THE NETWORK ANALYSIS OF THE INTERBANK INTERDEPENDENCE AND IDENTIFICATION OF SYSTEMICALLY IMPORTANT BANKS

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INTRODUCTION

Having learned from the recent financial crisis, regulators around the world have come to the conclusion that it is necessary to identify systemically important institutions and identify the causes of systemic risks early, otherwise the states themselves had to pay for the consequences of financial imbalances, thus causing the problem of moral hazard to society. In order to develop public policies that can effectively prevent the fragility of institutions that create systemic failure in a country's financial system, regulators and academics now need to better understand and study all possible causes of systemic imbalances. One of the most important issues in managing systemic risk and ensuring systemic stability is the creation of indicators and methodologies to assess systemically important institutions in the system. Financial system stabilization policies always rely on such measures.

Financial markets, in turn, are linked to each other through intermediary transactions involving multiple intermediaries. Financial market systemic risk is the risk that these "linking" or "single" transactions and other types of interconnections facilitate the spread of financial vulnerability in the system. This complex network of financial interconnections is extended by the financial needs (either to increase savings or to attract resources) of all sectors of the economy: non-financial companies, households and government. By redistributing the savings of the named sectors of the economy to the "needy", the financial system represents its significant function for the economy. Thus, systemic risk, more broadly defined, refers to the risk that widespread financial vulnerability in the financial market may adversely affect the growth and welfare of the economy as a whole.

Systemic risk is a key issue in banking and has two main components: banks' exposure to common risk factors and the dangers of a domino effect, as banks are interconnected through a complex system of relationships. In such a system, the failure of one institution can affect the financial position of others in a chain reaction. From an abstract point of view, the system of relationships between financial credit institutions can be viewed as a network in which banks form the nodes of the network and interbank relationships form the financial links. From a financial stability point of view, it is interesting to understand how the structure of this interbank network affects the financial stability of the banking system as a whole.

Both in Western and Russian literature there is an opinion that the mechanism of spreading systemic risk is a system of interrelationships through which new institutions and markets are drawn into the spiral of crisis [2]. The financial system consists of intermediaries, payment and settlement systems and trade mechanisms that support them. Intermediaries are linked to each other through direct transactions,

through the interbank market and the system of investment and financial transactions by other intermediaries. The network of credit relationships between financial institutions plays a key role in the study of systemic risk contagion.

It is known that banks are interconnected by a complex system of credit relationships. In such a system, the insolvency of one institution may affect the financial situation of others and further affect the financial situation of the entire banking system in a chain reaction (Figure 1). The economic distress of an insolvent bank may spread to other banks through interbank linkages, where interbank relationships may represent a conduit for contagion.

How can financial fragility initially have autonomous significance and then spread so widely that the consequences eventually reach systemic proportions? Researchers on the impact of systemic risk over the past decade have identified three significant factors that can cause this to happen.

First, it is the manifestation of the "domino effect" (in foreign literature in this case the word "contagion" is used, which is literally interpreted as "contagion", "infection"). The failure of one financial intermediary can lead to the failure of other financial intermediaries, even if the latter have not invested in the same risks and are not subject to the same area of exposure to the initial shock.

Second, large financial imbalances can accumulate for a long time and then crack abruptly. Hyman Minsky, in his theory, describes how in good times, income-generating investment gains "feed" financial markets with huge financial resources, and meanwhile neglect their accumulating risk. Barely insignificant events can lead to increased risk and internal credit complications that later adversely affect numerous intermediaries and markets.

Third, negative shocks in the aggregate can adversely affect intermediaries and markets at the same time. History shows that many banking crises have been associated with economic downturns. Note that these three factors can occur either independently or cumulatively.

Today's financial marketplace tends to be increasingly interdependent. This interconnectedness is the result of, among other things, the consolidation in a single financial institution of various financial and business activities previously conducted by different independent organizations, the common reliance on critical market instruments, the use of common ratings, and the broad exposure to certain assets. This complex web of contractual and behavioral relationships can create and rapidly spread risks throughout the system. Increased interdependence and shared risk exposure made financial institutions susceptible to shocks.

As already mentioned, macroprudential policy is designed to regulate the interdependencies among financial institutions, whether explicit contractual relationships or implicit implicit linkages that arise from their common exposure to financial risks. The main objective of macroprudential policy is to determine the interdependence of financial institutions and markets, as their common effects on economic variables create systemic risks. The use of complex financial instruments and the involvement of credit relationships in complex structures, thus increasing the

degree of interconnectedness makes it vulnerable to the rapid spread of failures. Over the past ten years, contractual interconnectedness among financial institutions has grown due to the use of complex financial instruments to transfer risk to various market participants in various forms. The collapses of Bear Stearns, Lehman Brothers and AIG, and the liquidity litigation of many of the world's major banks have forced the public consciousness of the interconnectedness of financial institutions. Systemic risks can also arise from herd and procyclical behavior of institutions. Interconnectedness can also be implicit. The global financial crisis is the result of the common exposure of financial institutions to elements that change during the economic cycle [3]. The peak of the cycle is characterized by increased competition between financial institutions, increasing asset values, lower risk premiums, availability of credit and other forms of financing. In order to take advantage of such conditions, financial institutions naturally begin to expand their portfolios, hence the increasing interconnectedness of financial institutions. However, there comes a time when the cycle enters its next phase, the "boom" ends and asset prices begin to decline. Cheap short-term instruments become less and less available and assets are seen as riskier. As a consequence, asset price movements, liquidity and credit availability intensify. Banks of the period "booms" as transformers of finance fund long-term assets with short-term resources, thereby allowing their clients to do the opposite. In addition, even regulators have been on the side of increasing universal exposure to cyclical risks. This policy of the regulators is reflected in the choice of mark-to-market (mark-to-market) asset valuation and accounting, and the use of global ratings in credit risk assessment by the regulators themselves [4]. Following the regulators, institutions with high confidence continue to use the assessments of credit rating agencies in the course of their daily activities. This is a clear sign of herd behavior of the market, which is one of the factors of the systemic shock. In such examples, institutions repeat actions not among themselves, but after the regulator. This phenomenon is the main difference between the ultimate goals and objectives of micro and macroprudential regulation.

The global financial crisis has emphasized the peculiarity of systemic risk, which has a devastating impact on the stability of the entire financial system. As it became clear from the consequences of the crisis, one of the most important tasks facing regulators today is to reform the financial system in such a way as to effectively reduce the impact of systemic risks. In the post-crisis economic literature, the relevance of studying the financial stability of financial intermediation systems, especially systemic risk, has increased dramatically. And thus, there has been an interest in studying the contagion effect of systemic risk in financial intermediation systems.

There are a number of features of financial systems that make them particularly susceptible to systemic risk factors. The first common feature of a financial system is what we call external factors. In particular, they refer to the complex and dynamic network of exposures among major financial market participants. Thus, in stable times they may provide an effective mechanism for risk

transfer, but in the event of a crisis, they become a dangerous channel for "contagion" of the system to that stress. As a consequence, the risk at the system level may be higher than the sum of individual risks. The second key feature of the financial system is the asymmetry of information. An additional problem in the financial system, which is its third feature, is illiquid assets, asset-liability maturity mismatch.

One of the key element in the chaos and crisis phases is speed. The speed of unfolding events is often not clearly modeled. But this is one of the biggest challenges for policymakers. Financial crises are by no means a new phenomenon, but the speed of their transmission has accelerated enormously over the past few decades. Whereas the sovereign debt crisis in the 1980s occurred within a year, the Asian financial crisis unfolded over months, not years. Many factors have contributed to this acceleration, including the process of global financial integration, technological advances enabling the instantaneous transmission of information around the world, and the accumulation of global imbalances over a long period of time.

Even if we understand the nature of systemic risk and know the basic approaches to analyzing its various forms, there are still other major challenges for macroprudential supervision. One challenge is to be able to gather all the information needed to identify systemic risks at an early stage. To contain systemic risks, macroprudential supervision needs to have a good understanding of all parts of the financial system that are relevant to risks of "contagion" (or "domino effect"), endogenous accumulation, imbalances, and macro shocks. Some of this data, is difficult to collect and aggregate. There are some financial sectors about which much less is known than others. Compare banks or insurance companies, for example, in terms of their leverage ratio. Although individual hedge funds are not currently believed to be a source of significant systemic risk, it is necessary and important to assess the relevance of this industry in analyzing the cyclicality of the financial system.

The topic of measuring the relationship between systemically important intermediaries (known in the Western literature as "TBTF" - too big to fail) is particularly challenging. The point is that that effective exchange of information between macroprudential and microprudential supervisors is an important element in the identification of systemic risk factors. Other challenges are more analytical in nature. The economic models that we have at our disposal, at the present time, do not capture the necessary magnitudes of systemic risk. For example, despite progress in the development of macro-stress testing, its shortcoming is that such an assessment does not capture the two-way interaction between financial vulnerability and the performance of the economy as a whole. Standard macroeconomic models often do not represent a developed financial market and thus have a linear character. Systemic shocks involve specific nonlinearities and, in any case, cannot be analyzed without an appropriate view of the financial market. The latter challenge is explained by the following. As noted earlier, regulators now face great difficulty in predicting the impact of defaults, in part because of the lack of a transparency of the financial

system structure, as well as the lack of methodology for monitoring systemic risks. The task of determining adequate indicators of systemic risks is nowadays actualized due to the complexity of the modern structure of the financial system, and thus a more objective assessment of the systemic importance of financial institutions and an objective basis for assessing the effectiveness of macroprudential regulation becomes necessary. Macroprudential policy thus attracts the attention of regulators. In 2009, Bernanke proposed the possibility of creating a systemic risk authority, whose responsibilities include monitoring the rapidly growing interaction of markets, assessing possible changes in new products, assessing the risk of spillovers between financial institutions and markets, the mutual impact of closely interconnected institutions, and identifying possible regulatory gaps.

One method to facilitate (responsiveness) macroprudential supervision is to identify systemically important institutions in the structure of intermediary financial relationships. The network of credit relationships between financial institutions plays a key role in investigating the contagion of systemic risk.

METHODS

It is known that banks are interconnected by a complex system of credit relationships. In such a system, the insolvency of one institution may affect the financial situation of others and further affect the financial situation of the entire banking system by a chain reaction. The economic distress of an insolvent bank may spread to other banks through interbank relationships, where interbank relationships may represent a channel for contagion. In economic science, authors like Allen and Gale, Freixas, Turner and others have initiated the study of the properties of networks in the study of financial systems in terms of constructing topologies and identifying the qualities inherent in these structures. The authors of works in this direction believe that the application of network theory can provide the regulator with the most important information about the state of "health" of the analyzed banks [5]. This approach allows applying the results of general network theory, which is widely used in other scientific disciplines such as physics, computer science, electric power, astronomy, ecology, biotechnology, neuroscience, epidemiology, etc. This methodology was later adopted by economists and most central banks, applying it in their internal research work on macroprudential regulation. Research results and active interest in this direction among researchers-economists of the CIS has not yet reached the world level, and in Kazakhstan's economic science has not yet been observed. This circumstance served as a challenge for us to conduct this research for Kazakhstan financial intermediation market.

Network analysis methodologies provide a set of tools for problem formulation, analysis and solution. As such, a network consists of two types of elements, nodes (vertices) and the links between them (connections, edges). An edge can have a weight (thickness) representing the importance of the connection between nodes. An intuitive way to analyze a network is to show it as a graph (visualize it).

We interpret the interbank market as a network in which the banks themselves form the nodes (vertices) and the claims and liabilities between them define the edges (arcs) of this network.

The work uses methods of network analysis from information theory. Calculations on the part of empirical analyses were carried out using specialized programs in the field of information theory research: ucinet 6.0, kumonote, gephi 8.0 and a specialized Internet platform fna.fi .

To conduct a network analysis of Kazakhstan's banking system, we use quarterly data on interbank claims and liabilities of the National Bank of Kazakhstan for Q4 2011 and 2012 (Figures 6 and 7).

The data are taken for 2 years for the purpose of comparative analysis, to what extent there has been a change in the topology of the interbank networks over the year, and we also do this to find out the consistency of the impact of the same systemically important banks on the whole system. Due to confidentiality and hard-to-access data, this study concentrates only on observations of only two years and 37 banks, as this study did not include one bank out of 38, whose name remains unknown to us. But the essence of the analysis is not to build the dynamics of changes in the structure of networks, the most important outcome for us is the macroprudential objective, namely to identify the level of centrality of vertices in the networks, which in turn determines the levels of systemic importance of a particular bank.

So, the structure of the Kazakh banking system is modeled as a network of 37 vertices, where the vertices are banks. The vertices of the networks are connected by edges, which represent the interconnectedness between banks, represented by the network of interbank assets and liabilities.

As shown in Figures 2 to 5, the networks consist of 37 nodes and 135, 174, 176, and 139 ribs, respectively. The amount of thickness of the edges corresponds to their weights, describing higher values with darker shades. The graphical representation of the networks assumes the existence of a small group of banks linked by high value connections. We find that only a small number of banks and the connections between them account for the majority of all interbank relationships. We can see the role of hub banks in these networks is taken by banks numbered 11, 16, 17, 21, 22, 27, 28 and 29. While the others remain in the peripheral zones.

The analysis of interbank borrowing volumes shows that the largest borrowing bank in 2011 is bank No. 36. And bank No. 21 is in demand in the system for placing loans. The largest lending to the banking system was by bank No. 8. The most diversified lending was by bank #25. The trend of the most concentrated bank in terms of attracting loans from other banks continues for bank #21. The largest placement of borrowed funds was made by bank No. 24 in 2012. In terms of volumes of interbank deposits and other liabilities in 2011, the leaders were: Bank No. 11 and Bank No. 35. A year later - only bank No. 35. These statistical results give us a preliminary assessment for analyzing systemically important links in the structure of the banking system.

To begin the structural analysis, we evaluate the following types of matrices: see formulas 1 and 2. In information theory (from which network analysis originates), in order to construct networks, data must be represented as a matrix of adjacencies.

We represent direct interbank linkages by two types of matrices: the claims matrix (A) and the liabilities matrix (L):

$$\mathrm{A} = \begin{array}{c} \\ b_1 \\ b_2 \\ \dots \\ bi \end{array} \begin{array}{c} \begin{array}{cccc} b_1 & b_2 & \dots & b_j \end{array} \\ \begin{pmatrix} a_{1,1} & a_{2,1} & \dots & a_{i,1} \\ a_{1,2} & a_{2,2} & \dots & a_{i,2} \\ \dots & \dots & \dots & \dots \\ a_{1,j} & a_{2,j} & \dots & a_{i,j} \end{pmatrix} \end{array}, \tag{1}$$

and

$$\mathrm{L} = \begin{array}{c} \\ b_1 \\ b_2 \\ \dots \\ b_i \end{array} \begin{array}{c} \begin{array}{cccc} b_1 & b_2 & \dots & b_j \end{array} \\ \begin{pmatrix} l_{1,1} & l_{2,1} & \dots & l_{i,1} \\ l_{1,2} & l_{2,2} & \dots & l_{i,2} \\ \dots & \dots & \dots & \dots \\ l_{1,j} & l_{2,j} & \dots & l_{i,j} \end{pmatrix} \end{array}, \tag{2}$$

where:
b i,j are the vertices of the matrix, i=j=1.37,
a i, j are the requirements of bank j (lender) in bank i (borrower),
l i, j are the obligations of bank j (borrower) in bank i (lender).

Matrices are further represented as networks in order to describe and analyze their topologies (structures of nodes and edges between them). The nodes and edges of the structure together represent the topology of the network. As noted by the "fathers" of this branch of science, Barabashi and Bonabo, the stage of topology construction in the analysis of networks is the most important, because it provides important information about the stability and efficiency of the analyzed systems [5].

Table 1 shows that the structure of Kazakhstan's interbank market is a scale-free network (by another name, scale-invariant network). This means that this network topology has all the properties of scale-free networks.

If we pay attention to the statistics in the table, we can see that the degree of networks based on interbank assets is larger than networks in terms of interbank liabilities.

This circumstance results that banks are exposed to systemic risk through the channel of interbank assets rather than liabilities, and thus, in this study, other things being equal, the channel of systemic risk contagion in the balance sheet of banks will be to a greater extent its resource-forming part.

In order to describe the network structure of the interbank market in Kazakhstan, we need to look at the primary properties of networks, namely the extent and size of networks. We present these properties in detail in Table 1. The size of networks explains the number of connections between nodes, while the degree is the number of nodes.

The analysis of the network structure makes it possible to assess the level of network centrality. The measure of centrality in this study provides an opportunity to measure the degree of systemic importance of the vertices we analyze (in this case, banks).

According to network theory, in each network, a particular node has the highest level of centrality than the others, according to a particular measure. Centrality indicates how close a node is to the center of the network. In other words, if a node has a high influence (or importance) on the network, the closer it is to the center of the network. There are several types of graph centrality measures. The most commonly used are the following four: degree centrality measure, closeness centrality measure, betweenness centrality measure, and eigenvector centrality statistics [6].

The degree centrality measure is defined as the number of edges passing through the same node (i.e., the number of links that a node has). The measure is calculated by the following formula:

$$C_D(V) = \frac{\deg(v)}{n-1},$$

where
$C_D(V)$ represents the power centrality of vertex v, n is the number of vertices in the network,
deg(v) is the number of connections from vertex v to another [7].

The degree centrality measure counts the number of neighbors of each node. It is a local measure that takes into account only the links immediately adjacent to the node.

While degree centrality evaluates the importance of a node at the local level, the proximity measure determines its importance at the overall system level. The proximity measure cannot be used for separately lying (unconnected) nodes. The proximity measure is defined as the average geodesic (shortest) distance (i.e., the shortest path) between a particular node and all other nodes connected to it.

The measure of remoteness of vertices is inversely proportional to the measure of closeness, which is defined as the sum of the geodesic distances of all

vertices. This statement can be displayed in the form of the following formula:

$$C_C(V) = \frac{1}{\sum_j d_{ij}}$$

where
i and j are the vertices of the analyzed network,
d_{ij} is the geodesic (shortest) the distance between vertices i and j

The proximity measure defines the distance from a particular vertex (bank) to all others in the network. The closer a vertex is to the others, the more preferred (system) it is in the network.

The measure of intermediate centrality is also a measure of the centrality of a node in the network. It is equal to the sum of the shortest paths from all nodes with all other nodes that pass through this node:

$$C_B(V) = \sum_{ij} \frac{d_{ij}(v)}{d_{ij}} \quad ,$$

where
dij is the geodesic (shortest) the distance between vertices i and j,
dij(v) is geodesic (shortest) the distance between vertices i and j passing through vertex v.

RESULTS AND DISCUSSION

We determined systemically important links in the network by comparing the values of the measure of degree centrality of each node with statistical averages (Table 2, 3). The measure of degree centrality of the network structure of the RK banking system is presented in Tables 1 and 2. From the point of view of credit resources allocation, the systemically important banks in the RK are (in descending order): In 2011 (4-quarter) banks numbered 21, 35, 19, 11, 25, 7 and 37. In 2012 (4-.quarter) banks numbered 21, 35, 11,19, 37, 16, 7, 32, 6 and 29.

In terms of placement of deposit resources and other liabilities, the systemically important banks in the Republic of Kazakhstan are (in descending order of the centrality measure): In 2011 (4-quarter) banks numbered 11, 35, 37, 21, 19, 16, 6, 27, 20 and 7. In 2012 (4th quarter) banks numbered 35, 11, 37, 21, 16, 29 and 6.

Descriptive statistics, derived by statistical applications, serve as a guide in identifying systemically significant links from the entire set of indicator values (Tables 6, 7).

Thus, in 2011 (4-quarter) the number of systemically important banks in

terms of credit resources placement reaches 34; and in 2012 (4-quarter) - 35 (tables 4 and 6, figure 5).

In 2011 and 2012 (4-quarter), the number of systemically important banks in terms of deposits and other liabilities is smaller than in the previous description and reaches 26 (tables 5 and 7, figure 7).

According to the measure of eigenvector centrality (Bonasich approach), a vertex has the highest level of system importance if it is connected to a set of vertices with strong connections. In our analysis, the following vertices (banks) took the highest value according to the eigenvector centrality metric: In 2011 (in descending order), banks numbered 22, 20, 33, 19 and 24. In 2012, banks numbered 34, 23, 36, 24 and 16.

Comparing the results of the two years, it can be argued that Bank 24 is systemically important to the system because it interacts with hub banks on a relatively constant basis more often than the others.

The measure of intermediate centrality of the network structure of the Kazakh banking system is presented in Tables 8 and 9. In terms of credit resources allocation, the systemically important banks in the Republic of Kazakhstan are (in descending order): In 2011 (4th quarter), banks numbered 21, 19, 11, 22, 27, 8, 35, 6, 29 and 25. In 2012 (4th quarter), banks numbered 21, 19, 8, 11, 6, 16, 22, 1, 27 and 26.

In terms of placement of deposit resources and other liabilities, the systemically important banks of Kazakhstan are (in descending order of centrality):

1) In 2011 (Q4), banks numbered 11, 19, 21, 6, 35, 25, 34, 16, 29, 17, 27, 2 and 14.

2) In 2012 (Q4), banks numbered 21, 25, 11, 16, 6, 19, 8, 35 and 26.

So, we can conclude that the banks numbered 21, 19 and 11 are systemically important for the banking system of Kazakhstan. These banks can expose the system to systemic risks both individually and as a group, i.e. the highest degree of the level of systemic importance belongs to three banks of Kazakhstan (Figure 8).

Thus, the development and application of regulatory measures against systemically important banks should be supported by scientific arguments. The regulator should not be unsubstantiated in this case, but should have any (scientific) grounds for applying macroprudential measures against those who create crisis situations for the economy. The size of a bank's assets or capital should not be the only grounds for the regulator to apply macroprudential measures. Since banks do not have relevant information on the network structure of the financial system, they are more than likely unable to accurately assess the correlation of their portfolios with other banks and thus will not be able to conduct optimal risk management. Only a central supervisor at the "head" of the system is

able to properly map the financial network in a macroprudential risk analysis.

Thus, banking macroprudential regulation should also be provided for interbank borrowing activities. In stable times, the volume of the interbank loan market is small and, accordingly, the risks are also low. But in times of crisis interbank loans amplify systemic risk, so the appropriate absorbers of such borrowing should be much larger and sufficient [8].

According to scholars' assessments, Basel III does not provide adequate measures to regulate systemically important financial institutions. Instead, it is proposed to focus on market transparency. While increased capital buffers may help build confidence among market participants, they are not sufficient to counteract herd behavior among market participants. Asymmetric information among market participants should be reduced. Three categories of systemic importance should be introduced: low, medium and high [8].

Banks that have high systemic importance in volatile dynamics are categorized in the medium systemic importance category; and those that almost always appear at the high systemic importance level will be categorized in the high systemic importance group; and the rest in the low category. Due to enhanced reporting and data publication for systemically important financial institutions, there is no benefit to keeping the name of the NWFI secret. All market participants will be informed of the level of systemic importance and that this level may change over time. Regulators could publish quarterly updates on the risk ranking system. This categorization is necessary for banks themselves to be able to respond to market actions and in a sufficiently timely manner. This may be useful for early predetermination of additional regulatory requirements for NWFIs, which is often referred to as a "tax" by Western academics because of its similarities.

CONCLUSIONS

So, the results of the research presented in this chapter allow us to draw the following conclusions. Using the method of network analysis from information theory, a methodology for identifying the Central Bank of the Republic of Kazakhstan was developed for the first time, along with which, a topology of interbank relations was built, the values of the coefficients of systemic significance for all STBs of the Republic of Kazakhstan were calculated, on the basis of which proposals and recommendations for improving regulatory measures of systemically important banks of the Republic of Kazakhstan were formed

TABLES AND FIGURES

Table 1 - Descriptive characteristics of network structures of the interbank market of Kazakhstan in 2011 and 2012.

Network name	Number of connections in networks	Network size	Degree of network
Topology of interconnectedness of RK banks through the network of assets by 2011 results	176	37	0.21
Interconnectivity topology of RK banks through the network of liabilities by results of 2011	135	37	0.27
Topology of interconnectedness of RK banks through the network of assets by 2012 results	174	37	0.21
Interconnectivity topology banks of the RK through the network of liabilities by the results of 2012	139	37	0.27
Note - Compiled by the author on the basis of NBRK data			

Table 2 - Measure of degree centrality of banks for Q4 2011 and 2012. Linkage between banks - lending

4Q 2011.			4Q 2012.		
Name of banks	Degree measure bank centrality	Comparison with average value	Name of banks	Degree measure bank centrality	Comparison with the average
1	2	3	4	5	6
bank 21	24283180	20857846	bank 21	25910886	22934597
bank 35	19312720	15887386	bank 35	23464396	20488107
bank 19	17041328	13615994	bank 11	10770373	7794084
bank 11	15288558	11863224	bank 19	9851854	6875565
bank 25	14423020	10997686	bank 37	9144869	6168580
bank 7	12893201	9467867	bank 16	5306515	2330226
bank 37	7345018	3919684	bank 7	4068818	1092529
bank 16	3174151	-251183	bank 32	3513784	537495
bank 8	2894562	-530772	bank 6	3248782	272493
bank 6	2350460	-1074874	bank 29	3098278	121989
bank 27	2175583	-1249751	bank 24	2075626	-900663
bank 20	1669245	-1756089	bank 5	1940229	-1036060
bank 29	1102796	-2322538	bank 25	1555074	-1421215
bank 1	898028	-2527306	bank 8	1132277	-1844012
bank 22	760044	-2665290	bank 1	1038828	-1937460
bank 2	316169	-3109165	bank 27	728049	-2248240
bank 24	205779	-3219555	bank 31	699170	-2277119
bank 10	200916	-3224418	bank 22	558650	-2417639
bank 5	184998	-3240336	bank 15	544662	-2431627
bank 32	99725	-3325609	bank 10	502140	-2474149
bank 34	97195	-3328139	bank 2	438671	-2537618
bank 4	13206	-3412128	bank 20	259099	-2717190
bank 31	3586	-3421748	bank 34	258439	-2717850
bank 9	2560	-3422774	bank 26	7553	-2968736
bank 14	1026	-3424308	bank 4	3974	-2972315
bank 15	114	-3425220	bank 14	1026	-2975263
bank 12	112	-3425222	bank 3	600	-2975689
bank 3	78	-3425256	bank 17	60	-2976229
bank 18	0	-3425334	bank 12	0	-2976289
bank 26	0	-3425334	bank 18	0	-2976289
bank 13	0	-3425334	bank 9	0	-2976289
bank 23	0	-3425334	bank 23	0	-2976289
bank 33	0	-3425334	bank 33	0	-2976289
bank 30	0	-3425334	bank 30	0	-2976289
bank 17	0	-3425334	bank 13	0	-2976289
bank 36	0	-3425334	bank 36	0	-2976289
bank 28	0	-3425334	bank 28	0	-2976289
Descriptive statistics	Mean	3425334		Mean	2976288.75
	Sum	127000000		Sum	110122680
	Minimum	0		Minimum	0
	Maximum	24283180		Maximum	25910886
	N of Obs	37		N of Obs	37
Note - Compiled by the author on the basis of NBRK data					

Table 3 - Measure of degree centrality of banks as of Q4 2011 and 2012. Communication between banks - placement of deposits and other liabilities

4Q 2011.			4Q 2012.		
Name of banks	A measure of degree centrality jar	Comparison with the average	Name of banks	A measure of degree centrality jar	Comparison with the average
1	2	3	4	5	6
bank11	14722438	13054389.25	bank35	25418776	23458188.88
bank35	14397613	12729564.25	bank37	11456926	9496338.875
bank37	7246099	5578050.25	bank11	9573441	7612853.875
bank21	5313499	3645450.25	bank21	5965776	4005188.875
bank19	4659897	2991848.25	bank16	5709713	3749125.875
bank16	3099129	1431080.25	bank29	3550807	1590219.875
bank6	2407107	739058.25	bank6	3117151	1156563.875
bank27	2151352	483303.25	bank5	1930073	-30514.125
bank20	1956712	288663.25	bank19	1392803	-567784.125
bank7	1907569	239520.25	bank32	987688	-972899.125
bank29	1102536	-565512.75	bank27	807099	-1153488.125
bank8	1008067	-659981.75	bank22	525105	-1435482.125
bank22	724899	-943149.75	bank10	502140	-1458447.125
bank4	400414	-1267634.75	bank15	410983	-1549604.125
bank24	205311	-1462737.75	bank2	406320	-1554267.125
bank5	184953	-1483095.75	bank20	258986	-1701601.125
bank34	100678	-1567370.75	bank34	258424	-1702163.125
bank32	99724	-1568324.75	bank24	130547	-1830040.125
bank1	10662	-1657386.75	bank8	90840	-1869747.125
bank25	7376	-1660672.75	bank7	14843	-1945744.125
bank2	5947.6	-1662101.15	bank1	12687	-1947900.125
bank31	3586	-1664462.75	bank25	9851	-1950736.125
bank14	1026	-1667022.75	bank26	8529	-1952058.125
bank26	941	-1667107.75	bank14	1026	-1959561.125
bank17	197	-1667851.75	bank17	792	-1959795.125
bank12	48	-1668000.75	bank31	370	-1960217.125
bank10	24	-1668024.75	bank4	14	-1960573.125
bank28	0	-1668048.75	bank3	14	-1960573.125
bank15	0	-1668048.75	bank18	0	-1960587.125
bank33	0	-1668048.75	bank33	0	-1960587.125
bank18	0	-1668048.75	bank13	0	-1960587.125
bank36	0	-1668048.75	bank30	0	-1960587.125
bank13	0	-1668048.75	bank23	0	-1960587.125
bank9	0	-1668048.75	bank9	0	-1960587.125
bank30	0	-1668048.75	bank28	0	-1960587.125
bank3	0	-1668048.75	bank36	0	-1960587.125
bank23	0	-1668048.75	bank12	0	-1960587.125
Descriptive statistics	Mean	1668048.75		Mean	1960587.125
	Sum	61717804		Sum	72541728
	Minimum	0		Minimum	0
	Maximum	14722438		Maximum	25418776
N of Obs	37		N of Obs	37	
Note - Compiled by the author on the basis of NBRK data					

Table 4 - Measure of proximity and remoteness of banks for Q4 2011 and 2012. Relationship between banks - lending

2011 .			2012 .		
Bank name	Level summit remoteness	Level proximity to the summit	Bank name	Level summit remoteness	Level proximity to the summit
1	2	3	4	5	6
bank 17	378	9.524	bank 30	354	10.169
bank 30	387	9.302	bank 36	356	10.112
bank 36	388	9.278	bank 13	363	9.917
bank 28	392	9.184	bank 9	366	9.836
bank 13	394	9.137	bank 23	367	9.809
bank 33	396	9.091	bank 17	375	9.6
bank 26	397	9.068	bank 33	376	9.574
bank 23	400	9	bank 21	376	9.574
bank 18	411	8.759	bank 28	378	9.524
bank 21	411	8.759	bank 19	379	9.499
bank 34	411	8.759	bank 27	381	9.449
bank 19	412	8.738	bank 18	383	9.399
bank 25	414	8.696	bank 25	384	9.375
bank 16	415	8.675	bank 29	384	9.375
bank 11	416	8.654	bank 8	385	9.351
bank 27	418	8.612	bank 1	385	9.351
bank 22	418	8.612	bank 35	385	9.351
bank 35	420	8.571	bank 22	387	9.302
bank 29	420	8.571	bank 6	387	9.302
bank 24	421	8.551	bank 11	388	9.278
bank 1	423	8.511	bank 15	391	9.207
bank 8	423	8.511	bank 16	392	9.184
bank 6	424	8.491	bank 24	392	9.184
bank 15	425	8.471	bank 2	393	9.16
bank 2	429	8.392	bank 12	393	9.16
bank 10	429	8.392	bank 37	395	9.114
bank 20	429	8.392	bank 10	397	9.068
bank 5	430	8.372	bank 5	397	9.068
bank 4	431	8.353	bank 32	398	9.045
bank 9	431	8.353	bank 20	398	9.045
bank 14	432	8.333	bank 4	400	9
bank 7	432	8.333	bank 7	400	9
bank 12	433	8.314	bank 14	402	8.955
bank 37	437	8.238	bank 31	410	8.78
bank 31	445	8.09	bank 3	414	8.696
bank 3	448	8.036	bank 26	432	8.333
bank 32	1332	2.703	bank 34	1332	2.703
Note - Compiled by the author on the basis of NBRK data					

Table 5 - Measure of proximity and remoteness of banks as of Q4 2011 and 2012. Relationship between banks - placement of deposits and other liabilities

2011 .			2012 .		
Bank name	Level of remoteness peaks	Proximity level peaks	Bank name	Level of remoteness peaks	Proximity level of the peak
1	2	3	4	5	6
bank32	117	30.769	bank21	54	66.667
bank21	127	28.346	bank19	55	65.455
bank19	128	28.125	bank11	59	61.017
bank11	130	27.692	bank6	66	54.545
bank6	141	25.532	bank37	66	54.545
bank35	142	25.352	bank16	69	52.174
bank25	143	25.175	bank35	69	52.174
bank27	145	24.828	bank24	71	50.704
bank16	148	24.324	bank29	83	43.373
bank37	148	24.324	bank17	87	41.379
bank7	148	24.324	bank7	88	40.909
bank17	149	24.161	bank25	88	40.909
bank31	154	23.377	bank3	89	40.449
bank34	157	22.93	bank27	90	40
bank20	158	22.785	bank2	95	37.895
bank29	162	22.222	bank22	96	37.5
bank10	163	22.086	bank32	98	36.735
bank8	169	21.302	bank14	99	36.364
bank4	169	21.302	bank20	101	35.644
bank1	170	21.176	bank4	102	35.294
bank22	171	21.053	bank15	104	34.615
bank24	172	20.93	bank8	121	29.752
bank14	172	20.93	bank1	123	29.268
bank26	190	18.947	bank26	150	24
bank5	195	18.462	bank31	181	19.89
bank12	205	17.561	bank34	185	19.459
bank2	1152	3.125	bank5	1261	2.855
bank15	1332	2.703	bank10	1296	2.778
bank3	1332	2.703	bank12	1332	2.703
bank18	1332	2.703	bank18	1332	2.703
bank9	1332	2.703	bank9	1332	2.703
bank23	1332	2.703	bank23	1332	2.703
bank33	1332	2.703	bank33	1332	2.703
bank30	1332	2.703	bank30	1332	2.703
bank13	1332	2.703	bank13	1332	2.703
bank36	1332	2.703	bank36	1332	2.703
bank28	1332	2.703	bank28	1332	2.703
Note - Compiled by the Bank on the basis of NBRK data.					

Table 6 - Descriptive statistics to determine the level of proximity and remoteness of banks in the interconnectedness network in 2011 and 2012. Linkage between banks - lending

statistical characterization	2011		2012	
	inFarness	inCloseness	inFarness	inCloseness
Mean	441.946	8.482	412.838	9.131
Sum	16352	313.824	15275	337.852
Minimum	378	2.703	354	2.703
Maximum	1332	9.524	1332	10.169
Number of Obs	37	37	37	37
Note - Compiled by the author on the basis of NBRK data				

Table 7 - Descriptive statistics to determine the level of proximity and remoteness of banks in the interconnectedness network in 2011 and 2012. Linkage between banks - placement of deposits and other liabilities

Statistical characterization	2011		2012	
	inFarness	inCloseness	inFarness	inCloseness
Mean	501.216	17.248	460.378	30.018
Sum	18545	638.168	17034	1110.674
Minimum	117	2.703	54	2.703
Maximum	1332	30.769	1332	66.667
Number of Obs	37	37	37	37
Note - Compiled by the author on the basis of NBRK data				

Table 8 - Measure of banks' intermediate centrality as of Q4 2011 and 2012. Linkage between banks - lending

4Q 2011.		4Q 2012.	
Title banks	A measure of intermediate bank centrality	Title banks	A measure of intermediate bank centrality
bank 21	274.613	bank 21	317.125
bank 19	236.515	bank 19	217.326
bank 11	124.47	bank 8	120.886
bank 22	79.32	bank 11	113.16
bank 27	74.911	bank 6	75.628
bank 8	60.111	bank 16	48.128
bank 35	46.394	bank 22	46.276
bank 6	41.836	bank 1	38.711
bank 29	38.743	bank 27	38.452
bank 25	34.687	bank 26	37.826
Note - Compiled by the author on the basis of NBRK data			

Table 9 - Measure of banks' intermediate centrality as of Q4 2011 and 2012. Linkage between banks - placement of deposits and other liabilities

4Q 2011.		4Q 2012.	
Title banks	A measure of intermediate bank centrality	Title banks	A measure of intermediate bank centrality
1	2	3	4
bank11	282.76	bank21	330.76
bank19	157.604	bank25	182.324
bank21	138.379	bank11	177.276
bank6	115.962	bank16	156.487
bank35	110.422	bank6	134.308
bank25	73.197	bank19	107.668
bank34	65.085	bank8	106.433
bank16	50.477	bank35	79.254
bank29	48.776	bank26	70.5
bank17	47.953		
bank27	46.624		
bank2	44.283		
bank14	39.667		
Note - Compiled by the author on the basis of NBRK data			

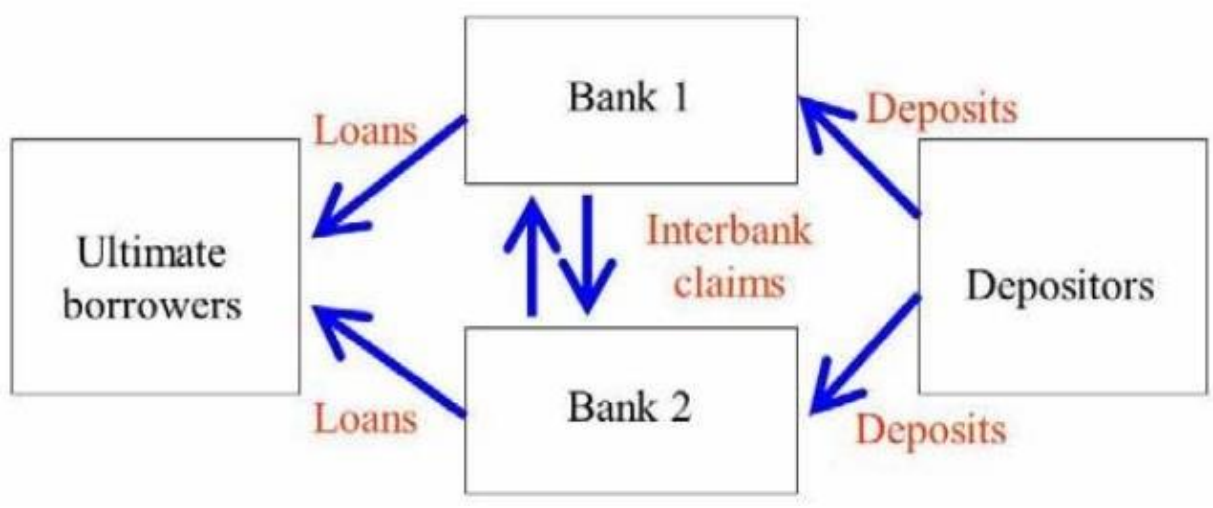


Figure 1 - Standard structure of directions of financial flows in the banking market
Note - Source [1]

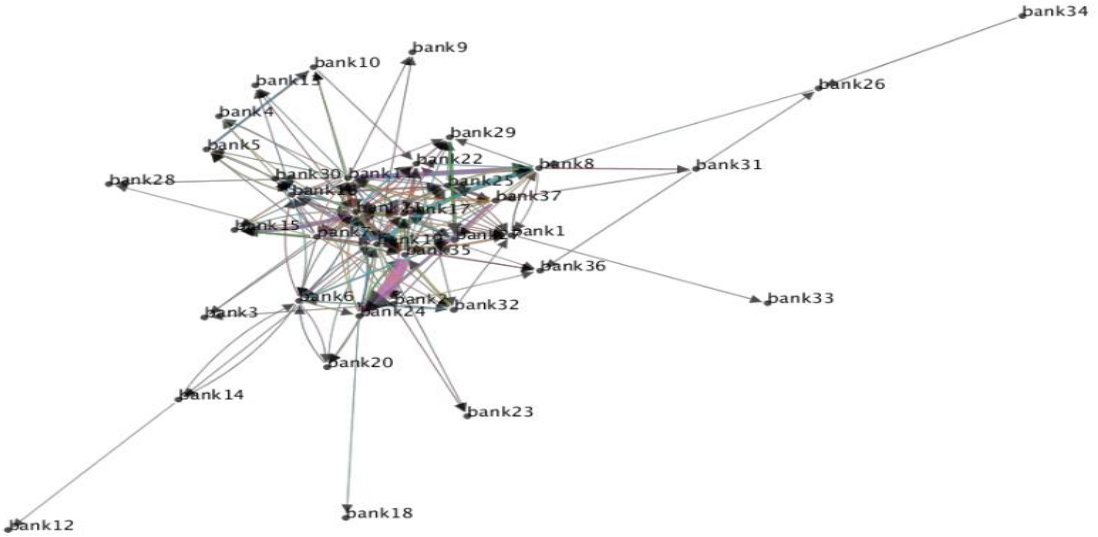


Figure 2 - Interconnectedness of the Kazakh banks through the network of assets at the end of 2011. Note - Compiled by the author on the basis of NBRK data

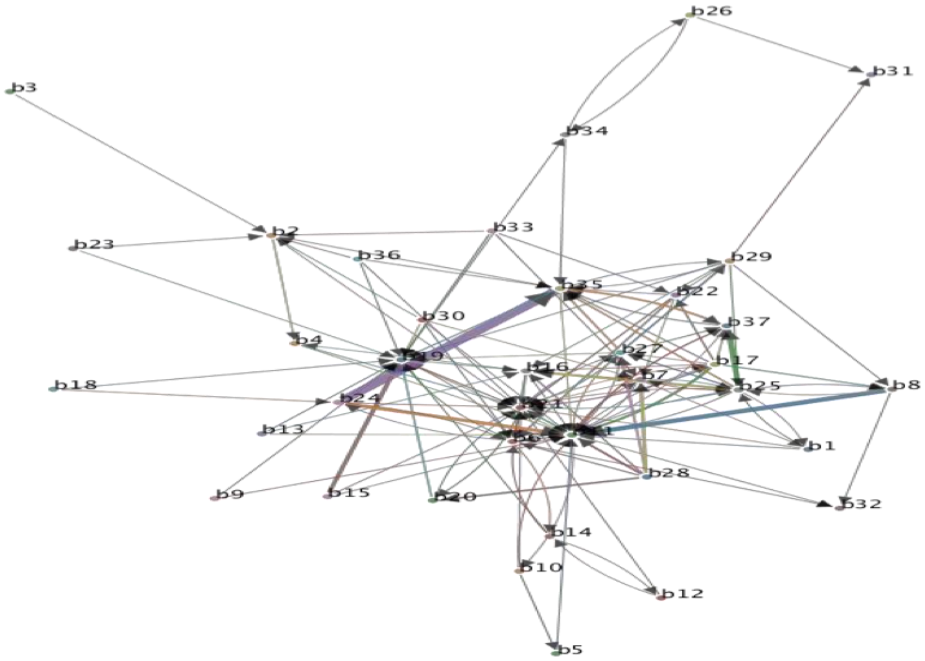


Figure 3 - Interconnectedness of the RK banks through the network of assets at the end of 2012. Note - Compiled by the author on the basis of NBRK data

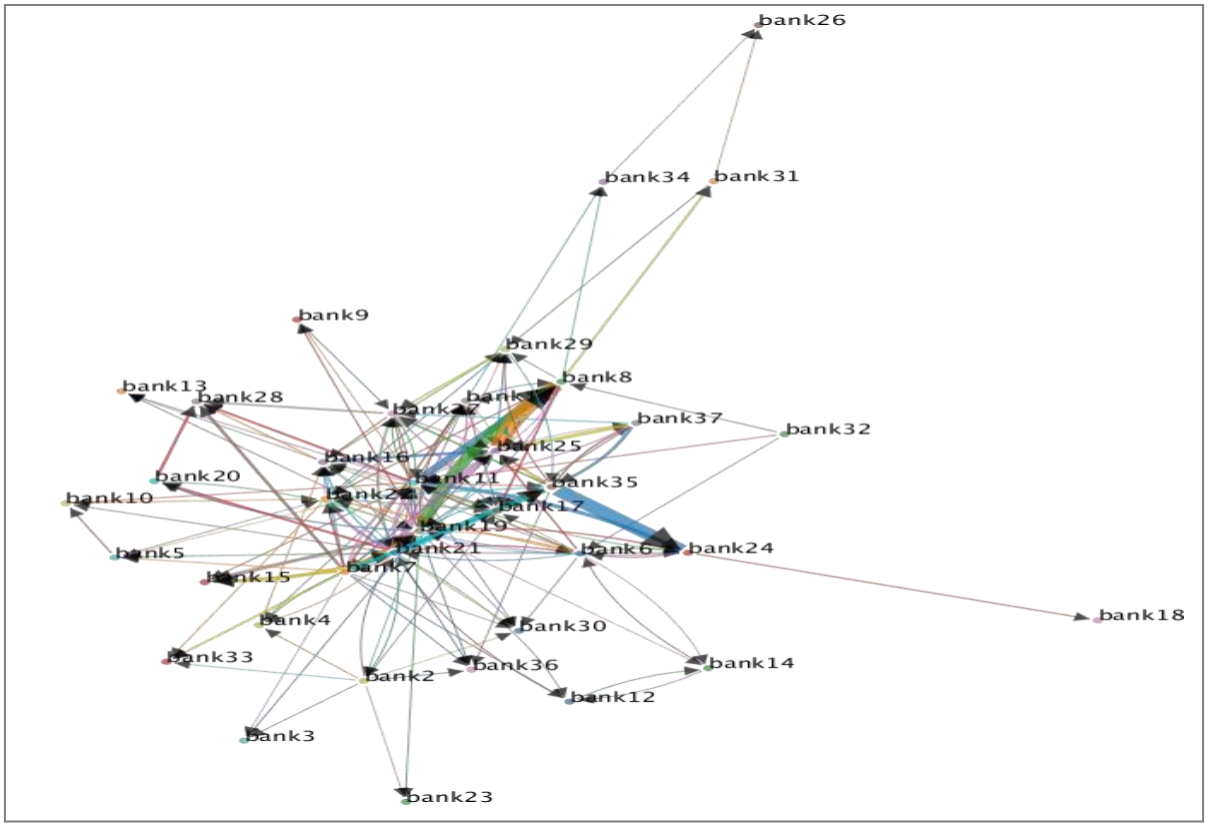


Figure 4 - Interconnectedness of the RK banks through the network of liabilities at the end of 2011. Note - Compiled by the author on the basis of NBRK data

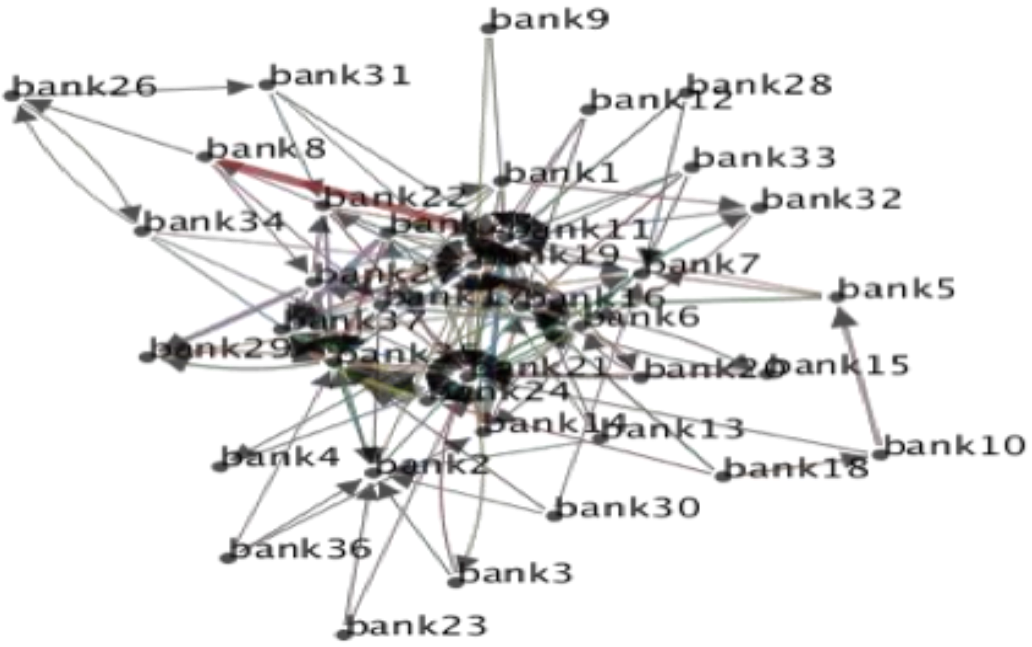


Figure 5 - Interconnectedness of the RK banks through the network of liabilities at the end of 2012. Note - Compiled by the author on the basis of NBRK data

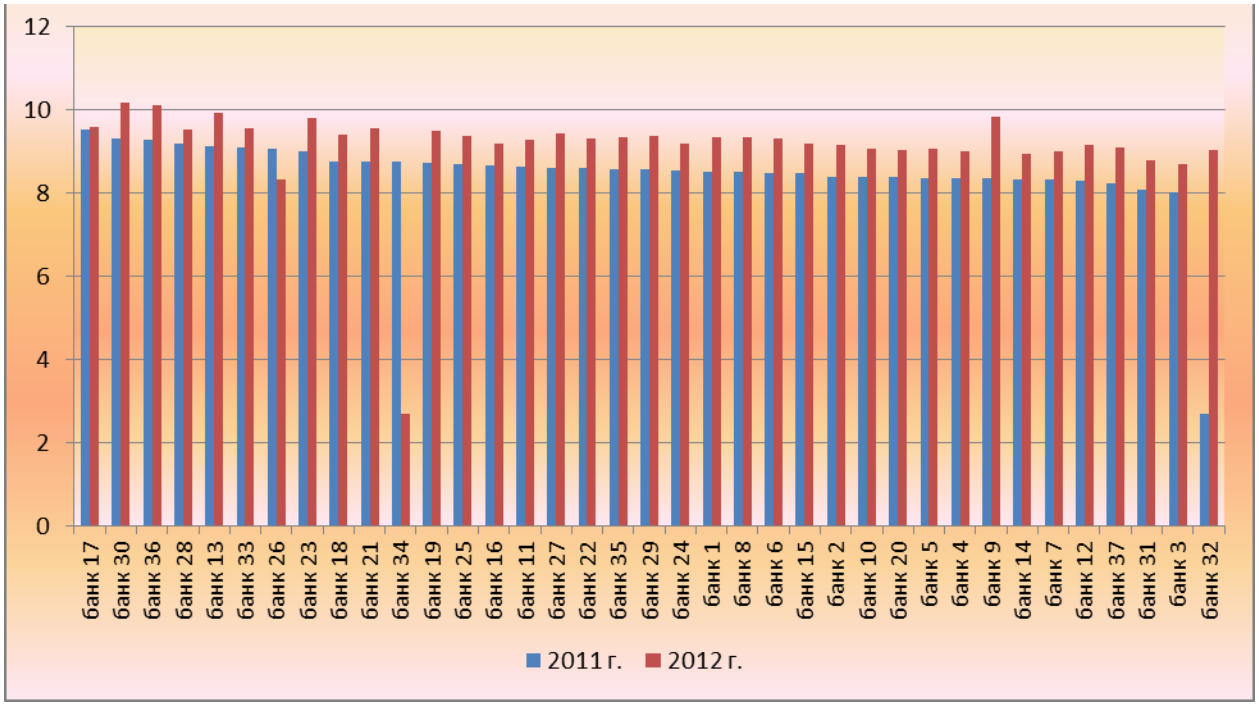


Figure 6 - Proximity level of banks in the interconnectedness network through lending in 2011 and 2012. Note - Compiled by the author on the basis of NBRK data

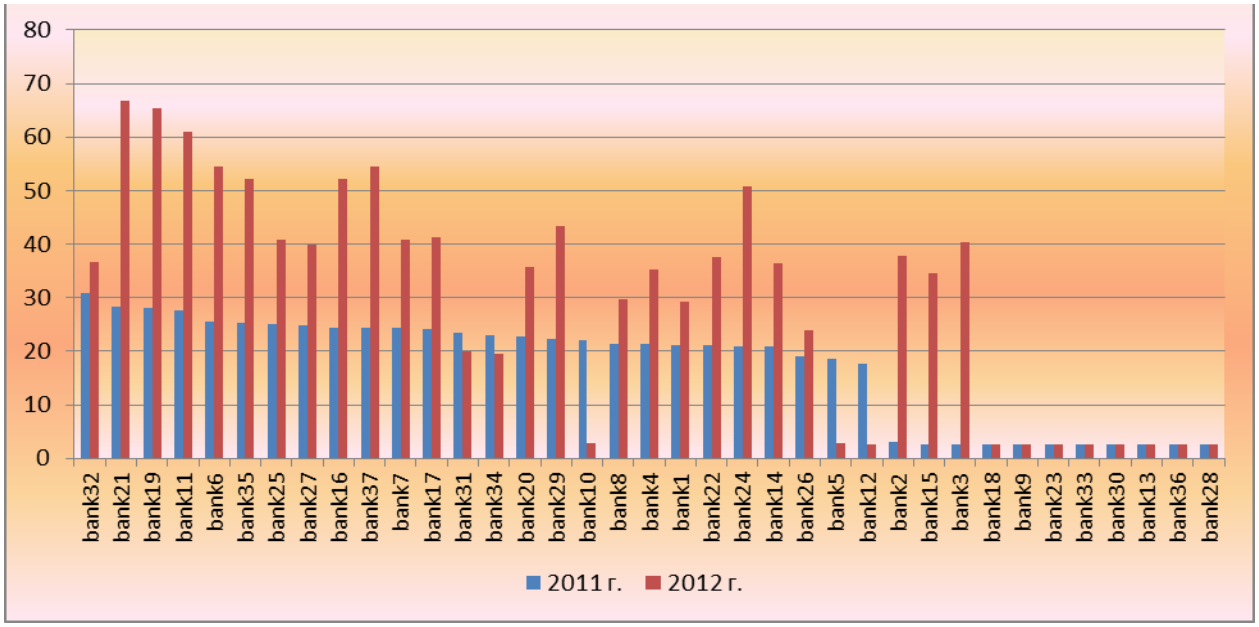


Figure 7 - Proximity level of banks in the interconnectedness network by placing deposits and other liabilities in 2011 and 2012. Note - Compiled by the author on the basis of NBRK data

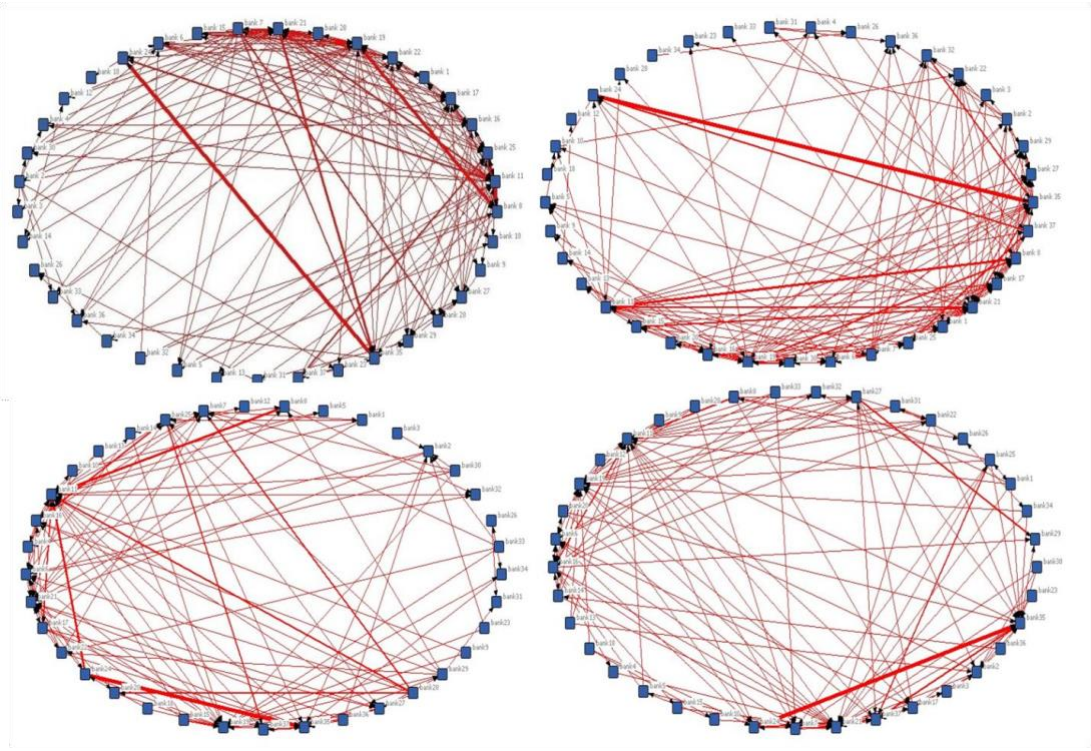


Figure 8 - Optimized topology of graphs (networks) of interdependence of the RK banks
Note - Compiled by the author

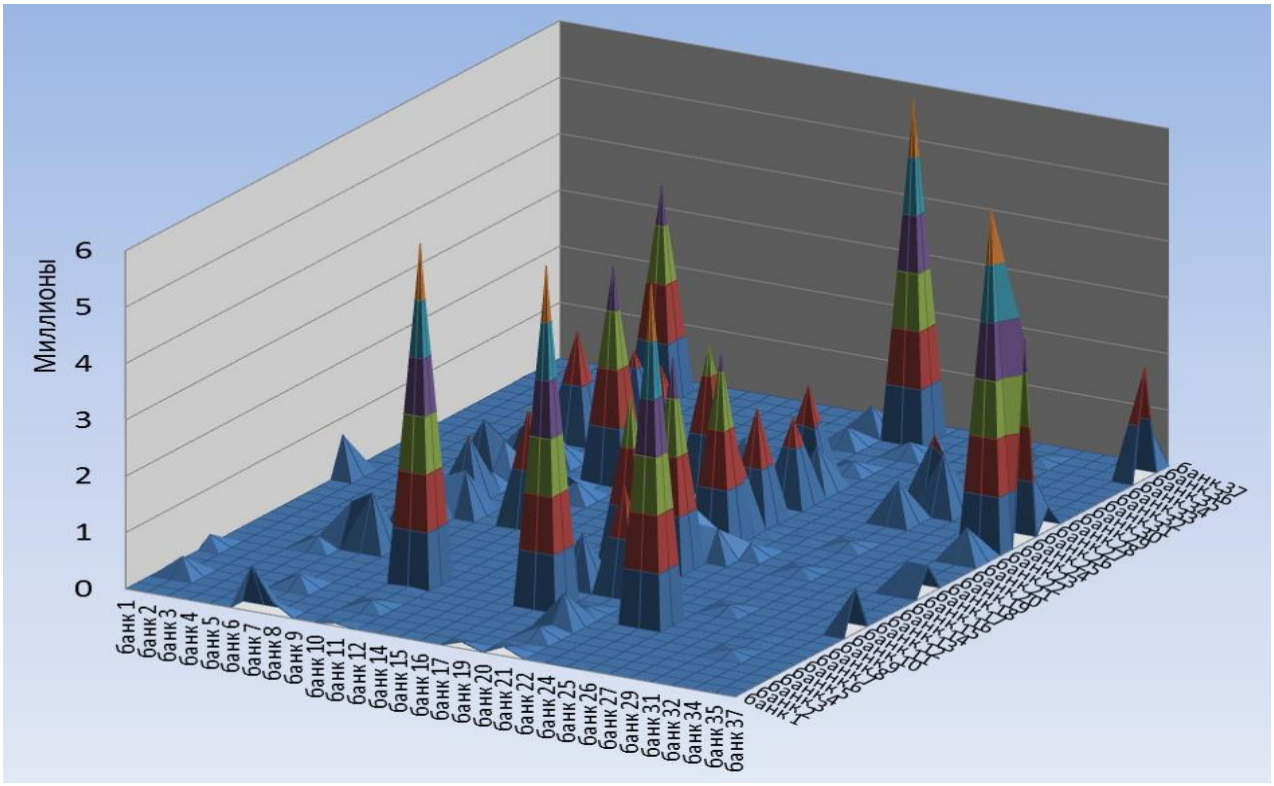


Figure 9 - Levels of bilateral interconnectedness in the interbank market based on 4Q2012 results. Note - Compiled by the author

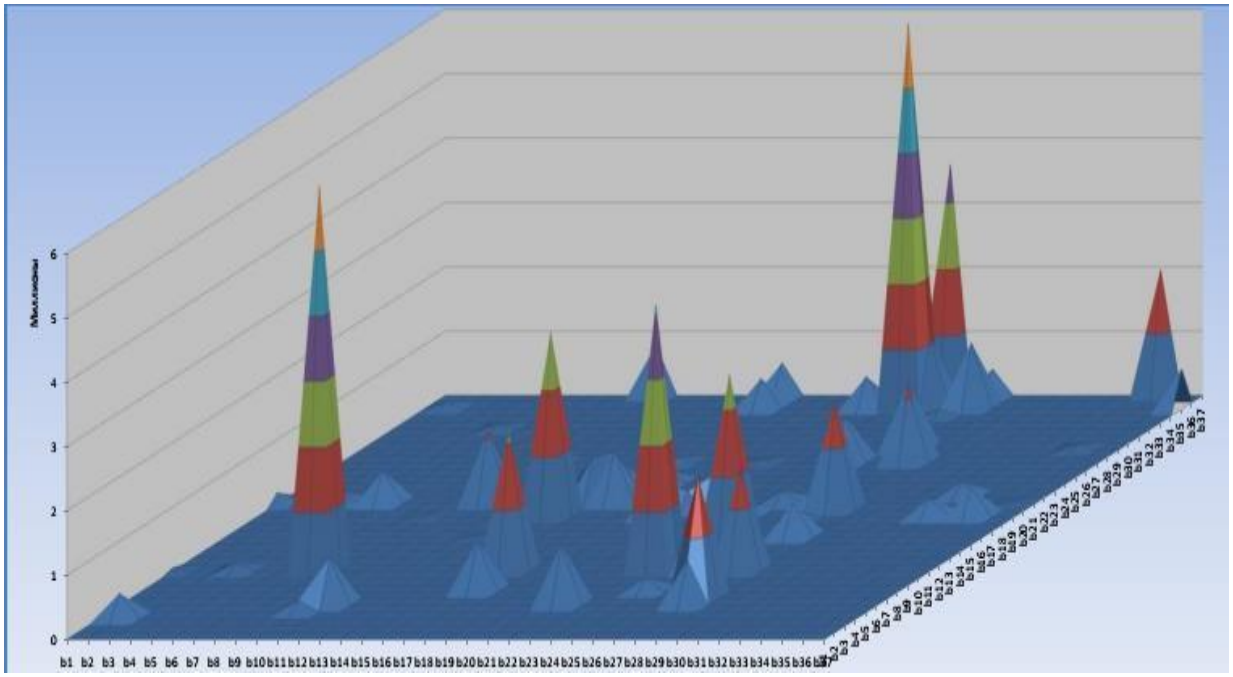


Figure 10 - Levels of bilateral interconnectedness in the interbank market based on 4Q2011 results. Note - Compiled by the author

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