ORIGINAL PAPER

DOI: 10.26794/2587-5671-2024-28-2-192-205
UDC 339.138(045)
JEL A14, G01, G15

Evolution of COVID-19 Impact on Russian Stock Market: Panic Effect

Yu.V. Egorova[a], A.N. Nepp[b], I.I. Tishchenko[c]
[a] Ufa University of Science and Technology, Ufa, Russia;
[a, b] Ural Federal University named after the First President of Russia Boris Yeltsin, Ekaterinburg, Russia;
[b] Ural Institute of Management of the Russian Academy of National Economy and Public Administration, Yekaterinburg, Russia;
[c] Higher School of Economics, Moscow, Russia

ABSTRACT

Over the past few years, many research papers have referred to stock market volatility in relation to investor attention and sentiment and our article adds to the current literature on financial market reactions to the economic consequences of COVID-19. An event such as an outbreak of an infectious disease causes a negative change in investor sentiment, which strongly influences their investment decisions and, consequently, stock market prices. The **subject** of the study is the mutual influence of stock market characteristics and market sentiment, during a COVID-19 pandemic crisis. The **purpose** of the study is to provide empirical support for the hypothesis of indirect impact of uncertainty and panic under the COVID-19 pandemic on the dynamics of the stock market in Russia. The World Health Organization and experts forecast that the world will face more than one crisis related to the spread of infectious diseases in the future, so understanding the mechanisms of mutual influence of sentiment and financial markets remains relevant. In this study, we take a novel approach to deriving an indicator for panic that has not been used before. We perform econometric modeling using a Vector Autoregressive Model (VAR) and a Vector Error Correction Model (VECM), which allows us to describe in the model not only the long-term equilibrium but also the dynamics towards it. As a **result**, we got consistent and efficient estimates of the long-term and short-term effects of panic and mortality rates on the volatility of the RTS stock index and found that the market reaction to COVID-19 changed as the pandemic spread: the effects of uncertainty and panic, while having a significant impact at the beginning of the crisis, faded away. The **conclusions** obtained in the analysis of the Russian stock market dynamics coincide with those obtained by other authors in their analysis of markets in other countries over a similar period.

Keywords: pandemic; COVID-19; stock markets; stock indices; panic; RTS; VAR model; ECM

For citation: **Egorova Yu.V., Nepp A.N., Tishchenko I.I. Evolution of COVID-19 impact on Russian stock market: panic effect. *Finance: Theory and Practice.* 2024;28(2):192-205. DOI: 10.26794/2587-5671-2024-28-2-192-205**

INTRODUCTION

The COVID-19 pandemic, which started in China in 2019 and quickly expanded throughout the globe, has impacted people's life in a variety of contexts. Significant changes have affected health care, tourism, transport, many economic aspects. As good economic indicators, financial markets responded most quickly to the pandemic crisis and experienced strong fluctuations. For example, US stock markets collapsed in response to pandemic news, and the S&P 500 fell by 20% in March 2020 [1].

From the point of view of the financial markets, the COVID-19 pandemic was a "black swallow" event that was new and unpredictable, causing panic among people and strong fluctuations in the financial markets [2]. The relevance of this research reflects the increase in publications of scientific papers assessing the impact of the COVID-19 pandemic on economic processes, which can be grouped according to several criteria.

Firstly, it is possible to distinguish between the direct and indirect effects of the pandemic on the financial markets. The paper examining the stock exchanges has shown that COVID-19 has a strong positive impact on the volatility of each exchange. A more detailed analysis of the work revealed some of the pandemic's multifaceted effects. According to the U.S. research [3], shares in some industries (gas, software development, healthcare) yielded high positive returns, while the share value in other sectors (oil, real estate, tourism) fell sharply. In the paper [4], the direct and indirect effects of the pandemic on the financial markets were reviewed attractive thoroughly, and the importance of the indirect influence of COVID-19 over the direct effects was defended in context with the growth of social networks and the Internet.

Secondly, studies on how to measure the strength of a pandemic could be grouped. A large number of studies are using statistics on confirmed cases of disease or deaths from COVID-19 due to the availability of this data in the public domain. Studies show that cases of disease and death from COVID-19 have a negative impact on stock returns worldwide [5–7], although the results are ambiguous as to whether cases [8] or deaths [9] have the greatest impact. Furthermore, there is criticism of the use of morbidity and mortality statistics for cross-country comparisons because of different methods of accounting in different countries and different periods even in one country under review.

In the case of research, the quantitative assessment of the impact of COVID-19 is based on the attention and mood of the market. So, various researchers apply Google Search Trends calculations to terms related to COVID-19 and widely use them as a proxy to the attention of retail investors [10, 11]. The use of proxy data makes sense when one considers economic psychology: when people are unclear about particular events, they search for pertinent information more actively [12–14]. However, Google searches related to COVID-19 can be seen as a measure of uncertainty or fear for investors [11, 15, 17]. Study of the impact of changes in COVID-19 related Google Search Trends report the negative impact on the stock markets of developed and developing countries [7, 11, 17–20]. It was also found that the intensity of exposure to COVID-19 Google search trends varies over time and across countries, industries and firms [11, 17, 21]. The debate over whether search trends reflect attention, uncertainty, or both is ongoing. Economic psychology explains the mechanisms of the relationship between the search for information and uncertainty, fear of the unknown [12, 14], which negatively affect the economy. This implies a decrease in expected future cash flows and an increased acceptance of risk, resulting in a higher risk premium and a lower stock market level [11]. The nature of Google Search Trends differs from other existing market uncertainty indicators, such as VIX, which reflect general information about risk and rejection of risk to a particular event [17].

Market sentiment is measured by some researchers using the media response. For example, the developed daily media attention index to the pandemic counts publications on financial topics and finds the share of publications related to the pandemic. The paper [14] showed that increased media attention had a negative impact on equity returns worldwide. On the contrary, C.O. Cepoi [22] believes that media noise has had a weak positive impact on share returns.

Another category of research examines the impact of government response measures, such as lockdown and incentives, on financial markets. Studies document both the negative [17] and the positive [14] impact of governments' response to global stock market returns. Incentives have been found to have a positive effect on share returns [23, 24]. On the contrary, social distancing and lockdown had a negative impact on share returns [8, 25].

MATERIALS AND METHODS

This study attempts to assess the impact of the pandemic on the Russian stock market, taking into account the level of uncertainty and panic measured by Google Trends. Traditionally, econometric time series models are used to study the impact of COVID-19 on the profitability and volatility of the stock market.

We use the vector autoregression model (VAR) and the vector error correction model (VECM). The use of VAR is especially useful for describing the dynamic behaviour of financial time series. While VECM allows you to describe in the model not only the long-term equilibrium, but also the dynamics of movement to it.

Data from several sources were used to achieve the purpose of the study. The characteristics of the Russian stock market reflect the daily data of the RTS index values. The RTS index is a price, market capitalisation-weighted composite index of the Russian stock market, including the most liquid shares of the largest Russian issuers.[1] The yield of the Russian stock market was calculated according to the following formula:

$$R_t = lnP_t - lnP_{t-1}, \qquad (1)$$

where R_t — return on the stock market; P_t and P_{t-1} — the closing price on the stock market (at the moment *t*) and the close price of the previous day (at the moment *t* — 1), respectively.

We calculate five-day moving volatility according to the following formula:

$$V_t = \sqrt{\frac{\sum_{t=1}^{5}(R_t - \overline{R_t})^2}{4}}, \qquad (2)$$

where $\overline{R_t}$ — five-day average yield of the RTS index.

The stability of the results under different smoothing orders was checked (*Appendix, Table 1*). However, we understand that applying too much smoothing order will lead to the loss of the panic effect, which manifests itself within a few days (which is confirmed by our calculations), will violate the structural characteristics of the series. *Table 1* of the *Appendix* shows the ECM evaluation coefficients for the last subperiod under consideration under different smoothing orders. You can see that when changing the smoothing order in any of the coefficients there was no change in the sign, significance or any significant change in values. With an increase in the smoothing order, there is a slight decrease in the effect of the factors under consideration, which is quite logical, since the influence of the effects under consideration is quite short-term. Following Š. Lyócsa [15] and O. Erdem [16], we reached a 5-day average in yields.

Another endogenous variable included in the model is weekly Google Trends data on queries reflecting interest in pandemic development.[2] For five key queries reflecting interest in COVID-19, an indicator was taken — interest in time, reflecting the search interest of Russian users. The value of 100 has the most popular request for the period under review, the rest are normalized to the maximum. After the main component transformation, the first component was selected as the variable describing the greatest variance in the data.

The number of registered deaths due to COVID-19 (number of deaths per million population) is considered as an exogenous variable.[3]

The data were analysed for the period from 1.03.2020 to 31.12.2021. In Russia, the first case of COVID-19 was registered on 31January 2020. The first case of registered death due to COVID-19 was registered on 19 March 2020.

A moving average with a smoothing interval of five days was used to fill in the gaps in the data. Descriptive statistics on the data are given in the *Table 1*.

---

[1] Source of data — Moscow Stock Exchange. URL: www.moex.com (accessed on 01.06.2022).

[2] URL: https://trends.google.com/ (accessed on 01.06.2022).

[3] Esteban Ortiz-Ospina, Joe Hasell, Bobbie Macdonald, Diana Beltekian and Max Roser (2020) — "Coronavirus Pandemic (COVID-19)". Published online at OurWorldInData.org. URL: https://ourworldindata.org/coronavirus (accessed on 01.06.2022).

Table 1

Descriptive Statistics

Variable name	Minimum	Average	Median	Maximum	Standart deviation
Volatility	0	0.006	0.005	0.023	0.003
1st component	–1.537	0.25	–0.234	8.836	1.571
New deaths per mln people	0.001	3.173	2.68	8.345	2.292

Source: Compiled by the authors.

Analysis of descriptive statistics shows that the stock market yield is a fairly volatile variable, the maximum volatility value was observed on 29.03.2020 and was 0.023. The highest values of registered mortality due to COVID-19 per million people are on 22.11.2021 — and the maximum was 8,345 people. The graph (*Fig. 1*) shows the dynamics of changes in the indicators included in the study for the entire period under review and the sub-periods highlighted in color.

We choose the two most indicative, in our opinion, and interesting for the study of the period of the impact of the pandemic on the Russian stock market: the first period from 26.03.2020 to 24.04.2020, when mortality, panic and uncertainty about the pandemic increased sharply; the second period — from 05.10.2021 to the end of 2021, when, according to the data, peak mortality values were observed (*Fig. 1*) and there was an increase in uncertainty and panic, reflected both in search activity and in the media.[4] On these periods, we will show the impact of panic on the volatility of the RTS stock index and demonstrate the differences between these periods to find out the direction of evolution of the impact of the pandemic on the stock market. Correlation matrices of indicators for the selected subperiods and the entire observation period are given in the *Table 2*.

The observed correlation values reflect the direct relationship between the panic indicator and the number of deaths per million populations throughout the period under review and are significant at all standard levels of significance. In the second subperiod, the significance of this correlation disappears. In the total sample, the relationship between volatility and mortality reveals a negative correlation, because, as can be seen in *Fig. 1*, in the considered interval, the volatility of the RTS stock index tends to decrease, while mortality is increasing. On subperiods, the relationship between volatility and mortality reveals a positive correlation significant for the second subperiod. A direct significant link in panic and mortality indicators meets expectations.

In matrix-vector designations in general, the VAR model has the form:

$$\overrightarrow{X_t} = \vec{a} + A_1\vec{X}_{t-1} + A_2\vec{X}_{t-2} + \ldots + A_p\vec{X}_{t-p} + \vec{\varepsilon}_t, \qquad (3)$$

where $\vec{\varepsilon}_t$ — vector white noise with zero expectation.

In our case, the vector $\overrightarrow{X_t}$ is two-component: the first component is the calculated volatility of V_t, the 2nd component of $pca1_t$ — is a series that is selected by the method of the main component from the pandemic-relevant Google Trends queries.

We supplement the VAR model with exogenous regressor *deaths* — the number of

[4] This can be confirmed by analyzing the company's panic index data Ravenpack. URL: coronavirus.ravenpack.com (accessed on 01.06.2022).

Fig. 1. **Dynamics of Indicators**

Source: Compiled by the authors.

registered deaths due to COVID-19 and the specification like this:

$$\overrightarrow{X_t} = \vec{a} + \sum_{i=1}^{p} \vec{a}_i \overrightarrow{X_{t-i}} + \sum_{j=0}^{q} \vec{b}_j \overrightarrow{Y_{t-j}} + \vec{\varepsilon}_t, \qquad (4)$$

where the number of lags $p = 3$ (see the tests below), $q = 0$,

$$X_t = (V_t\ ; pca1_t), Y_t = deaths.$$

Since VAR is closely related to the stagnation study, we use the Augmented DF test (ADF) and the Elliot, Rothenberg and Stock Unit Root Test (DF GLS). The test results shown in *Table 3* indicate variations in volatility, panic and mortality. The transition to the first differences makes it possible to assert that all processes are stationary in the first difference, i.e. they are processes of type I(1) (*Table 3*).

It is known that the same assessment methods and diagnostic procedures are applicable for both stationary and non-stationary type I(1) regressors, if the latter are integrated. Therefore, the key issue is testing the presence of co-integration of non-stationary processes.

We use Johansen's methodology to test the availability of co-integration and search for the number of co-integration relationships. Based on theoretical and logical considerations, we decided to assume the absence of a trend in the co-integration ratio and the presence of a free member in it (since the visual inspection of the data and preliminary estimates indicate the presence of a linear trend in the data, and the trend should be present in the long-term ratio). The test results given in *Table 4* indicate the presence of one co-integration ratio.

Table 2

Correlation Matrices

The entire period	Volatility	1st component	New deaths per million
Volatility	1.000	−0.239***	−0.189***
1st component	−0.239***	1.000	0.484***
New deaths per million	−0.189***	0.484***	1.000
I subperiod			
Volatility	1.000	0.468	0.277
1st component	0.468	1.000	0.878***
New deaths per million	0.277	0.878***	1.000
II subperiod			
Volatility	1.000	−0.325***	0.467***
1st component	−0.325***	1.000	−0.166
New deaths per million	0.467***	−0.166	1.000

Source: Compiled by the authors.

Note: *, **, *** 10%, 5%, 1% significance, respectively.

Table 3

Stationarity Tests

Variable name	Elliot, Rothenberg and Stock Unit Root Test	
	I(0)	I(1)
	t-statistics	
Volatility	−1.0258	−17.6193***
1st component	−2.0244**	−5.7475***
New deaths per million	−0.1662	−4.0315***

Source: Compiled by the authors.

Примечание / Note: *, **, *** соответственно 10%, 5%, 1% значимости / *, **, *** respectively 10%, 5%, 1% of significance.

Table 4

Johansen Cointegration Test

Number of cointegrating relationships	Observed statistics	Critical value, 5% significance
R <= 3	3.29	9.24
R <= 2	9.65	15.67
R <= 1	24.71	22
R = 0	34.35	28.14

Source: Compiled by the authors.

The choice of the lag in the construction of the VAR model was based on the information criteria of Akaike (AIC), Schwarz (BIC), Hannan-Quin (HQ) and the likelihood ratio test (LR), as well as the subsequent analysis of the autocorrelation function of residues (using the Portmanto test, p-value = 0.74 at H0: no autocorrelation in the remains of the model). Following the results of these criteria, the number of lags in the VAR model for levels is assumed to be 3.

RESULTS AND DISCUSSION

The results of the VAR evaluation of the model for the first and second subperiods are given in *Tables 5* and *6* (the table shows the results of only the first part of the VAR model, reflecting the impact of panic on the stock market).

V.l*i* — *i*-th lag of volatility; pca1i — *i*-th lag of the first principal component on Google queries reflecting interest in pandemic development; trend — time factor; deaths — number of reported deaths due to COVID-19.

It should be noted that quantitative interpretation of VAR estimates is impossible due to the peculiarities of its construction. Nevertheless, we can detect a reaction of market volatility to the degree of uncertainty and panic due to COVID-19 in both periods under consideration. Stock market volatility reacts more strongly to panic and uncertainty in the first period, in the second period the effect decreases and becomes weak [we observe a low value of coefficients before the panic variable (pca1) and its lags and a decrease in the value of coefficients in the

Table 5

VAR Estimation Results for Both Sub-Periods

Name	VAR 1	VAR 2
V.l1	0.249	0.625***
	(0.223)	(0.114)
pca1.l1	0.155	−0.001
	(0.090)	(0.001)
V.l2	−0.137	−0.019
	(0.227)	(0.134)
pca1.l2	−0.295	0.002
	(0.197)	(0.002)
V.l3	−0.306	−0.120
	(0.209)	(0.109)
pca1.l3	0.360*	−0.002+
	(0.156)	(0.001)
Const	0.345**	−0.007*
	(0.098)	(0.003)
Trend	0.000	0.000
	(0.001)	(0.000)
Deaths	−0.096+	0.002***
	(0.055)	(0.000)
Num.Obs.	24	83
R2	0.737	0.648
R2 Adj.	0.596	0.610

Source: Compiled by the authors.

Note: + $p < 0,1$, * $p < 0,05$, ** $p < 0,01$, *** $p < 0,001$.

second period compared to the first one]. Also, the significance, manifested in later lags, indicates some delay in the stock market reaction to panic. The variable responsible for mortality turns out to be significant and contradicts expectations in the first period, which may be due to the imperfection of registration and accounting of deaths from COVID-19 in the initial period. In addition, taking into account the additional factors operating in the market during this period (for example, the struggle between Saudi Arabia and Russia over oil supplies and prices), we can cautiously formulate these expectations.

The co-integration of variables allows us to represent the relationship between them as an ECM error correction model for each of the subperiods. With the help of this model, it is possible to describe not only the long-term balance, but also the dynamics of movement to it. In this model, short-term changes in the dependent variable are proportional to the change in the factor. However, if such dynamics leads to a deviation from the long-term dependence, the change in the dependent variable is also adjusted in proportion to this deviation. This error correction mechanism and guarantees the fulfilment of long-term dependence.

Despite the fact that Johansen's methodology is the most common approach, this method is very sensitive to the choice of variables and their lags. An alternative approach that does not have these disadvantages is the dynamic least squares method (DOLS), which takes into account the possible endogeneity of regressors. The DOLS procedure involves building a model:

$$\begin{aligned} v_t &= a_0 + a_1 pca1_t + a_2 deaths_t + a_3 \Delta pca_{t-1} + a_4 \Delta pca_t + \\ &+ a_5 \Delta pca_{t+1} + a_6 \Delta deaths_{t-1} + a_7 \Delta deaths_t + a_8 \Delta deaths_{t+1}. \end{aligned} \tag{4}$$

It should be noted that the MNC assessments in this case are super-reliable. The assessment of model residues for stationarity allows us to draw a conclusion about their stationarity. Test statistics for balances are equal for the first subperiod: −2.9561*** (−2.66 critical value at the 1% significance level) and for the second subperiod: −2.4941** (−1.94, —2.59 critical values at the 5% significance levels and 1% significant levels).

Then the ECM model can be presented as:

$$\begin{aligned} \Delta v_t &= b_0 + b_1 \Delta v_{t-1} + b_2 \Delta v_{t-2} + b_3 \Delta v_{t-3} + b_4 \Delta pca1_{t-1} + \\ &+ b_5 \Delta pca1_{t-2} + b_6 \Delta pca1_{t-3} + b_7 \Delta deaths_{t-1} + \\ &+ b_8 \Delta deaths_{t-2} + b_9 \Delta deaths_{t-3} + b_{10} z_{t-1} + e_t, \end{aligned} \tag{5}$$

where

$$z_{t-1} = v_{t-1} - \hat{v}_{t-1} \tag{6}$$

The evaluation results for both subperiods are presented in the *Table 6*.

Results of autocorrelation and stationarity balances for ECM models are shown in *Fig. 2*: model balances are stationary, no autocorrelation, as further confirmed by tests.

Model coefficients allow us to draw a conclusion about the long-term and short-term effects of panic and mortality on volatility. As in the VAR model, we see that their influence in the second subperiod is much weaker than in the first. In both the long and short term, the impact of panic on volatility is significant, the connection is direct, which is consistent with a priori expectations. In the second subperiod, the significance and direction of communication in the panic variable remains, but its influence is greatly reduced.

The coefficients reflecting the impact of mortality do not correspond to the a priori assumptions in both the long-term and short-term part of the model built on the first subperiod. These results are consistent with the results of the VAR model for the first subperiod and are probably explained by the same factors. In the second sub-period, the influence of mortality on volatility is also significant, the connection is direct. We see an impact in the long and short term, comparable in strength.

To verify the results obtained in the article, we check the adequacy of the model on

Table 6

ECM Estimation Results for Both Sub-Periods

Name	SR ECM 1	LR DOLS 1	SR ECM 2	LR DOLS 2
(Intercept)	0.299***	0.274**	−0.011***	−0.012**
	(0.020)	(0.068)	(0.001)	(0.004)
pca1	0.190***	0.173**	0.000***	0.000*
	(0.013)	(0.045)	(0.000)	(0.000)
Δpca1, l1	−0.311***	−0.401*	0.002***	0.003+
	(0.029)	(0.171)	(0.000)	(0.002)
Deaths	−0.101***	−0.140*	0.002***	0.003***
	(0.009)	(0.060)	(0.000)	(0.000)
Δdeaths, l1	0.171*	0.299	0.011***	0.018
	(0.060)	(0.268)	(0.002)	(0.019)
z, l1	1.013***		1.008***	
	(0.074)		(0.025)	
Δpca1		0.093		−0.003
		(0.213)		(0.003)
Δpca1, f1		0.036		0.002
		(0.133)		(0.002)
Δdeaths		0.086		0.013
		(0.285)		(0.023)
Δdeaths, f1		0.177		−0.024
		(0.168)		(0.019)
Num, Obs,	24	25	82	83
R2	0.966	0.660	0.973	0.422
R2 Adj,	0.956	0.489	0.971	0.359
+ p < 0,1, * p < 0,05, ** p < 0,01, *** p < 0,001.				

Source: Compiled by the authors.

Note: + p < 0,1, * p < 0,05, ** p < 0,01, *** p < 0,001.

l1" corresponds to index t – 1, ", f1" corresponds to index t + 1.

samples corresponding to two other bursts of queries (*Fig. 1* and *Appendix, Table 2*).

The conclusions obtained in the analysis of the dynamics of the Russian stock market coincide with the conclusions obtained by other authors when analyzing the markets of other countries for the same period [26, 27]. Stock markets are reacting quickly to the COVID-19 pandemic, but this response changes over time depending on the stage of the pandemic. For example, the study [27] concluded that the stock market reacted

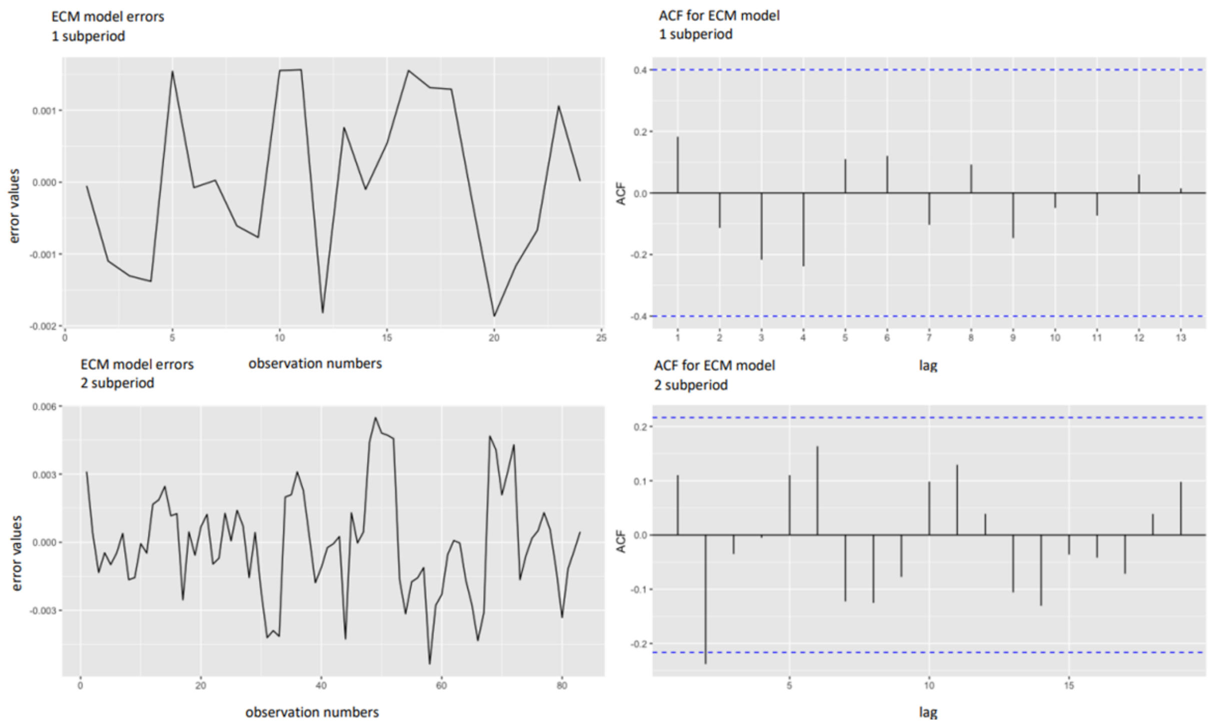

Fig. 2. **Dynamics of Indicators**

Source: Compiled by the authors.

negatively and strongly in the first periods of the COVID-19 pandemic, then the reaction began to decline.

CONCLUSION

We focused on the history of the COVID-19 pandemic's influence, and based on the literature, we discovered that market reaction to Covid-19 has shifted. The investigation was performed with VAR auto-regression models and the ECM vector error correction model. Most of the impact of uncertainty and panic indicated in search inquiries has been reduced, with little impact on stock markets in the post-crisis period.

Since the purpose of this study was not the task of forecasting, many external factors (level of government measures to support the financial market of the country, index of world stock markets, prices of standard stock market determinants: oil, gold, etc.) were not taken into account. The World Health Organization does not rule out the emergence of new strains of COVID, it is important not only to identify the direct and indirect effects of the influence of the pandemic, but also to predict the yield and volatility on the basis of known information. Methods of measuring panic reflected by the media and social media deserve special attention.

ACKNOWLEDGEMENTS

The research was supported by the Russian Foundation for Basic Research within the framework of the scientific project "Pandemic and mass hysteria. Effects and Minimization of Negative Effects on Stock Market No. 20–04–60158. Viruses". B.N. Yeltsin Ural Federal University, Ekaterinburg, Russia.

REFERENCES

1. Jin L., Zheng B., Ma J., et al. Empirical study and model simulation of global stock market dynamics during COVID-19. *Chaos, Solitons & Fractals*. 2022;159:112138. DOI: 10.1016/j.chaos.2022.112138

2. Szczygielski J.J., Charteris A., Bwanya P.R., Brzeszczyński J. Which COVID-19 information really impacts stock markets? *Journal of International Financial Markets, Institutions and Money*. 2023;84:101592. DOI: 10.1016/j.intfin.2022.101592
3. Mazur M., Dang M., Vega M. COVID-19 and the March 2020 stock market crash. Evidence from S&P1500. *Finance Research Letters*. 2021;38:101690. DOI: 10.1016/j.frl.2020.101690
4. Egorova Yu.V., Nepp A.N. The impact of epidemics on economic development and financial markets: A structured overview. *Vestnik Moskovskogo universiteta. Seriya 6: Ekonomika = Moscow University Economics Bulletin*. 2021;(6):28–53. URL: https://www.elibrary.ru/item.asp?id=47576052 (In Russ.).
5. Al-Awadhi A.M., Alsaifi K., Al-Awadhi A., Alhammadi S. Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. *Journal of Behavioral and Experimental Finance*. 2020;27:100326. DOI: 10.1016/j.jbef.2020.100326
6. Ali M., Alam N., Rizvi S.A.R. Coronavirus (COVID-19) — an epidemic or pandemic for financial markets. *Journal of Behavioral and Experimental Finance*. 2020;27:100341. DOI: 10.1016/j.jbef.2020.100341
7. Capelle-Blancard G., Desroziers A. The stock market is not the economy? Insights from the COVID-19 crisis. *SSRN Electronic Journal*. 2020. DOI: 10.2139/ssrn.3638208
8. Ashraf B.N. Economic impact of government interventions during the COVID-19 pandemic: International evidence from financial markets. *Journal of Behavioral and Experimental Finance*. 2020;27:100371. DOI: 10.1016/j.jbef.2020.100371
9. Adekoya A.F., Kofi Nti I. The COVID-19 outbreak and effects on major stock market indices across the globe: A machine learning approach. *Indian Journal of Science and Technology*. 2020;13(35):3695–3706. DOI: 10.17485/IJST/v13i35.1180
10. Da Z., Engelberg J., Gao P. In search of attention. *The Journal of Finance*. 2011;66(5):1461–1499. DOI: 10.1111/j.1540–6261.2011.01679.x
11. Smales L.A. Investor attention and global market returns during the COVID-19 crisis. *International Review of Financial Analysis*. 2021;73:101616. DOI: 10.1016/j.irfa.2020.101616
12. Dzielinski M. Measuring economic uncertainty and its impact on the stock market. *Finance Research Letters*. 2012;9(3):167–175. DOI: 10.1016/j.frl.2011.10.003
13. Da Z., Engelberg J., Gao P. The sum of all FEARS investor sentiment and asset prices. *The Review of Financial Studies*. 2015;28(1):1–32. DOI: 10.1093/rfs/hhu072
14. Castelnuovo E., Tran T.D. Google it up! A Google trends-based uncertainty index for the United States and Australia. *Economics Letters*. 2017;161:149–153. DOI: 10.1016/j.econlet.2017.09.032
15. Lyócsa Š., Baumöhl E., Výrost T., Molnár P. Fear of the coronavirus and the stock markets. *Finance Research Letters*. 2020;36:101735. DOI: 10.1016/j.frl.2020.101735
16. Erdem O. Freedom and stock market performance during COVID-19 outbreak. *Finance Research Letters*. 2020;36:101671. DOI: 10.1016/j.frl.2020.101671
17. Szczygielski J.J., Bwanya P.R., Charteris A., Brzeszczyński J. The only certainty is uncertainty: An analysis of the impact of COVID-19 uncertainty on regional stock markets. *Finance Research Letters*. 2021;43:101945. DOI: 10.1016/j.frl.2021.101945
18. Costola M., Iacopini M., Santagiustina C.R.M.A. Public concern and the financial markets during the COVID-19 outbreak. arXiv:2005.06796. 2020. URL: https://arxiv.org/pdf/2005.06796.pdf
19. Lu N., Cheng K.-W., Qamar N., et al. Weathering COVID-19 storm: Successful control measures of five Asian countries. *American Journal of Infection Control*. 2020;48(7):851–852. DOI: 10.1016/j.ajic.2020.04.021
20. Papadamou S., Fassas A., Kenourgios D., Dimitriou D. Direct and indirect effects of COVID-19 pandemic on implied stock market volatility: Evidence from panel data analysis. Munich Personal RePEc Archive. MPRA Paper. 2020;(100020). URL: https://mpra.ub.uni-muenchen.de/100020/1/MPRA_paper_100020.pdf
21. Ramelli S., Wagner A.F. Feverish stock price reactions to COVID-19. *The Review of Corporate Finance Studies*. 2020;9(3):622–655. DOI: 10.1093/rcfs/cfaa012

22. Cepoi C.-O. Asymmetric dependence between stock market returns and news during COVID-19 financial turmoil. *Finance Research Letters*. 2020;36:101658. DOI: 10.1016/j.frl.2020.101658
23. Ashraf B.N. Stock markets' reaction to COVID-19: Cases or fatalities? *Research in International Business and Finance*. 2020;54:101249. DOI: 10.1016/j.ribaf.2020.101249
24. Narayan P.K., Phan D.H.B., Liu G. COVID-19 lockdowns, stimulus packages, travel bans, and stock returns. *Finance Research Letters*. 2021;38:101732. DOI: 10.1016/j.frl.2020.101732
25. Aggarwal S., Nawn S., Dugar A. What caused global stock market meltdown during the COVID pandemic — lockdown stringency or investor panic? *Finance Research Letters*. 2021;38:101827. DOI: 10.1016/j.frl.2020.101827
26. Oyelami L.O., Ogbuagu M.I., Saibu O.M. Dynamic interaction of COVID-19 incidence and stock market performance: Evidence from Nigeria. *Annals of Data Science*. 2022;9(5):1009–1023. DOI: 10.1007/s40745–022–00407–7
27. Alzyadat J.A., Asfoura E. The effect of COVID-19 pandemic on stock market: An empirical study in Saudi Arabia. *The Journal of Asian Finance, Economics and Business*. 2021;8(5):913–921.

ABOUT THE AUTHORS

Yulia V. Egorova — Cand. Sci (Tech.), Assoc. Prof., Department of Business Economics of the Institute of Economics and Management, Ufa University of Science and Technology, Ufa, Russia; Researcher, B.N. Yeltsin Ural Federal University, Ekaterinburg, Russia
https://orcid.org/0000-0002-7032-5826
Corresponding author:
jvegorova@mail.ru

Alexander N. Nepp — Cand. Sci (Econ.), Assoc. Prof., researcher, Ural Federal University named after the first President of Russia B.N. Yeltsin, Yekaterinburg, Russia; Assoc. Prof., Ural Institute of Management of the Russian Academy of National Economy and Public Administration, Yekaterinburg, Russia
https://orcid.org/0000-0002-7226-2689
anepp@gmail.com

Ilya I. Tishchenko — Master's student, Department of Applied Economics, Faculty of Economic Sciences, Higher School of Economics, Moscow, Russia
https://orcid.org/0000-0001-7649-8624
i.i.tishchenko@gmail.com

Conflicts of Interest Statement: The authors have no conflicts of interest to declare.

The article was submitted on 05.06.2022; revised on 02.07.2022 and accepted for publication on 27.08.2022.
The authors read and approved the final version of the manuscript.

APPENDIX

Table 1

ECM Estimation Results for the Last Sub-Period in Question at Different Smoothing Orders

Name	SR 3	SR 5	SR 7	SR 10
(Intercept)	−0.0150***	−0.0110***	−0.0092***	−0.0065***
	(0.0016)	(0.0008)	(0.0003)	(0.0001)
pca1	−0.0008***	−0.0005***	−0.0004***	−0.0003***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Δpca1.l1	0.0024***	0.0018***	0.0015***	0.0011***
	(0.0003)	(0.0002)	(0.0001)	(0.0000)
Deaths	0.0033***	0.0024***	0.0020***	0.0015***
	(0.0002)	(0.0001)	(0.0000)	(0.0000)
Δdeaths.l1	0.0232***	0.0115***	0.0085***	0.0066***
	(0.0034)	(0.0016)	(0.0007)	(0.0002)
z.l1	1.0032***	1.0083***	0.9973***	0.9991***
	(0.0234)	(0.0250)	(0.0174)	(0.0107)
Num Obs.	82	82	82	82
R2	0.969	0.973	0.990	0.997
R2 Adj.	0.967	0.971	0.989	0.997

+p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001
SR 3, SR 5, SR 7, SR 10 – ECM evaluation results for different smoothing orders (n = 3, 5, 7, 10 respectively)

Source: Compiled by the authors.

Table 2

ECM Estimation Results for Both Sub-Periods

Name	SR ECM1	SR ECM2	SR ECM3	SRECM4
(Intercept)	0.2992***	0.0013*	0.0026***	−0.0110***
	(0.0195)	(0.0006)	(0.0001)	(0.0008)
pca1	0.1898***	−0.0026***	−0.0001***	−0.0005***
	(0.0128)	(0.0004)	(0.0000)	(0.0000)
Δpca1.l1	– 0.3114***	0.0158***	0.0012***	0.0018***
	(0.0287)	(0.0031)	(0.0002)	(0.0002)
Deaths	−0.1008***	0.0042***	0.0002***	0.0024***
	(0.0091)	(0.0004)	(0.0000)	(0.0001)
Δdeaths.l1	0.1714*	0.0072	0.0056***	0.0115***
	(0.0605)	(0.0046)	(0.0009)	(0.0016)

Table 2 (continued)

Name	SR ECM1	SR ECM2	SR ECM3	SRECM4
z.l1	1.0133***	0.9993***	1.0061***	1.0083***
	(0.0737)	(0.0502)	(0.0194)	(0.0250)
Num Obs.	24	45	66	82
R2	0.966	0.927	0.979	0.973
R2 Adj.	0.956	0.918	0.977	0.971
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001				
	LR ECM1	LR ECM2	LR ECM3	LR ECM4
(Intercept)	0.2736**	0.0002	0.0031***	−0.0123**
	(0.0683)	(0.0028)	(0.0009)	(0.0037)
pca1	0.1732**	−0.0043*	0.0001	−0.0004*
	(0.00449)	(0.0018)	(0.0002)	(0.0002)
Deaths	−0.1399*	0.0048*	0.0000	0.0026***
	(0.0601)	(0.0019)	(0.0003)	(0.0005)
Δpca1.l1	−0.4014*	0.0156	0.0000	0.0032+
	(0.1708)	(0.0225)	(0.0022)	(0.0018)
Δpca1	0.0925	0.0045	0.0014	−0.0030
	(0.2131)	(0.0290)	(0.0029)	(0.0028)
Δpca1.f1	0.0359	−0.0048	−0.0014	0.0022
	(0.1326)	(0.0208)	(0.0021)	(0.0018)
Δdeaths.l1	0.2993	0.0091	0.0089	0.0181
	(0.2678)	(0.0153)	(0.0075)	(0.0187)
Δdeaths	0.0856	0.0243	−0.0051	0.0126
	(0.2847)	(0.0156)	(0.0081)	(0.0226)
Δdeath.f1	0.1773	0.0188	−0.0056	−0.0238
	(0.1678)	(0.0164)	(0.0080)	(0.0188)
Num Obs.	25	46	67	83
R2	0.660	0.262	0.057	0.422
R2 Adj.	0.489	0.103	−0.073	0.359
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001				

Source: Compiled by the authors.