THE IMPACT OF INFORMATION ABOUT THE CORONAVIRUS PANDEMIC ON FINANCIAL MARKETS

Elena Fedorova, Svetlana Ledyaeva, Nikita Razuvaev

METHOD AND DATA

The study utilizes data from various sources including market quotes of indices and interest rates on a daily basis, information on Covid-19 morbidity, mortality, vaccination, Google Trends data on popular Covid-19-related queries, as well as texts and news headlines for China, Russia and the United States in the period from January 1, 2020, to December 31, 2021.

Model description

Modeling of profitability indices is carried out by nowcasting of the dependent variables. This allows us to measure the explanatory power of exogenous variables and answer the question whether the current yield of the index depends on the current values of regressors.

For estimations we utilize HARX-GARCH model. The model consists of two components describing the dynamics of the mean value μ_t and shocks ϵ_t:

$$r_t = \mu_t + \epsilon_t$$

$$\epsilon_t = \sigma_t e_t \qquad (1),$$

where $r_t = \frac{y_t}{y_{t-1}} - 1$ denotes index`s yield in time t. We assume that $e_t \sim \mathrm{N}(0, 1)$. Volatility dynamics σ_t is described by the process of generalized autoregressive conditional heteroskedasticity GARCH (p, q) that allows the model to count for the heteroscedasticity of target variables:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \, \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^2 \qquad (2),$$

where p=1 denotes the order of symmetric shocks and q=1 – the number of conditional variance lags. The dynamics of the mean value μ_t is described by the heterogeneous autoregressive model HARX (p, L), which includes the mean values of the dependent variable for the previous period, 5 and 22 days before the current period. The model is widely used in the literature on volatility forecasting and allows to take into account the medium and long-term frequency of index trading:

$$\mu_t = \mu + \sum_{i=1}^{p} \phi_i \, \bar{\mu}_{t-L_i:t-1} + \gamma_1^T controls_t + \gamma_2^T official\_info_t + \gamma_3 gtrends_t + \gamma_4^T news_t + \varepsilon_t \qquad (3),$$

where $\bar{\mu}_{t-L_i:t-1} = \frac{1}{L_i} \sum_{j=1}^{L_i} \mu_{t-j}$ is the average value of the variable between time points $t - L_i$ and $t - 1$, $controls_t$ – control variables, $official\_info_t$ – vector of characteristics of official information about Covid-19, $gtrends_t$ – Google trends index, $news_t$ – vector of news variables. In the study we utilize parameters $p = 3$, $L = [1, 5, 22]$. The model was evaluated using the arch library for the Python programming language.

Data description

Core variables

To construct the target variables, we utilize the closing prices of the largest market indices for China, USA, and Russia. We particularly consider composite indices aggregating information about the movement of entire financial market. For the USA we have chosen the Standard and Poor`s 500 index (S&P500) that reflects the market value of the country`s largest 500 companies. Chinese market is represented by Shanghai Shenzhen CSI 300 index that includes 300 largest companies which trade on Shanghai and Shenzhen Stock Exchanges. For Russia we utilize the IMOEX (Moscow Interbank Currency Exchange) index that is published by Moscow stock exchange and includes 50 most liquid shares of Russian issuers. In addition to composite indices, industry indices have been also selected: Dow Jones consumer goods (DJCG) and transport (struck) indicators for the USA, Wholesale and retail trade (GSP: Sh&S) and transport (GSP: T) for China, and MOEXCN and MOEXTN for Russia.

Second, we include Covid-19-related variables, namely, new reported infection cases, new reported deaths from Covid-19, number of vaccinations per 100 million people, and index of the stringency of Covid-19 restrictions. The index is based on nine restrictions` measures including introduction of non-working days, travelling and movement restrictions, cancelation of public events, etc. and is represented by values in the range of 0-100 with 0 indicating no restrictions.

Finally, we include several control variables. We consider trading volumes for the indices under consideration (described in the beginning of this subsection), London Interbank Bid Rate in US dollars (USD LIBOR interest rate) for the United States, the Shanghai Interbank Bid Rate (Shanghai Interbank Offered Rate) for China, and the RUONIA Index and Average rates for Russia. All the described variables are summarized in Appendix A.

Google trends` indices

Data on the popularity of queries from *Google Trends* provide valuable information about the attention of society to certain topics and problems. In this study we construct the aggregate index of attention to vaccination issues basing on search queries for each country in Google. In Table 1 we report terms used for data filtration from *Google Trends*.

Table 1: Kew words used for *Google Trends* data filtration

Country	Key words
USA	'vaccination', 'vaccine', 'test covid', 'test antibody', 'Pfizer', 'Moderna', 'Novavax'
China	'疫苗 接种' (vaccination), '疫苗', (vaccine), 'covid test', 'CoronaVac', 'Sinovac', 'Sinopharm'
Russia	'вакцинация' (vaccination), 'вакцина' (vaccine), 'тест на антитела' (anti-body test), 'тест на ковид' (covid test), 'qr код' (qr code), 'Спутник V' (Sputnik V), 'ЭпиВакКорона' (ApiVacCorona), 'Спутник Лайт' (Sputnik Light), 'КовиВак' (CoviVac)

Google Trends data determines the popularity of each concrete inquiry in Google search at any moment of time. Hence, for each key word we construct a time series of its popularity that ranges from 0 (inquiries for this key word are absent) to 100 (maximum number of inquiries for the key word in the studied time period).

To construct the aggregated index of the search activity we utilize principal component analysis (PCA) and weighting method based on pairwise correlations. The correlation index looks as follows:

$$I = w_1 I_1 + w_2 I_2 + \cdots + w_n I_n$$

$$w_i = \frac{\sum_{j=1}^{n} \rho_{ij}}{\sum_{i=1}^{n} \sum_{j=1}^{n} \rho_{ij}} \qquad (4),$$

where *i* is the aggregated index, I_i is the index of popularity of the key word *i*, w_i is the weight of the key word *i*, ρ_{ij} is the coefficient of pair correlation between the indices i and j (the usage of coefficients of partial correlation does not change the results). Hence, each index is assigned with a weight that is proportional to its relationship with other indices. We get the final index by scaling the initial index from 0 to 100 based on the index minimum and maximum values:

$$I_t^* = 100 \cdot \frac{I_t - \min_t I_t}{\max_t I_t - \min_t I_t} \quad (5).$$

On Figures 1-3 we present the final indices` dynamics.

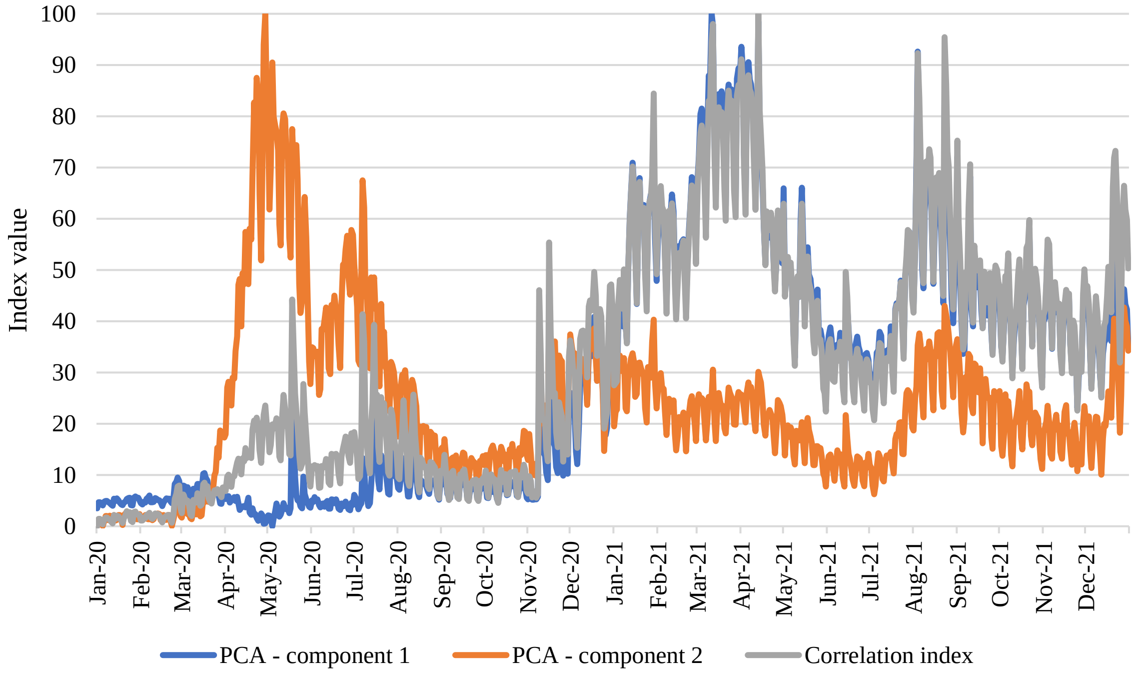

Figure 1: Vaccination google trends` indices for the USA
Source: Authors calculations

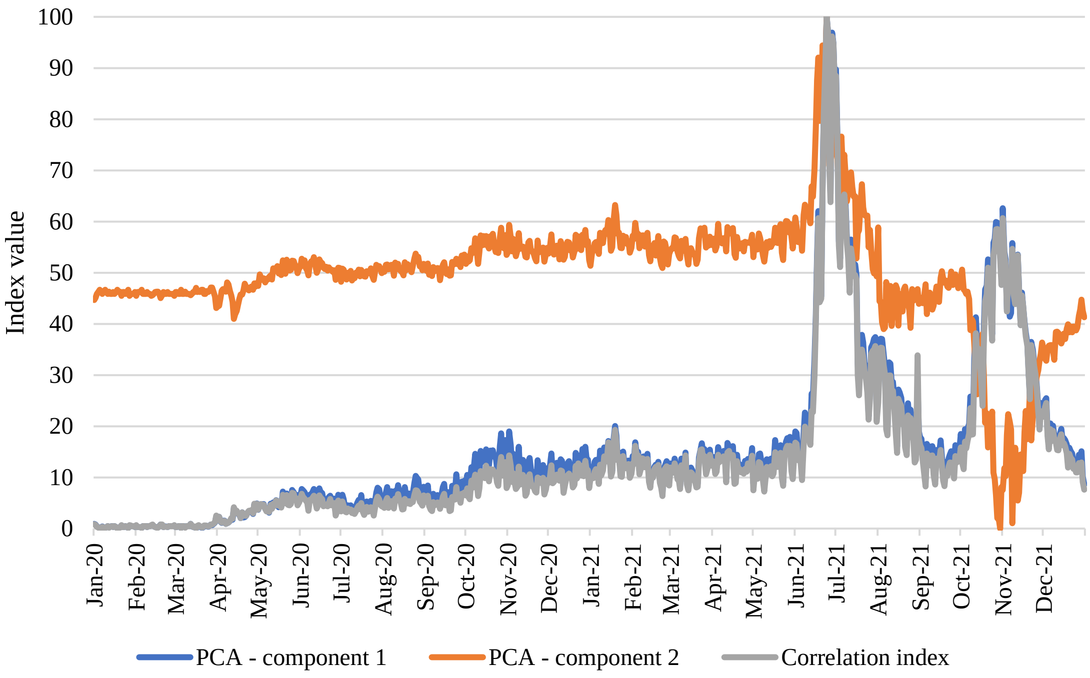

Figure 2: Vaccination google trends` indices for Russia
Source: Authors calculations

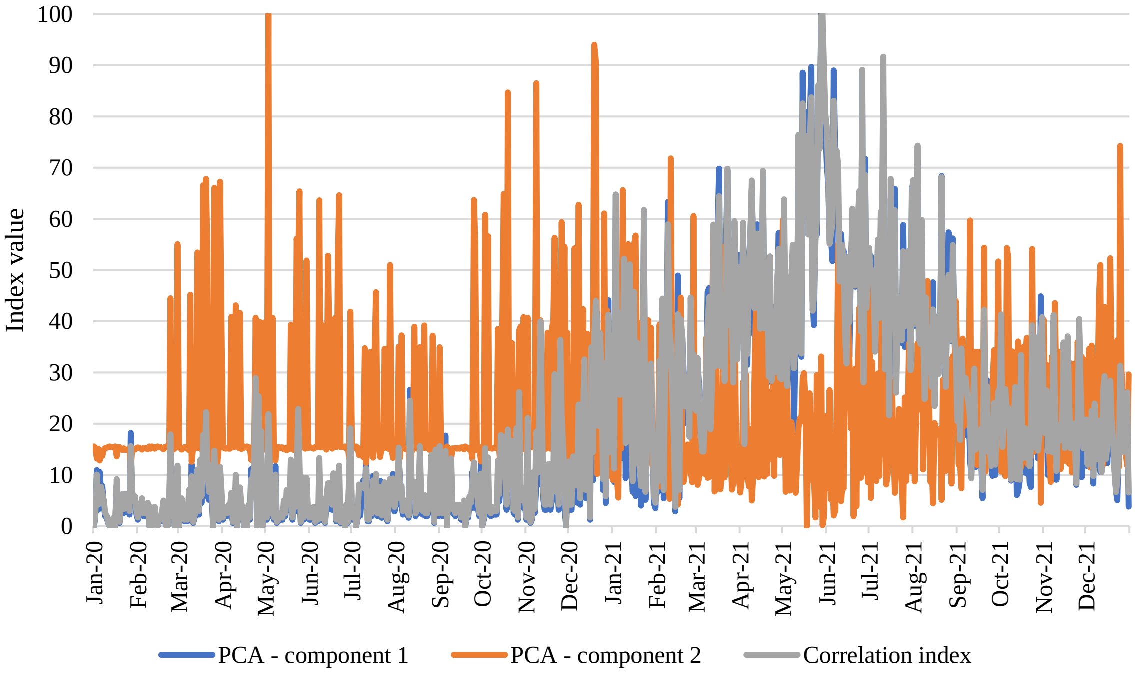

Figure 3: Vaccination google trends` indices for China
Source: Authors calculations

In table 2 we report weights of indices of key words, which represent the relative contribution of each key word to countries' correlation indices. The weights also show how each key word is correlated with the rest of the key words. Keywords with higher weights tend to have common trend components while lower weights mean the dominance of noisy components.

Table 2: Weights of indices of key words

USA		**China**		**Russia**	
Key word	*Weight*	*Key word*	*Weight*	*Key word*	*Weight*
vaccination	0.169	疫苗 接种	0.181	вакцинация (vaccination)	0.085
vaccine	0.157	疫苗 (vaccine)	0.244	вакцина (vaccine)	0.077
test covid	0.124	covid test	0.111	тест на антитела (anti-body test)	0.104
test antibody	0.089	coronavac	0.119	тест на ковид (covid test)	0.099
pfizer	0.147	sinovac	0.188	qr код (qr code)	0.117
moderna	0.179	sinopharm	0.157	спутник v (sputnik v)	0.165
novavax	0.136			эпиваккорона (**EpiVacCorona**)	0.110
				спутник лайт (sputnik light)	0.125
				ковивак (covivac)	0.118

News indices

In the study of pandemic impact on financial markets, it is very important to count for the news background that shapes the mood and expectations of investors. In this paper for each country under consideration we consider established national publishing house as a news source. For the US we utilize the newspaper *the New York Times*1 that is one of the key sources of official information in the country. For China we consider *Chinadaily*2, the largest English-language portal in China providing news and business information. It has the widest print circulation of any English-language newspaper in China. Finally, for Russia we utilize **Russia's** leading news agency *TASS*3.

For the news analysis we utilize textual approach. News texts are presented in two languages – English (for the US and China) and Russian (for Russia). There are also texts in Spanish in one of the sections of *The New York Times* and individual words in Chinese on the *Chinadaily portal*.

1 nytimes.com

2 chinadayly.com.cn

3 tass.ru

For uniformity of methodology, the headlines and news texts of the TASS edition have been translated into English using Facebook's fairseq model, trained on the WMT19 News Translation (Ng et al., 2019) that outperforms in quality similar models with transformer architecture. In addition, all newspaper articles were cleared by removing all tokens except punctuation and the Roman characters, and discarding articles in languages other than English.

The text tonality has been evaluated by the FinBERT model (Huang et al. 2020) - a transformer with BERT architecture. The language model was pre-trained on a sample of corporate annual and quarterly reports, financial analysts' reports and conference call transcripts on profit and loss, and then trained to classify proposals from analytical financial reports with a sample size of 10 thousand proposals. Thus, the model can predict the probability distribution of a text to be of positive, negative or neutral tonality.

The model advantages over other methods of assessing tonality, such as Bag-Of-Words or Word2Vec, include no need for text preprocessing and that the order, weight and connections of words (tokens) in the text are taken into account. However, this approach also has disadvantages: 1) Limitation of the input layer of the model to 512 tokens (words, punctuation or parts of words). We solve this issue by splitting large texts of news articles (more than 512 tokens, no more than 1-2% of the sample in each edition) into parts, and then taking the mean value of all predictions to obtain the tonality of the entire text; 2) Data offset with respect to the training sample (both the distribution of words [tokens] and the length of texts [articles and titles]) that can disrupt the operation of the model, leading to noisy or false conclusions.

On Figure 4 we present the class ratios (neutral, positive, and negative) for the articles` headings and texts. All articles. We should note that the distributions in the news sample differ significantly from the distribution of classes in the training sample, where 36% of the texts are positive, 46% - neutral and 18% - negative (Huang et al., 2020).

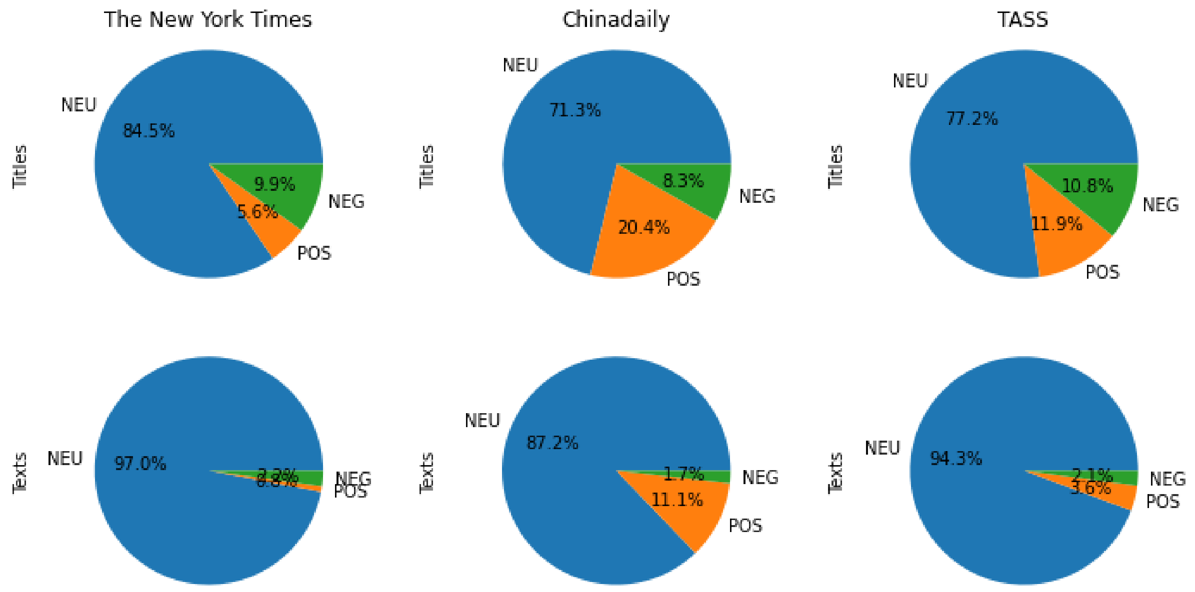

Figure 4: The news tonality by country
Note: The tonality indices of the news of the daily frequency were allocated by averaging the probability of the classes of headlines and articles. Neutral tonality was not included in the simulation as it can be derived from negative and positive tonality.
Source: Authors calculations

Considering the dynamics of the sentiment of news headlines and texts for each country, we observe the following. During the entire studied period the Covid-19-related news in the US has been dominated by headlines and texts with a negative tone (Figure 5).

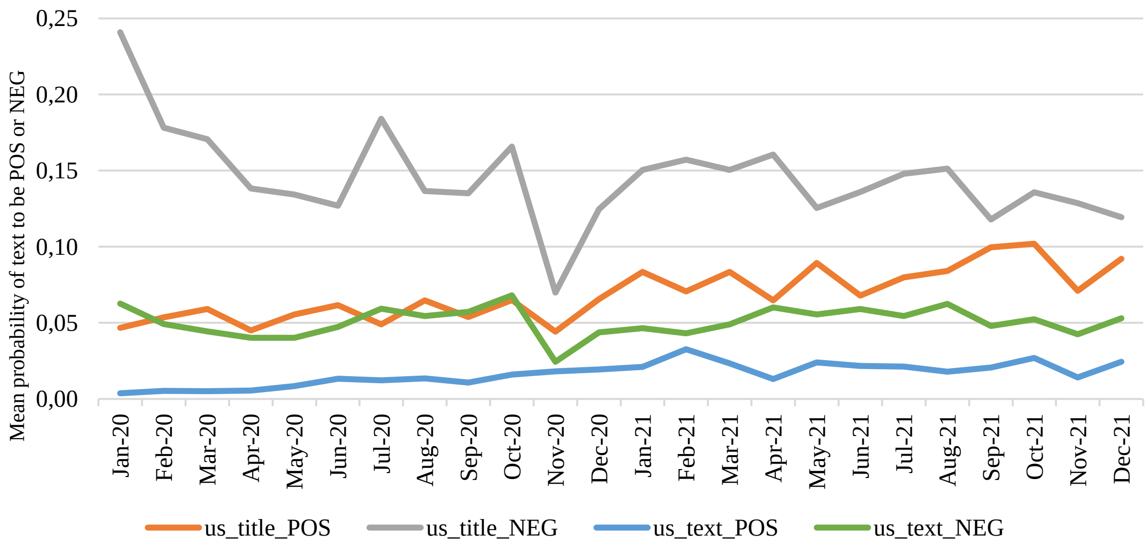

Figure 5: Covid-19-related news sentiment dynamics in the USA
Source: Authors calculations

The situation in China is different (see Figure 6). In the studied period news headlines and texts with a positive sentiment have been strongly dominating.

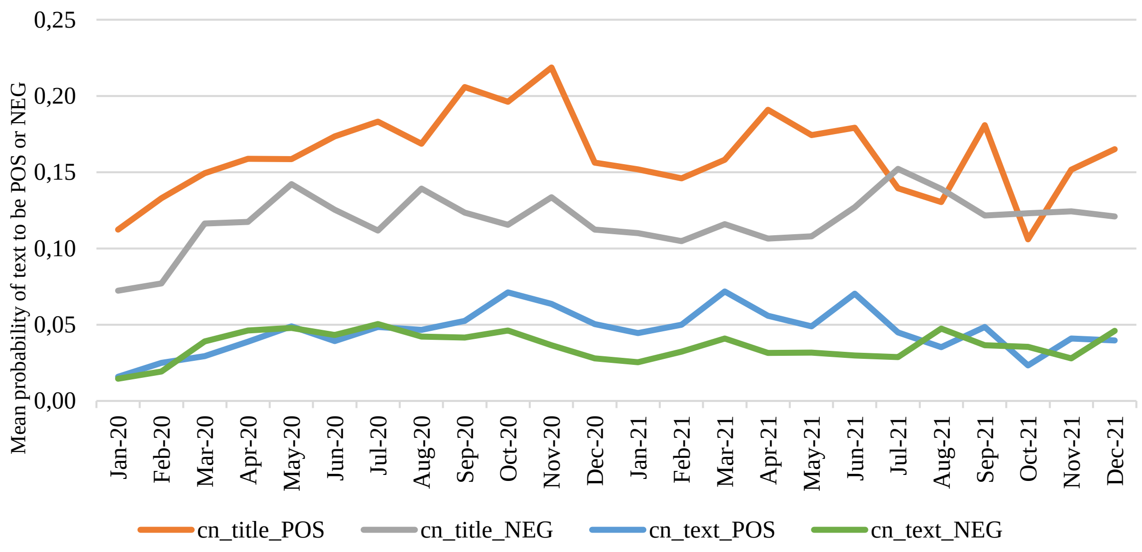

Figure 6: Covid-19-related news sentiment dynamics in China
Source: Authors calculations

In the beginning of the studied period negative headlines and texts prevailed in Russia`s Covid-19-related news articles, but in the summer of 2020 the trend has changed to opposite (Figure 7).

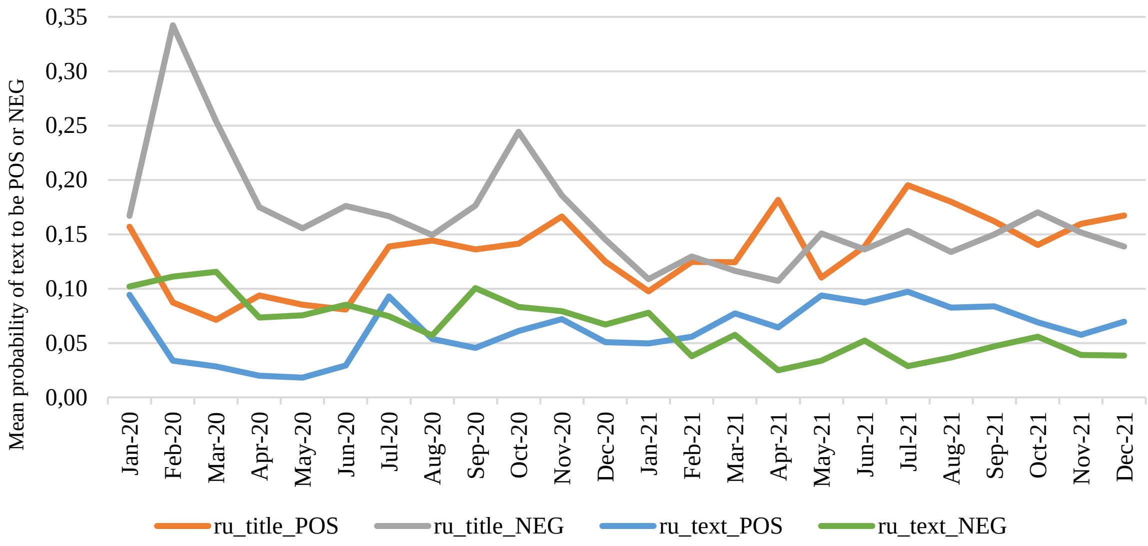

Figure 7: Covid-19-related news sentiment dynamics in Russia
Source: Authors calculations

Data thematic modelling

Covid-19-related media news can be divided into several topics. To perform this task, we utilize Latent Dirichlet Allocation (LDA) to reveal a set of topics for each country based on relevant key words. In thematic modelling each text from the sample has a distribution on a finite number of topics whereas each topic represents a distribution on words (Hoffman et al. 2010). In this paper we used LDA implementation from scikit-learn package for Python.

To apply the LDA algorithm, we first need to process the text – reduction to lowercase, removing punctuation, stop words and words that make noise in the text (e.g., the name of the publication is indicated in each headline of The New York Times), lemmatization (bringing the word to normal (dictionary) form). Text processing was carried out using the NLTK library and regular expressions. After that the corpus of texts was converted into a matrix of the frequency of words in the news articles. In this study we restrict the term frequency matrix to one thousand words. It includes words found in less than 95% of articles and more than 2 times to discard those terms that can be found almost in every article as they do not distinguish topics, and not to consider rare words as the topics should consist of repetitive terms.

Finally, we apply the LDA algorithm with the number of topics equal to 50 and 5 iterations of stochastic gradient descent to the term frequency matrix of news publication. Then it is possible to obtain distributions of terms for each topic and probabilities of each newspaper article belonging to a particular topic. Among the topics revealed, those related to the coronavirus pandemic were highlighted and logically divided into three main blocks. Since the algorithm has been applied separately to each newspaper, not all logical blocks are represented in each of the countries which also shows the difference in attitude to the Covid pandemic in media attention.

In the news of the first block, we name it as "science and public health service", countries` governments inform people about restrictions imposed due to the spread of Covid-19, and also publish official data on the number of cases, vaccinated and dead. The news in this block often mention vaccination, production of vaccines and the course of vaccination programs. In Table 3 we report LDA results for core topics` identification for this block.

Table 3: LDA results for the news modelling for the block of news on science and public health service

Country	Topic	Words which correspond to the topic
USA	1	vaccine, covid, people, coronavirus, health, virus, covid 19, vaccinated, vaccination, variant
	2	data, death, case, reported, number, state, county, report, health, average
	3	dr, mask, virus, people, wear, wearing, university, health, face, coronavirus
China	1	vaccine, covid, covid 19, vaccination, country, dose, health, million, people, trial
	2	case, covid, covid 19, confirmed, reported, health, test, infection, testing, confirmed case
	3	medical, hospital, wuhan, patient, hubei, province, coronavirus, novel, coronavirus, epidemic
	4	covid 19, state, death, coronavirus, country, people, case, percent, health, pandemic
Russia	1	ministry, medical, industry, mask, russian, ministry industry, production, federation, coronavirus, equipment
	2	drug, medical, coronavirus, health, medicine, disease, patient, covid, state, government

Covid-19-related restrictions have changed the work of many public and private institutions. School, colleges, and universities were closed, employers had to transfer their employees to remote mode, many public events have been canceled. News on these issues form our second block on societal pandemic-related changes. In Table 4 we report LDA results for core topics` modelling for this block. As the LDA algorithm chooses topics based on the distribution of words in documents and TASS mainly provides economic news, topics related to societal pandemic-related changes was not revealed so Russia was not considered in the news analysis for this block.

Table 4: LDA results for the news modelling for the block of societal pandemic-related changes

Country	**Topic**	**Words which correspond to the topic**
USA	1	student, school, college, university, test, class, percent, pandemic, plan, high
	2	coronavirus, virus, pandemic, positive, test, tested, case, state, people, home
	3	people, johnson, london, britain, park, lockdown, british, coronavirus, home, government
	4	covid, coronavirus, state, virus, covid 19, health, worker, home, public, pandemic
China	1	virus, coronavirus, people, mask, novel, outbreak, novel coronavirus, health, public, spread
	2	film, video, online, pandemic, work, covid, covid 19, people, art, home

Covid-19-pandemic caused global economic crisis accompanied by significant increases in unemployment worldwide and large losses in economic sectors most vulnerable in the pandemic realities. The governments provided support to affected businesses, for example, by allocating subsidies. News discussing these issues form our third block on economic consequences of the pandemic. We should note that news in economic block often mention vaccine-related issues. In Table 5 we report LDA results for core topics` identification for this block. Similar to the absence of the topic of societal pandemic-related changes in Russia USA was not considered in the news analysis for this block due to the lower presence of the news related to the economic consequences of the pandemic or higher presence of other logical blocks.

Table 5: LDA results for the news modelling for the block of economic consequences of the pandemic

Country	**Topic**	**Words which correspond to the topic**
China	1	pandemic, covid, covid 19, global, world, economy, country, economic, china, crisis
Russia	1	economy, country, pandemic, world, coronavirus, economic, crisis, global, according, situation
	2	vaccine, forecast, 2021, growth, gdp, coronavirus, 2022, according, vaccination, 2020
	3	business, support, measure, russian, entrepreneur, president, putin, industry, federation, work
	4	vaccine, sputnik, russian, million, coronavirus, people, country, vaccination, labor, registered

For each logical block we construct indices by summing the probabilities of relevant LDA topics for each newspaper article and aggregating articles on a daily basis by taking the mean. On Figures 8-10 we depict the news trends by topic in the studied period for each country.

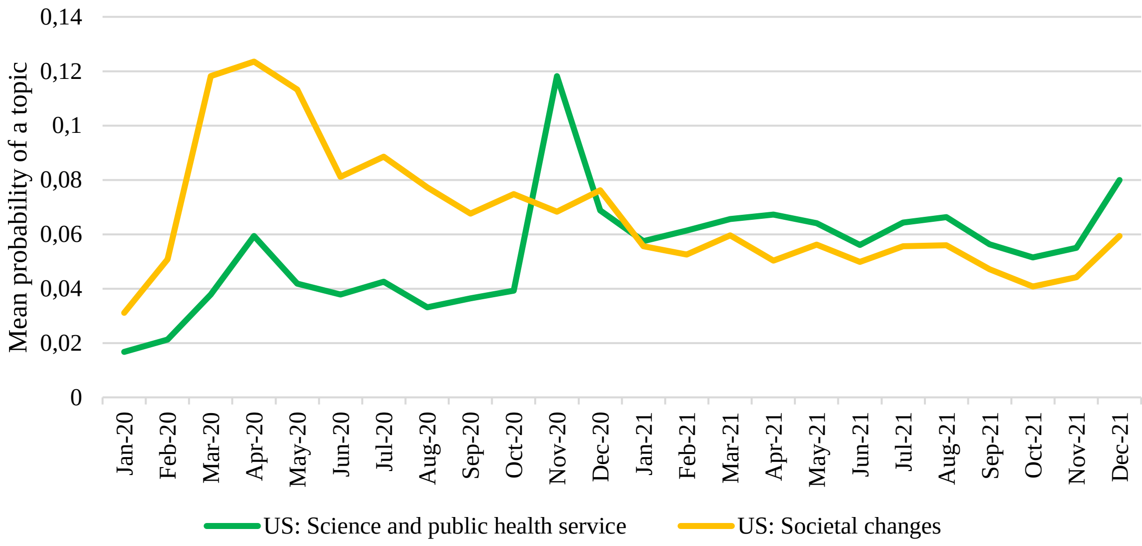

Figure 8: Frequency of news hits in the selected topic group: USA
Source: Authors` calculations

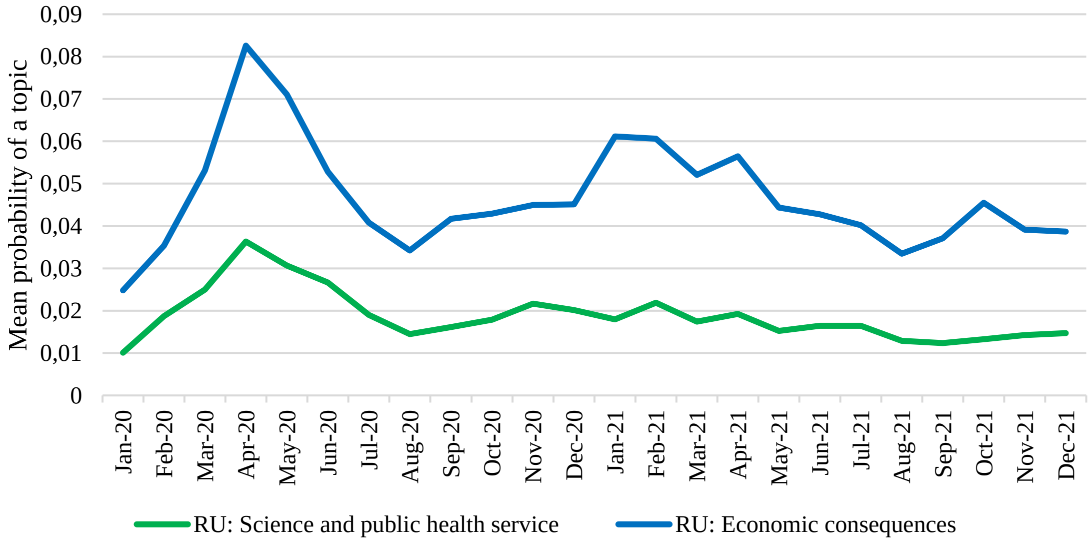

Figure 9: Frequency of news hits in the selected topic group: Russia
Source: Authors` calculations

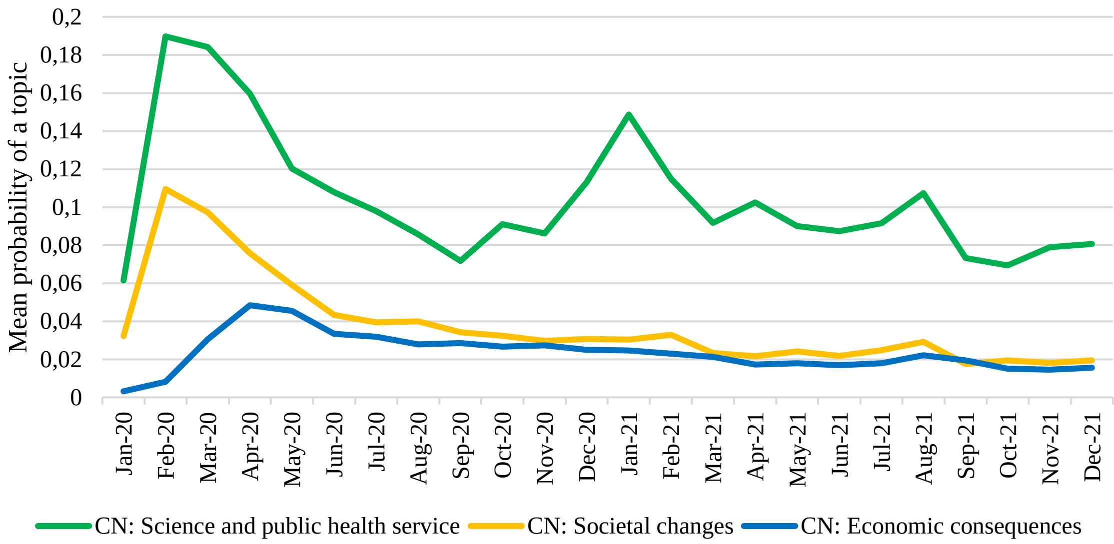

Figure 10: Frequency of news hits in the selected topic group: China
Source: Authors` calculations

As we can observe, in all three countries the largest upsurge of news on Covid-19 has occurred in the spring of 2020 after the World Health Organization (WHO) on March 11, 2020, has declared the novel coronavirus (COVID-19) outbreak a global pandemic. The second largest news` spike has occurred in winter 2021 when the second largest coronavirus pandemic wave has started to develop (see, e.g., Kunno et al. 2021). On average, news on societal and economic consequences of pandemic dominated news which have been discussing healthcare issues. However, we should note that in China healthcare-related news slightly dominated news on societal effects of pandemic though news on economic consequences of coronavirus outbreak dominated overall.

On Figures 11-13 we present average sentiment of the news by theme and by country.

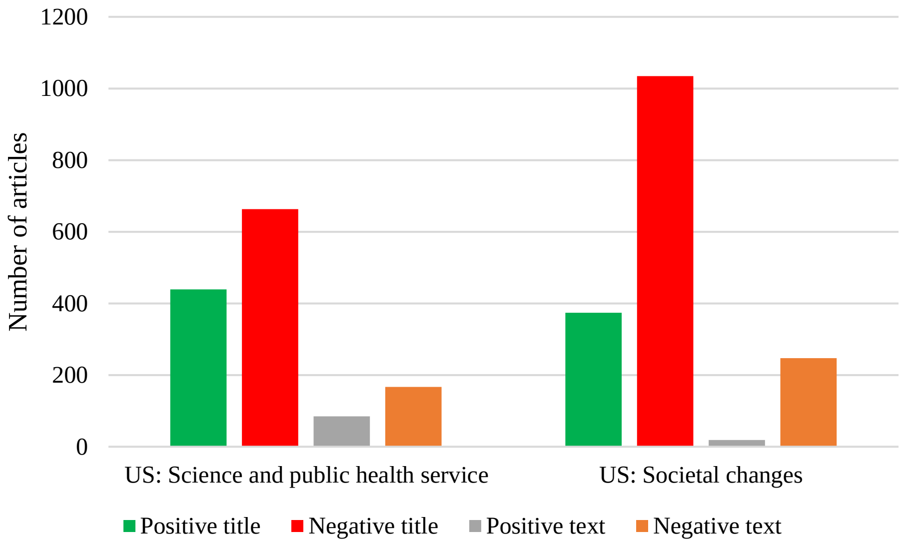

Figure 10: Sentiment of news by theme: USA

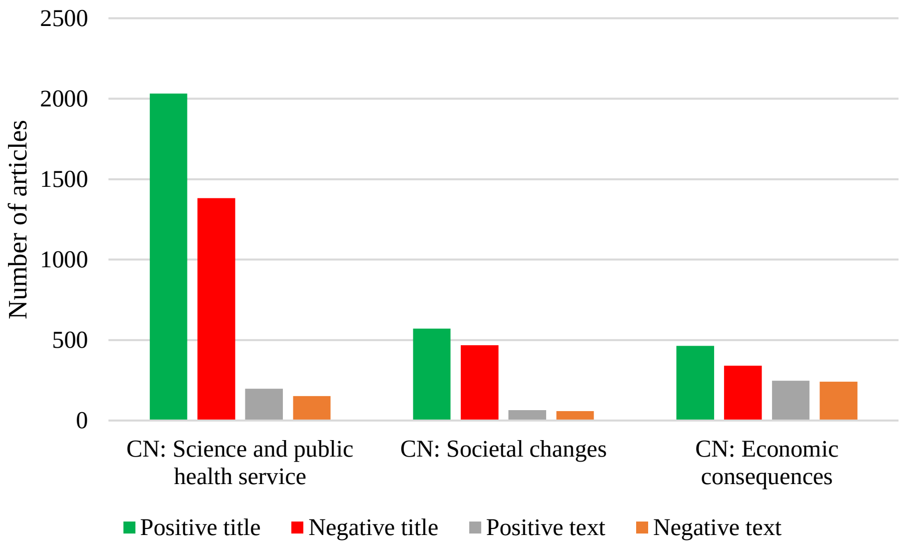

Figure 10: Sentiment of news by theme: China

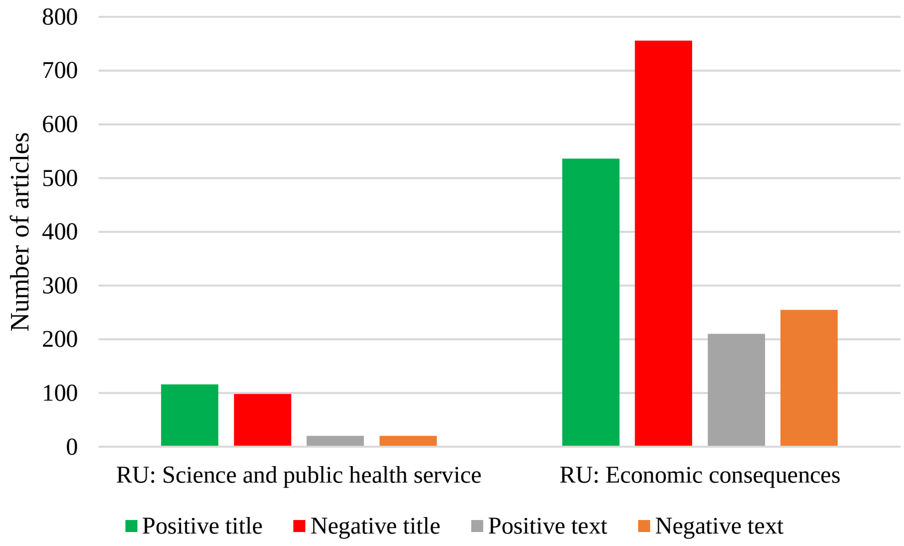

Figure 10: Sentiment of news by theme: Russia

Empirical results

Baseline results

We should note that indices of financial markets` profitability (our target variables) suffer from stationarity. To make the respective variables non-stationary, we apply log transformation to the data using “log()” function, then perform first difference transformation “*[z(t) - z(t-1)]” to our series and finally* scale the series from 0 to 100 based on minimum and maximum values. Descriptive statistics of all the initial variables used in estimations is reported in Appendix B.

The baseline HARX-GARCH model results are presented in Tables 6-8.

Table 6: HARX-GARCH model results for the US composite financial performance indices

Variable	HARX-GARCH	HARX-GARCH-O	HARX-GARCH-OG	HARX-GARCH-OGN
R2	0.0617	0.1009	0.1006	0.1174
R2_adj	0.0458	0.0779	0.0755	0.0791
Const	0.364 (1.749)	-0.343 (1.726)	-0.309 (1.722)	-1.283** (1.719)
i...ice[0:1]	-0.095*** (0.051)	-0.103*** (0.052)	-0.103*** (0.052)	-0.090*** (0.051)
i...ice[0:5]	-0.188** (0.140)	-0.221** (0.147)	-0.225** (0.149)	-0.240** (0.148)
i...ice[0:22]	-0.295** (0.319)	-0.584*** (0.323)	-0.599*** (0.321)	-0.631*** (0.314)
ind_comp_vol	-0.010*** (0.004)	-0.017*** (0.005)	-0.017*** (0.005)	-0.019*** (0.005)
overnight_ind	-0.008 (0.021)	-0.008 (0.020)	-0.008 (0.020)	0.005 (0.020)
overnight_1m	0.002 (0.005)	0.001 (0.005)	0.001 (0.005)	0.003 (0.005)
overnight_3m	0.007** (0.005)	0.005** (0.005)	0.005** (0.005)	0.004** (0.004)
overnight_6m	0.002 (0.007)	0.001 (0.007)	0.001 (0.007)	-0.002 (0.006)
omega	0.069*** (0.033)	0.056*** (0.022)	0.056*** (0.022)	0.050*** (0.020)
alpha[1]	0.280*** (0.110)	0.230*** (0.064)	0.232*** (0.067)	0.273*** (0.081)
beta[1]	0.696*** (0.093)	0.740*** (0.048)	0.739*** (0.049)	0.714*** (0.051)
new_cases		-0.006*** (0.004)	-0.005** (0.005)	-0.005** (0.005)
new_death		0.003 (0.004)	0.002 (0.004)	0.001 (0.004)
total_vaccinations_per_hundred		0.003** (0.002)	0.004** (0.003)	0.003** (0.003)
stringency_index		0.015*** (0.006)	0.015*** (0.006)	0.014*** (0.006)
gtrend_corr			-0.002 (0.003)	-0.001 (0.003)
news_count				0.019*** (0.009)
title_POS				0.002** (0.003)
title_NEG				-0.005** (0.003)
text_POS				0.005** (0.004)
text_NEG				-0.015*** (0.004)
topic_health				-0.001 (0.010)
topic_societal_chnges				0.002 (0.005)

Table 7: HARX-GARCH model results for China`s composite financial performance indices

Variables	HARX-GARCH	HARX-GARCH-O	HARX-GARCH-OG	HARX-GARCH-OGN
R2	0.0125	0.018	0.0238	0.038
R2_adj	-0.0049	-0.0082	-0.0045	-0.0078
Const	0.215 (0.528)	-0.130 (0.571)	-0.000 (0.572)	-0.500 (0.782)
i...ice[0:1]	0.026 (0.052)	0.023 (0.052)	0.021 (0.052)	0.019 (0.053)
i...ice[0:5]	-0.036 (0.124)	-0.038 (0.126)	-0.018 (0.127)	0.007 (0.133)
i...ice[0:22]	-0.342** (0.319)	-0.500** (0.320)	-0.510** (0.317)	-0.536*** (0.319)
ind_comp_vol	0.004** (0.004)	0.005** (0.004)	0.005** (0.004)	0.005** (0.004)
overnight_ind	0.000 (0.005)	-0.000 (0.005)	-0.000 (0.005)	0.001 (0.005)
overnight_1m	-0.018** (0.014)	-0.020** (0.014)	-0.020** (0.014)	-0.022** (0.014)
overnight_3m	-0.008 (0.029)	-0.005 (0.029)	-0.006 (0.029)	-0.012 (0.029)
overnight_6m	0.018 (0.029)	0.016 (0.029)	0.016 (0.029)	0.025** (0.029)
omega	0.074*** (0.035)	0.073*** (0.037)	0.074*** (0.038)	0.070*** (0.034)
alpha[1]	0.094*** (0.037)	0.094*** (0.039)	0.095*** (0.040)	0.096*** (0.039)
beta[1]	0.857*** (0.042)	0.857*** (0.045)	0.856*** (0.047)	0.856*** (0.044)
new_cases		0.012 (0.035)	0.011 (0.036)	0.015 (0.039)
new_death		-0.027 (0.131)	-0.027 (0.133)	-0.037 (0.142)
total_vaccinations_per_hundred		-0.002** (0.002)	0.000 (0.003)	0.001 (0.003)
stringency_index		0.005** (0.003)	0.005** (0.003)	0.005** (0.003)
gtrend_corr			-0.005** (0.004)	-0.005** (0.004)
news_count				0.003 (0.009)
title_POS				0.010*** (0.004)
title_NEG				0.001 (0.005)
text_POS				-0.006** (0.004)
text_NEG				-0.002 (0.005)
topic_health				-0.001 (0.011)
topic_economic_consequencies				0.003 (0.006)
topic_societal_chnges				0.001 (0.013)

Table 8: HARX-GARCH model results for Russia`s composite financial performance indices

Variables	HARX-GARCH	HARX-GARCH-O	HARX-GARCH-OG	HARX-GARCH-OGN
R2	0.0149	0.0306	0.0313	0.0392
R2_adj	-0.0018	0.0058	0.0044	-0.0025
Const	0.495*** (0.242)	0.073 (0.373)	0.057 (0.374)	0.157 (0.410)
i...ice[0:1]	0.010 (0.049)	0.011 (0.050)	0.010 (0.050)	0.002 (0.050)
i...ice[0:5]	0.034 (0.131)	0.037 (0.131)	0.032 (0.131)	0.051 (0.131)
i...ice[0:22]	-0.016 (0.287)	-0.121 (0.303)	-0.115 (0.302)	-0.138 (0.303)
ind_comp_vol	-0.008** (0.006)	-0.008** (0.006)	-0.008** (0.006)	-0.009** (0.006)
overnight_ind	-0.003** (0.005)	-0.004** (0.005)	-0.004** (0.005)	-0.004** (0.005)
overnight_1m	-0.006** (0.004)	-0.004** (0.004)	-0.004** (0.004)	-0.004** (0.004)
overnight_3m	0.007*** (0.004)	0.009*** (0.004)	0.009*** (0.004)	0.009*** (0.004)
overnight_6m	-0.002** (0.004)	-0.000 (0.004)	-0.000 (0.004)	-0.000 (0.004)
omega	0.026*** (0.015)	0.025*** (0.014)	0.026*** (0.014)	0.026*** (0.014)
alpha[1]	0.080*** (0.032)	0.079*** (0.032)	0.078*** (0.032)	0.079*** (0.032)
beta[1]	0.899*** (0.031)	0.900*** (0.030)	0.901*** (0.030)	0.900*** (0.030)
new_cases		0.001 (0.005)	0.003 (0.006)	0.003 (0.006)
new_death		-0.005** (0.006)	-0.006** (0.006)	-0.005** (0.007)
total_vaccinations_per_hundred		-0.001 (0.004)	0.000 (0.004)	0.000 (0.004)
stringency_index		0.005** (0.003)	0.005** (0.003)	0.004** (0.004)
gtrend_corr			-0.003** (0.003)	-0.002** (0.003)
news_count				0.001 (0.004)
title_POS				-0.004** (0.004)
title_NEG				-0.003** (0.004)
text_POS				0.001 (0.005)
text_NEG				0.007** (0.008)
topic_health				0.003 (0.012)
topic_economic_consequencies				-0.003 (0.006)

From the results we can make several conclusions. First, countries` financial performance indices have been differently affected by Covid spread, lethality, vaccination level and restrictive policies. While the US index was negatively affected by the number of cases and Russia`s index was negatively impacted by the number of deaths, China`s index has not been affected by these two indicators. Vaccination level positively affected the dynamics of financial performance index only in the US. Finally, the stringency of restrictive anti-pandemic policies positively affected financial performance indices in all three countries.

Next, we find that pandemic-related google search affected composite financial performance indices in China and Russia but not in the US. In particular, more respective search activities negatively affected the indices. This is in line with our expectations since pandemic-related google search enquiries tend to increase when negative consequences of the pandemic accumulate.

Finally, the sentiment of Covid-related news has had an expected impact on the US and Russia`s indices. Both the US and Russia`s indices have been positively affected by Covid-related news with positive sentiments and negatively – by negative news. China`s index was negatively affected by negative news though positive news did not have an impact.

The results for the effects of the dominance of pandemic-related news topics are rather mixed. On one hand, China`s index has not been affected by the respective indicators. On the other, higher frequency of Covid-related news in the area of healthcare has had positive impact on Russia`s index while higher frequency of the news on societal consequences of the pandemic positively affected the US financial performance index.

In Appendices C and D, we present baseline results for consumer and transport sectors` financial performance indices. Though the results do not differ conceptually from the baseline there are some interesting nuances in findings for sectors. For the US, the effects of the number of cases (i.e., the level of Covid spread) and Covid-related news` sentiment are less important for both sectors` indices compared to composite index. On the other hand, for consumer sector we find significant negative impact of pandemic-related Google search activities on the index. For China, on the contrary, we find that the number of Covid cases negatively affect the financial performance index in consumer sector while the respective coefficient is insignificant for the composite and transport sector indices. Finally, for Russia we find that the number of Covid cases and Covid-related deaths differently affects sectoral performance. While consumer sector`s performance is not affected by Covid-related deaths, the impact of the number of cases is negative. On the other hand, transport sector performance is positively affected by the number of cases while the number of deaths affects the index negatively. We further find that news on economic consequences of the pandemic negatively affect Russian transport sector`s financial performance index.

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Appendix A: Initial variables` summary

Table A1: Variables` summary

Short name	Full name	Reported days (out of 731 days)	Data source
Target variables (indices)			
us_ind_comp_close_price	S&P 500, closing price, USD	504	finance.yahoo.com
us_ind_wr_close_price	Dow Jones U.S. Consumer Goods Index, closing prices, USD	505	finance.yahoo.com
us_ind_tr_close_price	Dow Jones Transportation Average, closing price, USD	504	finance.yahoo.com
ru_ind_comp_close_price	Index IMOEX, closing price, RUB	505	finam.ru
ru_ind_wr_close_price	Index MOEXCN, closing price, RUB		finam.ru
ru_ind_tr_close_price	Index MOEXTN, closing price, RUB		finam.ru
cn_ind_comp_close_price	Shanghai Shenzhen CSI 300, closing price, CNY	486	finam.ru
cn_ind_wr_close_price	Shenzhen Stock Exchange: Wholesale & Retail, closing price, CNY		szse.cn
cn_ind_tr_close_price	Shenzhen Stock Exchange: Transportation, closing price, CNY		
Covid-19-related variables			
{us, ru, cn}_new_cases	New reported cases of Covid-19 infection	729	covid19.who.int
{us, ru, cn}_new_death	New registered cases from Covid-19 infection		
{us, ru, cn}_total_vaccinations_per_hundred	Total number of vaccinations per 100 million people	384 (us), 281 (ru) и 297 (cn)	ourworldindata.org
{us, ru, cn}_stringency_index	Stringency index of Covid-19-related restrictions	710 (us), 701 (ru), 710 (cn)	
Control variables			
{us, ru, cn}_ind_{comp, wr, tr}_vol	Trading volumes of the targeted variables/indices	The same as for the indices	
us_overnight_{ind, 1m, 3m, 6m}	USD LIBOR interest rate	494	iborate.com
ru_overnight_{ind, 1m, 3m, 6m}	RUONIA Index and Average	731	cbr.ru
cn_overnight_{ind, 1m, 3m, 6m}	Shanghai Interbank Offered Rate	499	shibor.org

Appendix B: Descriptive statistics of the variables

Table B1: Descriptive statistics

Variable	**Mean**	**St. dev.**	**Min**	**25%**	**50%**	**75%**	**Max**
us_ind_comp_close_price	3742,55	608,15	2237,40	3275,69	3726,95	4298,24	4793,06
us_ind_comp_vol	4,38	1,36	1,89	3,40	4,07	4,98	9,88
us_ind_wr_close_price	812,51	138,84	469,67	691,28	861,53	919,53	1062,83
us_ind_wr_vol	0,39	0,10	0,14	0,32	0,37	0,44	0,82
us_ind_tr_close_price	12512,47	2652,90	6703,63	10864,44	12604,12	14812,15	17039,38
us_ind_tr_vol	1,45	0,89	0,39	0,88	1,19	1,73	8,42
ru_ind_comp_close_price	3323,19	508,29	2112,64	2884,66	3341,10	3787,26	4287,52
ru_ind_comp_vol	84,52	25,41	23,46	66,81	83,48	98,96	248,73
ru_ind_wr_close_price	7886,60	1319,79	4764,19	6567,43	8432,18	8960,24	9596,56
ru_ind_wr_vol	5,21	5,74	1,01	3,22	4,16	5,63	116,90
ru_ind_tr_close_price	1380,67	131,54	1004,05	1310,37	1364,43	1433,15	1813,63
ru_ind_tr_vol	1,43	1,11	0,18	0,73	1,14	1,71	9,48
cn_ind_comp_close_price	4734,39	501,41	3530,31	4519,30	4881,40	5057,13	5807,72
cn_ind_comp_vol	2348,48	631,27	330,00	2221,25	2500,00	2761,00	3082,00
cn_ind_wr_close_price	1479,89	99,63	1275,96	1413,33	1456,54	1519,19	1871,00
cn_ind_wr_vol	1,07	0,44	0,53	0,76	0,91	1,27	3,48
cn_ind_tr_close_price	1282,37	147,45	981,53	1174,10	1277,96	1388,53	1698,78
cn_ind_tr_vol	0,34	0,11	0,15	0,26	0,31	0,39	0,80
us_overnight_ind	0,22	0,43	0,05	0,07	0,08	0,08	1,58
us_overnight_1m	0,31	0,45	0,07	0,10	0,13	0,17	1,73
us_overnight_3m	0,41	0,48	0,11	0,16	0,22	0,28	1,90
us_overnight_6m	0,44	0,46	0,15	0,19	0,25	0,36	1,91
ru_overnight_ind	2,18	0,06	2,08	2,14	2,18	2,23	2,31
ru_overnight_1m	5,23	1,05	4,00	4,18	5,07	6,06	7,60
ru_overnight_3m	5,22	0,97	4,15	4,19	5,06	6,03	7,28
ru_overnight_6m	5,26	0,90	4,18	4,35	5,15	6,11	6,87
cn_overnight_ind	1,78	0,46	0,60	1,53	1,86	2,12	3,28
cn_overnight_1m	2,34	0,37	1,30	2,30	2,39	2,58	2,90
cn_overnight_3m	2,46	0,40	1,39	2,37	2,49	2,69	3,14
cn_overnight_6m	2,57	0,40	1,48	2,48	2,62	2,84	3,18
us_new_cases	73446,43	67312,53	0,00	25291,00	53941,00	108544,00	473688,00
us_new_death	1122,80	902,30	0,00	485,00	897,00	1613,00	5077,00
ru_new_cases	14403,27	10682,46	0,00	6234,00	10595,00	22850,00	41335,00
ru_new_death	423,68	357,85	0,00	117,00	379,00	669,00	1254,00
cn_new_cases	180,77	719,63	0,00	26,00	49,00	104,00	15152,00
cn_new_death	7,82	52,18	0,00	0,00	0,00	2,00	1290,00
us_total_vaccinations_per_hundre	84,29	47,38	0,01	41,19	100,40	119,48	155,72
us_stringency_index	58,22	16,64	0,00	52,31	62,50	68,98	75,46
ru_total_vaccinations_per_hundre	43,68	28,90	0,02	17,25	41,18	64,62	100,31
ru_stringency_index	49,77	16,94	8,33	40,28	47,69	58,80	87,04
cn_total_vaccinations_per_hundre	102,60	62,92	0,10	35,37	120,61	154,69	196,32
cn_stringency_index	71,67	9,34	26,39	66,43	75,46	78,24	81,94
us_news_count	145,95	63,67	0,00	83,00	161,00	184,00	910,00
cn_news_count	160,62	85,54	22,00	71,00	184,00	208,50	1081,00
ru_news_count	118,20	75,10	5,00	33,50	135,00	168,00	499,00
us_title_POS	0,07	0,07	0,00	0,01	0,06	0,11	0,44
us_title_NEG	0,15	0,11	0,00	0,08	0,14	0,21	0,66
cn_title_POS	0,16	0,09	0,00	0,10	0,15	0,21	0,52
cn_title_NEG	0,11	0,07	0,00	0,06	0,11	0,16	0,51
ru_title_POS	0,12	0,17	0,00	0,00	0,06	0,18	1,00
ru_title_NEG	0,16	0,20	0,00	0,00	0,10	0,24	1,00
us_text_POS	0,02	0,03	0,00	0,00	0,01	0,02	0,29
us_text_NEG	0,05	0,05	0,00	0,02	0,04	0,07	0,43
cn_text_POS	0,04	0,04	0,00	0,02	0,03	0,06	0,25
cn_text_NEG	0,04	0,03	0,00	0,01	0,03	0,05	0,24
ru_text_POS	0,05	0,09	0,00	0,00	0,02	0,07	0,95
ru_text_NEG	0,06	0,11	0,00	0,00	0,02	0,08	1,00
us_topic_health	0,05	0,03	0,01	0,04	0,05	0,06	0,47
us_topic_societal_changes	0,07	0,03	0,01	0,05	0,06	0,08	0,19
ru_topic_health	0,02	0,01	0,00	0,01	0,02	0,02	0,20
ru_topic_economic_consequences	0,05	0,03	0,00	0,03	0,04	0,06	0,22
cn_topic_health	0,12	0,06	0,02	0,08	0,10	0,14	0,45
cn_topic_societal_changes	0,04	0,03	0,00	0,02	0,03	0,04	0,23
cn_topic_economic_consequences	0,02	0,01	0,00	0,01	0,02	0,03	0,08
us_gtrend_corr	32,06	23,29	0,00	10,67	30,48	48,69	100,00
ru_gtrend_corr	13,86	15,75	0,00	4,59	9,99	14,41	100,00
cn_gtrend_corr	21,41	20,14	0,00	5,00	14,80	33,51	100,00

Appendix C: Baseline results for consumer`s sector financial performance indices

Table C1: HARX-GARCH model results for the US consumer`s sector financial performance indices

Variables	HARX-GARCH	HARX-GARCH-O	HARX-GARCH-OG	HARX-GARCH-OGN
R2	0.031	0.0466	0.0453	0.0597
R2_adj	0.0146	0.0222	0.0188	0.0189
Const	0.641 (2.105)	0.307 (2.140)	0.390 (2.137)	0.191 (2.261)
i...ice[0:1]	-0.040** (0.054)	-0.043** (0.053)	-0.040** (0.053)	-0.050** (0.054)
i...ice[0:5]	-0.015 (0.127)	-0.100** (0.138)	-0.120** (0.140)	-0.076 (0.141)
i...ice[0:22]	-0.236** (0.253)	-0.566*** (0.264)	-0.622*** (0.261)	-0.534*** (0.258)
overnight_ind	-0.013 (0.025)	-0.017** (0.025)	-0.017** (0.025)	-0.014 (0.026)
overnight_1m	0.003 (0.007)	0.003 (0.007)	0.003 (0.007)	0.004 (0.007)
overnight_3m	0.013*** (0.006)	0.012*** (0.006)	0.012*** (0.006)	0.012*** (0.006)
overnight_6m	-0.002 (0.008)	-0.003 (0.007)	-0.002 (0.007)	-0.003 (0.007)
omega	0.063** (0.053)	0.072*** (0.041)	0.068*** (0.039)	0.077** (0.051)
alpha[1]	0.149*** (0.073)	0.184*** (0.064)	0.185*** (0.064)	0.190*** (0.076)
beta[1]	0.811*** (0.095)	0.776*** (0.070)	0.778*** (0.069)	0.765*** (0.090)
ind_wr_vol	-0.010*** (0.004)	-0.010*** (0.005)	-0.011*** (0.005)	-0.011*** (0.005)
new_cases		0.001 (0.005)	0.005** (0.005)	0.002 (0.006)
new_death		-0.000 (0.006)	-0.001 (0.006)	-0.000 (0.006)
total_vaccinations_per_hundred		-0.002** (0.002)	0.001 (0.003)	0.001 (0.003)
stringency_index		0.012*** (0.006)	0.012*** (0.006)	0.009** (0.006)
gtrend_corr			-0.005*** (0.003)	-0.006*** (0.003)
news_count				0.004 (0.010)
title_POS				0.005** (0.004)
title_NEG				-0.001 (0.004)
text_POS				0.003 (0.005)
text_NEG				-0.011*** (0.006)
topic_health				0.008** (0.010)
topic_societal_changes				0.002 (0.006)

Table C2: HARX-GARCH model results for China`s consumer`s sector financial performance indices

Variables	HARX-GARCH	HARX-GARCH-O	HARX-GARCH-OG	HARX-GARCH-OGN
R2	0.0567	0.0599	0.0611	0.0659
R2_adj	0.04	0.0348	0.0339	0.0214
Const	0.053 (0.572)	0.080 (0.604)	0.245 (0.637)	-0.063 (0.705)
i...ice[0:1]	0.164*** (0.056)	0.161*** (0.057)	0.157*** (0.058)	0.158*** (0.056)
i...ice[0:5]	-0.278*** (0.114)	-0.271*** (0.115)	-0.260*** (0.114)	-0.281*** (0.116)
i...ice[0:22]	0.003 (0.312)	-0.041 (0.331)	0.029 (0.355)	0.026 (0.378)
overnight_ind	0.010** (0.007)	0.010** (0.007)	0.011** (0.007)	0.011*** (0.006)
overnight_1m	-0.031*** (0.017)	-0.031*** (0.017)	-0.031*** (0.017)	-0.031*** (0.017)
overnight_3m	-0.019 (0.035)	-0.020 (0.035)	-0.020 (0.035)	-0.019 (0.036)
overnight_6m	0.043** (0.031)	0.044** (0.031)	0.044** (0.032)	0.045** (0.032)
omega	0.043** (0.059)	0.045** (0.065)	0.052 (0.077)	0.055** (0.075)
alpha[1]	0.051** (0.038)	0.052** (0.039)	0.055** (0.042)	0.059** (0.043)
beta[1]	0.922*** (0.068)	0.919*** (0.072)	0.913*** (0.083)	0.906*** (0.082)
ind_wr_vol	0.004 (0.006)	0.005** (0.007)	0.002 (0.008)	0.002 (0.011)
new_cases		-0.013** (0.019)	-0.015** (0.020)	-0.014** (0.020)
new_death		0.005 (0.080)	0.013 (0.082)	-0.002 (0.085)
total_vaccinations_per_hundred		0.001 (0.002)	0.003** (0.003)	0.003** (0.003)
stringency_index		-0.001 (0.004)	-0.001 (0.004)	-0.001 (0.004)
gtrend_corr			-0.004** (0.004)	-0.005** (0.005)

news_count				0.009** (0.006)
title_POS				0.004** (0.004)
title_NEG				-0.000 (0.004)
text_POS				-0.004** (0.005)
text_NEG				0.005** (0.006)
topic_health				0.010** (0.011)
topic_economic_consequences				-0.004 (0.006)
topic_societal_changes				-0.006 (0.016)

Table C3: HARX-GARCH model results for Russia`s consumer`s sector financial performance indices

Variables	**HARX-GARCH**	**HARX-GARCH-O**	**HARX-GARCH-OG**	**HARX-GARCH-OGN**
R2	0.0057	0.0267	0.0166	0.0318
R2_adj	-0.0112	0.0018	-0.0107	-0.0102
Const	0.610*** (0.260)	0.126 (0.431)	0.324 (0.630)	0.667** (0.495)
i...ice[0:1]	0.022 (0.057)	0.026 (0.056)	0.023 (0.057)	0.023 (0.056)
i...ice[0:5]	0.040 (0.128)	0.041 (0.125)	0.034 (0.126)	0.026 (0.121)
i...ice[0:22]	-0.244** (0.251)	-0.397** (0.244)	-0.525*** (0.303)	-0.585*** (0.244)
overnight_ind	0.001 (0.005)	0.002 (0.005)	0.001 (0.005)	0.001 (0.005)
overnight_1m	-0.007*** (0.004)	-0.005** (0.005)	-0.007** (0.005)	-0.005** (0.004)
overnight_3m	-0.004** (0.004)	-0.002 (0.004)	-0.002 (0.004)	-0.003** (0.004)
overnight_6m	0.000 (0.003)	0.004** (0.003)	0.004** (0.004)	0.004** (0.004)
omega	0.049** (0.049)	0.048** (0.050)	0.160** (0.159)	0.145** (0.122)
alpha[1]	0.118** (0.078)	0.116** (0.075)	0.223** (0.185)	0.233** (0.157)
beta[1]	0.836*** (0.113)	0.838*** (0.112)	0.633*** (0.301)	0.635*** (0.241)
ind_wr_vol	0.004 (0.007)	0.003 (0.007)	0.003 (0.010)	-0.000 (0.010)
new_cases		0.008*** (0.004)	0.008*** (0.004)	0.009*** (0.004)
new_death		-0.012*** (0.005)	-0.012*** (0.005)	-0.013*** (0.005)
total_vaccinations_per_hundred		0.002 (0.004)	0.001 (0.005)	-0.000 (0.004)
stringency_index		0.005** (0.004)	0.004** (0.005)	0.005** (0.004)
gtrend_corr			0.001 (0.003)	0.001 (0.002)
news_count				-0.001 (0.003)
title_POS				-0.005** (0.004)
title_NEG				-0.005** (0.004)
text_POS				0.005** (0.005)
text_NEG				0.009** (0.007)
topic_health				0.003 (0.011)
topic_economic_consequences				-0.018*** (0.005)

Appendix D: Baseline results for transport sector financial performance indices

Table D1: HARX-GARCH model results for the US transport sector financial performance indices

Variables	**HARX-GARCH**	**HARX-GARCH-O**	**HARX-GARCH-OG**	**HARX-GARCH-OGN**
R2	0.0408	0.06	0.06	0.0419
R2_adj	0.0246	0.0359	0.0338	0.0002
Const	-1.296 (3.941)	-2.204 (4.250)	-2.239 (4.279)	-1.580 (3.683)
i...ice[0:1]	-0.022 (0.067)	-0.016 (0.067)	-0.016 (0.069)	-0.017 (0.055)
i...ice[0:5]	-0.135** (0.139)	-0.167** (0.177)	-0.168** (0.184)	-0.131** (0.129)
i...ice[0:22]	0.153 (0.381)	-0.113 (0.405)	-0.130 (0.407)	-0.023 (0.299)
overnight_ind	-0.012 (0.046)	-0.010 (0.049)	-0.010 (0.049)	-0.026 (0.042)
overnight_1m	0.013** (0.013)	0.014** (0.013)	0.014** (0.013)	0.005 (0.014)
overnight_3m	0.005 (0.010)	0.004 (0.012)	0.004 (0.012)	0.012** (0.011)
overnight_6m	0.017** (0.016)	0.015** (0.021)	0.014 (0.022)	0.024*** (0.014)
omega	0.233** (0.292)	0.235** (0.315)	0.232** (0.337)	0.314*** (0.157)
alpha[1]	0.184** (0.195)	0.191** (0.217)	0.191** (0.230)	0.325** (0.213)
beta[1]	0.735*** (0.271)	0.725*** (0.302)	0.726*** (0.323)	0.585*** (0.196)
ind_tr_vol	0.017** (0.017)	0.008 (0.021)	0.008 (0.022)	0.011** (0.015)

new_cases		-0.010 (0.016)	-0.009 (0.018)	-0.019** (0.014)
new_death		0.005 (0.018)	0.004 (0.019)	0.012** (0.010)
total_vaccinations_per_hundred		0.003** (0.003)	0.004** (0.005)	0.004** (0.005)
stringency_index		0.013** (0.016)	0.014** (0.017)	0.007** (0.007)
gtrend_corr			-0.002 (0.005)	-0.001 (0.006)
news_count				0.021** (0.015)
title_POS				0.013*** (0.006)
title_NEG				-0.000 (0.005)
text_POS				-0.001 (0.007)
text_NEG				-0.020*** (0.007)
topic_health				-0.003 (0.017)
topic_societal_changes				0.005 (0.009)

Table D2: HARX-GARCH model results for China`s transport sector financial performance indices

Variables	**HARX-GARCH**	**HARX-GARCH-O**	**HARX-GARCH-OG**	**HARX-GARCH-OGN**
R2	0.0367	0.042	0.0495	0.0572
R2_adj	0.0197	0.0165	0.022	0.0123
Const	-0.397** (0.486)	-0.729** (0.570)	-0.535** (0.560)	-1.174** (0.738)
i...ice[0:1]	0.118*** (0.052)	0.115*** (0.053)	0.110*** (0.053)	0.116*** (0.053)
i...ice[0:5]	-0.157** (0.114)	-0.157** (0.115)	-0.144** (0.114)	-0.164** (0.117)
i...ice[0:22]	-0.387** (0.259)	-0.398** (0.257)	-0.457*** (0.256)	-0.433*** (0.260)
overnight_ind	0.003 (0.006)	0.002 (0.006)	0.003 (0.006)	0.004 (0.006)
overnight_1m	-0.012** (0.017)	-0.013** (0.017)	-0.014** (0.017)	-0.014** (0.017)
overnight_3m	0.017 (0.037)	0.017 (0.037)	0.016 (0.037)	0.012 (0.037)
overnight_6m	-0.007 (0.031)	-0.008 (0.031)	-0.006 (0.030)	0.002 (0.031)
omega	0.087*** (0.048)	0.091*** (0.051)	0.094*** (0.050)	0.087*** (0.048)
alpha[1]	0.040*** (0.021)	0.037*** (0.021)	0.036*** (0.021)	0.040*** (0.023)
beta[1]	0.920*** (0.023)	0.921*** (0.024)	0.921*** (0.024)	0.920*** (0.022)
ind_tr_vol	0.019*** (0.005)	0.018*** (0.005)	0.017*** (0.005)	0.017*** (0.005)
new_cases		-0.005 (0.022)	-0.005 (0.022)	-0.002 (0.021)
new_death		0.007 (0.074)	0.004 (0.073)	-0.014 (0.075)
total_vaccinations_per_hundred		0.000 (0.002)	0.005** (0.004)	0.006** (0.004)
stringency_index		0.005** (0.005)	0.004** (0.004)	0.004** (0.004)
gtrend_corr			-0.009** (0.006)	-0.007** (0.006)
news_count				0.010** (0.008)
title_POS				0.007** (0.005)
title_NEG				-0.002 (0.006)
text_POS				-0.009** (0.006)
text_NEG				0.003 (0.007)
topic_health				0.009 (0.017)
topic_economic_consequences				0.002 (0.006)
topic_societal_changes				-0.003 (0.014)

Table D3: HARX-GARCH model results for Russia`s transport sector financial performance indices

Variables	**HARX-GARCH**	**HARX-GARCH-O**	**HARX-GARCH-OG**	**HARX-GARCH-OGN**
R2	0.0274	0.0218	0.0207	0.021
R2_adj	0.0109	-0.0032	-0.0065	-0.0215
Const	-0.258** (0.348)	-0.290 (0.574)	-0.310 (0.704)	-0.246 (0.592)
i...ice[0:1]	-0.041 (0.083)	-0.058 (0.105)	-0.058 (0.130)	-0.064** (0.086)
i...ice[0:5]	0.214** (0.175)	0.241*** (0.144)	0.224** (0.179)	0.221** (0.140)
i...ice[0:22]	-0.133 (0.213)	-0.194 (0.299)	-0.194 (0.331)	-0.203** (0.271)
overnight_ind	0.002 (0.007)	0.002 (0.006)	0.001 (0.007)	-0.000 (0.007)
overnight_1m	-0.004** (0.005)	-0.005** (0.006)	-0.004 (0.007)	-0.004** (0.005)
overnight_3m	0.000 (0.005)	0.002 (0.005)	0.003 (0.005)	0.003 (0.005)
overnight_6m	0.005** (0.005)	0.009*** (0.005)	0.009*** (0.005)	0.010*** (0.005)
omega	0.097 (0.147)	0.128** (0.172)	0.121 (0.246)	0.131** (0.132)
alpha[1]	0.187** (0.179)	0.231** (0.243)	0.222 (0.338)	0.233** (0.182)

beta[1]	0.759*** (0.245)	0.703*** (0.301)	0.714*** (0.429)	0.697*** (0.226)
ind_tr_vol	0.012** (0.008)	0.011** (0.009)	0.011** (0.009)	0.010** (0.009)
new_cases		0.008** (0.006)	0.009** (0.006)	0.009** (0.006)
new_death		-0.012** (0.010)	-0.012** (0.010)	-0.012** (0.009)
total_vaccinations_per_hundred		-0.001 (0.004)	-0.000 (0.005)	-0.001 (0.004)
stringency_index		-0.001 (0.006)	-0.001 (0.007)	-0.001 (0.006)
gtrend_corr			-0.003** (0.003)	-0.003** (0.003)
news_count				-0.002 (0.004)
title_POS				0.001 (0.005)
title_NEG				0.000 (0.005)
text_POS				0.005** (0.006)
text_NEG				0.007** (0.008)
topic_health				0.014** (0.011)
topic_economic_consequences				-0.010*** (0.006)

Appendix E

Table E1: HARX-GARCH model results for the US composite financial performance index with adding moving averages for the previous 5 days

Variables	HARX-GARCH-R5	HARX-GARCH-O-R5	HARX-GARCH-OG-R5	HARX-GARCH-OGN-R5
R2	0.1103	0.1355	0.1357	0.1565
R2_adj	0.0856	0.096	0.0922	0.086
Const	-4.481** (3.262)	-3.713** (3.245)	-3.685** (3.269)	-7.463*** (3.671)
i...ice[0:1]	-0.110*** (0.051)	-0.109*** (0.052)	-0.111*** (0.052)	-0.092*** (0.051)
i...ice[0:5]	-0.073 (0.139)	-0.147** (0.157)	-0.147** (0.157)	-0.169** (0.152)
i...ice[0:22]	-0.464** (0.298)	-0.669*** (0.329)	-0.683*** (0.321)	-0.747*** (0.312)
ind_comp_vol	-0.028*** (0.007)	-0.028*** (0.007)	-0.028*** (0.007)	-0.031*** (0.007)
overnight_ind	-0.008 (0.020)	-0.006 (0.020)	-0.006 (0.019)	-0.001 (0.019)
overnight_1m	0.005** (0.006)	0.005** (0.006)	0.004** (0.006)	0.006** (0.006)
overnight_3m	0.009*** (0.005)	0.009*** (0.005)	0.009*** (0.005)	0.007** (0.005)
overnight_6m	-0.003 (0.008)	-0.004 (0.008)	-0.003 (0.008)	-0.009** (0.008)
ind_comp_vol_rolling_5	0.028*** (0.007)	0.021*** (0.008)	0.020*** (0.008)	0.017*** (0.008)
overnight_ind_rolling_5	0.060** (0.049)	0.047** (0.049)	0.048** (0.049)	0.087*** (0.050)
overnight_1m_rolling_5	-0.018** (0.015)	-0.022** (0.016)	-0.020** (0.016)	-0.016** (0.016)
overnight_3m_rolling_5	-0.022** (0.020)	-0.029** (0.020)	-0.029** (0.020)	-0.025** (0.018)
overnight_6m_rolling_5	0.035*** (0.014)	0.033*** (0.014)	0.032*** (0.014)	0.029*** (0.016)
omega	0.058*** (0.029)	0.052*** (0.019)	0.052*** (0.019)	0.044*** (0.018)
alpha[1]	0.229*** (0.105)	0.208*** (0.057)	0.209*** (0.059)	0.254*** (0.087)
beta[1]	0.741*** (0.091)	0.760*** (0.044)	0.759*** (0.045)	0.732*** (0.061)
new_cases		0.009 (0.013)	0.008 (0.013)	0.002 (0.013)
new_death		-0.000 (0.008)	-0.000 (0.008)	0.004 (0.007)
total_vaccinations_per_hundred		0.006 (0.012)	0.006 (0.012)	0.006 (0.011)
stringency_index		0.014** (0.015)	0.014** (0.015)	0.006 (0.013)
new_cases_rolling_5		-0.013** (0.017)	-0.010 (0.018)	-0.006 (0.016)
new_death_rolling_5		-0.002 (0.010)	-0.002 (0.010)	-0.003 (0.009)
total_vaccinations_per_hundred_rolling_		-0.005 (0.012)	-0.003 (0.012)	-0.001 (0.011)
stringency_index_rolling_5		0.000 (0.016)	0.000 (0.016)	0.003 (0.014)
gtrend_corr			0.004 (0.006)	0.007** (0.006)
gtrend_corr_rolling_5			-0.005** (0.007)	-0.010** (0.007)
news_count				0.005 (0.009)
title_POS				0.002 (0.003)
title_NEG				-0.003** (0.004)
text_POS				0.004** (0.004)
text_NEG				-0.019*** (0.005)
topic_health				-0.008** (0.010)
news_count_rolling_5				0.033*** (0.019)
title_POS_rolling_5				-0.004 (0.008)
title_NEG_rolling_5				-0.001 (0.010)
text_POS_rolling_5				-0.005 (0.010)

text_NEG_rolling_5				0.006 (0.010)
topic_health_rolling_5				0.021** (0.024)
topic_societal_changes				-0.013*** (0.007)
topic_societal_changes_rolling_5				0.022*** (0.010)

Table E2: HARX-GARCH model results for the US consumer sector financial performance index with adding moving averages for the previous 5 days

Variables	**HARX-GARCH-R5**	**HARX-GARCH-O-R5**	**HARX-GARCH-OG-R5**	**HARX-GARCH-OGN-R5**
R2	0.0558	0.0711	0.0698	0.064
R2_adj	0.0296	0.0287	0.0231	-0.014
Const	-6.833*** (3.586)	-5.696** (3.623)	-5.656** (3.589)	-11.606*** (4.821)
i...ice[0:1]	-0.052** (0.054)	-0.055** (0.053)	-0.052** (0.053)	-0.053** (0.055)
i...ice[0:5]	0.015 (0.134)	-0.103** (0.147)	-0.118** (0.150)	-0.115** (0.142)
i...ice[0:22]	-0.284** (0.260)	-0.558*** (0.257)	-0.607*** (0.255)	-0.713*** (0.280)
overnight_ind	-0.029** (0.027)	-0.034** (0.026)	-0.035** (0.026)	-0.043** (0.028)
overnight_1m	0.005 (0.008)	0.005 (0.008)	0.005** (0.008)	0.006** (0.008)
overnight_3m	0.014*** (0.007)	0.014*** (0.007)	0.014*** (0.007)	0.014*** (0.007)
overnight_6m	-0.008** (0.008)	-0.008** (0.008)	-0.008** (0.008)	-0.009** (0.008)
overnight_ind_rolling_5	0.102*** (0.046)	0.075** (0.046)	0.077*** (0.045)	0.143*** (0.061)
overnight_1m_rolling_5	-0.016** (0.020)	-0.015** (0.021)	-0.016** (0.021)	-0.013 (0.022)
overnight_3m_rolling_5	-0.022** (0.018)	-0.021** (0.018)	-0.022** (0.018)	-0.014** (0.017)
overnight_6m_rolling_5	0.045*** (0.022)	0.054*** (0.022)	0.055*** (0.022)	0.059*** (0.024)
omega	0.058** (0.048)	0.071** (0.045)	0.072** (0.044)	0.084** (0.122)
alpha[1]	0.143*** (0.069)	0.185*** (0.075)	0.189*** (0.076)	0.242** (0.226)
beta[1]	0.820*** (0.089)	0.774*** (0.084)	0.770*** (0.084)	0.714*** (0.272)
ind_wr_vol	-0.015*** (0.006)	-0.012*** (0.006)	-0.012*** (0.006)	-0.011*** (0.006)
ind_wr_vol_rolling_5	0.011** (0.008)	0.005 (0.008)	0.003 (0.008)	-0.002 (0.010)
new_cases		0.027*** (0.012)	0.026*** (0.013)	0.016** (0.017)
new_death		-0.007 (0.011)	-0.007 (0.011)	-0.000 (0.012)
total_vaccinations_per_hundred		-0.002 (0.013)	0.001 (0.013)	-0.002 (0.014)
stringency_index		0.006 (0.019)	0.006 (0.019)	-0.009 (0.020)
new_cases_rolling_5		-0.035*** (0.017)	-0.032*** (0.017)	-0.021** (0.020)
new_death_rolling_5		0.012** (0.014)	0.011** (0.014)	0.007 (0.013)
total_vaccinations_per_hundred_rolling_		-0.001 (0.013)	-0.002 (0.013)	0.004 (0.015)
stringency_index_rolling_5		0.006 (0.020)	0.005 (0.020)	0.013** (0.018)
gtrend_corr			-0.005** (0.007)	-0.005** (0.007)
gtrend_corr_rolling_5			0.002 (0.008)	0.003 (0.009)
news_count				-0.007 (0.014)
title_POS				0.004** (0.004)
title_NEG				0.001 (0.005)
text_POS				0.003 (0.006)
text_NEG				-0.015** (0.010)
topic_health				0.014** (0.013)
news_count_rolling_5				0.043*** (0.026)
title_POS_rolling_5				0.003 (0.010)
title_NEG_rolling_5				-0.003 (0.011)
text_POS_rolling_5				-0.005 (0.014)
text_NEG_rolling_5				0.016** (0.016)
topic_health_rolling_5				-0.033** (0.026)
topic_societal_changes				-0.014*** (0.008)
topic_societal_changes_rolling_5				0.030*** (0.017)

Table E3: HARX-GARCH model results for the US transport sector financial performance index with adding moving averages for the previous 5 days

Variables	**HARX-GARCH-R5**	**HARX-GARCH-O-R5**	**HARX-GARCH-OG-R5**	**HARX-GARCH-OGN-R5**
R2	0.028	0.024	0.0239	0.0612
R2_adj	0.0009	-0.0207	-0.0253	-0.0172
Const	-2.130 (6.940)	-2.593 (6.066)	-2.654 (6.038)	-10.423** (8.982)

i...ice[0:1]	-0.015 (0.061)	-0.016 (0.056)	-0.015 (0.056)	-0.017 (0.070)
i...ice[0:5]	-0.187** (0.143)	-0.223** (0.137)	-0.222** (0.136)	-0.266** (0.214)
i...ice[0:22]	0.157 (0.311)	0.057 (0.321)	0.053 (0.312)	-0.022 (0.302)
overnight_ind	-0.020 (0.045)	-0.017 (0.044)	-0.017 (0.043)	-0.019 (0.038)
overnight_1m	0.013** (0.016)	0.011** (0.014)	0.012** (0.014)	0.013** (0.011)
overnight_3m	0.012** (0.012)	0.013** (0.012)	0.013** (0.012)	0.010** (0.010)
overnight_6m	0.013** (0.013)	0.010** (0.013)	0.010** (0.013)	0.012** (0.016)
overnight_ind_rolling_5	0.011 (0.098)	-0.002 (0.084)	-0.002 (0.083)	0.076** (0.095)
overnight_1m_rolling_5	-0.031** (0.031)	-0.022** (0.033)	-0.023** (0.031)	-0.023** (0.033)
overnight_3m_rolling_5	-0.033** (0.039)	-0.037** (0.035)	-0.035** (0.034)	-0.012 (0.037)
overnight_6m_rolling_5	0.064** (0.055)	0.072** (0.048)	0.071** (0.047)	0.055*** (0.032)
omega	0.244** (0.194)	0.263** (0.160)	0.264*** (0.150)	0.210*** (0.108)
alpha[1]	0.217** (0.170)	0.259** (0.177)	0.263** (0.168)	0.259*** (0.133)
beta[1]	0.700*** (0.205)	0.655*** (0.192)	0.651*** (0.179)	0.673*** (0.139)
ind_tr_vol	0.007 (0.020)	0.004 (0.021)	0.006 (0.021)	0.014 (0.028)
ind_tr_vol_rolling_5	0.015** (0.021)	0.002 (0.024)	0.001 (0.023)	-0.027 (0.082)
new_cases		0.003 (0.019)	0.004 (0.019)	-0.001 (0.018)
new_death		0.005 (0.014)	0.004 (0.014)	0.007 (0.014)
total_vaccinations_per_hundred		0.010** (0.014)	0.012** (0.014)	0.014** (0.014)
stringency_index		0.050** (0.040)	0.051** (0.040)	0.036** (0.044)
new_cases_rolling_5		-0.026** (0.024)	-0.028** (0.025)	-0.026** (0.024)
new_death_rolling_5		0.009 (0.016)	0.010 (0.017)	0.009 (0.015)
total_vaccinations_per_hundred_rolling_		-0.009 (0.015)	-0.012** (0.015)	-0.012** (0.014)
stringency_index_rolling_5		-0.040** (0.044)	-0.041** (0.043)	-0.025 (0.048)
gtrend_corr			-0.007 (0.011)	-0.008** (0.010)
gtrend_corr_rolling_5			0.009** (0.012)	0.009** (0.011)
news_count				0.009 (0.020)
title_POS				0.007** (0.005)
title_NEG				-0.002 (0.005)
text_POS				0.006** (0.009)
text_NEG				-0.021*** (0.009)
topic_health				0.005 (0.018)
news_count_rolling_5				0.036** (0.041)
title_POS_rolling_5				0.013** (0.017)
title_NEG_rolling_5				0.017** (0.015)
text_POS_rolling_5				-0.024** (0.018)
text_NEG_rolling_5				-0.005 (0.021)
topic_health_rolling_5				0.002 (0.037)
topic_societal_changes				0.011** (0.012)
topic_societal_changes_rolling_5				0.004 (0.026)

Table E4: HARX-GARCH model results for China`s composite financial performance index with adding moving averages for the previous 5 days

Variables	**HARX-GARCH-R5**	**HARX-GARCH-O-R5**	**HARX-GARCH-OG-R5**	**HARX-GARCH-OGN-R5**
R2	0.0191	0.0395	0.0474	0.1012
R2_adj	-0.0093	-0.0062	-0.0025	0.0184
Const	-0.474 (0.734)	-0.840** (0.753)	-0.764** (0.743)	-1.970*** (1.062)
i...ice[0:1]	0.020 (0.053)	0.008 (0.052)	0.007 (0.052)	-0.017 (0.050)
i...ice[0:5]	-0.031 (0.128)	-0.058 (0.129)	-0.030 (0.130)	-0.059 (0.133)
i...ice[0:22]	-0.362** (0.318)	-0.533*** (0.317)	-0.538*** (0.315)	-0.776*** (0.346)
ind_comp_vol	0.004 (0.006)	0.005** (0.006)	0.004** (0.006)	0.003 (0.006)
overnight_ind	-0.002 (0.005)	-0.002 (0.005)	-0.001 (0.005)	-0.001 (0.005)
overnight_1m	-0.015** (0.018)	-0.017** (0.018)	-0.018** (0.018)	-0.019** (0.017)
overnight_3m	-0.030** (0.034)	-0.031** (0.034)	-0.027** (0.034)	-0.019 (0.033)
overnight_6m	0.019 (0.033)	0.021 (0.032)	0.019 (0.032)	0.009 (0.031)
ind_comp_vol_rolling_5	0.000 (0.009)	0.002 (0.008)	0.001 (0.008)	0.003 (0.008)
overnight_ind_rolling_5	0.016** (0.015)	0.018** (0.015)	0.018** (0.015)	0.031*** (0.014)
overnight_1m_rolling_5	-0.004 (0.025)	-0.006 (0.024)	-0.005 (0.024)	-0.023** (0.024)
overnight_3m_rolling_5	0.057** (0.053)	0.069** (0.052)	0.067** (0.053)	0.046** (0.050)

overnight_6m_rolling_5	-0.033** (0.049)	-0.044** (0.047)	-0.045** (0.048)	-0.006 (0.049)
omega	0.076*** (0.036)	0.079*** (0.038)	0.079*** (0.039)	0.063*** (0.032)
alpha[1]	0.097*** (0.041)	0.108*** (0.047)	0.112*** (0.051)	0.113*** (0.048)
beta[1]	0.852*** (0.044)	0.840*** (0.050)	0.835*** (0.054)	0.843*** (0.051)
new_cases		-0.022** (0.025)	-0.025** (0.025)	-0.022** (0.027)
new_death		-0.006 (0.130)	0.018 (0.132)	0.008 (0.151)
total_vaccinations_per_hundred		0.004 (0.011)	0.006 (0.012)	0.001 (0.012)
stringency_index		0.014*** (0.007)	0.014*** (0.007)	0.015*** (0.007)
new_cases_rolling_5		0.102*** (0.061)	0.106*** (0.062)	0.114*** (0.066)
new_death_rolling_5		-0.143** (0.190)	-0.178** (0.194)	-0.097 (0.235)
total_vaccinations_per_hundred_rolling_		-0.006 (0.011)	-0.008** (0.012)	-0.002 (0.012)
stringency_index_rolling_5		-0.011** (0.007)	-0.010** (0.007)	-0.008** (0.007)
gtrend_corr			-0.013*** (0.006)	-0.017*** (0.006)
gtrend_corr_rolling_5			0.012** (0.008)	0.019*** (0.009)
news_count				-0.001 (0.010)
title_POS				0.005** (0.004)
title_NEG				0.003 (0.005)
text_POS				-0.007** (0.005)
text_NEG				-0.001 (0.005)
topic_health				0.009 (0.017)
topic_economic_consequences				-0.004 (0.008)
news_count_rolling_5				0.029** (0.026)
title_POS_rolling_5				0.025*** (0.009)
title_NEG_rolling_5				-0.014** (0.012)
text_POS_rolling_5				-0.020*** (0.011)
text_NEG_rolling_5				-0.000 (0.012)
topic_health_rolling_5				-0.021** (0.024)
topic_economic_consequences_rolling_5				0.023*** (0.011)
topic_societal_changes				0.036*** (0.021)
topic_societal_changes_rolling_5				-0.054*** (0.028)

Table E5: HARX-GARCH model results for China`s consumer sector financial performance index with adding moving averages for the previous 5 days

Variables	HARX-GARCH-R5	HARX-GARCH-O-R5	HARX-GARCH-OG-R5	HARX-GARCH-OGN-R5
R2	0.0917	0.1009	0.1083	0.1302
R2_adj	0.0654	0.0581	0.0616	0.05
Const	-1.188** (0.763)	-1.228** (0.786)	-1.134** (0.838)	-2.563*** (0.858)
i...ice[0:1]	0.134*** (0.062)	0.125*** (0.063)	0.119*** (0.065)	0.074** (0.064)
i...ice[0:5]	-0.365*** (0.126)	-0.362*** (0.129)	-0.355*** (0.128)	-0.333*** (0.119)
i...ice[0:22]	0.020 (0.303)	-0.034 (0.325)	0.018 (0.361)	0.117 (0.424)
overnight_ind	0.002 (0.007)	0.002 (0.007)	0.002 (0.007)	0.002 (0.007)
overnight_1m	-0.016** (0.020)	-0.017** (0.020)	-0.017** (0.020)	-0.015** (0.019)
overnight_3m	-0.003 (0.039)	-0.004 (0.039)	0.000 (0.039)	0.007 (0.037)
overnight_6m	-0.006 (0.033)	-0.008 (0.033)	-0.010 (0.033)	-0.022** (0.032)
overnight_ind_rolling_5	0.047*** (0.021)	0.048*** (0.021)	0.048*** (0.021)	0.056*** (0.018)
overnight_1m_rolling_5	-0.040** (0.032)	-0.040** (0.032)	-0.042** (0.031)	-0.045** (0.030)
overnight_3m_rolling_5	-0.043 (0.069)	-0.037 (0.070)	-0.041 (0.072)	-0.061** (0.073)
overnight_6m_rolling_5	0.105*** (0.062)	0.102** (0.063)	0.105** (0.064)	0.137*** (0.068)
omega	0.030 (0.072)	0.033 (0.074)	0.039 (0.093)	0.098** (0.137)
alpha[1]	0.042** (0.051)	0.046** (0.051)	0.048** (0.058)	0.084** (0.074)
beta[1]	0.937*** (0.091)	0.932*** (0.092)	0.926*** (0.111)	0.851*** (0.153)
ind_wr_vol	0.017** (0.018)	0.019** (0.018)	0.018** (0.018)	0.010 (0.018)
ind_wr_vol_rolling_5	-0.016** (0.018)	-0.014** (0.018)	-0.015** (0.019)	-0.022** (0.020)
new_cases		-0.036** (0.022)	-0.038*** (0.023)	-0.043*** (0.025)
new_death		0.026 (0.146)	0.044 (0.152)	0.069 (0.157)
total_vaccinations_per_hundred		-0.008** (0.011)	-0.005 (0.011)	-0.012** (0.011)
stringency_index		0.004** (0.006)	0.005** (0.006)	0.008** (0.007)
new_cases_rolling_5		0.077** (0.049)	0.077** (0.051)	0.077** (0.058)

new_death_rolling_5		-0.142** (0.180)	-0.154** (0.189)	-0.212** (0.249)
total_vaccinations_per_hundred_rolling_		0.010** (0.011)	0.008** (0.011)	0.016** (0.011)
stringency_index_rolling_5		-0.005** (0.007)	-0.005** (0.007)	-0.007** (0.008)
gtrend_corr			-0.013*** (0.007)	-0.017*** (0.007)
gtrend_corr_rolling_5			0.011** (0.009)	0.016*** (0.009)
news_count				-0.001 (0.008)
title_POS				0.002 (0.005)
title_NEG				0.002 (0.005)
text_POS				-0.005** (0.005)
text_NEG				0.006** (0.006)
topic_health				0.032*** (0.018)
topic_economic_consequences				-0.010** (0.009)
news_count_rolling_5				0.055*** (0.020)
title_POS_rolling_5				0.011** (0.010)
title_NEG_rolling_5				-0.009** (0.012)
text_POS_rolling_5				-0.018*** (0.011)
text_NEG_rolling_5				0.013** (0.013)
topic_health_rolling_5				-0.047*** (0.024)
topic_economic_consequences_rolling_5				0.011** (0.013)
topic_societal_changes				0.016** (0.024)
topic_societal_changes_rolling_5				-0.003 (0.033)

Table E6: HARX-GARCH model results for China`s transport sector financial performance index with adding moving averages for the previous 5 days

Variables	**HARX-GARCH-R5**	**HARX-GARCH-O-R5**	**HARX-GARCH-OG-R5**	**HARX-GARCH-OGN-R5**
R2	0.0562	0.0798	0.089	0.1033
R2_adj	0.0289	0.0359	0.0413	0.0206
Const	-1.517*** (0.713)	-1.872*** (0.779)	-1.678*** (0.748)	-1.986*** (1.053)
i...ice[0:1]	0.088** (0.054)	0.070** (0.054)	0.065** (0.055)	0.009 (0.053)
i...ice[0:5]	-0.118** (0.118)	-0.128** (0.119)	-0.115** (0.119)	-0.165** (0.131)
i...ice[0:22]	-0.339** (0.258)	-0.377** (0.258)	-0.436*** (0.253)	-0.444*** (0.249)
overnight_ind	0.002 (0.006)	0.001 (0.006)	0.001 (0.006)	0.003 (0.007)
overnight_1m	-0.022** (0.021)	-0.023** (0.021)	-0.024** (0.020)	-0.034*** (0.021)
overnight_3m	0.004 (0.042)	0.002 (0.043)	0.004 (0.041)	-0.000 (0.042)
overnight_6m	-0.002 (0.035)	-0.002 (0.035)	-0.003 (0.034)	-0.001 (0.034)
overnight_ind_rolling_5	0.024** (0.020)	0.028** (0.020)	0.031** (0.020)	0.040*** (0.021)
overnight_1m_rolling_5	0.032** (0.031)	0.032** (0.031)	0.030** (0.031)	0.045** (0.030)
overnight_3m_rolling_5	0.059** (0.069)	0.075** (0.068)	0.065** (0.066)	0.088** (0.067)
overnight_6m_rolling_5	-0.067** (0.064)	-0.082** (0.064)	-0.071** (0.063)	-0.100** (0.068)
omega	0.094*** (0.053)	0.102** (0.077)	0.103** (0.081)	0.906*** (0.481)
alpha[1]	0.043*** (0.025)	0.050** (0.033)	0.047** (0.032)	0.198** (0.125)
beta[1]	0.913*** (0.029)	0.903*** (0.050)	0.904*** (0.053)	0.387** (0.237)
ind_tr_vol	0.033*** (0.008)	0.034*** (0.007)	0.033*** (0.008)	0.033*** (0.008)
ind_tr_vol_rolling_5	-0.019*** (0.009)	-0.019*** (0.009)	-0.020*** (0.009)	-0.020*** (0.010)
new_cases		-0.030** (0.021)	-0.033** (0.021)	-0.044*** (0.016)
new_death		-0.078** (0.096)	-0.056 (0.094)	0.002 (0.086)
total_vaccinations_per_hundred		-0.022** (0.015)	-0.019** (0.016)	-0.028*** (0.016)
stringency_index		0.015** (0.010)	0.014** (0.009)	0.022*** (0.010)
new_cases_rolling_5		0.113*** (0.057)	0.116*** (0.057)	0.117*** (0.044)
new_death_rolling_5		-0.092 (0.147)	-0.124** (0.146)	-0.148** (0.172)
total_vaccinations_per_hundred_rolling_		0.022** (0.016)	0.025** (0.016)	0.035*** (0.015)
stringency_index_rolling_5		-0.012** (0.011)	-0.011** (0.010)	-0.017** (0.010)
gtrend_corr			-0.008** (0.009)	-0.017*** (0.009)
gtrend_corr_rolling_5			-0.003 (0.011)	0.012** (0.013)
news_count				0.005** (0.008)
title_POS				0.009** (0.006)
title_NEG				0.007** (0.007)
text_POS				-0.008** (0.007)

text_NEG				0.004 (0.008)
topic_health				0.020** (0.021)
topic_economic_consequences				-0.016** (0.010)
news_count_rolling_5				0.023** (0.024)
title_POS_rolling_5				0.002 (0.012)
title_NEG_rolling_5				-0.037*** (0.013)
text_POS_rolling_5				-0.014** (0.013)
text_NEG_rolling_5				0.008 (0.017)
topic_health_rolling_5				-0.032** (0.029)
topic_economic_consequences_rolling_5				0.023*** (0.013)
topic_societal_changes				0.029** (0.026)
topic_societal_changes_rolling_5				-0.031** (0.031)

Table E7: HARX-GARCH model results for Russia`s composite financial performance index with adding moving averages for the previous 5 days

Variables	**HARX-GARCH-R5**	**HARX-GARCH-O-R5**	**HARX-GARCH-OG-R5**	**HARX-GARCH-OGN-R5**
R2	0.0145	0.0492	0.0501	0.0806
R2_adj	-0.0129	0.0058	0.0024	0.0039
Const	0.601** (0.534)	-0.500** (0.682)	-0.445 (0.687)	-0.858** (0.787)
i...ice[0:1]	0.011 (0.049)	0.003 (0.050)	0.000 (0.050)	-0.013 (0.050)
i...ice[0:5]	0.029 (0.131)	0.044 (0.132)	0.043 (0.134)	-0.000 (0.136)
i...ice[0:22]	-0.023 (0.288)	-0.153 (0.309)	-0.184 (0.314)	-0.196 (0.325)
ind_comp_vol	-0.009** (0.007)	-0.011** (0.008)	-0.011** (0.008)	-0.009** (0.008)
overnight_ind	-0.003 (0.006)	-0.003 (0.006)	-0.003 (0.006)	0.000 (0.006)
overnight_1m	-0.006** (0.006)	-0.006** (0.006)	-0.006** (0.006)	-0.010** (0.007)
overnight_3m	0.007** (0.006)	0.005** (0.006)	0.005** (0.006)	0.004 (0.006)
overnight_6m	-0.001 (0.005)	-0.001 (0.005)	-0.001 (0.005)	-0.001 (0.005)
ind_comp_vol_rolling_5	0.002 (0.010)	0.004 (0.010)	0.003 (0.010)	-0.000 (0.011)
overnight_ind_rolling_5	-0.005 (0.015)	0.003 (0.016)	0.001 (0.017)	-0.003 (0.018)
overnight_1m_rolling_5	0.001 (0.008)	0.003 (0.008)	0.004 (0.008)	0.012** (0.009)
overnight_3m_rolling_5	0.002 (0.010)	0.009** (0.012)	0.008** (0.012)	0.011** (0.011)
overnight_6m_rolling_5	-0.003 (0.008)	0.001 (0.012)	0.002 (0.012)	-0.001 (0.013)
omega	0.025*** (0.015)	0.025*** (0.014)	0.024*** (0.013)	0.024*** (0.014)
alpha[1]	0.080*** (0.032)	0.079*** (0.033)	0.078*** (0.032)	0.081*** (0.035)
beta[1]	0.899*** (0.031)	0.901*** (0.031)	0.902*** (0.030)	0.899*** (0.033)
new_cases		-0.024** (0.022)	-0.021** (0.024)	-0.023** (0.024)
new_death		-0.020** (0.020)	-0.018** (0.020)	-0.014** (0.020)
total_vaccinations_per_hundred		-0.001 (0.005)	-0.001 (0.005)	0.000 (0.005)
stringency_index		-0.015** (0.014)	-0.018** (0.015)	-0.026*** (0.015)
new_cases_rolling_5		0.028** (0.024)	0.027** (0.024)	0.025** (0.024)
new_death_rolling_5		0.011 (0.020)	0.007 (0.021)	0.012 (0.022)
total_vaccinations_per_hundred_rolling_		-0.004 (0.013)	0.000 (0.014)	-0.011** (0.015)
stringency_index_rolling_5		0.022** (0.015)	0.025** (0.016)	0.031*** (0.016)
gtrend_corr			0.005 (0.011)	0.007** (0.010)
gtrend_corr_rolling_5			-0.007 (0.012)	-0.010** (0.012)
news_count				-0.003 (0.005)
title_POS				-0.003 (0.005)
title_NEG				-0.002 (0.004)
text_POS				-0.007** (0.006)
text_NEG				-0.000 (0.009)
topic_health				-0.009** (0.013)
topic_economic_consequences				-0.003 (0.008)
news_count_rolling_5				0.008** (0.007)
title_POS_rolling_5				-0.009** (0.010)
title_NEG_rolling_5				-0.013** (0.011)
text_POS_rolling_5				0.045*** (0.015)

text_NEG_rolling_5				0.046*** (0.022)
topic_health_rolling_5				0.052** (0.032)
topic_economic_consequences_rolling_5				-0.009 (0.013)

Table E8: HARX-GARCH model results for Russia`s consumer sector financial performance index with adding moving averages for the previous 5 days

Variables	**HARX-GARCH-R5**	**HARX-GARCH-O-R5**	**HARX-GARCH-OG-R5**	**HARX-GARCH-OGN-R5**
R2	0.003	0.0473	0.0421	0.092
R2_adj	-0.0247	0.0038	-0.006	0.0163
Const	0.883** (0.557)	-0.086 (0.750)	0.197 (0.799)	0.811** (0.737)
i...ice[0:1]	0.027 (0.056)	0.032 (0.056)	0.028 (0.057)	0.007 (0.057)
i...ice[0:5]	0.012 (0.126)	0.022 (0.126)	0.026 (0.121)	-0.041 (0.117)
i...ice[0:22]	-0.261** (0.258)	-0.373** (0.258)	-0.533*** (0.298)	-0.671*** (0.255)
overnight_ind	0.003 (0.005)	0.004** (0.006)	0.003 (0.005)	0.006** (0.006)
overnight_1m	-0.010*** (0.006)	-0.010*** (0.006)	-0.013*** (0.007)	-0.010** (0.007)
overnight_3m	-0.002 (0.006)	-0.003 (0.007)	-0.002 (0.006)	-0.003 (0.007)
overnight_6m	0.001 (0.004)	0.002 (0.004)	0.001 (0.005)	0.002 (0.005)
overnight_ind_rolling_5	-0.006 (0.015)	-0.000 (0.016)	0.002 (0.016)	-0.013** (0.019)
overnight_1m_rolling_5	0.008** (0.008)	0.011** (0.008)	0.012** (0.008)	0.016*** (0.009)
overnight_3m_rolling_5	-0.007** (0.010)	-0.005 (0.011)	-0.007 (0.012)	-0.008** (0.011)
overnight_6m_rolling_5	0.000 (0.007)	0.007 (0.011)	0.005 (0.015)	0.003 (0.013)
omega	0.048** (0.049)	0.046** (0.048)	0.173** (0.111)	0.109** (0.144)
alpha[1]	0.118** (0.081)	0.117** (0.078)	0.250** (0.154)	0.208** (0.148)
beta[1]	0.836*** (0.116)	0.838*** (0.113)	0.593*** (0.222)	0.685*** (0.279)
ind_wr_vol	0.015*** (0.008)	0.015*** (0.008)	0.014** (0.009)	0.012** (0.008)
ind_wr_vol_rolling_5	-0.037*** (0.014)	-0.037*** (0.014)	-0.040*** (0.015)	-0.045*** (0.015)
new_cases		0.002 (0.018)	-0.011 (0.018)	-0.002 (0.020)
new_death		-0.041*** (0.016)	-0.044*** (0.016)	-0.046*** (0.017)
total_vaccinations_per_hundred		0.002 (0.005)	0.001 (0.005)	0.001 (0.005)
stringency_index		-0.016** (0.016)	-0.019** (0.014)	-0.020** (0.016)
new_cases_rolling_5		0.008 (0.019)	0.020** (0.018)	0.011 (0.019)
new_death_rolling_5		0.026** (0.018)	0.032** (0.021)	0.034*** (0.020)
total_vaccinations_per_hundred_rolling_		0.000 (0.013)	-0.003 (0.014)	-0.002 (0.018)
stringency_index_rolling_5		0.022** (0.016)	0.023** (0.015)	0.030*** (0.017)
gtrend_corr			0.018** (0.013)	0.020** (0.013)
gtrend_corr_rolling_5			-0.016** (0.014)	-0.018** (0.014)
news_count				0.005** (0.004)
title_POS				-0.005** (0.004)
title_NEG				0.001 (0.004)
text_POS				0.002 (0.006)
text_NEG				0.001 (0.008)
topic_health				-0.001 (0.014)
topic_economic_consequences				-0.013*** (0.007)
news_count_rolling_5				-0.005 (0.008)
title_POS_rolling_5				-0.001 (0.008)
title_NEG_rolling_5				-0.027*** (0.012)
text_POS_rolling_5				0.020** (0.014)
text_NEG_rolling_5				0.038*** (0.022)
topic_health_rolling_5				0.013 (0.028)
topic_economic_consequences_rolling_5				-0.016** (0.012)

Table E9: HARX-GARCH model results for Russia`s transport sector financial performance index with adding moving averages for the previous 5 days

Variables	HARX-GARCH-R5	HARX-GARCH-O-R5	HARX-GARCH-OG-R5	HARX-GARCH-OGN-R5
R2	0.0244	0.0513	0.0464	0.0434
R2_adj	-0.0027	0.008	-0.0014	-0.0364
Const	-0.860** (0.562)	-1.607*** (0.739)	-1.542*** (0.728)	-2.251*** (0.882)
i...ice[0:1]	-0.040 (0.078)	-0.070** (0.076)	-0.074** (0.079)	-0.128** (0.079)
i...ice[0:5]	0.214** (0.166)	0.256*** (0.129)	0.222** (0.136)	0.150** (0.128)
i...ice[0:22]	-0.198** (0.239)	-0.218** (0.287)	-0.245** (0.306)	-0.246** (0.321)
overnight_ind	0.003 (0.007)	0.001 (0.007)	0.001 (0.007)	0.001 (0.007)
overnight_1m	-0.008** (0.006)	-0.007** (0.007)	-0.007** (0.007)	-0.011*** (0.007)
overnight_3m	-0.009** (0.007)	-0.012*** (0.007)	-0.012*** (0.007)	-0.013*** (0.007)
overnight_6m	0.008** (0.005)	0.007** (0.005)	0.007** (0.005)	0.005** (0.005)
overnight_ind_rolling_5	0.017** (0.016)	0.028*** (0.016)	0.026** (0.017)	0.021** (0.016)
overnight_1m_rolling_5	0.002 (0.008)	-0.001 (0.010)	0.000 (0.009)	0.010** (0.009)
overnight_3m_rolling_5	0.024*** (0.012)	0.029*** (0.014)	0.028*** (0.014)	0.021** (0.013)
overnight_6m_rolling_5	-0.016** (0.012)	-0.002 (0.016)	-0.001 (0.017)	0.010 (0.016)
omega	0.096** (0.107)	0.119** (0.090)	0.113** (0.096)	0.119*** (0.057)
alpha[1]	0.207** (0.157)	0.264*** (0.155)	0.266** (0.169)	0.341*** (0.144)
beta[1]	0.743*** (0.193)	0.683*** (0.169)	0.685*** (0.184)	0.619*** (0.122)
ind_tr_vol	0.011** (0.011)	0.011** (0.011)	0.011** (0.011)	0.011** (0.012)
ind_tr_vol_rolling_5	-0.001 (0.014)	-0.002 (0.014)	-0.003 (0.014)	-0.000 (0.013)
new_cases		-0.006 (0.024)	-0.003 (0.027)	-0.015 (0.025)
new_death		-0.027** (0.019)	-0.025** (0.019)	-0.018** (0.021)
total_vaccinations_per_hundred		-0.001 (0.004)	-0.001 (0.004)	0.002 (0.004)
stringency_index		-0.033*** (0.013)	-0.039*** (0.013)	-0.047*** (0.012)
new_cases_rolling_5		0.014 (0.026)	0.014 (0.028)	0.029** (0.025)
new_death_rolling_5		0.013 (0.020)	0.009 (0.021)	0.001 (0.023)
total_vaccinations_per_hundred_rolling_		-0.012** (0.011)	-0.006 (0.012)	-0.014** (0.010)
stringency_index_rolling_5		0.034*** (0.014)	0.039*** (0.014)	0.047*** (0.013)
gtrend_corr			0.011** (0.011)	0.021** (0.015)
gtrend_corr_rolling_5			-0.016** (0.011)	-0.029*** (0.014)
news_count				-0.008*** (0.004)
title_POS				-0.000 (0.005)
title_NEG				-0.003** (0.004)
text_POS				-0.008** (0.006)
text_NEG				0.009** (0.009)
topic_health				0.007 (0.013)
topic_economic_consequences				-0.009** (0.008)
news_count_rolling_5				0.008** (0.007)
title_POS_rolling_5				-0.004 (0.008)
title_NEG_rolling_5				0.015** (0.012)
text_POS_rolling_5				0.061*** (0.016)
text_NEG_rolling_5				0.004 (0.019)
topic_health_rolling_5				0.055*** (0.033)
topic_economic_consequences_rolling_5				-0.014** (0.012)