Известия Саратовского университета. Новая серия. Серия: Экономика. Управление. Право. 2023. Т. 23, вып. 3. С. 278–292
Izvestiya of Saratov University. Economics. Management. Law, 2023, vol. 23, iss. 3, pp. 278–292
https://eup.sgu.ru https://doi.org/10.18500/1994-2540-2023-23-3-278-292, EDN: QHNHVA

Article

Systemic risk in Russian financial market: A Δ*CoVaR* approach

A. R. Faizliev

Saratov State University, 83 Astrakhanskaya St., Saratov 410012, Russia

Alexey R. Faizliev, faizlievar1983@mail.ru, https://orcid.org/0000-0001-6442-4361

Abstract. ***Introduction.*** Recent financial crises have highlighted the need for increased attention to systemic risks and indicators to track them. This study is devoted to the assessment of systemic risk, which is a popular subject of economic research. The paper analyzes systemic risks in the Russian stock market for companies included in the RTS index. ***Theoretical analysis*.** We will focus on one common measure of systemic risk, *CoVaR*, which is the notional value at risk (notional VaR), defined as the change in the value of a financial system (asset) at risk versus another asset (system) in decline. The *CoVaR* risk measure is a powerful risk management tool and can be viewed as a simultaneous measure of system vulnerability, allowing the identification of assets that are classified as systemically important. ***Empirical analysis***. The study tests the hypothesis of structural changes in the risk propagation network over time and looks at various measures of strength centrality, betweenness centrality, eigenvector centrality and Page Rank to identify assets that can propagate negative shocks through the network. ***Results***. The results show that during the shocks of 2014 and 2020 the Russian stock market was exposed to more systemic risk and greater interconnectedness between assets. Shares of Sberbank and Tatneft contributed significantly to this risk during the political crisis and beyond, with company size not a dominant factor.
Keywords: financial stability, systemic risk, conditional value at risk, macroeconomic models, stock markets, market graph

Acknowledgements: This work was supported by the Russian Science Foundation (project No. 23-21-00305).

For citation: Faizliev A. R. Systemic risk in Russian financial market: A Δ*CoVaR* approach. *Izvestiya of Saratov University. Economics. Management. Law*, 2023, vol. 23, iss. 3, pp. 278–292. https://doi.org/10.18500/1994-2540-2023-23-3-278-292, EDN: QHNHVA

Научная статья

УДК 330.43

Системный риск на российском финансовом рынке: подход Δ*CoVaR*

А. Р. Файзлиев

Саратовский национальный исследовательский государственный университет имени Н. Г. Чернышевского, Россия, 410012, г. Саратов, ул. Астраханская, д. 83

Файзлиев Алексей Раисович, кандидат экономических наук, доцент кафедры теории функций и стохастического анализа, faizlievar1983@mail.ru, https://orcid.org/0000-0001-6442-4361

Аннотация. ***Введение.*** Современные финансовые кризисы обусловливают необходимость повышенного внимания к системным рискам и индикаторам для их отслеживания. Данное исследование посвящено оценке системного риска, являющейся востребованным предметом экономических исследований. В работе анализируются системные риски на российском фондовом рынке для компаний, входящих в индекс РТС. ***Теоретический анализ.*** Исследуется одна из распространенных мер системного риска *CoVaR*, которая представляет собой условную стоимость под риском (условный VaR), определяемую как изменение стоимости финансовой системы (актива), подверженной риску, в зависимости от другого актива (системы), находящегося в состоянии спада. Мера риска *CoVaR* является мощным инструментом управления рисками, и ее можно рассматривать как одновременную меру уязвимости системы, позволяя выделить активы, которые относятся к категории системно значимых. ***Эмпирический анализ.*** В исследовании проверяется гипотеза о структурных изменениях в сети распространения рисков с течением времени и рассматриваются различные показатели strength centrality, betweenness centrality, eigenvector centrality and Page Rank для выявления активов, которые могут распространять негативные потрясения по сети. ***Результаты.*** Результаты показывают, что во время потрясений 2014 и 2020 гг. российский фондовый рынок был подвержен большему системному риску и большей взаимосвязанности активов. Акции компаний «Сбербанк» и «Татнефть» внесли значительный вклад в этот риск во время политического кризиса и в последующие периоды, при этом размер компании не был доминирующим фактором.
Ключевые слова: финансовая стабильность, системный риск, условная стоимость под риском, макроэкономические модели, фондовые рынки, рыночный граф

Благодарности: Исследование выполнено при финансовой поддержке Российского научного фонда (проект № 23-21-00305).

Для цитирования: *Faizliev A. R.* Systemic risk in Russian financial market: A Δ*CoVaR* approach [*Файзлиев А. Р.* Системный риск на российском финансовом рынке: подход Δ*CoVaR*] // Известия Саратовского университета. Новая серия. Серия: Экономика. Управление. Право. 2023. Т. 23, вып. 3. С. 278–292. https://doi.org/10.18500/1994-2540-2023-23-3-278-292, EDN: QHNHVA

Introduction

Today the world economy is a complex system with a high degree of interconnectedness both between the economies of different countries and between different sectors of the national economy.

The global financial and economic crisis of 2008 led to a rethinking of the relationship between the financial sector and macroeconomics. He showed how closely interconnected financial stability within the national economy and the state of the entire global financial system, and how quickly financial contagion can spread between countries.

A simultaneous decline in all segments of the financial market (stock market, banking sector, money and foreign exchange market, etc.), which subsequently had a negative impact on the dynamics of the real sector, was observed in almost all countries. As a result, it became clear that the acceleration of integration processes between countries not only has positive aspects in the form of a more dynamic development of the world economy, but can also cause financial imbalances to be transmitted to almost all national segments of the global economic space. If earlier the financial sector was considered only as a technical condition for the development of the real economy, now it is financial instability that is being considered as the main cause of problems in the real sector, and financial indicators are actively considered in macroeconomic models.

The concept of systemic risk, which implies the effect of contagion, is usually considered in the context of the financial sector. The spread of risks can also occur in other sectors of the economy, but the consequences of the realization of systemic risk in the financial sector pose the greatest threat to the economy. Moreover, the dynamics of the financial (stock) market also affects the real sector of the economy. The volatility of output in the phases of the business cycle largely depends on the level of volatility in the financial market. The emerging instability in the financial market may lead to negative consequences for the real sector, primarily through a decrease in lending and a lack of liquidity. On the other hand, causality is not necessarily directed from the financial system to the real sector. An important question is whether the price dynamics of financial assets is really determined by fundamental and market factors, or whether it is dominated by other unaccounted sources of information, such as market sentiment, the subjective goals of investors, or clear adjustments by government regulators.

For Russia, as an economy integrated into the global financial system since 2013, the problem of systemic crises is particularly acute. Despite the introduction of economic sanctions against Russia, which partly isolated our country in the global economic space and played a positive role in reducing global systemic risks, it is impossible to stop this process completely. Assessment and management of systemic risk is becoming one of the priority tasks in modern economy. To increase the systemic strength of the financial sector, it is necessary to develop a warning system for possible future crises. This seems possible, since a modern financial sector has now been formed in Russia, which makes it possible to analyze the existing economic ties in terms of stable patterns and long-term forecasts.

In recent years, to assess the stability and stability of the financial sector, regulators (the central bank) use macroprudential stress testing. This approach makes it possible to identify systemic risks based on the analysis of the structure of relationships between financial institutions, the transmission of risks and their changes over time.

The introduction of lockdowns due to the unfavorable epidemiological situation, price instability in the commodity market, sanctions factors that impede the movement of foreign capital, only increase the importance of ensuring financial stability function. All these events are reflected in the volatility in the world markets, including the Russian financial market. Under these conditions, the regulator needs to assess adequately the financial sector's resilience to current shocks and their potential increase in the future. This requires, among other things, the identification of links between economic institutions (industries, sectors, companies, etc.).

Timely identification of these links and their impact on different institutions of economic sectors helps to prevent systemic risks. Systemic risk is a threat to the entire financial and economic system. The so-called "dominant effect" of individual institutions and sectors of the economy in distress leads to deep depressions in other sectors of the economy [1–3]. Therefore, it is important to identify companies that are particularly sensitive to systemic shocks and are able to spread them to the rest of the market. Such companies can affect the entire system if they are in decline. Obviously, it will not be enough to limit the risks of an individual company, since the definition of systemic risk takes into account not only the risk associated with an individual company but also the risk for the entire economy (system). Thus, the prediction and prevention of factors contributing to the systemic risk emergence and development is an important task of modern science.

Two approaches are generally considered to measure systemic risk. The first approach involves assessing the systemic risk associated with an individual company, considering individual factors [4]. The first approach involves assessing the systemic risk associated with an individual company, considering individual factors. The other is based on network analysis and evaluates the connections between companies [5]. This approach allows us to detect a possible domino effect in case of one company's default.

This paper considers the network approach to the study of systemic risks, and we will focus on one of the common measures of systemic risk *CoVaR*, which uses the probability distribution of an asset's return. The *CoVaR* measure was proposed by the American economists Adrian, Tobias and Brunnermeier, Markus in their works [6, 7]. The *CoVaR* risk measure is the conditional value at risk (conditional VaR), defined as the change in the value of the financial system (asset) at risk, depending on another asset that is in a state of decline. This indicates the systemic nature of the risk measure, implying the mutual spillover of risk from other companies and parallel dynamics of institutions. Thus, unlike the *VaR* risk measure, which focuses on the risk of an individual institution, *CoVaR* assesses risks for the entire financial system. Today the *CoVaR* risk measure is a powerful risk management tool and can be considered as a simultaneous measure of system vulnerability. Moreover, the *CoVaR* risk measure, along with other indicators of systemic risk, makes it possible to identify assets that are classified as systemically important.

To analyze the relationship between companies in terms of systemic risk, we propose to use the graph theory approach. As noted above, one of the key aspects of modern economic systems is that they are complex systems consisting of a large number of interdependent parts. The more complex the system is, the more interconnected its parts are and the more complex behavior they demonstrate. The analysis of such market networks has attracted increasing attention in the last decade. For the first time the concept of a market graph was considered in the work [8]. The market network is a weighted graph whose nodes are shares of companies and the weights of the edges determine the similarity in their behavior. As a rule, the value of the correlation coefficient is considered as such a similarity measure. Many studies apply and develop the market graph approach. As a rule, these are empirical studies based on real market data. Many works analyze various structural properties and attributes of market graphs, such as maximum cliques, maximum independent sets, degree distribution [8–10], clustering [11], market graph [12], graph dynamics [13]. Papers [14–17] explore the features of individual financial markets. Paper [18] proposes various similarity measures as an alternative to correlation.

In this study, a dynamic risk measure model $\Delta CoVaR$ is used to quantify the strength of links between companies in a market graph. For jointly normally distributed random variables, $\Delta CoVaR$ will be close to the correlation coefficient, being essentially a function of conditional correlations, volatilities, and *VaR*. But unlike correlation, which assesses the relationship between companies in both calm and turbulent periods of time, the definition of $\Delta CoVaR$ allows you to explore the relationship between companies, as well as identify which institutions are most at risk during financial crises. The main goal of the study is to study the various characteristics of such a market graph in dynamics, identify key companies in the network, determine the duration of shock impact on risk propagation, and study structural changes in the risk propagation network. The analysis is based on Russian financial market data from January 2012 to February 2022 (2613 trading days). The data used to estimate *CoVaR* is daily data on the performance of shares of 29 large companies traded on the Moscow Stock Exchange. In the empirical part of the article, the quantile regression method is used to estimate $\Delta CoVaR$. To determine directed weighted relationships between assets, the LASSO regularization procedure for selecting significant factors (assets) was used when constructing a quantile regression.

It should be noted that most of the work on the study of systemic risks was focused on relatively stable financial markets. However, it is also of scientific interest to study the behavior of the distribution networks of systemic risks for financial markets, which were extremely volatile during the analyzed period and experienced many different shocks. The Russian financial market was chosen as the object of study in our work for the following reasons.

First, from 2012 to 2022, the Russian economic system was affected by numerous negative factors and shocks (while during this period the economies of most other countries showed stable growth after the 2008 crisis):

– political crisis in Ukraine in 2014;

– structural problems of the Russian economy and low GDP growth compared to other countries due to the imposition of sanctions against Russia;

– the collapse of the national currency, caused, among other things, by the fall in oil prices in the second half of 2014;

– the introduction of new sanctions against Russia, as well as another drop in oil prices in 2018;

– the crisis caused by the COVID-19 pandemic, which led to a sharp drop in oil prices in early 2020;

– financial and economic uncertainty caused by the political crisis in connection with the deployment of Russian troops near the borders with Ukraine in 2021–2022.

All of the above factors and shocks had a negative impact on the stability of the Russian stock market, making it rather volatile and unpredictable. These characteristics make it interesting for our analysis, allowing us to see how systemic risk networks behave in unstable financial systems.

This document is divided into four main parts. The introduction briefly discusses the sources of systemic risk as well as the existing literature regarding systemic risk assessments. Section 2 covers the theoretical background needed to understand and apply the Δ*CoVaR* risk measure. Methods for estimating Δ*CoVaR* are also presented here. Section 3 presents the results of systemic risk analysis for the Russian stock market using graph theory methods. Conclusions are drawn at the end.

Theoretical analysis

Definition of *CoVaR*

First, recall that the risk value (*VaR*) of the random variable $X_{i,t}$ is implicitly defined as a q-quantile:

$$Pr\left(X_{i,t} \leq VaR_{i,t,q}\right) = q, \qquad (1)$$

where $X_{i,t}$ are the log returns of the asset *i*, for which $VaR_{i,t}^{q}$ is determined. The index *t* means that the value of *VaR* depends on macro variables of the state of the economy M_{t-1}. For small values of $q < 0.1$, the value of $VaR_{i,t}^{q}$ is usually a negative number, and a larger risk will correspond to a higher modulo $VaR_{i,t}^{q}$. It is obvious that in the context of the definition of *VaR* $X_{i,t}$ means “return loss”. To date, the value of *VaR* is one of the most – is one of the most common measures of risk. A more detailed description of *VaR* can be found in the book [19].

Next, we define *CoVaR* implicitly in terms of the quantile *q* of the conditional probability distribution, as proposed in [6] or [7]:

$$Pr\left(X_{j,t} \leq CoVaR_{j|i,t,q} | R_{i,t}\right) = q, \qquad (2)$$

where $CoVaR_{j|i,t,q}|R_{i,t}$ is the value equal to $VaR_{j,t,q}$ of institute *j* under the condition $X_{i,t} = VaR_{j,t,q}$, and macrostate vector M_{t-1}. Obviously, $R_{i,t}$ refers to a decline in *i* when its stock return is equal to its *VaR*, i.e. $X_{i,t} = VaR_{i,t,q}$. In the case of the median (usual) state of the institution *i*, the profitability of its shares will be equal to its median, i.e. $X_{i,t} = VaR_{i,t,0.5}$ [6, 7].

The definition of *CoVaR* allows you to study the spillover effects of the entire financial network (system) and explore which institutions are most at risk during financial crises. The risk measure *CoVaR* is directional, i.e. the value of *CoVaR* calculated for some company 1 under the condition of the decline of company 2 is not equal to the value of *CoVaR* calculated for company 2 under the condition of the crisis of company 1.

Estimation Method: Quantile Regression

In this work, the quantile regression method is used to study *CoVaR*. A dynamic model is considered, which assumes that the values of *CoVaR* change over time depending on exogenous factors. The dynamic model makes it possible to take into account macroeconomic indicators which in a real economy will have a significant impact on the level of risk. The inclusion of macroeconomic indicators and the consideration of changes in the values in question over time are the basis of the *CoVaR* dynamic model [6].

Denote by M_{t-1} the vector of state variables. In order to fix the changes over time in the joint distribution of the returns $X_{i,t}$ and $X_{j,t}$ of the *i* and *j* institutions, we need to make assumptions about the form of the dependence of the conditional and unconditional quantiles ($CoVaR_{i,t,q}$ and $VaR_{i,t,q}$) from state variables. This will then allow modeling the evolution of conditional distributions over time.

Then, in the framework of the dynamic model, calculations begin with constructing a *q*-quantile regression that describes the dependence of the predicted value of the *q*-quantile of profitability $X_{j|i,t}$ of company *j* depending on company *i*, taking into account lagging state variables M_{t-1}:

$$X_{i,t} = \alpha_i + \gamma_i M_{t-1} + \epsilon_{i,t}, \qquad (3)$$

$$X_{j|i,t} = \alpha_{j|i} + \gamma_{j|i} M_{t-1} + \beta_{j|i} X_{i,t} + \epsilon_{j|i,t}. \quad (4)$$

Then, based on the constructed regressions (3),(4), predictive values are found, which are used for subsequent calculations:

$$\widehat{VaR}_{i,t,q} = \hat{\alpha}_i + \hat{\gamma}_i M_{t-1}, \quad (5)$$

$$\widehat{CoVaR}_{j|i,t,q} = \hat{\alpha}_{j|i} + \hat{\gamma}_{j|i} M_{t-1} + \hat{\beta}_{j|i} \widehat{VaR}_{i,t,q}. \quad (6)$$

Finally, the value of the dynamic $\Delta CoVaR$ is the difference between the *CoVaR* of company *j* provided that company *i* is in decline, and *CoVaR* of company *j*, given the normal state of company *i*:

$$\Delta\widehat{CoVaR}_{j|i,t,q} = \widehat{CoVaR}_{j|i,t,q} - \widehat{CoVaR}_{j|i,t,0.5} = \\ = \hat{\beta}_{j|i}\left(\widehat{VaR}_{i,t,q} - \widehat{VaR}_{i,t,0.5}\right). \quad (7)$$

As noted above, for jointly normally distributed random variables, $\Delta\widehat{CoVaR}$ is related to the correlation coefficient, and *CoVaR* corresponds to the conditional variance. The conditionality of the *CoVaR* risk measure reduces the variance, while adverse events in other companies increase the expected losses.

Next, let's move on to the monetary terms $\Delta CoVaR$:

$$\Delta^{\$}\widehat{CoVaR}_{j|i,t,q} = Cap_i \cdot \Delta\widehat{CoVaR}_{j|i,t,q}. \quad (8)$$

As a result, we obtain a set of values $\Delta^{\$}\widehat{CoVaR}_{j|i,t,q}$ for the corresponding pair of companies, taking into account the size (capitalization) of the company *i*, which allows us to compare institutions of different sizes. For this purpose, we quantify the size of the market capital of companies as the product of the number of shares of companies and their current value. Then, in this formulation, the risk of financial institution *j* is calculated through $VaR^{\$}$ of institution *i*. State variables in this case should not be considered as independent risk factors, but as conditional variables that change the conditional mean and volatility.

We are interested in the value $\Delta^{\$}\widehat{CoVaR}_{j|i,t,q}$, which just reflects the degree of interconnectedness. Given the direction of the systemic risk $\Delta^{\$}CoVaR$, it is advisable to measure the mutual influence in both directions. If *j* is the weighted average return of the stock index, and *i* is the return of company *i*, then we get the contribution of $\Delta^{\$}CoVaR$ of company *i* to systemic risk. If *j* is a company, and *i* corresponds to a stock index, then we get the company's exposure to systemic risk.

This approach allows you to identify the key elements of systemic risk. However, pairwise quantile regression is assumed. Since two companies are interacting in a non-isolated environment, all other interaction effects must also be taken into account. In this regard, we expand the two-dimensional model to a higher dimension by including more variables (assets). That is, in the formula (6) M_{t-1} and $\widehat{VaR}_{i,t,q}$ can be considered as a vector. In this case, it is necessary to carry out the selection of variables. In this study, the LASSO-based variable selection method was used.

LASSO Penalized Quantile Regression

We used the A Tail Risk Network approach proposed in [20]. It is assumed that the composition of the variables that affect the size of the conditional quantile should include lagged values of factors specific to each of the firms and the influence of other companies. When evaluating quantile regression models, use regularization methods to select significant variables. Edge weights in A Tail Risk Network are calculated from the marginal effects of the variables in the regression dependencies.

In the first step, we estimate *VaR* for each company using linear quantile regression at the quantile level $q = 0.05$ using the equations (3), (5). Next, a network of company systemic (tail) risks interdependence is constructed using quantile regression with selection of variables to estimate the contribution to systemic risk as a result of changes in the respective company. The spread of tail risks across the network from one company to another indicates the interconnectedness of systemic risk and the presence of network spillovers. To do this, it is necessary to define the main element of the network: the *CoVaR* risk. As in the (2) equation, X_j represents a single company, and *j*'s *CoVaR* is estimated based on its information set [21, 22]:

$$X_{j,t} = \beta_{j|R_j}^{\mathsf{T}} R_{j,t} + \epsilon_{j,t}, \quad (9)$$

$$\widehat{CoVaR}_{j|\tilde{R}_j,t,q}^{NET} = \hat{\beta}_{j|\tilde{R}_j}^{\mathsf{T}} \tilde{R}_{j,t}, \quad (10)$$

$$\Delta\widehat{CoVaR}_{j|i,t,q}^{NET} = \widehat{CoVaR}_{j|i,t,q}^{NET} - \widehat{CoVaR}_{j|i,t,0.5}^{NET}, \quad (11)$$

$$\Delta^{\$}\widehat{CoVaR}_{j|i,t,q}^{NET} = Cap_{j,t} \cdot \Delta\widehat{CoVaR}_{j|i,t,q}^{NET}, \quad (12)$$

$$\widehat{D}_{j|\tilde{R}_{j,t}} = \frac{\Delta^{\$}\widehat{CoVaR}_{j|i,t,q}^{NET}}{\sum_l Cap_{l,t}}. \quad (13)$$

Here $R_{j,t} = \{X_{-j,t}, M_{t-1}\}$ is the information set where $X_{-j,t} = \{X_{1,t}, X_{2,t}, \dots, X_{n,t}\}$ – explanatory variables including logarithmic returns of companies other than *j*-th.

Define $\beta_{j|R_j} = \{\beta_{j|-j}, \beta_{j|M}\}^{\mathsf{T}}$. There is no time symbol *t* in the parameters because the model is tuned based on a single fixed window estimate.

In the future, the sliding time window procedure will be applied to estimate the parameters for all windows.

We define $\tilde{R}_{j,t} = \{\widehat{VaR}_{-j,t,q}, M_{t-1}\}$, where $\widehat{VaR}_{-j,t,q}$ are the estimated *VaR*s from (5) for all companies except *j*-th and $\hat{\beta}_{j|\tilde{R}_j} = \{\hat{\beta}_{j|-j}, \hat{\beta}_{j|M}\}^{\mathsf{T}}$. *CoVaR* from the (10) equation represents the network risk caused by the tail-event and includes the influence of companies excluding the *j*-th, as well as the influence of macro variables. Finally, the dynamic $\Delta CoVaR^{NET}$ from the (11) equation measures how much other companies increase systemic risk of company *j*.

We denote the part of *j*'s systemic risk that can be attributed to *i* in dollar terms by $\Delta^{\$}\widehat{CoVaR}^{NET}_{j|i,t,q}$.

The LASSO regularization procedure was used to select significant factors when constructing the quantile regression. Estimated coefficients $\hat{\beta}_{j|\tilde{R}_j}$ minimize the quantile regression objective function with a penalty:

$$f\left(\beta_{j|R_j}\right) = \frac{1}{n}\sum_{i=1}^{n}\rho_q\left(y_i - x_i^{\mathsf{T}}\beta_{j|R_j}\right) + \lambda\left\|\beta_{j|R_j}\right\|_1, \quad (14)$$

where $\rho_q(u) = u\big(q - I(u<0)\big)$.

Thus, this approach makes it possible to select systemically important institutions for each company in all sliding time windows.

$\widehat{D}_{j|\tilde{R}_j}$ is equal to the ratio of the increase in the cost measure of risk associated with the *i* covariate to the total capitalization of the analyzed assets. $\widehat{D}_{j|\tilde{R}_j} = \{\widehat{D}_{j|-j}\}^{\mathsf{T}}$ is a componentwise expression, where $\widehat{D}_{j|-j}$ reflects the side effects of the spread of risk among selected companies and allows us to characterize their evolution in the network. It should be noted that only relationships between company *j* in relation to other companies ($\widehat{D}_{j|-j}$) are included for network analysis. The $\widehat{D}_{j|M}$ macro state variables are not included because we are interested in side effects among companies in network analysis. In fact, when going from *CoVaR* risk to Δ*CoVaR*, macro state variables are eliminated by themselves.

The change in Δ*CoVaR* from normal to recession whicl measures the contribution of the risk of company i*i* to the risk of company *j* is of special interest. In this study, we redefine the contribution of systemic risk as a percentage change in Δ*CoVaR*, standardized by companies' market capitalization. There are several reasons for adopting a new definition of the contribution to systemic risk. First, Δ*CoVaR*, defined as a simple change in *CoVaR* by Adrian and Brunnermeier [1], is not standardized, which may not be an appropriate indicator for comparison. Second, Δ*CoVaR*, defined as a percentage change in *CoVaR* in Juan Reboredo and Andrea Ugolini [23], allows for a negative scaling denominator, which can change the sign of Δ*CoVaR* and bring to misleading results. As a reminder, Δ*CoVaR* must decrease with the dependency parameter. The new definition of Δ*CoVaR* allows, among other things, to take into account the size (market capital) of companies.

Let us define the estimation window in terms of *s*. Now we can build a directed tail risk network. The weighted adjacency matrix for all companies at the $\widehat{D}^s_{j|i}$ th window A_s (15) includes the absolute values in the upper triangular matrix (impact of company *i* on company *j*) and $widehatD^s_{i|j}$ in the lower triangular matrix (impact of company *j* on company *i*).

$$A_s = \begin{pmatrix} 0 & \widehat{D}^s_{1|2} & \cdots & \widehat{D}^s_{1|n} \\ \widehat{D}^s_{2|1} & 0 & \cdots & \widehat{D}^s_{2|n} \\ \vdots & \vdots & \ddots & \vdots \\ \widehat{D}^s_{n|1} & \widehat{D}^s_{n|2} & \cdots & 0 \end{pmatrix}. \quad (15)$$

This matrix shows the total connectivity of the variables in the *s* window. It is sparse and off-diagonal because the variable cannot be regressed onto itself. The rows of this matrix correspond to the incoming edges for the variable in the corresponding row, and the columns correspond to the outgoing edges for the variable in the corresponding column.

Network topological features

It is of interest how the level of systemic risk in the network changes over time. Graph density (edge density), which characterizes the interconnectedness of the network, can be considered as a measure of the overall systemic risk. However, the density of the graph does not take into account the weight of the edges. Therefore, we propose to generalize this measure of interconnectedness. Note that, unlike the degree of a node, the node strength takes into account not only the number of directly connected edges but also the weights of the edges. Since the spread of risk is directional, it is of interest to single out both companies that spread risk and companies that absorb risks. That out-strength (in-strength) is used to measure the ability of each company to infect (absorb) risk. These directional measures show the outgoing and incoming connectivity of each company. The out-strength (OS) of company *i* is equal to the sum of the weights $\left|\widehat{D}^{s}_{j|i}\right|$ of outgoing edges from company *i* to other companies:

$$OS_i = \sum_{j=1}^{n} \left|\widehat{D}_{j|i}\right|.$$

In-strength (IS) of company *i* is equal to the sum of weights $\left|\widehat{D}_{i|j}\right|$ of incoming edges from other companies to company *i*:

$$IS_i = \sum_{j=1}^{n} \left|\widehat{D}_{i|j}\right|.$$

Then the following ratio can be considered as the level of systemic risk of the network (Total Strength):

$$TS = \sum_{i=1}^{n} O\,S_i = \sum_{i=1}^{n} I\,S_i.$$

Concentration can be another indicator that captures changes in systemic risk. For example, [24] showed that the more concentrated the network is, the higher is the systemic risk. Concentration is an important indicator of network structure and signals the density of interconnectedness. As an indicator of network concentration, it is proposed to take the Herfindahl-Hirschman index (*HHI*) which for the network will have the following ratio:

$$HHI = \sum_{i=1}^{n} \left(\frac{E_i}{E_d}\right)^2.$$

Where E_i is the number of edges included in node *i*, E_d is the total number of edges in the network. Therefore, this ratio means the degree of relative connections of node *i*.

Empirical analysis

In this paper, we observe and analyse topological properties of the RTS network using the risk measure $\Delta CoVaR$. The list of considered companies by sectors of the economy is given in Table 1. The sample includes daily stock price quotes of 29 largest Russian companies for the period from 01.01.2012 to 24.02.2022 (T = 2613 trading days). Most of the companies under consideration belong to the energy and industrial sectors of the economy.

Table 1

List of companies by sector

Sector	Ticker	Name
Basic Materials	ALRS	Alrosa
	CHMF	Severstal
	GMKN	Nornickel
	MAGN	Magnitogorsk Iron and Steel Works
	NLMK	NLMK Group
	PHOR	Company PhosAgro
	PLZL	Polyus
	POLY	Polymetal
Communications Services	AFKS	AFK Sistema
	MTSS	MTS
	RTKM	Rostelecom
Consumer Defensive and Consumer Cyclical	MGNT	Magnit
	MVID	M. Video
Energy (Oil & Gas)	GAZP	Gazprom
	LKOH	Lukoil
	NVTK	Novatek
	ROSN	Rosneft
	SNGS	Surgutneftegas
	TATN	Tatneft
	TRNFP	Transneft
Financial Services	SBER	Sberbank of Russia
	VTBR	VTB Bank
Industrials (Airlines)	AFLT	Aeroflot
Real Estate	LSRG	LSR Group
	PIKK	PIK Group
Utilities	FEES	FGC UES
	HYDR	RusHydro
	IRAO	Inter RAO
	UPRO	Unipro

State variables M_{t-1} should not be treated as independent risk factors but as conditional variables that change the conditional mean and volatility. It should also be noted that the choice of state variable vector components should be approached very carefully [6]. When studying various processes, it is necessary to select appropriate macroeconomic indicators that affect them. In particular, if we are talking about the economic system as a whole, then such indicators will be the Gross Domestic Product (including per capita), the Gross National Product, the inflation rate, the key rate of the Central Bank, etc. If we are talking about the financial system, since it is mostly connected with the banking sector and the stock market, then the factors under consideration should include the rate on government bonds and bills, the key rate of the Central Bank, the yield of stock market indices, etc.

In the study, the following values were taken as macro variables: the RTS volatility index; liquidity spread defined as the difference between the REPO rate and the yield on government bonds; BRENT oil price level; dollar to ruble exchange rate. The choice of these indicators is due to the fact that each of them considers the financial and economic system of the Russian Federation from a certain point of view, and together they allow us to talk about the influence of macroeconomic factors in general.

Instead of the regression on system return, we will look at two indices that define the structure of companies' interconnectedness: the Systemic Risk Receiver index and the Systemic Risk Emitter index. They will allow to measure the contribution of each company to systemic risk and, accordingly, to identify systemically important companies.

To analyze systemic risks determined by the $\Delta CoVaR$ measure, this paper proposes the following approaches:

1) estimation of the $\Delta CoVaR$ model over the entire period under consideration, taking into account macro variables;

2) sliding time window procedure;

3) study of structural changes in the risk distribution network.

The first approach provides a general (averaged) picture of the risk distribution network. Thus, $\Delta CoVaR$ is estimated for all companies over the considered period of 10 years. Estimation is done by applying the dynamic $\Delta CoVaR$ quantification model described in subsection 2.2 and the A Tail Risk Network approach with selection of variables using the LASSO regularization procedure (subsection 2.3).

Figure 1 shows an example of $\widehat{VaR}$ (thin black line), $\widehat{CoVaR}^{NET}$ (thinner blue line) and $\Delta\widehat{CoVaR}^{NET}$ (thinner red line) for Sberbank at the quantile level $q = 0.05$, i.e. a 5% quantile was taken for estimation (e.g. when Sberbank is dependent variable, then the independent variables include 16 other companies returns respectively and 5 macro state variables). It can be seen from the above graphs that the estimate of the conditional VaR is always lower than the unconditional one. This indicates the need to take into account systemic risks. This pattern is observed for all the companies under consideration. We also note the successful choice of macro variables for the dynamic $\Delta CoVaR$ model.

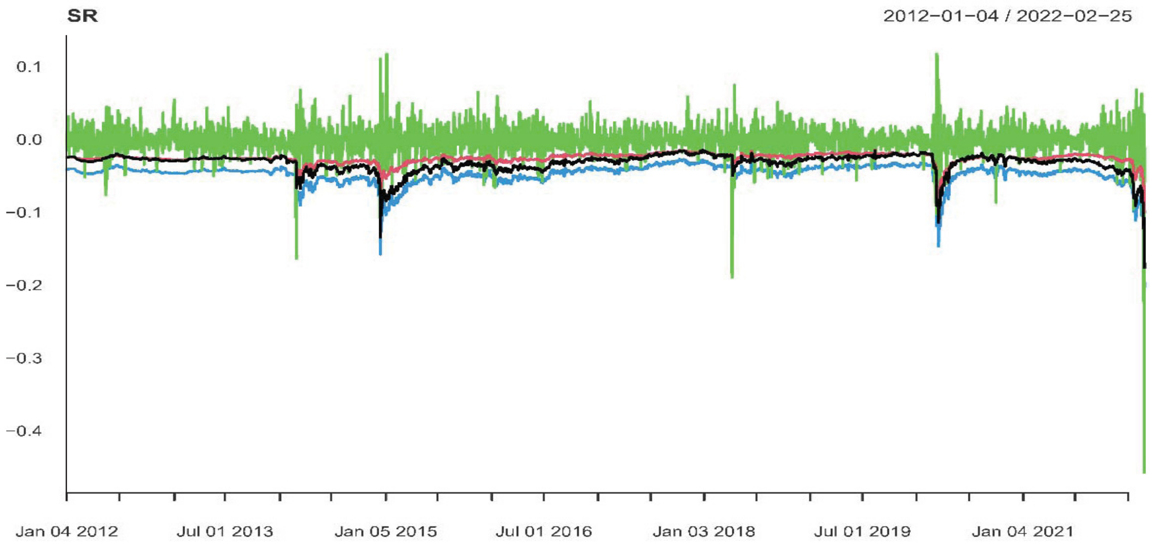

Fig. 1. Log return of Sberbank (thinner green line), VaR (thinner black line), $\widehat{CoVaR}^{NET}$ (thinner blue line) and $\Delta\widehat{CoVaR}^{NET}$ (thinner red line) for $q = 0.05$, window size = 2613 (color online)

Since we also obtained the matrix of the general connectivity of variables A_s in the window s, where s corresponds to the entire period under consideration, we can construct a graph implemented for this period. We show significant directional relationships between pairs of 29 company stocks over the entire period (Figure 2). The node size for company i corresponds to the value of the net risk transfer/acceptance to or from other variables ($OS_i - IS_i$). The red (blue) color of a node indicates that the variable is a network transmitter (receiver) in the risk propagation system. The color of the edge corresponds to the magnitude of the pair risk spread. The green and orange edges correspond to the fifth and tenth percentiles of all pairwise directed links. As can be seen from the figure, the companies most exposed to risk are mainly the banking and energy sectors of the economy. At the same time, the list of companies that transfer risk is extensive and fairly evenly distributed.

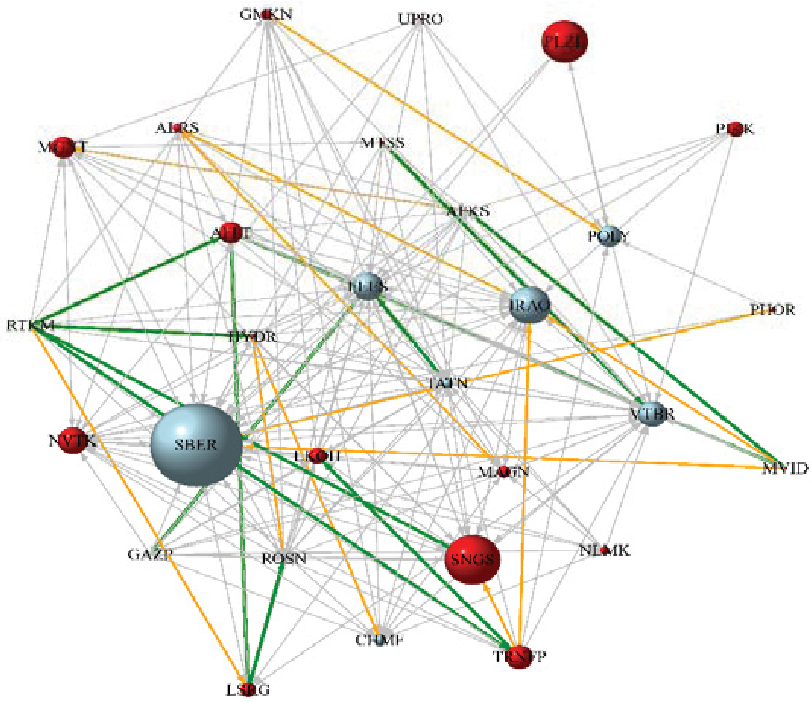

Fig. 2. Graph implemented for the entire period (color online)

The second approach allows to explore the evolution of market graph (how systemic risk changes over time). The size of the sliding window is taken equal to one calendar year (≈ 252 days). The sliding window is shifted by 1 month (≈ 22 days). We acknowledge that by choosing different window sizes and data rates, the results may vary. The choice of the optimal window size and data frequency requires a separate study that is beyond the scope of this work. In the next step, the $\Delta CoVaR$ based risk network is also estimated by applying a dynamic $\Delta CoVaR$ quantification model. As a result, 122 adjacency matrices A_s, $s = 1, \ldots, 122$ were constructed and $\Delta CoVaR$ based risk network metrics were analyzed. This paper presents the results for $q = 0.05$, $\lambda = 0.0005$.

Figure 3 shows an important indicator of network structure: Total Strength and Herfindahl-Hirschman Index (HHI) for all period (time corresponds to the end of the sliding window). It can be seen that Total Strength and the degree of concentration are strongly correlated. In the figure one can see sharp jumps (2014, 2015, 2018, 2020, 2022 years) in the density of the network. As you know, these periods correspond to the political, economic and pandemic crisis. A stronger inter-company relationship occurs during a more volatile period, hence a greater spillover risk (greater secondary risk) represented by the $\Delta CoVaR$ risk measure. These results agree with Adams, Fuess, Gropp [25]. It is worth noting that the level of systemic risk increased sharply even before the start of the military operation on February 24, 2022. Also, shortly before the significant drop in oil prices and the COVID-19 lockdown (March 2020), the level of systemic risk already started to increase.

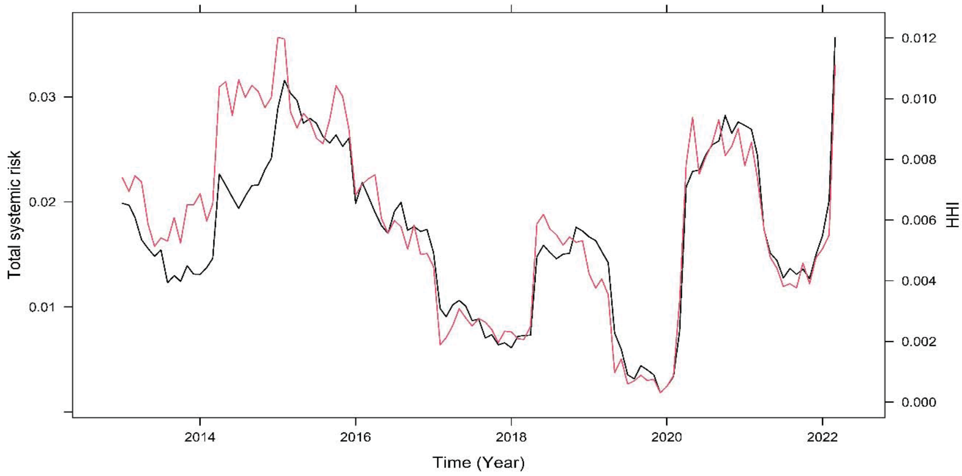

Fig. 3. Dynamics of the total systemic risk (thinner black line) and Herfindahl – Hirschman Index (thinner red line) (color online)

It is also of interest to identify the most important companies that are distributors of systemic risk. These are nodes with high propagation efficiency (powerful distributors) that are more likely to propagate negative shocks to a large portion of the network. These important knots can be used in practical applications for financial risk management, such as controlling the spread of shocks and making the economic system more resilient to negative events.

To find key nodes in a network, one can use known measures of centrality on a graph, such as degree centrality. It must be understood, however, that the location of a vertex may be more important than its degree. For example, if two companies have the same degree but different network position (one is located at the periphery and the other is connected to the most central set), then they may have different negative shock propagation efficiencies. Thus, highly connected assets with a high degree may not be the best propagators of negative shocks, while less connected assets associated with the center of the market graph can strongly stimulate the process of shock propagation. Therefore, different measures of centrality can be used to find important companies in a directed market graph. In our opinion, the most appropriate measures of centrality in the context of our study are:

- Strength Centrality (allows to identify companies with the highest weight of incoming and outgoing links);
- Betweenness Centrality (allows to identify connecting companies ("bridge companies") through which systemic risk spreads);
- Page Rank (allows to find vulnerable companies that are most at risk);
- Eigenvector centrality (allows to determine which nodes (companies) are part of the cluster of influence).

We calculate given centrality measures for each node (company) for all sliding windows. We then rank company stocks in descending order, select the top 5 stocks for each measure, and combine them to create important assets. Table 2 shows the results for sliding windows corresponding to calendar years. The table also lists the top companies by measures of centrality for the entire period under review. As can be seen, over the entire period the leaders in all measures of centrality partly coincide. It is quite expected that these are predominantly banks (SBER, VTBR), which are leaders in all measures of centrality, and oil companies (ROSN, TATN), which are in the top in all measures of centrality, with the exception of Betweenness Centrality, where we find energy companies (FEES, NVTK, IRAO) along with the banks. The list of companies included in these tops by measures of centrality is unstable over time. Interestingly, during and after the 2020 pandemic, Sberbank fell out of the top in almost all measures of centrality, where oil and gas companies dominated.

We note that the In-Strength centrality, Page Rank and Eigenvector centrality measures give very similar results for sub-periods. Thus, it is safe to say that companies with a high In-Strength centrality score are also the most exposed to systemic risk and are part of the cluster of influence. The leaders in betweenness centrality through which systemic risk spreads most often include SBER and TATN.

During the first shock event (the political crisis in Ukraine in 2014), GAZP, VTBR and Sberbank

Table 2

Top 5 companies by period

Period	Active	In-Strength	Active	Out-Strength	Active	Page Rank	Active	Betw. Centr.	Active	Eigen. Centr.
All	SBER	0.0677	SBER	0.0235	SBER	0.1269	SBER	0.2817	SBER	1.0000
	VTBR	0.0491	VTBR	0.0219	VTBR	0.0984	VTBR	0.2050	VTBR	0.7861
	FEES	0.0490	TATN	0.0216	FEES	0.0835	FEES	0.1548	TATN	0.6357
	TATN	0.0411	IRAO	0.0214	TATN	0.0807	NVTK	0.1283	FEES	0.6210
	IRAO	0.0309	MAGN	0.0214	ROSN	0.0680	IRAO	0.1164	ROSN	0.5660
2012	VTBR	0.0031	GAZP	0.0056	VTBR	0.1213	VTBR	0.4921	VTBR	1.0000
	HYDR	0.0029	SBER	0.0026	FEES	0.1138	SNGS	0.2831	HYDR	0.8056
	SNGS	0.0023	ROSN	0.0014	HYDR	0.0905	SBER	0.1481	FEES	0.6025
	TATN	0.0019	NVTK	0.0014	NLMK	0.0688	NLMK	0.1389	SNGS	0.5578
	FEES	0.0018	SNGS	0.0013	MAGN	0.0682	GAZP	0.1243	TATN	0.3672
2013	CHMF	0.0018	GAZP	0.0026	CHMF	0.1466	TATN	0.3175	CHMF	1.0000
	GMKN	0.0015	SBER	0.0025	NLMK	0.1021	GAZP	0.1667	NLMK	0.9194
	NLMK	0.0012	ROSN	0.0013	MAGN	0.0916	ROSN	0.1587	MAGN	0.5301
	MAGN	0.0011	LKOH	0.0009	IRAO	0.0885	NVTK	0.1508	TATN	0.5056
	RTKM	0.0011	VTBR	0.0007	FEES	0.0862	SBER	0.1310	GMKN	0.4943
2014	NVTK	0.0033	GAZP	0.0051	FEES	0.0881	NVTK	0.4061	MTSS	1.0000
	MTSS	0.0025	SBER	0.0041	AFLT	0.0796	SBER	0.2725	FEES	0.7711
	FEES	0.0018	NVTK	0.0028	SBER	0.0773	MTSS	0.2646	GMKN	0.6388
	GAZP	0.0018	ROSN	0.0028	NVTK	0.0692	AFKS	0.2566	AFLT	0.6119
	LSRG	0.0018	AFKS	0.0025	MAGN	0.0644	TATN	0.1852	VTBR	0.5092
2015	TATN	0.0031	GAZP	0.0039	TATN	0.1166	ROSN	0.4220	TATN	1.0000
	ROSN	0.0024	ROSN	0.0034	SNGS	0.1157	SBER	0.3638	LKOH	0.9444
	LKOH	0.0020	SBER	0.0021	LKOH	0.0742	SNGS	0.3598	ROSN	0.8116
	GAZP	0.0015	LKOH	0.0018	FEES	0.0651	GAZP	0.3056	GAZP	0.6205
	FEES	0.0011	SNGS	0.0015	SBER	0.0603	TATN	0.2460	SNGS	0.3239
2016	SBER	0.0027	SBER	0.0032	NLMK	0.1341	SBER	0.5899	SBER	1.0000
	TATN	0.0020	ROSN	0.0027	CHMF	0.1296	LKOH	0.5132	ROSN	0.8052
	ROSN	0.0015	GAZP	0.0022	MAGN	0.0941	CHMF	0.3175	LKOH	0.7697
	LKOH	0.0015	LKOH	0.0015	SBER	0.0624	ROSN	0.3135	TATN	0.6145
	NLMK	0.0008	CHMF	0.0006	LKOH	0.0617	NLMK	0.1733	VTBR	0.6097
2017	TATN	0.0008	SBER	0.0012	MTSS	0.1311	VTBR	0.2831	AFKS	1.0000
	AFKS	0.0007	ROSN	0.0009	HYDR	0.1276	HYDR	0.2434	HYDR	0.8171
	HYDR	0.0007	GAZP	0.0007	FEES	0.1060	SNGS	0.1693	MTSS	0.7889
	AFLT	0.0007	NVTK	0.0005	AFKS	0.1043	NLMK	0.1336	FEES	0.5002
	ALRS	0.0007	SNGS	0.0004	AFLT	0.0694	ROSN	0.1270	AFLT	0.4944
2018	SBER	0.0025	SBER	0.0050	SBER	0.1767	SBER	0.4854	GMKN	1.0000
	GMKN	0.0022	ROSN	0.0025	GMKN	0.1421	GMKN	0.2407	POLY	0.6535
	PLZL	0.0018	LKOH	0.0017	POLY	0.0975	IRAO	0.1138	SBER	0.6407
	VTBR	0.0014	GMKN	0.0015	PLZL	0.0891	NLMK	0.1124	PLZL	0.5676
	POLY	0.0012	NVTK	0.0010	NLMK	0.0709	ALRS	0.0979	VTBR	0.5185
2019	SBER	0.0006	GAZP	0.0006	SBER	0.1625	GAZP	0.0979	SBER	1.0000
	HYDR	0.0003	SBER	0.0005	HYDR	0.0911	VTBR	0.0714	HYDR	0.8837
	TATN	0.0003	NVTK	0.0002	GAZP	0.0797	SBER	0.0701	GAZP	0.6018
	GAZP	0.0002	PLZL	0.0002	PLZL	0.0720	SNGS	0.0635	MAGN	0.0685
	POLY	0.0002	MAGN	0.0001	POLY	0.0716	MAGN	0.0556	ROSN	0.0281
2020	TATN	0.0064	ROSN	0.0045	TATN	0.1270	ROSN	0.4947	TATN	1.0000
	ROSN	0.0031	GAZP	0.0035	ROSN	0.1020	TATN	0.1931	ROSN	0.4747
	IRAO	0.0024	LKOH	0.0035	IRAO	0.0873	LKOH	0.1905	LKOH	0.3762
	LKOH	0.0019	SBER	0.0033	LKOH	0.0855	IRAO	0.1680	GAZP	0.2348
	GAZP	0.0019	NVTK	0.0022	POLY	0.0772	GAZP	0.1627	IRAO	0.2089
2021	TATN	0.0025	ROSN	0.0030	NLMK	0.1276	GAZP	0.3439	TATN	1.0000
	GAZP	0.0022	GAZP	0.0028	MAGN	0.0916	GMKN	0.2910	NVTK	0.7569
	NVTK	0.0019	SBER	0.0026	CHMF	0.0862	ROSN	0.2778	GAZP	0.6231
	ROSN	0.0015	LKOH	0.0019	TATN	0.0794	CHMF	0.1944	ROSN	0.6064
	VTBR	0.0013	GMKN	0.0013	GAZP	0.0638	NVTK	0.1759	VTBR	0.5018

(SBER) have the highest value and are the main recipients of tail risk. During the 2020 pandemic, the oil and gas (TATN, ROSN, LKOH, GAZP) and energy (IRAO) sectors of the economy receive the largest incoming links. This is quite natural, since in 2020 there was "turbulence" in the oil market. Before the start of the military operation in Ukraine in 2022, the oil company Rosneft (ROSN) was exposed to the greatest systemic risks.

As for the Out-Strength dynamics, it can be noted that the distribution of the external force differs from the distribution of the internal force and is relatively uniform. During the political crisis of 2014, companies with a strong connection to Out-Strength: GAZP, SBER, NVTK, ROSN and AFK Sistema (AFKS). This list of companies is quite expected, with the exception of AFKS which extended its risks mainly to MTSS. This is quite natural, since AFK Sistema is the main shareholder of MTSS. Introduction of new sanctions in April 2018 primarily affected the systemic risk structures of SBER and ROSN. During the 2020 pandemic, we note a relatively small uniform increase in Out-Strength for almost all the companies under consideration. This is well explained by the lockdown, the imposition of restrictions, as well as external factors associated with the oil crisis. We note a relatively calm period of recovery after the pandemic, which gave way to a new political crisis in Ukraine. This led to the fact that the SBER bank, as well as the oil and gas sector of the economy (ROSN, LKOH, GAZP) increased the distribution of risks through the network.

In general, the higher the out-strength value is, the stronger is the ability of one company to spread residual risk to other companies. However, interconnectedness alone will not determine the systemic importance of each company. Therefore, we use the PageRank index, which takes into account both the interconnectedness and the influence of neighboring nodes.

The PageRank value for most companies is less than 0.1, while only a few companies have a high PageRank, indicating that they can act as influential companies in the Russian stock market. It can be noted that for most of the time interval under consideration, the largest bank in Russia, Sberbank, was a system-forming institution until the 2020 pandemic when oil companies seized this role. Thus, Sberbank is an important institution of the national economy with the characteristics of a high connection with other sectors of the economy. It comes as no surprise since the banking sector provides financial support to the development of enterprises in many industries, and if the financial industry is in a state of recession, it will affect the development of the entire industry chain. The leadership of Sberbank is also confirmed by the betweenness centrality indicator. Throughout the considered time horizon, with the exception of the pandemic period, it was the main "bridge" for the spread of systemic risks.

During the pandemic, the leadership in terms of PageRank passed to oil companies (TATN, ROSN, LKOH). It is quite expected that during the period of the collapse in oil prices, these companies were at the center of the spread of risks.

Leadership in terms of eigenvector throughout the entire period under review was transferred from one company to another. During the political crisis of 2014–2015 SBER, VTBR, IRAO, FEES, AFLT, MAGN, CHMF, GMKN had a high degree of influence. As you can see, these are companies from different sectors of the economy. Since these companies are associated with many companies that also have high degrees of influence, they form a cluster of influence in this time period. In a relatively calm period (2018–2019), in addition to SBER, companies from the Basic Materials sector had a high degree of influence: POLY, PLZL, GMKN. During the pandemic, as well as the political crisis of 2022 in Ukraine, positions of oil companies (TATN, ROSN, LKOH) in the cluster of influence have strengthened.

We also compare the structure of graphs built over different periods. This period of time can be characterized as a transition from the crisis state of the Russian economy caused by political events in Ukraine, the imposition of sanctions and the depreciation of the national currency to a period of stable external conditions, a stable level of prices in the raw materials and oil markets, and relatively low volatility of most of the analyzed time series. During the relatively quiet period of 2012–2013, a significant positive NET-effect = $SO - SI$ (red) was observed for GAZP, which decreased over time, passing to SBER, LKOH, ROSN. The negative NET effect was typical for TATN, IRAO, FEES. During the 2014 crisis there were no cardinal changes in the structure of the risk distribution network. During the quiet periods of 2015–2017, the number of links as well as the NET effect is reduced. Since the imposition of new sanctions in April 2018, mainly SBER, but also ROSN and LKOH have put the system at significant risk. For companies in the steel sector such as GMKN, PLZL, POLY, as well as VTBR bank, incoming risks exceeded outgoing risks (blue) in this time period. As you can see from the graphs, the shock in April 2018 is limited to one month and starting from May 2018 systemic risks are reduced to the lowest level for the considered ten-year period. Interestingly, the composition of risk source and recipient companies during the 2014 and 2020 crises practically match. During the 2020 pandemic, TATN, IRAO, FEES and AFKS became the main risk recipients. GAZP, SBER, LKOH, ROSN and NVTK became risk distributors during this period, as well as during the political crisis in 2014. It is interesting that the increase in the overall level of systemic risks before the start of the military operation in Ukraine is mainly associated with an increase in the outgoing risks of SBER and GAZP.

The third approach will determine whether perturbations lead to structural changes in the risk propagation network. Table 3 shows pairwise correlations for graphs for various subperiods, built on the basis of the approach proposed in Section 2.3. To calculate the significance of relationships between graphs (Table 4), the QAP procedure [26] was used. Sub-periods were distinguished in such a way that they did not capture the moments of the onset of recessions in the economy. This made it possible to localize adverse events in the economy and track structural changes in the network after they occur. The following sub-periods have been identified:

1) 2012.01 – 2013.01 – a relatively quiet period;

2) 2013.02 – 2014.02 – the period preceding the political crisis in Ukraine in 2014;

3) 2014.04 –2015.04 – a turbulent period after the political events in Ukraine in February–March 2014, which also included the imposition of sanctions against Russia, the fall in oil prices and the collapse of the national currency;

4) 2016.01 – 2017.01 – a relatively quiet period;

5) 2017.02 – 2018.02 – a relatively quiet period, before the presidential elections and the introduction of new sanctions against Russia;

6) 2018.05 – 2019.03 – the period after the introduction of new sanctions;

7) 2019.04 – 2020.02 – a relatively quiet period, before the introduction of a lockdown due to the COVID-19 pandemic, as well as a collapse in oil prices;

8) 2020.04 – 2021.04 – the period of economic recovery after the effects of the COVID-19 pandemic;

9) 2021.05 – 2022.02 – a turbulent period accompanied by political tension in the country, preceding the military operation in Ukraine.

As we can see from Tables 3 and 4, there were practically no structural changes in the risk distribution network (adjacent and even distant graphs are significantly interconnected), with the exception of the 5th period (before the presidential elections and the introduction of new sanctions), after which the structure of the spread of risks moved into a new state. Interestingly, this period in the Russian economy can be characterized as a relatively calm period of stable economic growth, which also does not resemble previous periods, with the exception of the 3rd turbulent period for the Russian economy.

Table 3

Graph correlations for different sub-periods

	1	2	3	4	5	6	7	8	9
1	1.00	0.23	0.11	0.09	0.12	0.20	0.21	0.06	0.04
2	0.23	1.00	0.07	0.25	0.04	0.36	0.24	0.25	0.15
3	0.11	0.07	1.00	0.04	0.79	0.11	0.05	0.07	0.04
4	0.09	0.25	0.04	1.00	-0.00	0.23	0.17	0.25	0.22
5	0.12	0.04	0.79	-0.00	1.00	0.09	0.05	-0.01	0.01
6	0.20	0.36	0.11	0.23	0.09	1.00	0.17	0.28	0.27
7	0.21	0.24	0.05	0.17	0.05	0.17	1.00	0.33	0.19
8	0.06	0.25	0.07	0.25	-0.01	0.28	0.33	1.00	0.36
9	0.04	0.15	0.04	0.22	0.01	0.27	0.19	0.36	1.00

Table 4

***p*-value for graph correlation for different sub-periods**

Subperiods	1	2	3	4	5	6	7	8	9
1	0.00	0.00	0.03	0.04	0.02	0.00	0.00	0.09	0.16
2	0.00	0.00	0.05	0.00	0.09	0.00	0.00	0.00	0.00
3	0.02	0.03	0.00	0.11	0.00	0.02	0.04	0.03	0.10
4	0.03	0.00	0.08	0.00	0.37	0.00	0.00	0.00	0.00
5	0.02	0.10	0.00	0.34	0.00	0.03	0.06	0.44	0.30
6	0.00	0.00	0.02	0.00	0.02	0.00	0.00	0.00	0.00
7	0.00	0.00	0.05	0.00	0.06	0.01	0.00	0.00	0.00
8	0.11	0.00	0.03	0.00	0.45	0.00	0.00	0.00	0.00
9	0.20	0.00	0.09	0.00	0.28	0.00	0.00	0.00	0.00

Results

This article provides an analysis of systemic risks, the study of which has attracted increasing attention in recent years. The work is mainly empirical in nature, considering the "tail event" and network methods. A fairly simple risk measure $\Delta CoVaR$ was chosen as an indicator of Systemic risk, reflecting the directional, tail dependence between companies in the financial system taking into account their market capitalization. The dynamics of a network built on the basis of quantile regression to assess the systemic significance of financial institutions depending on their interconnectedness in the tails was considered.

$\Delta CoVaR$ expands the concept of systemic risk, complementing the measures designed to assess it within the framework of macroprudential policy. It can be concluded that $\Delta CoVaR$ is useful for better understanding how risk spreads through the stock market. It is easy to interpret, does not require a complex dataset, and can be used in conjunction with other risk indicators. This will help to better understand the risks that threaten the stability of the Russian stock market. It is important to note that the results of this study allow $\Delta CoVaR$ to be associated with reliably measured characteristics at the facility level. The $\Delta CoVaR$ risk measure, like any tail risk, is based on a relatively small number of extreme points. Therefore, unfavorable movements, especially after periods of stability, can lead to a significant increase in the tail risk measure. In contrast, characteristics such as company size can be reliably measured at higher frequencies. "Too big to fail" suggests that size is the dominant variable, and hence large institutions must face stricter regulations than smaller institutions. However, focusing only on size does not suggest that many smaller institutions are following the system. Our solution to this problem is to combine the strengths of both types of indicators by projecting $\Delta CoVaR$ onto multiple, more frequently observed variables, providing a tool to identify systemically important financial institutions. The approach proposed in this study allows for weighting the relative importance of different characteristics of firms.

Empirical results show that the relationship grows during times of crisis. Based on the connectivity structure, companies that accept risks and companies that spread systemic risks were identified. When evaluating the risk contributions between companies and the risk of each company's exposure to a system failure, it can be argued that SBER, TATN are the least stable companies and more sensitive to failures in other companies. On the other hand, the same SBER company is also the main supplier of systemic risks, alternately forming a cluster of influence together with the oil companies TATN, ROSN, LKOH. We cannot argue that larger companies contribute more to the risk of the Russian stock market than smaller companies, nor can we argue that companies with a high individual *VaR* contribute more to the risk of the Russian stock market than companies with lower individual *VaR*. Of all the companies in the RTS Index, PHOR, PIKK, UPRO appear to be the least sensitive to disasters in other companies than others. It should also be noted that during the time period we are considering, there were practically no significant structural changes in the risk distribution network. The exception was the relatively calm period before the presidential elections in March 2018 and the introduction of new sanctions against Russia in April 2018, after which the risk distribution network returned to its "usual" state. It is noteworthy that this calm period is similar in its structure to the distribution of risks to a rather turbulent period after the political events in Ukraine in February–March 2014, which also included the imposition of sanctions against Russia, the fall in oil prices and the collapse of the national currency.

References

1. Adrian T., Brunnermeier Markus K., Nguyen Hoai-Luu Q. *Hedge Fund Tail Risk. Quantifying Systemic Risk.* University of Chicago Press, 2013, pp. 155–174. https://doi.org/10.7208/chicago/9780226921969.003.0006
2. De Nicolo G., Lucchetta M. Systemic Risks and the Macroeconomy. In: Haubrich J., Lo A. (eds.) *Quantifying Systemic Risk.* National Bureau of Economic Research, Inc., 2011, pp. 113–148. Available at: https://EconPapers.repec.org/RePEc:nbr:nberch:12051 (accessed June 22, 2023).
3. Lehar A. Measuring systemic risk: A risk management approach. *Journal of Banking & Finance,* 2005, vol. 29, pp. 2577–2603. https://doi.org/10.1016/j.jbankfin.2004.09.007
4. Bisias D., Flood M., Lo A., Valavanis S. A Survey of Systemic Risk Analytics. *Annual Review of Financial Economics,* 2012, vol. 4. https://doi.org/10.2139/ssrn.1983602
5. Smaga P. The Concept of Systemic Risk. *Systemic Risk Centre Special Paper.* The London School of Economics and Political Science, 2014, vol. 5.
6. Adrian T., Brunnermeier M. K. COVAR. *NBER Working Papers, 17454.* National Bureau of Economic Research, Inc, 2011. https://doi.org/10.3386/w17454
7. Adrian T., Brunnermeier M. K. CoVaR. *American Economic Review*, 2016, vol. 106, iss. 7, pp. 1705–1741. https://doi.org/10.1257/aer.20120555

8. Boginski V., Butenko S., Pardalos P. M. Chapter 2: On structural properties of the market graph. In: Nagurney A. (ed.) *Innovations in Financial and Economic Networks,* 2004, pp. 29–45. https://doi.org/10.4337/9781035304998.00010
9. Boginski V., Butenko S., Pardalos P. Network models of massive datasets. *Computer Science and Information Systems*, 2004, vol. 1, iss. 1, pp. 75–89. https://doi.org/10.2298/CSIS0401075B
10. Xiao F., Liu X. F., Tse C. Dynamics of Network of Global Stock Markets. *Accounting and Finance Research*, 2012, vol. 1, iss. 2. https://doi.org/10.5430/afr.v1n2p1
11. Onnela J.-P, Saramaki J., Kertesz J., Kaski K. Intensity and coherence of motifs in weighted complex networks. *Physical Review E*, 2005, vol. 71, iss. 6. https://doi.org/10.1103/PhysRevE.71.065103
12. Emmert-Streib F., Dehmer M. Identifying critical financial networks of the DJIA: Toward a network-based index. *Complexity*, 2010, vol. 16, pp. 24–33. https://doi.org/10.1002/cplx.20315
13. Boginski V., Butenko S., Pardalos P. Mining market data: A network approach. *Computers & Operations Research*, 2006, vol. 33, iss. 1, pp. 3171–3184. https://doi.org/10.1016/j.cor.2005.01.027
14. Huang W. Q., Zhuang X. T., Yao S. A network analysis of the Chinese stock market. *Physica A: Statistical Mechanics and its Applications*, 2009, vol. 388, iss. 14, pp. 2956–2964. https://doi.org/10.1016/j.physa.2009.03.028
15. Namaki A., Shirazi A., Raei R., Jafari G. Network analysis of a financial market based on genuine correlation and threshold method. *Physica A: Statistical Mechanics and its Applications*, 2011, vol. 390, iss. 21–21, pp. 3835–3841. https://doi.org/10.1016/j.physa.2011.06.033
16. Sidorov S., Barabash V., Faizliev A. Analysis of the impact of sanctions on systemic risks for Russian. *Lecture Notes in Engineering and Computer Science*. Proceedings of the World Congress on Engineering 2017, WCE 2017. 2017, vol. 2229, pp. 380–384. EDN: XXIOLB
17. Androsov I., Faizliev A., Korotkovskaya E., Lunkov A., Mironov S., Petrov V., Sidorov S., Smolov F. Shock Diffusion Analysis for a Directed Market Network Constructed with Use of the Risk Measure CoVaR. *Journal of Physics: Conference Series*, 2019, vol. 1334, iss. 1, 012003. https://doi.org/10.1088/1742-6596/1334/1/012003
18. Kalyagin V. A., Koldanov A. P., Koldanov P. A., Pardalos P. M. Optimal decision for the market graph identification problem in a sign similarity network. *Annals of Operations Research*, 2018, vol. 266, pp. 313–327. https://doi.org/10.1007/s10479-017-2491-6
19. Jorion P. *Value at Risk: The New Benchmark for Managing Financial Risk*. 3rd ed. New York, McGraw-Hill, 2006. 602 p.
20. Hautsch N., Schaumburg J. and Schienle M. Financial Network Systemic Risk Contributions. *Review of Finance*, 2014, vol. 19, iss. 2, pp. 685–738. https://doi.org/10.1093/rof/rfu010
21. Hardle W. K., Wang W., Yu L. Systemic risk, Systemic risk network, Generalized quantile, Quantile single-index regression, Value at risk, CoVaR, Lasso. *Journal of Econometrics*, 2016, vol. 192, iss. 2, pp. 499–513. https://doi.org/10.1016/j.jeconom.2016.02.013
22. Zhang W., Zhuang X., Wang J., Lu Y. Connectedness and systemic risk spillovers analysis of Chinese sectors based on tail risk network. *The North American Journal of Economics and Finance*, 2020, vol. 54, 101248. https://doi.org/10.1016/j.najef.2020.101248
23. Reboredo J., Ugolini A. Systemic risk in European sovereign debt markets: A CoVaR-copula approach. *Journal of International Money and Finance,* 2015, vol. 51, pp. 214–244. https://doi.org/10.1016/j.jimonfin.2014.12.002
24. Fang L., Cheng J., Su F. Interconnectedness and systemic risk: A comparative study based on systemically important regions. *Pacific-Basin Finance Journal*, 2019, vol. 54, pp. 147–158. https://doi.org/10.1016/j.pacfin.2019.02.007
25. Adams Z., Fuss R., Gropp R. Spillover Effects among Financial Institutions: A State-Dependent Sensitivity Value-at-Risk Approach. *Journal of Financial and Quantitative Analysis*, 2014, vol. 49, iss. 3, pp. 575–598. https://doi.org/10.1017/S0022109014000325
26. Krackardt D. QAP partialling as a test of spuriousness. *Social Networks*, 1987, vol. 9, iss. 2, pp. 171–186. https://doi.org/10.1016/0378-8733(87)90012-8

Поступила в редакцию 19.04.2023; одобрена после рецензирования 09.06.2023; принята к публикации 12.06.2023
The article was submitted 19.04.2023; approved after reviewing 09.06.2023; accepted for publication 12.06.2023