Journal of Siberian Federal University. Humanities & Social Sciences 2024 17(12): 2284–2296

EDN: DBULXN УДК 336.76

Financial Contagion of Stock Markets from the Oil Market: DCC GARCH Analysis

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Received 24.05.2024, received in revised form 21.11.2024, accepted 03.12.2024

Abstract. In the context of financial globalization, the transmission of turbulence from one market to another is intensifying, which is called financial contagion. The article analyses the transmission of contagion from the world oil market to the stock markets of different countries during the COVID-19 pandemic and new anti-Russian sanctions, accompanied by global energy and food crises. The analysis involved the returns of 16 stock indices and Brent oil futures. Contagion was tested by constructing DCC GARCH models and calculating Student's t-test for potential crisis periods that were identified using a sliding window within periods of pandemic and new sanctions. The study found that oil market contagion to stock markets was on average higher during the 2020 pandemic shock, slightly lower during the 2021 energy crisis, and even lower during the period of new anti-Russian sanctions. It revealed the greater sensitivity of the European and American stock markets to turmoil in the oil market, the synchronicity of contagion of both European and American indices, the short duration of shocks in Asian markets and their low propensity for contagion from the oil market. It revealed an atypically high dependence of the Russian RTS index on the state of the oil market during the pandemic, which significantly decreased during the period of new anti-Russian sanctions. The results obtained can be used by institutional and individual investors when forming effective investment portfolios, and by regulatory authorities when managing financial stability during periods of external shocks in order to protect national interests.

Keywords: financial contagion, COVID-19 pandemic, global energy crisis, Brent oil futures, stock indices, DCC GARCH model.

Research area: Social Structure, Social Institutions and Processes; Economics.

The study was supported by the Russian Science Foundation grant No. 23–28–00453, https://rscf.ru/project/23–28–00453/

Citation: Malkina M. Yu. Financial contagion of stock markets from the oil market: DCC GARCH analysis. In: *J. Sib. Fed. Univ. Humanit. soc. sci.*, 2024, 17(12), 2284–2296. EDN: DBULXN



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Финансовое заражение фондового рынка от рынка нефти: DCC GARCH-анализ

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Аннотация. В условиях финансовой глобализации усиливается передача турбулентности от одних рынков другим. Этот процесс получил название финансового заражения. В статье анализируется передача заражения от мирового нефтяного рынка фондовым рынкам разных стран в период пандемии COVID-19 и новых антироссийских санкций, сопровождавшихся мировым энергетическим и продовольственным кризисами. В анализе участвовали доходности 16 фондовых индексов и фьючерсов нефти марки Brent. Тестирование заражения осуществлялось на основе построения DCC GARCH-моделей и теста Стьюдента для потенциальных периодов заражения, которые выявлялись с помощью скользящего окна внутри периода пандемии и новых санкций. В результате исследования доказано в среднем большее заражение фондовых рынков от биржевого рынка нефти в период пандемического шока 2020 года, несколько меньшее заражение в период энергетического кризиса 2021 года и еще меньшее заражение в период новых антироссийских санкций. Установлена большая чувствительность европейского и американского фондовых рынков к шокам нефтяного рынка, синхронность заражения европейских, а также американских индексов, кратковременность шоков на азиатских рынках и их низкая склонность к заражению от рынка нефти. Доказана нетипично высокая зависимость российского индекса РТС от состояния рынка нефти в период пандемии, которая в значительной степени снижается в период новых антироссийских санкций. Полученные результаты могут быть полезными институциональным и индивидуальным инвесторам при формировании эффективных инвестиционных портфелей, регулирующим органам при управлении финансовой стабильностью в периоды воздействия внешних шоков для защиты национальных интересов.

Ключевые слова: финансовое заражение, пандемия COVID-19, глобальный энергетический кризис, фьючерс нефти марки Brent, фондовые индексы, модель DCC GARCH.

Научная специальность: 5.4.4. Социальная структура, социальные институты и процессы (социологические науки); 5.2.4. Финансы.

Исследование выполнено за счет гранта Российского научного фонда № 23–28–00453, https://rscf.ru/project/23–28–00453/

Цитирование: Малкина М. Ю. Финансовое заражение фондового рынка от рынка нефти: DCC GARCH-анализ. *Журн. Сиб. федер. ун-та. Гуманитарные науки*, 2024, 17(12), 2284–2296. EDN: DBULXN

Introduction

The 20s of the 20th century were marked by increased global turbulence in world financial markets. The pandemic shock of 2020, which caused a sharp reduction in supplies and a collapse in prices on the oil market, gave way to the global energy crisis of 2021, accompanied by an acute shortage of energy resources (oil, gas, and electricity), a significant increase in natural gas prices and their volatility. The energy crisis worsened in 2022 in the context of the Russian-Ukrainian military conflict: the destruction of previous energy supply chains from Russia to developed countries caused shortage of energetic resources and a new rise in their prices. Due to interruptions in the supply of energy, fertilizers and grains, a food crisis broke out in the world in 2022–2023. At this time, stock markets in many countries showed a quick and sharp response to energy shocks. Scholars have intensified their research into financial contagion processes in global financial markets.

According to the definition given by Forbes and Rigobon (2002), financial contagion is not just a comovement, but a significant change in the nature and strength of market relationships under the impact of external shocks. Researchers discovered and studied different channels of transmission of financial contagion: trade, financial, informational, macroeconomic, political, etc. (Guidolin, Pedio, 2017; Grillini et al., 2022). The hypersensitivity of stock markets to oil shocks is also due to various reasons: the importance of oil as a factor of production; inclusion in stock indices of capitalization of oil companies and companies directly or indirectly related to the oil market; the behavior of brokers who combine oil futures and stock assets in their investment portfolios and similarly respond to negative market signals; the impact of oil prices on a number of macroeconomic parameters (such as exchange rates and inflation) and corresponding adjustments in state economic policy.

The purpose of this study is to identify and dynamically assess the financial contagion of stock markets in different countries from the Brent oil market during the period of pandemic, post-pandemic and new global shocks associated with the Russian-Ukrainian military conflict.

According to *the research hypothesis*, contagion of stock indices should be observed during a period of significant increase in turbulence in the oil market; meanwhile, stock markets of different countries should show different sensitivity to oil shocks. This can be explained by the different volume and structure of energy consumption in different regions of the world, different portfolio strategies of stock market players, and the peculiarities of national macroeconomic policies.

Literature Review

Previously, scientists studied the financial contagion of different markets during various crises: the crisis in Asian stock and debt markets (Chiang et al., 2007; Kenourgios et al., 2013), global financial crisis of 2008–200 (Syllignakis, 2011; Bonga-Bonga, 2018), mortgage crisis in the USA (Hemche et al., 2016), debt crisis in Europe (Alexandre, Heliodoro, 2019; Campos-Martins, Amado, 2022). More recent works are devoted to the analysis of financial contagion during the COVID-19 pandemic of 2020-2021 (Yıldırım et al., 2022; Chen et al., 2023; Zhang et al., 2023; Salem et al., 2024) and Russian-Ukrainian military conflict of 2022-2024 (Kayani et al., 2023; Mohammed et al., 2023; Mejri et al., 2024; Salem et al., 2024).

A number of researchers have studied the transmission of contagion within the same market or between similar markets: stock, debt, banking, foreign exchange, etc. They analysed the cross-country (Kenourgios et al., 2013; Bonga-Bonga, 2018), cross-industry (Malkina, Balakin, 2023; Wu et al., 2024), cross-company (Fijorek et al., 2021; Malkina, Rogachev, 2023) financial contagion.

Other researchers have explored the transmission of contagion between different types of markets. For example, Zhang et al. (2023) studied the spread of contagion between the banking, stock, insurance and real estate markets of China in 2009–2021. Using the DCC-GARCH-CONNECTEDNESS approach, Salem et al. (2024) analysed the joint movement of oil prices and exchange rates in 10 countries in 2018–2023 and proved the impact of COVID-19 and the Russian-Ukrainian military conflict on this relationship.

In the context of our research, the works devoted to the contagion of stock markets by the oil market are of particular interest. For example, Wen et al. (2022) analysed the spread of risk in the world oil market, Chinese markets for raw materials and stock assets. The authors concluded that the world oil market has a greater impact on Chinese commodity markets than on Chinese equity markets. Other authors (Chen, Sun, 2023) studied the two-way transmission of contagon between crude oil and energy-intensive sectors in China. They found that the worst contagion comes from crude oil to China's coal sector, followed by the petrochemical sector. However, in certain periods, crude oil itself becomes a net recipient of contagion from China's energyintensive sectors.

Zhang, Hamori (2021) used data from the US, Japan and Germany in 2020 to study the returns and volatility spillover in crude oil and stock markets during the 2020 COVID-19 pandemic. They concluded that the impact of COVID-19 on oil and stock market volatility exceeded that of the 2008 global financial crisis and has long-term consequences.

Liu et al. (2022) built a multidimensional CoVaR network to measure conditional financial contagion and the spread of risks from oil markets to stock markets of G20 countries. The authors found that North American countries were the most sensitive to oil shocks, while Asian countries did not feel them at all. Using the method of central co-moments of distribution, Xue et al. (2024) studied the contagion of stock indices of 13 countries from the Russian fuel export market during the COVID-19 pandemic and the Russian-Ukrainian military conflict. The authors concluded that stock markets were more exposed to financial contagion from the oil market during the Covid-19 pandemic and from the gas market during the Russian-Ukrainian conflict. They also proved that European countries suffered the most, while Asian countries showed significant resilience in both crises.

Our current study complements the studies presented above by using the method of constructing DCC GARCH models and the dynamic Student's test to assess the contagion of the main stock indices of the United States, Europe, Asia, Latin America and Russia from Brent oil futures during the pandemic and new anti-Russian sanctions. The calculation of dynamic conditional correlations in these models enables to trace changes in markets connectedness (Asaturov, Teplova, 2014; Guenichi et al., 2022; Nguyen et al., 2022). The sliding window method, also used in our study, tracks the waxing and waning of market contagion over time (Dajcman, 2013; Fry-McKibbin et al., 2022).

Data and Methods

The study used data from 2014 to April 2024 on average daily prices for Brent crude oil futures and major stock indices in the US, Europe, Asia, Latin America and Russia, provided by Investing. com, an international financial information and news website. Table 1 shows a list of stock indices tested for financial contagion from the oil market.

Index	Country	Index	Country				
S&P 500	USA	FTSE 100	Great Britain				
DJ Industrial	USA	Nikkei	Japan				
NASDAQ Composite	USA	Hang-Seng	Hong Kong				
STOXX 50	Eurozone	KOSPI	Republic of Korea				
DAX	Germany	Shanghai-Composite	China				
CAC 40	France	Taiwan Weighted	Taiwan				
FTSE MIB	Italy	BOVESPA	Brazil				
IBEX35	Spain	RTS	Russia				

Table 1. Major stock indices involved in the analysis

Source. Author's development

The intersession log returns of oil futures and stock indices are calculated based on their average daily prices (P_i) :

$$r_t = \ln(P_t) - \ln(P_{t-1}).$$
 (1)

These returns are further involved in the construction of DCC GARCH models developed by (Engle, 2022). Testing for contagion is carried out in several stages¹.

1. Constructing simple linear regressions of the return of each asset of the following type:

$$r_t = \mu + \varepsilon_t,\tag{2}$$

where μ is constant (intertemporal average return), ε_t are the model residuals in period t.

Calculation of conditional variance of residuals:

$$v_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta v_{t-1}^2$$
, (3)

 ω is unconditional variance of returns, α is

ARCH,
$$\beta$$
 is GARCH; $v_{t=0}^2 = \frac{\omega}{1 - \alpha - \beta}$. First α

and β are taken equal to zero, so $v_{t=0}^2 = \omega$. They are then derived from the DCC models through optimization.

2. *Building DCC GARCH models*. Conditional covariance matrix:

$$H_{t} = D_{t} \cdot R_{t} \cdot D_{t}, \qquad (4)$$

where $D_t = diag(v_t)$ is diagonal conditional

volatility matrix, where
$$v_t = \sqrt{v_t^2}$$
; R_t is dynamic

conditional correlation matrix with units on the main diagonal:

$$\mathbf{R}_{t} = \mathbf{Q}_{t}^{*-1} \cdot \mathbf{Q}_{t} \cdot \mathbf{Q}_{t}^{*-1}, \tag{5}$$

$$Q_{t} = (1 - a - b) \cdot \overline{Q} + a \cdot \varepsilon_{t-1} \cdot \varepsilon_{t-1}^{T}, \quad (6)$$

$$Q_t^* = \text{diag}(Q_t^{1/2}), \tag{7}$$

where Q_t is symmetric positive definite conditional covariance matrix of ε_t ; a and b are non-negative scalar parameters satisfying the condition a + b < 1 (selected as a result of optimization); \overline{Q} is initial (as well as long-term) unconditional covariance matrix, subject to a = 0and b = 0.

The selection of model parameters (α , β , ω a and b) is carried out based on maximizing the log-likelihood function:

$$\log L = \sum_{t=1}^{1} -\frac{1}{2} (n \ln \pi + \ln(\det H_t) + \epsilon_t H_t^{-1} \epsilon_t^T) \rightarrow max.$$
(8)

3. Diagnosis of contagion. Suspicion about the possible contagion of one asset by another arises when there are sharp jumps in conditional correlations (diagonal values in R₁). Contagion is ultimately confirmed if the sample average conditional correlation of two assets in the shock period $(\widehat{\rho_y})$ is statistically significantly higher than their sample average conditional correlation in the pre-crisis period $(\widehat{\rho_x})$. For this, the Student's t-test is calculated (Bonga-Bonga, 2018):

$$ST = \frac{\widehat{\rho_{y}} - \widehat{\rho_{x}}}{\sqrt{\frac{Var(\widehat{\rho_{y}})}{T_{y}} + \frac{Var(\widehat{\rho_{x}})}{T_{x}}}},$$
(9)

where $Var(\widehat{\rho_x})$ and $Var(\widehat{\rho_y})$ are sample variances of conditional correlation coefficients in the precrisis "x" and crisis "y" periods, respectively; T_x and T_y are number of observations in these periods.

The critical value of Student's t-test is determined for $T_y + T_x - 4$ degrees of freedom at a given significance level (in our case $\alpha = 0.005$). If ST > ST_{critical}, there is no reason to deny the spread of contagion from one asset to another.

When conducting such tests, it is important to clearly distinguish between the pre-crisis and crisis periods. A preliminary determination of the crisis period is carried out on the basis of the dynamics of the "realized volatility" of the oil futures return, which is the square of its residuals (ε_t^2) .

Fig. 1 shows a significant increase in market volatility of Brent oil futures return during the period of a sharp drop in oil prices in March-April 2020 (which coincides with the acute phase of the pandemic). There are also smaller bursts of volatility at the end of 2014, 2015 and 2016 (which are due to increased global tension during the

¹ When building DCC GARCH models, we used the video resource and Excel program provided by NEDL (https://www.youtube.com/watch?v=d1qEHNlpGog)



Fig. 1. Realized volatility of Brent crude oil (ϵ_t^2)

Source. Author's development



Fig. 2. Realized volatility of S&P 100 GLOBAL (ϵ_t^2)

Source. Author's development

period of Russia's annexation of Crimea and the introduction of the first anti-Russian sanctions). The surge in oil futures volatility in November 2021 is associated with the developing global energy crisis, and in 2022 with increased global tensions in the context of the Russian-Ukrainian military conflict and the introduction of new anti-Russian sanctions.

For comparison, Fig. 2 shows the realized volatility of the global S&P 100 index return. The dynamics of the global stock index as

a whole follows the dynamics of oil prices; however, bursts of volatility in the S&P 100 occur with some lag and with different intensity. A similar, although different, picture is typical for country stock indices.

Further, using a sliding window approach solves the problem of accurately determining the contagion period. The first (pre-crisis) window corresponds to a period with low (below average) oil volatility and includes observations from 18.09.2019 to

05.03.2020 inclusive. The number of observations in this period (T_x) for different tested pairs depends on the number of trading sessions and varies from 110 to 123. The second (tested as a crisis) window initially includes

43 consecutive observations starting from 06.03.2020 ($T_y = 43$), which corresponds to a period of increased oil volatility of the pandemic shock. Then the second window moves one observation forward, while the



Fig. 3. Dynamic conditional correlations of returns of Brent oil futures and stock indices Source. Author's development

first window remains stationary. The contagion test each time refers to the first date of the second window.

Results and their analysis

Fig. 3 shows the dynamic conditional correlations between the returns of Brent oil and the tested stock indices, calculated using formulas 1–8.



Fig. 3. Continued

Analysis of the data obtained leads to a number of conclusions. First, the figures convincingly indicate a significant short-term increase in the conditional correlation between the returns of Brent oil futures and all stock indices during the acute phase of the pandemic (March-June 2020). Second, a smaller surge in the correlation between a number of indices and oil futures is observed at the end of 2021, which is associated with the emerging energy crisis. Third, the global instability of 2022-2023 manifested itself in spikes and an increase in the range of fluctuations of the conditional correlation for a number of American and European indices, as well as in the Asian indices Nikei, Hang-Seng, Taiwan. Fourth, the indices of countries in the same region (USA, Europe, and Southeast Asia) show similar dynamics. Fifth, the Russian

RTS index shows a large and relatively stable relationship with oil futures. The growth of the conditional correlation for the RTS is not explosive, but rather long-term. However, during the period of Russia's special military operation in Ukraine and the introduction of new anti-Russian sanctions, the relationship between the RTS index and oil futures sharply decreases and then turns out to be significantly lower than in the previous period.

Fig. 4 shows the dynamics of contagion tests by groups of countries, calculated using formula 9. The horizontal line shows the critical Student's test value.

Analysis of the data obtained leads to a number of conclusions. First, the synchronicity of the dynamics of test statistics both for different European indices and for American indices indicates the simultaneity and equal



Fig. 4. Student's T-statistics for contagion and its critical value

Source. Author's development

intensity of contagion within the same region. Some exception is the NASDAQ Composite index, which shows significantly lower intensity and duration of contagion during the period of pandemic shock and energy crisis than the US S&P 500 and DJ Industrial indices. A certain, but much less synchronicity is inherent in the Asian indices, as well as the Brazilian BOVESPA with other indices. The dynamics of contagion of the RTS index from oil futures completely go beyond the general patterns. The largest and longest-lasting RTS contagion occurs during the pandemic; far less contagion takes place during the 2021 energy crisis. During the period of new sanctions, there was a significant decrease in the connection of the RTS with the world oil market.

Second, on average, American and European indices are characterized by significantly greater contagion from the oil market than the Brazilian BOVESPA and, even more so, Asian indices (where contagion is short-term and characteristic only of individual indices, such as the Hang-Seng). The Russian RTS index, on the contrary, before the new sanctions period shows the highest connection with the oil market; during this period the connection becomes insignificant.

Third, for American and European indices the pandemic turned out to be more contagious than the energy crisis. No such pattern was found for the Asian and Latin American indices. The peak of contagion of the Italian FTSE MIB in April 2023 may be associated with the approval of Lukoil's deal to sell its ISAB oil refinery on the island of Sicily to G.O.I. Energy.

Table 2 presents general statistics on the duration and intensity of contagion of various stock indices from Brent oil futures in the period under review.

These results also indicate greater sensitivity of US and European indices to oil shocks. Among European indices, the Italian FTSE MIB, Spanish IBEX 35 and British FTSE 100 demonstrate the strongest response to oil shocks. Asian indices show minimal propensity to receive contagion from the oil market. At the same time, no cases of contagion were detected for the Shanghai index. Among Asian indices, the Hong Kong Hang-Seng was the most affected. Brazil's BOVESPA showed a medium propensity for contagion, both in the number of confirmed cases and in intensity. The Russian RTS demonstrated the maximum intensity of contagion. However, a separate analysis before 02.24.2022, Russia's announcement of a special military operation (SMO) in Ukraine, and after this date leads to different conclusions. All cases of RTS contagion occur in the period before the SMO, with an incidence of 83.8 % and an intensity of 16.12.

Conclusion

Financial contagion manifests itself as an increase in the degree of interaction between

Index	Confirmed cases,%*	Intensity of contagion**	Index	Confirmed cases,%*	Intensity of contagion**		
S&P 500	47.7	3.642	FTSE 100	62.1	2.352		
DJ Industrial	51.5	3.036	Nikkei	5.0	0.281		
NASDAQ	20.7	1.100	Hang-Seng	17.6	0.757		
STOXX50	42.4	1.526	KOSPI	3.8	0.170		
DAX	53.4	2.308	Shanghai	0.0	-		
CAC 40	38.9	1.332	Taiwan	0.4	0.280		
FTSE MIB	64.2	3.555	BOVESPA	31.9	1.331		
IBEX35	50.2	2.945	RTS	42.7	16.200		

Table 2. Generalization of the financial contagion of stock indices from Brent oil futures in March 2020 – April 2024

* Calculated as the share of confirmed contagions in a dynamic window

** Calculated as the relative excess of the test statistic over its critical value in confirmed cases of contagion

different markets under the influence of external shocks.

This article tested the contagion of 16 major stock indices in the US, Europe, Asia, Latin America and Russia from Brent oil futures under conditions of pandemic and post-pandemic shocks, as well as shocks during the Russian special military operation in Ukraine. Contagion testing was carried out by constructing DCC GARCH models and calculating Student's t-statistics in a dynamic window, which made it possible to clearly identify periods of contagion and its intensity.

The study confirmed the contagion of the stock markets of the countries under study from the oil market both during the acute phase of the pandemic in 2020, the energy crisis in 2021, and global market turbulence amid the SMO and new anti-Russian sanctions in 2022–2023. Moreover, during the pandemic, the level of contagion of markets on average turned out to be noticeably higher than during periods of the energy crisis and new sanctions. American and European stock markets demonstrated significantly greater sensitivity to oil shocks than Latin American and, especially, Asian markets. Different Ameri-

can stock indices and European indices of different countries are characterized by synchronicity of contagion, which indicates their identical reaction to external shocks. The Russian RTS index demonstrated constant and greatest exposure to the influence of the global oil market before the start of the new sanctions period. With the entry into this period, RTS gradually and largely loses its sensitivity to the external oil market, which is explained both by the limitation of Russian oil supplies to foreign markets, regulation of its prices, and by the development of non-oil capitalization of the Russian stock market.

Thus, the research hypothesis that contagion of stock indices is observed during a period of significant increase in turbulence in the oil market, but stock markets of different countries show different sensitivity to oil shocks, was confirmed.

The methods used and the results obtained in this study are useful for exchange players when optimizing investment portfolios in the face of new external shocks, as well as for regulators when adjusting anti-crisis policies in conditions of global turbulence to protect national interests.

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