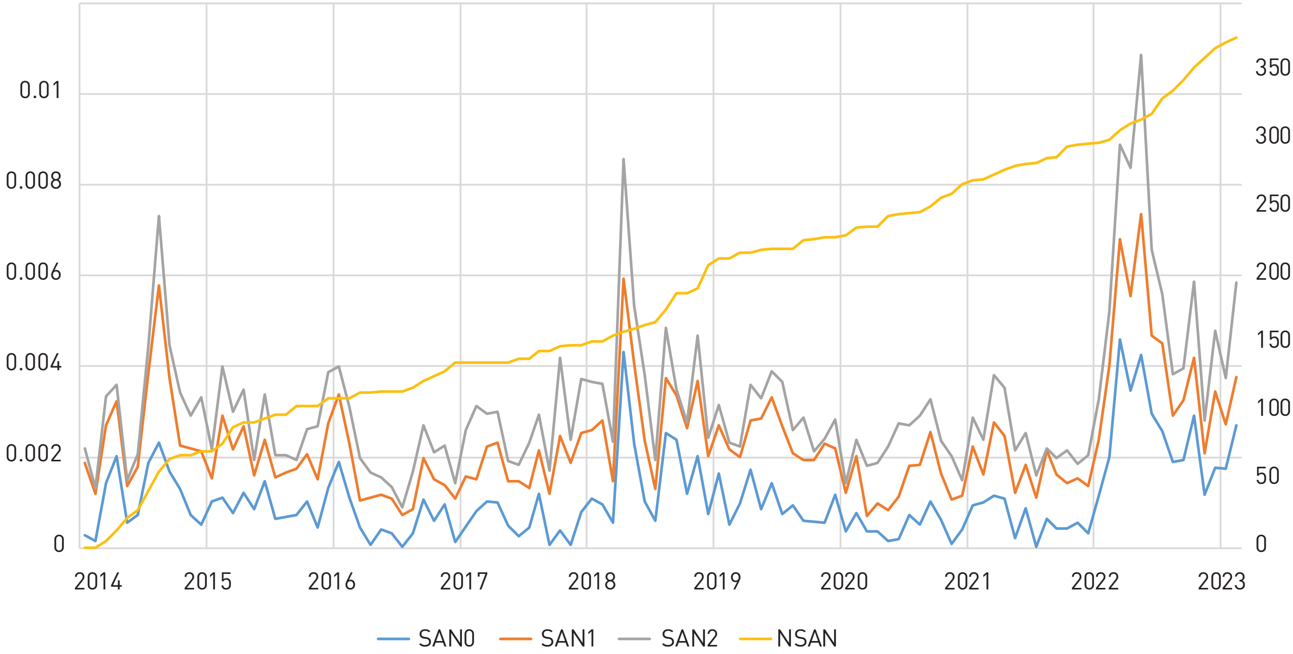
SAN2 – a maximally expanded index which includes rare words and collocations as well as words whose meaning may change significantly according to the context. Some of the words are taken twice. It consists of the following words: sanction, economic sanction, restriction, ban, blockage, block, barrier, 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.

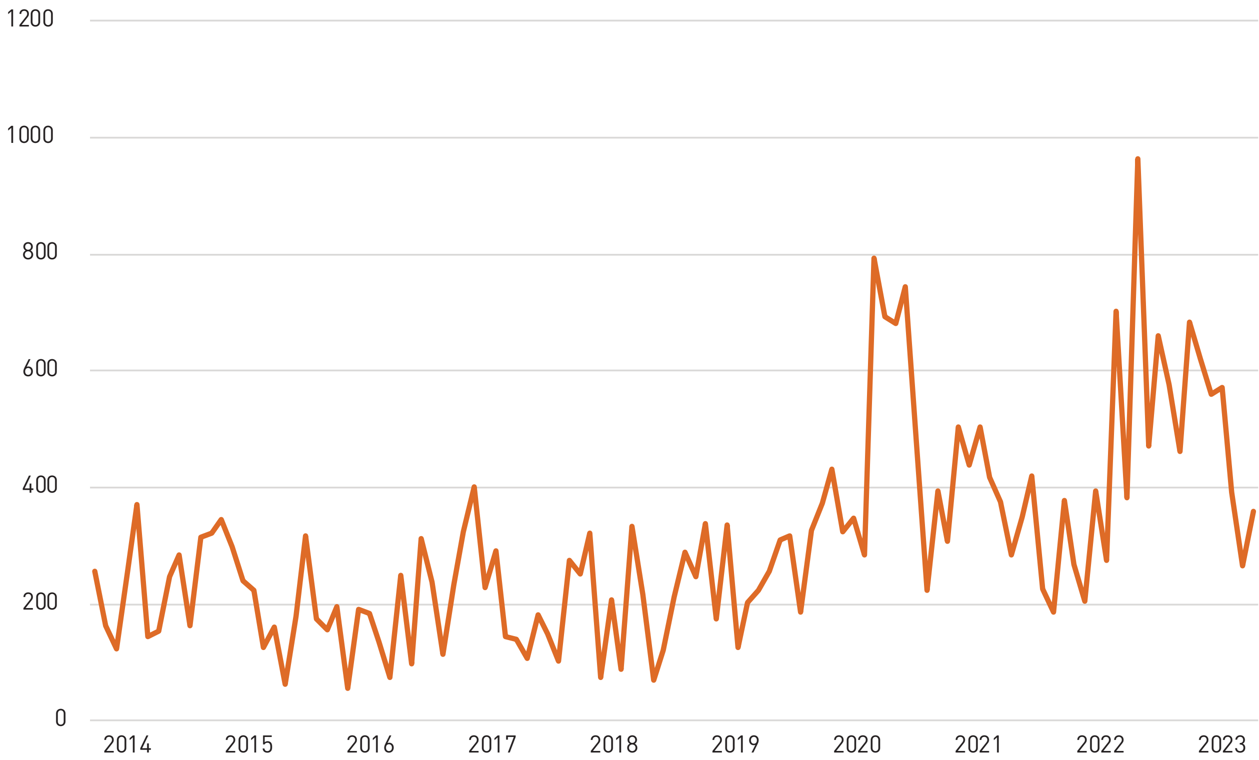
Figure 2 shows the values of the sanctions index calculated by means of text analysis and the NSAN cumulative index of imposed sanctions (or their packages) plotted against a second axis.

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

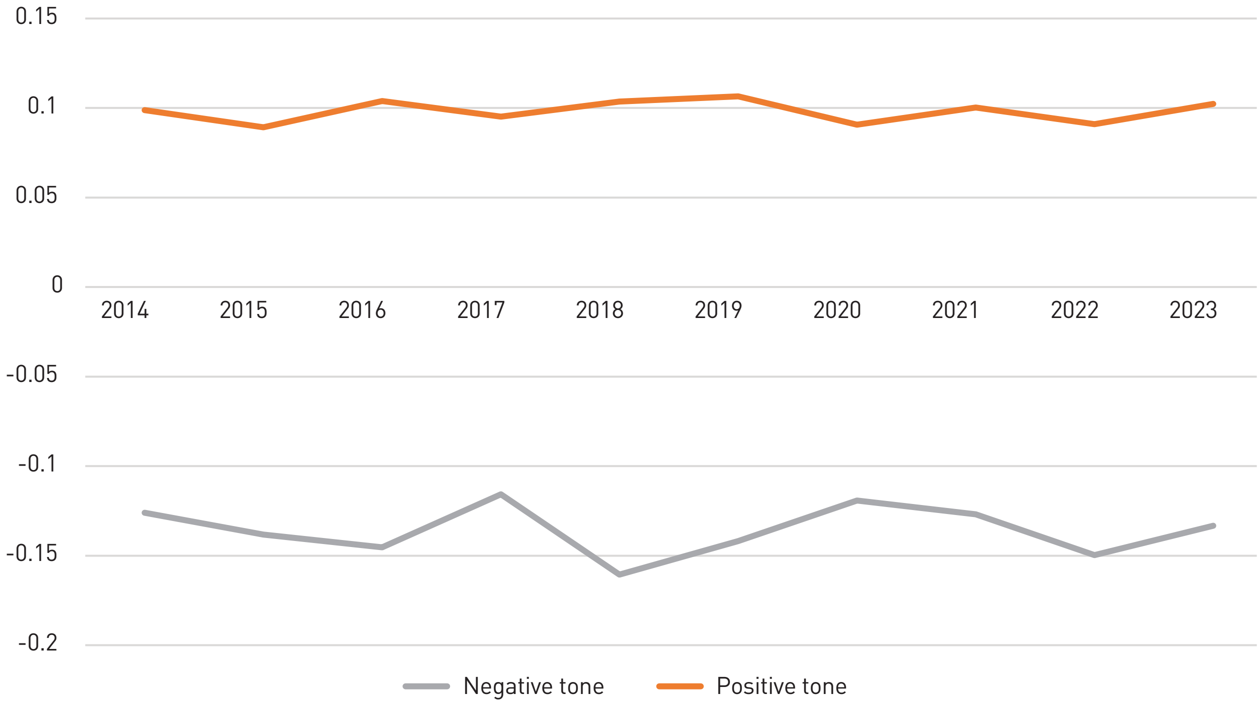


Figure 5. Fundamental economic indicators in 2014–2023 (the Brent oil price and the USD-RUB exchange rate are plotted on the left axis and the RUONIA rate on the right axis)

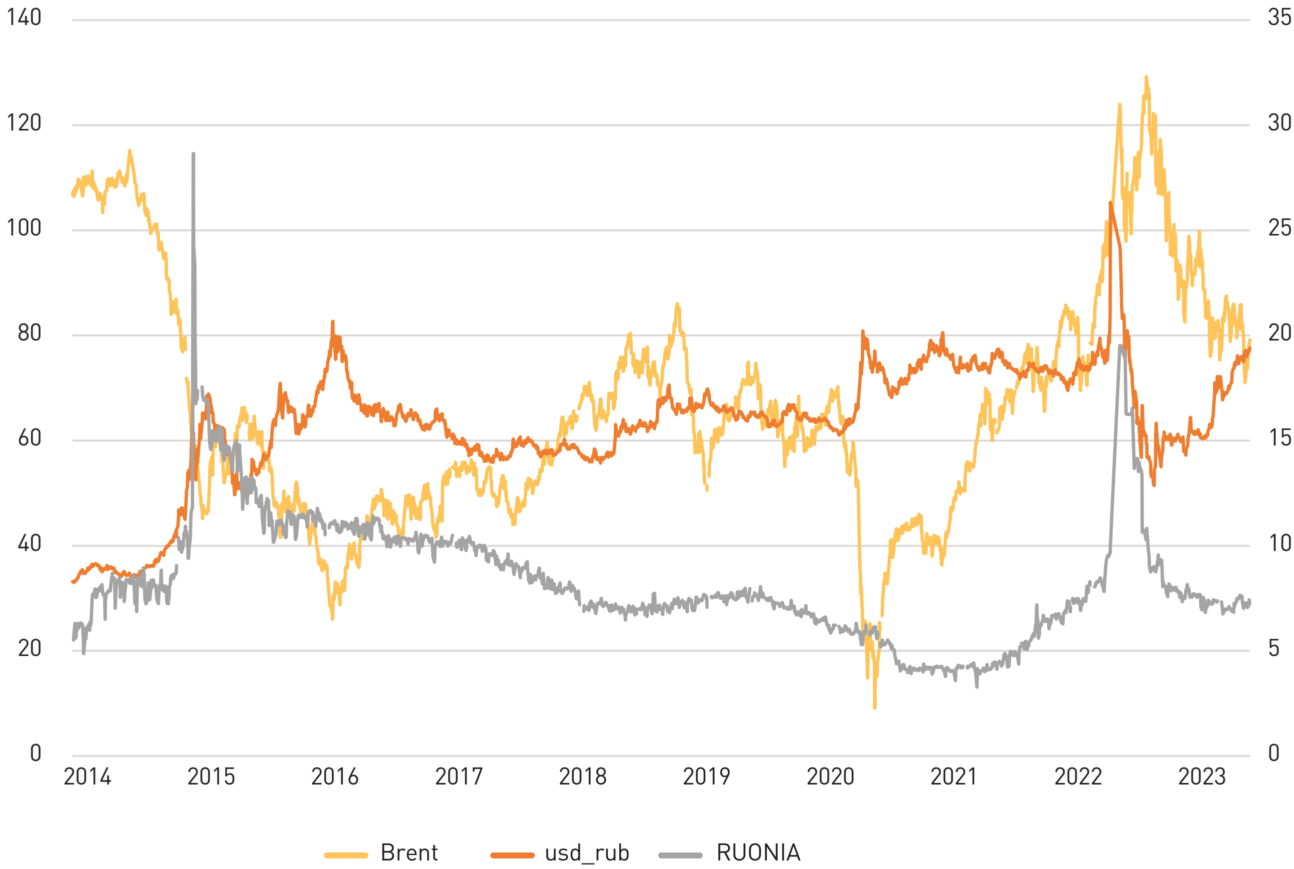


Figure 5 shows the dynamics of the fundamental economic indicators. As we see, the indicators fluctuated significantly during this period and so have to be checked for stationarity.

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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