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Transmission of Systemic Risk Between the Banking Systems of Asia-Pacific Countries and Russia

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ABSTRACT

The subject of this research is systemic risk transmission between financial sectors in the international financial market. **The purpose** of our paper is to determine topology characteristics for the network connecting banking systems in the Asia-Pacific region (APR) and Russia. Given the growing role of this region in the global financial market, its susceptibility to crises can be dangerous for other countries. This determines the **relevance** of our study. To build the network, we used the SRISK indicators, which reflect capital losses in the financial institutions' capital losses in case of a large-scale crisis. The networks were built with the use of the *NETS* algorithm, proposed by Barigozzi, M., & Brownlees, C. (2019). This **method** is based on sparse vector autoregressions estimated by LASSO. As a result of the application the algorithm, we get two networks **—**simultaneous interconnections and using the values of the lagged variables. The networks were constructed for the 2005–2020 time period and separately for sub-periods including the global financial crisis (2005–2013) and the COVID-19 pandemic period (2014–2020). Based on the **results** obtained, the networks over the entire time period seem to be quite susceptible to external risks. China, Japan, Singapore and Taiwan are the largest shock donors in this region. Russia mainly accepts risks, generated by other countries, in the period 2014–2020. Strengthened/weakened cooperation with the largest risk exporters in this region will increase/decrease the likelihood of systemic risk transfer to the Russian financial sector.

Keywords: systemic risk in the financial sector; network analysis; sparse vector autoregressions; Granger causality test; network topology; centrality

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INTRODUCTION

After the global financial and economic crisis of 2007–2009, researchers decided to actively investigate the subject of systemic risk in the financial industry. During that time period, the catastrophic effects of systemic risk implementation in the US financial sector were related to a prolonged local recession as well as the rapid diffusion of risk to other countries. This paper examines the later negative element of systemic crises, namely the transfer of risks between different countries' financial sectors.

The high interdependence of financial institutions both within national and international financial systems contributes to the development of the financial sector, but, on the other hand, creates the preconditions for a possible crisis due to the increasing risk of infection. Moreover, problems in the financial sector could spread to the real economy, causing lower industrial output, higher prices, and higher unemployment.

Asian countries experienced how rapidly financial contagion could grow in 1997–1998. At the present, it is important to determine whether similar events may arise in the future, how infection can develop today, and how rapidly risk can be transported to other countries. Furthermore, given the APR countries' growing dominance in the global financial system, the region's vulnerability to crises may pose a risk to other countries as well. All of this indicates the importance of our research, the purpose of which is to discover the characteristics of the network connecting the banking systems of the APR and Russia.

We used SRISK data from Volatility Laborator to build the network.[1] The SRISK index is currently recognized as the most accurate indicator of individual institutional losses in the event of a large-scale crisis [1]. The indicators for countries were obtained by summing the SRISK values for the largest national banks. The network was constructed using the NETS algorithm proposed by M. Barigozzi and C. Brownlees [2]. It is based on the construction of sparse vector autoregression, measured by the LASSO method.

The results indicate that the network of banking systems in the region is highly interdependent. This density generally indicates that the system is quite vulnerable to external shocks. At the same time, there are four countries that have a key influence on financial stability throughout the region: China, Japan, Singapore and Taiwan.

We examined how the network topology changed throughout the global financial and economic crises, as well as the COVID-19 pandemic lockdown. According to our estimations, the network density indicator grew from January 2014 to December 2020, indicating an increase in regional risk. The number of interconnections has increased in comparison with the period of the global financial crisis. It was also found that the number of "influential" nodes that could actually be "donors" of shocks has increased. While only Singapore was the largest source of shocks in the period from January 2005 to December 2013, Japan, Thailand, Taiwan and Hong Kong also added to the list of "donors" during the pandemic.

This study is intended to add to the literature on risk transmission between financial sectors in different countries. Using ATR countries as an example, we determined how the network's characteristics could change as a result of different crisis scenarios, as well as which countries are donors and risk-acceptors. A new element in our paper is the use of SRISK indices, rather than raw indicators, such as returns or volatility, to study risk transfer.

The paper is structured as follows: the first section provides an overview of the literature on the application of the network approach in finance; the following is a description of the data and methodology of the study; the third section presents an analysis of the results obtained; in the fourth — summary and direction of further research.

[1] URL: https://vlab.stern.nyu.edu/ (accessed on 20.06.2022).

REVIEW OF PREVIOUS STUDIES ON RISK TRANSMISSION IN THE FINANCIAL SECTOR

In recent years, network analysis has been actively used in financial research. It is based on the presentation of the objects of the system in the form of nodes of the graph, and the presence of relationships between them — as ribs.

Most theoretical research on financial sector network analysis examines how the density and shape of the network can affect the risk of infection and the possibility of a systemic crisis.

F. Allen and D. Gale [3] found that "complete" systems, where each object has connections with the others, are more stable. This view was also supported in the paper [4].

Later, in 2007, E. Nier and co-authors [5] modified a method of simulation to expand the F. Allen and D. Gale model, and came to the opposite conclusion: they identified a non-monotonous relationship between the degree of a connection of network participants and the probability of infection. Subsequently, M. Čihák and co-authors [6] showed that the dependency between the degree of interconnection of the system and its stability can be represented in the form of the letter M.

In 2015, P. Glasserman and H.P. Young [7] in their study that even small changes in the interconnection of banks can lead to a disproportionate increase in the risk of infection. Furthermore, according to the authors' calculations, losses in highly interconnected systems resulting from infection are, on the contrary, higher than in incomplete systems. The paper [8] also showed that when the shock value exceeds a certain threshold, a network of greater density becomes more fragile.

It is also important to remember that the source of the initial shock, as well as the degree of homogeneity among the participants, may have a role in determining its long-term viability. The authors of the paper [9] expect that the impact of shocks on the banking system will differ significantly according to where the shocks affect the network.

Much empirical research has been conducted on the global financial market. The study by C. Minoiu and J.A. Reyes [10], which examines a network based on data on cross-border borrowing and loan transactions between banks for 184 countries from 1978 to 2009, is one of the most popular papers in this area. According to the results of the study, the network as a whole was characterized by a high degree of interconnections and consequent instability, particularly in the run-up to the 2007–2009 crisis. A number of additional papers examine and confirm the topology of the global financial market during the 2007–2009 crisis [10–13].

However, later researchers [14], on the other hand, concluded that connectivity in the global banking network has decreased, while interdependence between players in regional networks has increased, and this trend has been determined to a greater extent by countries such as Australia, Canada, Hong Kong, and Singapore.

The purpose of this research is to examine the characteristics of the regional network, which includes the countries of the APR and Russia.

The earliest papers on a network approach to Asian countries were devoted to studying the interrelationships of Asian markets during the Asian financial crisis of 1997–1998. The paper [15] provides a complete overview of the literature on the analysis of infection during this period. Various statistical and econometric methods were used to construct networks — correlation analysis [16], Granger causality tests [17], quantum regression [18].

Subsequently, more elaborate methods were used for the construction of networks, in particular GARCH [19–22], dynamic conditional correlations [23], vector autoregression models [24–26]; copules [27, 28]. Despite the fact that there are many methods of building networks when it comes to causal relationships between participants, vector autoregression and Granger tests are most commonly used, given that the concept itself is most likely to reflect temporary correlation rather than real causality.

DATA AND METHODOLOGY

The methodology proposed by M. Barigozzi and C. Brownlees is used to analyze the risk

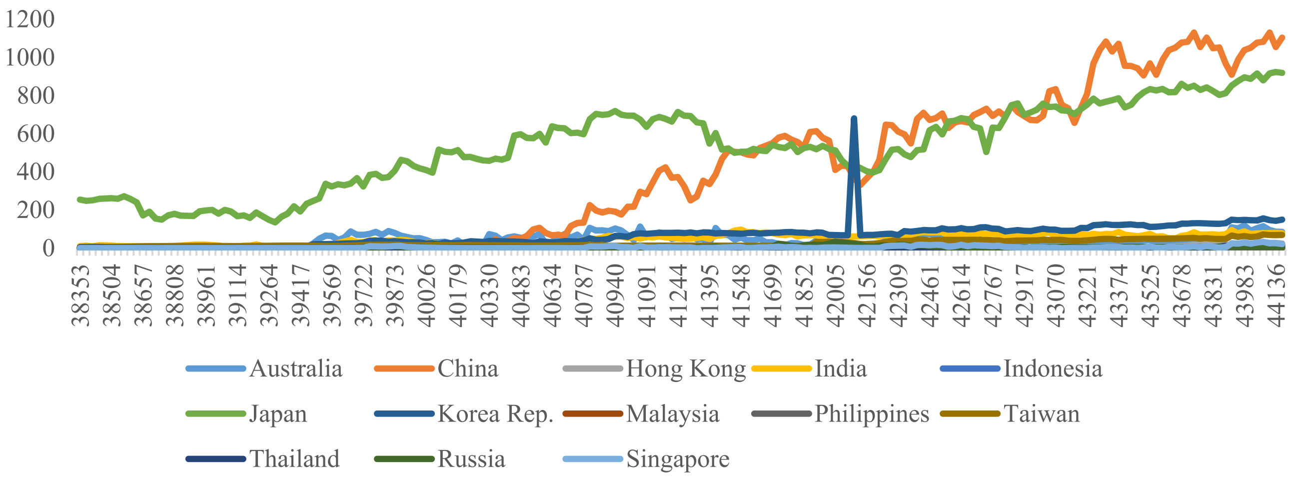

Fig. 1. **Dynamics of the National SRISK Indicators in 01.01.2005–31.12.2020**

Source: Author's calculations.

transmission between the APR countries and Russia [2].[2]

For data quality, we used monthly SRISK index values from the Volatility Laboratory website to build the network. The SRISK indicator for a particular bank represents the amount of capital losses of the institution under the condition of a catastrophic scenario in the financial market. Our sample covers 12 APR countries, including Russia.[3] Study period from 1 January 2005 to 31 December 2020, resulting in 192 observations per country.

Fig. 1 shows the dynamics of the SRISK national indicators. National systemic risk indicators have shown a growth trend since the start of the international financial and economic crisis in 2007–2009. At the same time, the level of SRISK varies and depends on the characteristics of the banking systems of these countries. The highest SRISK values are recorded in Japan and China.

In the first step of the analysis to "clean" the national SRISK indicators from the influence of market fluctuations, we pro-regressed these indicators to three global factors: the VIX volatility index, the global credit risk indicator TED Spread, and the US yield curve. Regression balances will continue to be used as indicators reflecting net risk dynamics in the countries concerned. The regression developed during the first stage indicates this:

$$SRISK = \alpha + \beta_1 VIX + \beta_2 TED + \beta_3 US\_YIELD + \varepsilon_i, \quad (1)$$

where *VIX* — Chicago Stock Exchange Volatility Index. It reflects the price volatility of options on the S&P 500; *TED* — the differential between the short-term interest rate on interbank loans and the rate on treasury bills; *US_YIELD* — the US yield curve, reflecting investors' expectations regarding the future interest rate structure; ε_i — the balances in the regression model [29–31].

Then we build sparse vector autoregression based on the residues obtained from the regression at the previous step. The variables of the diluted model, according to the *NETS* algorithm, are measured by LASSO, the loss function of which includes a penalty depending on the regulation parameter λ_T. Equation (2) presents the standard losses function for the LASSO method, equation (3) presents a formula for estimating coefficients for variables based on LASSO.

$$\ell(\theta, y_t, c) = \sum_{i=1}^{n} \left(y_{it} - \sum_{k=1}^{\rho} \sum_{j=1}^{n} \beta_{ijk} y_{jt-k} - \sum_{\substack{h=1 \\ h \neq i}}^{n} \gamma_{ih} y_{ht} \right)^2, \quad (2)$$

[2] The calculations were implemented in the NETS package for the R language.

[3] The sample included Australia, China, Hong Kong, India, Indonesia, Japan, South Korea, Malaysia, the Philippines, Taiwan, Thailand, Russia and Singapore.

$$\hat{\theta}_T = \arg\min_{\theta \in \mathbb{R}} \left\{ \frac{1}{T} \sum_{t=1}^{T} \ell(\theta, y_t, c) + \lambda_T{}^G \sum_{k=1}^{\rho} \sum_{j=1}^{n} \frac{|\alpha_{ij}|}{|\tilde{\alpha}_{Tijk}|} + \lambda_T{}^C \sum_{\substack{h=1 \\ h \neq i}}^{n} \frac{|\rho^{lh}|}{|\tilde{\rho}_T{}^{lh}|} \right\}. \quad (3)$$

The optimal value of the regulation parameter λ_T was selected on the basis of the Akaike and Bayesian criteria, and in our paper, it was set at the level of 0.001.

As a result of sparse VAR, we obtain a matrix of private correlation coefficients, reflecting simultaneous relationships between objects, as well as a matrix of coefficients, calculated on the basis of the Granger test. The VAR model can be described as follows:

$$y_{it} = \sum_{k=1}^{\rho} \sum_{j=1}^{n} \left(\alpha_{ijk} - \sum_{\substack{l=1 \\ l \neq i}}^{n} \rho^{il} \sqrt{\frac{c_{ll}}{c_{ii}}} \alpha_{ljk} \right) y_{jt-k} + \sum_{\substack{h=1 \\ h \neq i}}^{n} \left(\rho^{ih} \sqrt{\frac{c_{hh}}{c_{ii}}} \right) y_{ht} + u_{it}. \quad (4)$$

where y_{it} — residues from MNC-regressions built in the first step; α —autoregression parameter; ρ — specific correlation factors; c — elements of the diagonal of the concentration matrix; k — lag of model, which in our case is equal to 1.

The first equation describes the relationships between objects along the Granger, and the second is the simultaneous relationships among objects. Using the matrix of association for this equation, you can construct an unoriented graph reflecting simultaneous relationships between objects, and a directed graph for relationships on the Granger.

RESULTS OF EMPIRICAL RESEARCH

According to the results of the calculations, we have two networks: a network of simultaneous interrelations, obtained by means of private correlation coefficients, and a Granger network, which used SRISK index lags.

To start, we will provide a general feature of the networks based on many topological indicators (*Table 1*).

A network density measure is calculated as the ratio of the real connections in the network to the maximum possible number of connections, and the cluster coefficient characterizes the overall trend towards the formation of internally interconnected groups within the network. As shown in *Table 1*, these indicators are close to 1 for the Granger network. This suggests that the graph is tightly grouped, i.e. the shocks can "infect" quite a large number of countries. At the same time, the minimum average distance between nodes is 1.05, and the diameter of the network, i.e. the maximum distance between the nodes, is 2. These two indicators give us an idea of the minimum and maximum rates of potential shock spread in the network. The high degree of interdependence of countries in the region is also demonstrated by the proportion of interconnections, which represents 95% of the total possible number of connections. The assortment factor reflects network nodes' proclivity to join other nodes that share some features. In our case, the Granger network has no inclination to connect countries on a similar basis.

The network of simultaneous interconnections, as shown in *Table 1*, is sparser (the density measure is 0.5), and therefore more resistant to external shocks.

Different measures of centrality are used to determine the degree of "importance" of individual peaks in the graph. For the network of simultaneous interconnections, we have not been able to identify the central nodes, and for the Granger network, the corresponding indicators are given in *Table 2*.

The most commonly used indicators for characterizing "important" nodes are centrality by degrees, mediation and their own vector. The higher the degree of centrality, the more connections the node has with other nodes. The mediation centrality indicator characterizes the role of a node in the path between other network nodes. The high indicator indicates that this node can serve as a shock transmission channel. The centrality by its own vector takes into account both the centrality of the node

Table 1

Main Topological Indicators for the Network in 01.01.2005–01.01.2020

	Contemporaneous linkages	Granger linkages
Density measure	0.5	0.95
Clustering coefficient	1	0.99
Share of reciprocal links	1	0.96
Number of interconnections	78	71
Number of asymmetrical connections	0	6
Disconnectedness	0	1
Diameter	1	2
Average distance between nodes	1	1.05
Associativity	–	−0.10

Source: Author's calculations.

Table 2

Centrality Indicators for the Network of Granger Causalities in 01.01.2005–31.12.2020

	Degree	Closeness	Betweenness	Eigenvector	Bonachich	Alpha
Australia	23	0.083	0.455	0.966	0.079	−0.082
China	24	0.083	0.788	1.000	0.079	−0.122
Hong Kong	22	0.077	0.606	0.925	0.076	−0.082
India	22	0.077	0.606	0.928	0.080	−0.082
Indonesia	22	0.077	0.606	0.925	0.076	−0.082
Japan	24	0.083	0.788	1.000	0.079	−0.122
Republic of Korea	23	0.083	0.455	0.966	0.079	−0.082
Malaysia	22	0.077	0.364	0.928	0.074	−0.082
Philippines	20	0.067	0.364	0.847	0.068	−0.082
Russia	23	0.077	0.697	0.961	0.074	−0.122
Singapore	24	0.083	0.788	1.000	0.079	−0.122
Taiwan	24	0.083	0.788	1.000	0.079	−0.122
Thailand	23	0.083	0.697	0.961	0.079	−0.061

Source: Author's calculations.

itself and the centrality of its neighbors. High centrality on its own vector has nodes that have a large number of connections with other "central" nodes.

In our case, China, Japan, Singapore and Taiwan have the greatest degree of centrality. This means that if the shocks originate in these countries, they can be broadcast to a large number of other nodes.

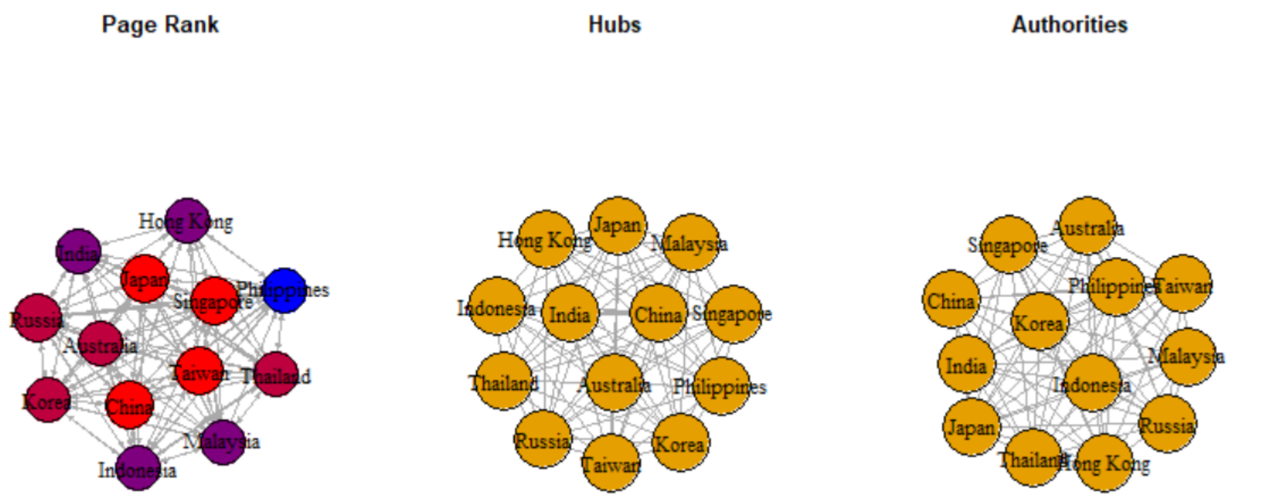

Fig. 2a. **Contemporaneous Networks on Page Rank, Hub Score and Authority Score Rankings for the Period 01.01.2005–01.01.2020**

Source: Author's calculations.

Note: Red corresponds to the highest value of the indicator, blue — to the lowes.

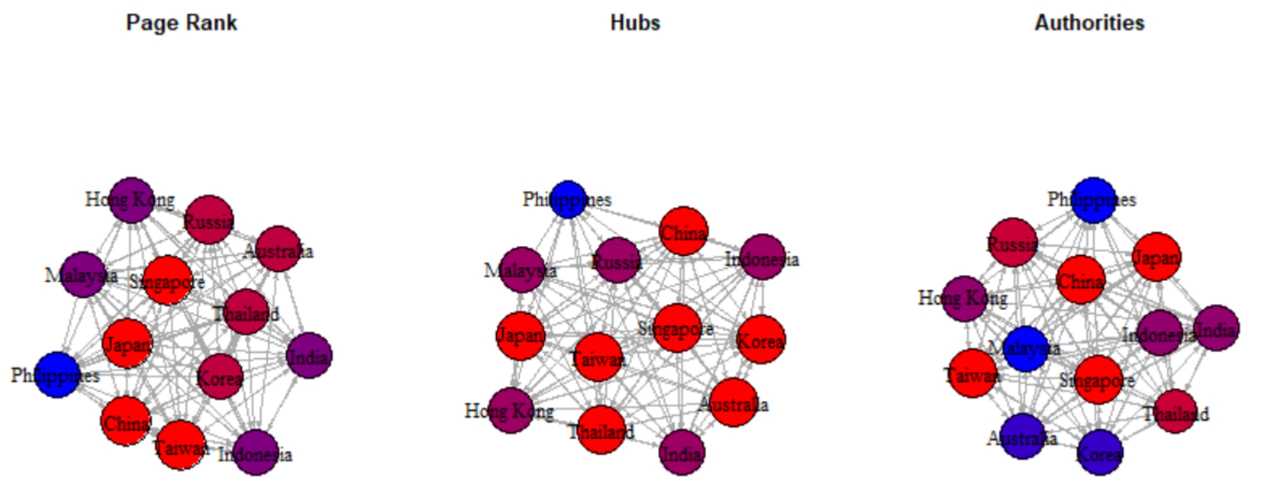

Fig. 2b. **Granger Causality Networks on Page Rank, Hub Score and Authority Score Rankings for the Period 01.01.2005–01.01.2020**

Source: Author's calculations.

The same leaders in mediation are China, Japan, Singapore, and Taiwan, but Australia, the Republic of Korea, and Thailand are also joining them. These countries act as channels for shock transmission. Given their degree of importance, the scale of the shock will be greatest in China, Japan, Singapore, and Taiwan.

Finally, the countries with the highest rates of centrality in their own vectors are China, Japan, Singapore and Taiwan. They are connected with other countries, which also have many connections. This emphasizes once again that the emergence of a crisis in one of these four countries will be the most destructive for the region.

Thus, when all criteria of centrality are considered, China, Japan, Taiwan, and Singapore will always be the most "important". The Philippines has the lowest centralization rates. This indicates that when it involves coordinating

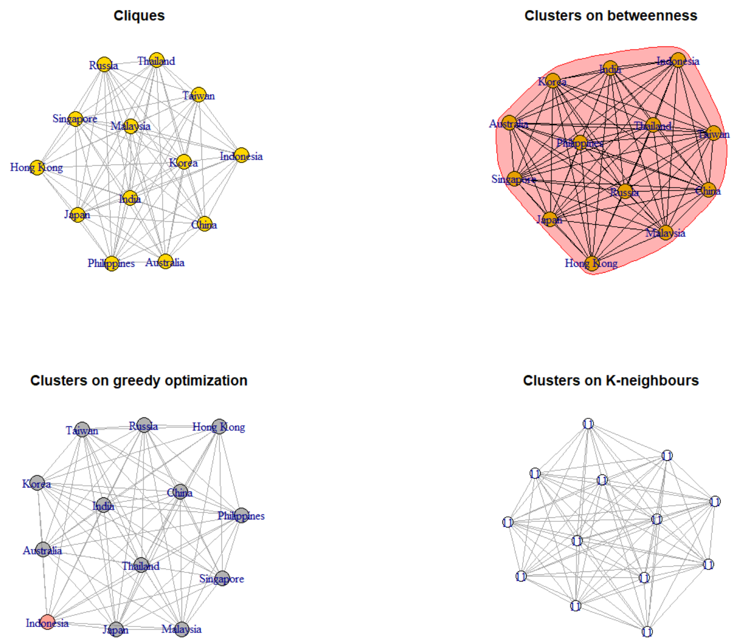

Fig. 3. **Cluster Identification in Granger Causality Network for the Period 01.01.2005–31.12.2020**

Source: Author's calculations.

Note: only one of the algorithms — on the evaluation of optimization of two clusters: to the first refers to Indonesia, to the second — all the other participants of the network. Other cluster algorithms are not observed.

macroprudential measures in the APR region, special consideration should be given to the state of the banking systems in the four countries stated above.

Also, in the analysis of the network to identify "influential" players, in addition to indicators of centrality, use such indicators as page rank, or Page Rank, suggested by L. Page and co-authors [32], hub score and authority score, calculated by J.M. Kleinberg algorithm [33].

According to *Fig. 2a* and *2b*, the highest rates of "authority" and mediation are found in the same four countries: China, Japan, Singapore, and Taiwan. It is also worth noting that Russia ranks well in terms of the indicator of authority. The Philippines' isolated participation has been established.

Finally, let's examine if we can identify individual clusters within the region itself. For this purpose, we have used a variety of methods to identify subgroups in the network: by proximity, by mediation, by label propagation algorithm, by modularity optimization, by K-core decomposition. However, we were unable to detect the established stable clusters neither within the network of simultaneous connections nor in the Granger network of connections.

We also examine how the network's structure changed as a result of situations of crisis. To that purpose, we are rewriting the entire procedure separately for the periods 01.01.2005–31.12.2013 and 01.01.2014–31.12.2020, which include the global financial and economic crisis of 2007–2009 as well as the COVID-19 pandemic lockdown.

From *Table 3*, the density measurements indicate that during the lockdown period, the network was the densest and therefore the most vulnerable. The ratio of interconnections has increased, and the average minimum distance between nodes has decreased, suggesting the potential for shocks to spread faster than during the global financial and economic crisis.

Furthermore, we also identify key countries in the network. In both sub-periods, we focused only on Granger networks, because the algorithm does not identify "influential" participants for the network of simultaneous connections.

Table 3

Main Topological Indicators for the Network 01.01.2005–01.01.2020

	01.01.2005–01.01.2020		01.01.2005–31.12.2013		01.01.2014–01.01.2020	
	Contemporaneous linkages	Granger linkages	Contemporaneous linkages	Granger linkages	Contemporaneous linkages	Granger linkages
Density measure	0.5	0.949	0.5	0.859	0.5	0.929
Clustering coefficient	1	0.987	1	0.975	1	1
Share of reciprocal links	1	0.959	1	0.866	1	0.924
Number of interconnections	78	71	78	58	78	67
Number of interconnections	0	6	0	18	0	11
Disconnectedness	0	1	0	2	0	0
Diameter	1	2	1	2	1	2
Average distance between nodes	1	1.051	1	1.14	1	1.07
Associativity	–	–0.101	–	–0.233	–	–0.188

Source: Author's calculations.

At the height of the global financial and economic crisis, Singapore became the leader in terms of "authority". At the same time, he has also acted as a major mediator in the transmission of crisis phenomena, along with China, Japan, Hong Kong, India, and the Republic of Korea. Indonesia, the Philippines and Malaysia were on the periphery of the network, as they had low Page Rank, "authority" and mediation values. During the period under review, these countries could not be a source of infection for other network participants.

In the period of lockdown, the picture of Page Rank (*Fig. 5*) and the intermediaries did not change much, but the "greatest authority" among the countries began to enjoy Japan, Thailand, Taiwan and Hong Kong. Singapore, as a result of crisis incidents, has disappeared from the network. The Philippines, Malaysia, and Indonesia remained unchanged as peripheral countries. During both crises, Russia only acted as a mediator in the risk transfer.

The cluster results for the networks of the subperiods under consideration are similar to those we obtained for the entire period.

So, considering the evolution of the networks of banking systems in the countries of the APR and Russia, we can conclude that during the lockdown period they became more fragile. The mediators of crisis phenomena in both crisis subperiods were the same: Hong Kong, Japan, Taiwan, Thailand, Singapore, Russia. Changes in risk "donor" composition: Singapore had the highest "authority" in 2005–2013 and Japan, Thailand, Taiwan and Hong Kong in 2014–2020.

The results of the analysis may be of interest to regulators. On the one hand, strengthening Russia's involvement with the APR countries contributes to the financial development of all participating countries. On the other hand, given the role of all participants in the network

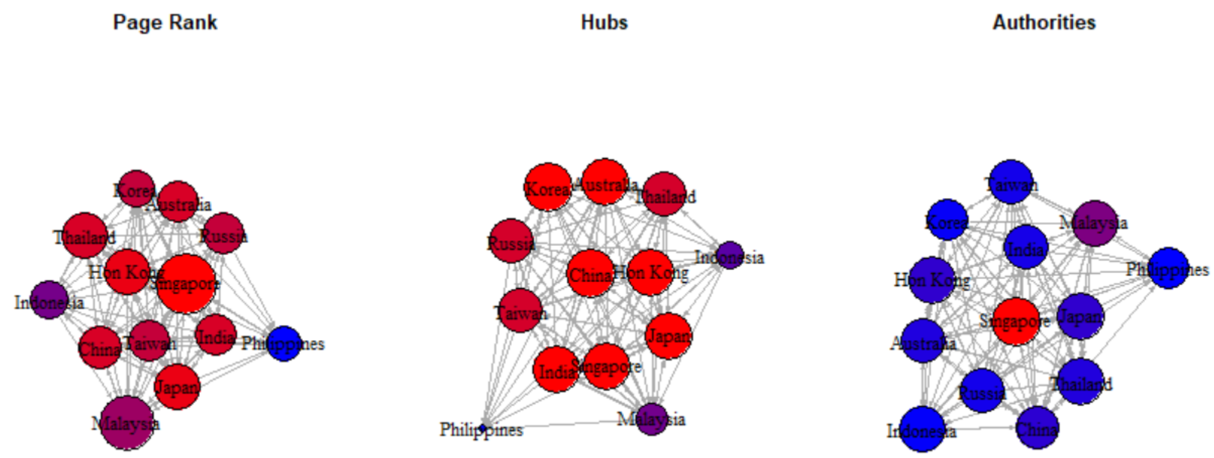

Fig. 4. **Granger Causality Networks on Page Rank, Hub Score and Authority Score Rankings for the Period 01.01.2005–01.12.2013**

Source: Author's calculations.

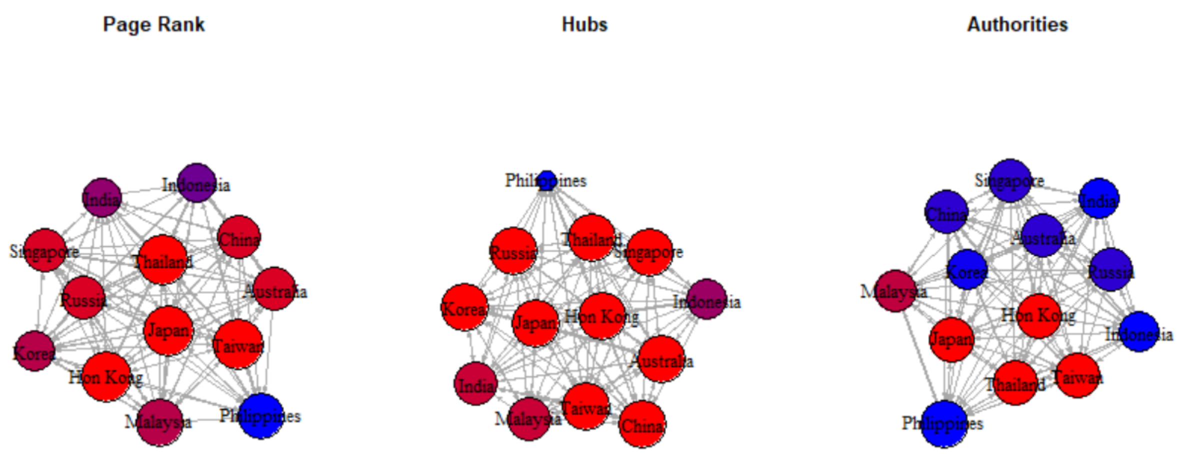

Fig. 5. **Granger Causality Networks on Page Rank, Hub Score and Authority Score Rankings for the Period 01.01.2014–01.12.2020**

Source: Author's calculations.

as risk acceptors or donors, it turns out that increasing the intensity of financial cooperation with China could increase the likelihood of the shocks being transmitted to Russia. At the same time, weakening financial ties with other major risk exporters — Japan, Singapore and Taiwan — helps to reduce the likelihood of infection for Russia.

It is evident that the high risk of contamination in the region is the opposite of increased commerce and financial cooperation among countries. Is it possible to reduce the degree of risk transmission without reducing cooperation? Strengthening domestic macro-prudential policies in each of the countries seems most obvious, taking into account the state of affairs in the partner countries: risk-exporting countries need to apply preventive macro-prudent instruments as soon as they notice signs of a bubble, knowing that their internal instability can spread to neighboring countries. Importing countries must take market conditions in the risk-exporter countries into account when monitoring financial stability in the internal market and developing hedging instruments against potential risks. Supranational coordination of domestic macro-prudential policy measures is also required to avoid arbitrage in regulations when tightening in one country results in a flow to neighboring countries with less stringent regulations.

Considering Russia's role as a risk recipient throughout the period under review, macroprudential policy cooperation with China, the greatest risk exporter, is becoming increasingly critical.

CONCLUSION

This paper examines the mechanism of risk transfer between the banking systems of the APR countries and Russia in the period from 2005 to 2020. The analysis was based on networks built using SRISK indices obtained using the NETS algorithm of M. Barigozzi and C. Brownlees [2].

The following results were obtained in the course of the paper: first, it was found that the banking systems of the countries concerned were highly interdependent, which was a sign of vulnerability in the event of a major external shock; second, we have identified a group of parties (China, Japan, Singapore, and Taiwan) whose banking system stability must be prioritized. The appearance of a shock in one of them will have catastrophic consequences for the entire region.

Considering the increased intensity of China-Russia financial cooperation, there is a greater possibility that Chinese shocks will be transferred to our country, although reducing connections with Japan, Singapore, and Taiwan, on the other hand, reduces the risk of infection.

Thirdly, we have analyzed how the network changes under the influence of different crisis episodes. It was revealed that the countries that could serve as a transmission mechanism for shocks remained the same in both cases, and the authoritative peaks changed. The number of shock donors has increased. Singapore played a key role during the global financial and economic crisis, followed by Japan, Thailand, Taiwan and Hong Kong.

Our paper is aimed at adding to current knowledge on the transfer of systemic risk between countries. Our research contributes in two ways: methodologically and substantively. Firstly, to analyze risk transmission in the network of banking systems in the APR region and Russia, we used a new methodology, more suitable for larger timeline panels. We also conducted a dynamic analysis of how the characteristics of the network changed over the period of three different crisis episodes. Secondly, from a substantive point of view, our contribution is to identify exporting countries, risk-importing countries and transferring countries. This information can be used to define the infection process in the APR and to develop control strategies.

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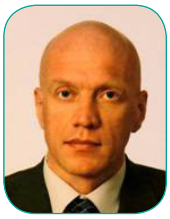

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