“Clustering of Russian banks: business models of interaction of the banking sector and the real economy”

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Abstract

This paper concentrates on the clustering analysis of Russian credit institutions in order to determine business models of the existing banks activity and expose the possibilities of effective cooperation with the real sector of the economy of the country.

Keywords: bank, clustering analysis, *k*-means method, Kohonen neural network, business model, real sector of economy.
JEL Classification: G21.

Introduction

In theory the system of the interaction between the state and the real sector of the economy is developing through financial intermediaries, and in this particular case through the banking system. The real sector of the economy and households receive financial flows through credit institutions.

In practice the mechanism of resources reallocation will function in another way (Table 1). The developed financial market with its high institutional provision level manifests the asymmetry in interaction between the banking sector and the real sector of the economy. It occurs due to the discrepancies in different rates of profitability and riskiness of the sectors within the generation of the investment income.

Table 1. Main discrepancies of the interaction between the Russian banking sector and the real sector

Discrepancies	Banking sector of economy	Real sector of economy
Profitability	25%	10%
Risks	Moderate risk level – oriented activities	High risk level of a project insolvency
Time of investment income generation	Short-term money – oriented activities	Long-term projects, requirement for long-term money

The shortage of the "long-term money" in the economy to be provided and invested for a long time period is the main problem of the banking system under current conditions. The development of the Russian Federation Central Bank transactions such as the additional issue of long bonds and refinancing credit institutions under the lower interest rates is considered by the contemporary economic theory and practice to be the means of overcoming this shortage. There is a possibility of granting long-term financial resources to the real sector of the economy directly through banks by means of the indicated methods, in the opinion of the analysts basing on the experience of foreign central banks.

However, the events of 2008-2010 have manifested that the refinancing mechanism prove inefficient in the Russian realities. The required resources obtained by the credit institutions have marshaled them to financial markets but not to the real sector of the economy.

Long-term financial resources provision creates an obstacle in terms of a time lag in profit earning as well as results in high enough costs and risks of non-payment of the allocated resources. Attracting long-term resources involves higher costs on interest rates and insecurity of these resources preservation for the period specified in the contract.

There occurs the conflict of interests between the Central Bank and credit institutions, when one party upon providing financial resources plans to use them for the long-term support of the real sector, and the other party applies the obtained resources for its own benefit to make a profit within the short term.

The research of Russian credit institutions based on the clustering analysis of their business strategies fulfillment may seem quite relevant in this respect. The topical issue of the contemporary monetary theory and practice is the identification of bank groups with different business models as well as with their potential opportunities of long-term lending to the real sector of the economy on the background of banking sector stability maintenance as a whole.

The goal of the present study is (1) the research of courses of such asymmetry, one of which, in our opinion, could be the institutional misalignment in the banking system; and (2) the monetary resources effective management tools development to ensure the interaction between the banking sector and the real sector of the economy.

For the purposes of the asymmetry in the interaction between the banking sector and the real sector of the economy research it appears advisable to fulfill the clustering analysis of Russian credit institutions' business strategies and to identify bank groups with different business models as well as with their potential opportunities of long-term lending to the real sector of the economy on the background of banking sector stability maintenance as a whole.

The clustering analysis in terms of a *k*-means method and Kohonen neural networks has been selected as a research tool. The selection of the clustering analysis is substantiated by the necessity to identify internal resources for the interaction between the banking sector and the real sector of the economy.

1. Literature review

Banks' clustering for identification of the banks and the banking system stability is in the focus of the research and practical studies in this area, not considering the interaction with the real sector of the economy which, respectfully, the banking business should be focused on. Contemporary research is focused on the identification of the banking system stability factors in the financial markets and financial services industry.

The paper [10] using the *k*-means method for clustering of 35 largest Austrian banks within the period 1995 to 2000 so as to identify strategic groups of credit institutions is the most close in its meaning to our study. The author has chosen the input parameters of the consolidated index of disposable funds, loans, interbank loans and deposits, deposits and profits, and operational losses. The results of the analysis offer five banks clusters, only three among them could be considered as strategic bank groups with regard to the homogeneity of the clusters. The remaining two clusters manifest indexes volatility. This paper discusses strategic groups of credit institutions and the possibility of their existence, but does not take into account the interaction with the population and the real economy.

Paper [8] divides 48 Polish banks into 5 identified strategic groups such as universal banks, corporate banks, retail banks, mortgage banks, regional banks and banks providing automobile loans. The observation sums up the results of the years within the period from 1999 to 2005. Clustering is based on regression analysis. Besides, the authors record banks migration. In this direction Russian scientist's research was also conducted. Author [3] analyzes the data of Russian banks in the period from 1997 to 1998 by functional focus of these banks. These developments have served as the basis of our work. The difference is that the goal of clustering is not the definition of the functions of credit institutions in the banking system, but the study of problems in the interaction of the banking and real sectors of the economy. As well as identifying the internal capacity of the Russian banks in long-term crediting of the real sector of the economy.

The clustering analysis in paper [7] identifies 5 business models of credit institutions in Australia, which correspond to certain factors determining the financial stability of credit institutions included in the group. Identified groups characterize only the financial stability of the banking system itself, but does not take into account the interaction with the population and the real economy.

Russian scientists are also studying the financial stability of credit institutions. Thus, publications [5, 6] divide credit institutions into large, medium and small size ones, as well as offer the fulfillment of clustering analysis in compliance with CAMELFS indexes of bank activity inside these groups. The group of large size banks comprises 11 business models (4 of which describe 95.1% of the made observations). The group of medium size banks comprises 13 business models (4 groups describe 96% of the made observations). And at last the group of small size banks comprises 28 business models (6 groups describe 90% of the made observations).

The clustering analysis is also used by rating agencies, both domestic (such as Expert RA) and foreign ones, to determine the financial stability of the credit institutions. However, the issues of interaction of banking and real sectors of the economy are also not taken into account, making the study one-sided.

Thus, a feature of the banking sector studies using cluster analysis lies in the variety of approaches and methods for assessing and forming groups of banks. There is no single approach to clustering of the banking system on various grounds. In our work, the Russian banking system clustering is performed by self-organizing neural networks of Kohonen. To compare the results with other types of cluster analysis, the cluster analysis by K-Means, which is present in majority of such studies, is also performed. The main object of study is the liquidity of credit institutions and the business models of interaction between banking and real sectors of the economy. That is, an attempt to combine the analysis of stability of the bank in terms of liquidity risk management and its interaction with the real sector of the economy and the population, is made.

2. Research methodology

The paper pays particular attention to the liquidity management method since a bank is an institution focused on the monetary and loan market. The liquidity of credit institutions is the most important index reflecting bank activities. Therefore, we have attempted to give comprehensive assessment of this index to improve our understanding of the possibilities for bank's interaction with the population and the real sector of the economy.

The reliability of the study is supported by the fact that the indexes calculation has been carried out basing on the current data of the Russian credit institutions disclosing their statements on the site of the Bank of Russia.

Clustering analysis is currently one of the most popular and advanced mathematical grouping methods both in economics and other existing sciences.

Clustering method enables data classification by various properties. Thus, if there is no possibility to logically divide the available data into different groups and the data base is too large, the mathematical clustering method will allow solving the task by means of the developed algorithms. There are a lot of clustering analysis methods; some of them allow to process only small amount of data (e.g. tree-like clustering), some methods are intended for classifying large data bases (e.g. a *k*-means method). Each method works by a unique algorithm; therefore, there appears a problem of choosing the best method for solving topical tasks. Moreover, the uniqueness of the algorithms causes different results of clustering within different solution methods. We have chosen a *k*-means method and Kohonen neural networks for clustering analysis of Russian banks determining the credit institutions activity strategies with regard to the liquidity.

The *k*-means method is the most popular clustering method which assumes the data division into a predetermined number of classes. Vector partition of the array in the process of clustering into the required number of groups occurs depending on the identified center of the defined cluster and the proximity of the set index from the center (Euclidean distance). The program divides the clusters by the maximal external variability and the minimal internal variability. The program recalculates the mass centre for the cluster at every iteration and forms a new grouping. The algorithm tends to minimize the total squared error of the cluster points from the cluster's center [11]:

$$V = \sum_{i=1}^{k} \sum_{x_j \in S_i} (x_j - \mu_i)^2 , \tag{1}$$

where k is the number of clusters, S_i are the clusters obtained, $i = 1,2, \dots , k$ and μ_i is the center of vector's mass; $x_j \in S_i$.

The neural network simulation is a relatively new method of data clustering in the contemporary science. Artificial neural networks are based on the human biological neural networks operation transforming the received information and communicating it to human consciousness. The simplest operation of a neural network involves three types of neurons such as input neurons, hidden neurons and an output neuron. Kohonen's neural networks are also widely used in research studies. A variation of Kohonen's Self Organizing Map (SOM) has been used for Kohonen neural networks. This method is based on non-linear programming able of mass data processing and network self-learning (Table 2). Kohonen's Self Organizing Maps differ fundamentally from any types of clustering since they are capable of unsupervised learning. Supervised learning assumes the existence of two data types (input data and output data), and the task of the network is to create the reflection of one data type onto the other. In case of the unsupervised learning the network will operate only with input data independently determining the structure of the output parameters. The self-learning permits to apply other data arrays to the trained network. For example, the data of the other countries could be applied to the trained network of the Russian banks. Thus, the present method makes it possible to increase the research area to banking systems of other countries. Kohonen's network is designed to identify clusters in data and to learn to understand the very structure of the input parameters. The Kohonen's network algorithm is similar to the k-means method and involves a method of successive iterations, however, Kohonen's model compresses the multidimensional input data space into the two-dimensional output space, while the vectors which are close to one another at the input will be close to one another in the topology map (Table 2).

Vectors of the input signals are processed one by one, and the nearest code vector ("Winner-take-all") $W_{j(x)}$ is found for each of them. Thereupon all code vectors W_l for which η_{jl} ($0 \le \eta_{j\,l} \le 1$) are calculated by the formula [11]:

$$W_l^{new} = W_l^{old} (1 - \eta_{j(x)l} \theta) + x \eta_{j(x)l} \theta , \tag{2}$$

where, $\theta \in (0,1)$ is a learning step. The neighbors of the winning code vector (as per priori specified proximity table) are transferred to the same side with the same vector, in proportion to the proximity degree.

Table 2. Main differences of the chosen clustering analysis methods

	k-means method (*k*-means)	Kohonen's neural network
Maximum amount of data array	No	No
Number of clusters	To be known in advance	To be known in advance

Table 2 (cont.). Main differences of the chosen clustering analysis methods

	k-means method (*k*-means)	Kohonen's neural network
Algorithm	There occurs the vector partition of the array into the required number of groups depending on the identified center of the defined cluster and the proximity of the set parameters from the center (Euclidean distance).	The algorithm is similar to the *k*-means method but Kohonen's model compresses the multidimensional input data space into the two-dimensional output space, when the vectors which are close to one another at the input will be close to one another in the topology map.
Learning	No	Unsupervised learning

The specified systems allow solving the tasks of data classification which can serve as a basis for further research of the chosen array.

3. Scope of research

Software product StatSoft 8.0 and analytical information on the official website of the Bank of Russia for 836 Russian credit institutions as of January 01, 2012 have been used for the research fulfillment. The banking system and statements allow to analyze banks every quarterly date. The initial sampling has been fulfilled basing on the multiple value of the banks quantity index. Further analysis is planned basing on the number of the dates.

The following values characterizing the banking system liquidity have been chosen for clustering analysis indexes:

- Equity capital level.
- Raised funds (deposits): accounts (up to 180 days, up to one year, up to 3 years, more than 3 years).
- Loans: overdraft (up to 180 days, up to one year, up to 3 years, over 3 years).
- Interbank credits (interbank loans): issued and obtained.

Such parameters have been chosen as they reflect the level of the interaction between the bank and the real sector of the economy.

All specified indexes have been calculated with reference to the currency of the bank total balance so as to exclude the scale effect at clustering by the *k*-means method (Table 3).

Table 3. Designation of analyzed indexes

Index	Designation
Equity capital / Balance	ECB
Deposits:	
Customers accounts / Balance	CAB
Deposits up to 180 days / Balance	D180B
Deposits up to 1 year / Balance	D1B
Deposits up to 3 years / Balance	D3B
Deposits over 3 years / Balance	Do3B
Loans:	
Overdraft / Balance	LOB
Loans up to 180 days / Balance	L180B
Loans up to 1 year / Balance	L1B
Loans up to 3 years / Balance	L3B
Loans over 3 years / Balance	Lo3B
Interbank loans:	
Issued interbank loans / Balance	IILB
Obtained interbank loans / Balance	OILB

Interbank loans differ fundamentally from the other indexes by the resources circulation environment (Figure 1). Whereas the deposits and loans circulate within the real sector of the economy, the population and the banking system, the interbank loan forms a process within in the banking system itself, as in this case the resources exchange is carried out solely among the banks. Consequently, both the issued and the obtained interbank loans shall be identified.

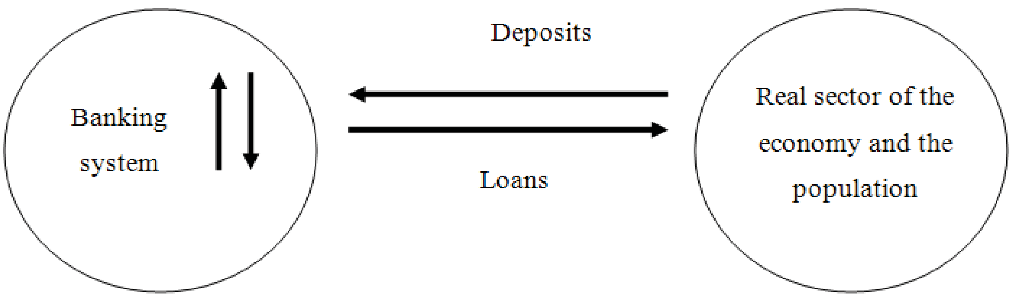


Fig. 1. Credit institutions resources distribution chain

The results of the dispersion analysis have manifested a significant impact of the analyzed variables on the clustering results. Thus, the segments differ by the selected variables. This is confirmed by the fact that at the probability level of 95%, *F*-statistics of the selected parameters is higher than the critical *F* value 2.62 (Table 4).

Table 4. Analyzed indexes' importance factors

Index	*F*-test	Index	*F*-test
ECB	656.45	LOB	9.18
CAB	742.58	L180B	20.75
D180B	16.51	L1B	83.99
D1B	48.04	L3B	115.68
D3B	132.09	Lo3B	33.70
Do3B	12.87	IIBL	71.64
-	-	OIBL	2.85

The clustering analysis by the *k*-means method required the application of the factor analysis to meet the requirements of uniformity and completeness of the available data. The factor analysis resulted in the identification of 13 factors, of which 8 factors explain 78.54% of the dispersion at the significance level of 0.95 (Table 5). The identified factors (Table 3) allow to reduce the correlation dependence among the initial parameters and to eliminate excess variables from further calculations. The most important parameters among the factors have been defined in the matrix of factor loadings. The mark of 0.5 on the Chaddock scale has been chosen as a significance test.

Table 5. Factor loadings matrix

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
ECB		-0,61332						
CAB								
D180B					0.659291			
D1B							0.54635	
D3B		0.511251						
Do3B				0.511538				-0.55343
LOB								
L180B	0.661641							
L1B	0.678683							
L3B			-0.74069					
Lo3B						0.802672		
IIBL		-0.72935						
OIBL				-0.77067				

For better understanding of the identified factors we give their description with reference to liquid resources types used in credit institutions (Appendix). Every factor has an individual value, and at the same time the identified factors can be divided into two big groups such as bank assets sources and loans (Table 6).

Table 6. Factors breakdown by type of activity and credit institution groups

Sources of bank assets	Bank loans
Factor 2: Equity capital, medium-term deposits and interbank loans	Factor 1: Short-term and medium-term loans
Factor 4: Long-term deposits and interbank loans	Factor 3: Long-term loans
Factor 5: Short-terms deposits (up to 6 months)	Factor 6: Overdraft loans
Factor 7: Short-terms deposits (up to 1 year)	
Factor 8: Long-term deposits	

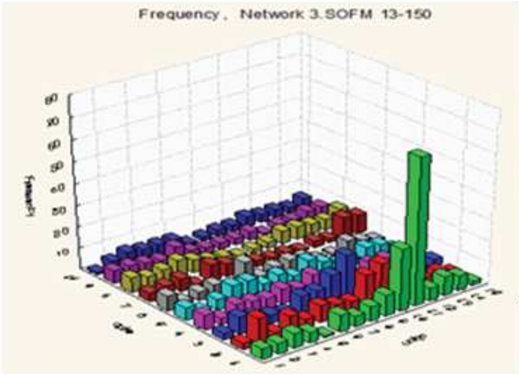
The obtained factors are used as key parameters for banks clustering by the *k*-means method in the research.

The initial parameter values have been used as input data at clustering by the Kohonen's self-organizing neural network method.

4. Description of results

The two most popular and advanced clustering methods, such as the *k*-means method and Kohonen neural networks, have been used to meet the set challenge.

We have identified the maximum value of 150 different bank clusters by means of the neural network simulating (Figure 2). This number has been obtained by detecting the amount of groups having no zero clusters. Clustering has indicated both individuality and high degree of influence rendered by each identified bank group on the money flow market despite the universality of banking activity.



Frequency spreadsheet (2012 итог)
Network: 3.SOFM 13-150
Samples: Train, Test

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	5	5	7	5	1	8	5	7	10	29	68	6	9	7	2
2	3	12	3	8	4	8	6	5	15	18	10	2	4	5	2
3	3	8	6	4	3	8	8	13	20	4	4	3	3	1	4
4	7	3	7	6	5	7	5	9	1	2	2	5	5	2	4
5	6	2	5	9	9	5	7	4	9	6	3	2	6	5	1
6	7	2	4	5	1	11	2	4	5	4	1	1	5	3	1
7	4	5	6	1	8	6	4	3	2	2	1	3	2	10	9
8	7	5	6	8	6	4	3	1	2	3	6	6	5	5	8
9	6	6	5	4	8	4	3	3	3	4	1	3	3	5	5
10	1	4	6	5	5	5	1	2	3	3	5	4	4	3	5

Fig. 2. Clustering into 150 groups by Kohonen's neural networks

The network error at a given number of groups comprises 0.019, i.e. it is in maximal proximity to the final set point of 0.02 (table value of minimum allowable error). The analysis of the network construction error has been carried out for identification of the optimal clusters number. The network error increases evenly as the number of the identified classes reduces, and an abrupt jump in the error value from 0.0498 to 0.0708 occurs between class10 and class 20 (Figure 3).

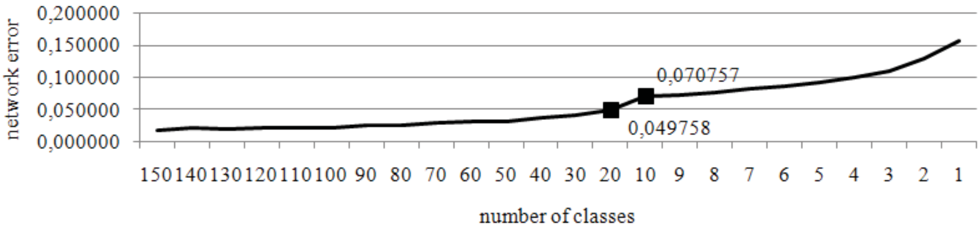


Fig. 3. Dependence of the Kohonen network error change on the number of identified classes (from 150 to 1)

It appeared that the maximum discontinuity is observed in the values of classes 11 and 10 during the step-by-step analysis of the network errors in the given class interval (Figure 4).

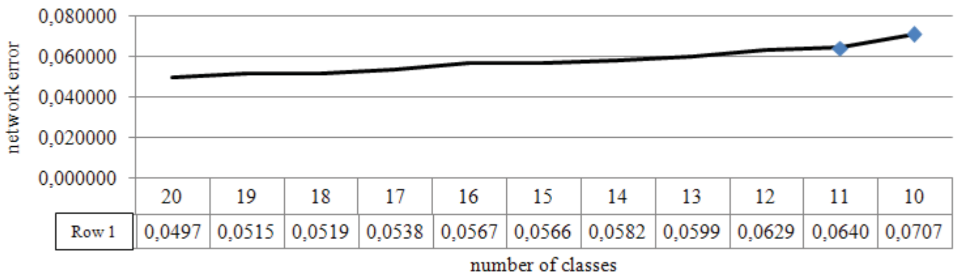


Fig. 4. Dependence of the Kohonen network error change on the number of identified classes (from 20 to 10)

Main statistical factors of clustering into 11 groups by Kohonen neural networks are shown in Table 7.

Table 7. Statistical data of 11 clusters of Kohonen neural network calculations

	Minimum (Train)	Maximum (Train)	Mean (Train)	Standard deviation (Train)	Minimum (Test)	Maximum (Test)	Mean (Test)	Standard deviation (Test)	Minimum (Overall)	Maximum (Overall)	Mean (Overall)	Standard deviation (Overall)
Equity capital	0.0	136384.4	6599.9	13657.5	0.0	97190.1	6431.4	11490.1	0.0	136384.4	6566.6	13251.6
Deposits accounts	0.0	158161.5	17638.7	22325.5	0.0	142761.7	17436.4	22567.3	0.0	158161.5	17598.8	22360.0
Deposits up to 180 days	0.0	220863.6	21292.2	23108.1	0.0	120081.5	21017.8	21497.1	0.0	220863.6	21238.0	22786.9
Deposits up to 1 year	0.0	274925.2	12267.7	21507.5	0.0	79073.7	12009.4	16164.4	0.0	274925.2	12216.7	20554.7
Deposits up to 3 years	0.00	49992.78	900.94	2565.83	0.00	17839.09	1170.59	2862.10	0.00	49992.78	954.16	2627.35

Table 7 (cont.). Statistical data of 11 clusters of Kohonen neural network calculations

	Minimum (Train)	Maximum (Train)	Mean (Train)	Standard deviation (Train)	Minimum (Test)	Maximum (Test)	Mean (Test)	Standard deviation (Test)	Minimum (Overall)	Maximum (Overall)	Mean (Overall)	Standard deviation (Overall)
Deposits over 3 years	0.0	346704.0	15579.4	35339.0	0.0	178547.0	15074.6	25880.6	0.0	346704.0	15479.7	33669.9
Loans up to 180 days	0.0	216073.0	6495.1	19826.0	0.0	122918.7	4917.6	15873.9	0.0	216073.0	6183.7	19112.4
Loans up to 1 year	0.0	158161.5	17638.7	22325.5	0.0	142761.7	17436.4	22567.3	0.0	158161.5	17598.8	22360.0
Loans up to 3 years	0.0	220863.6	21292.2	23108.1	0.0	120081.5	21017.8	21497.1	0.0	220863.6	21238.0	22786.9
Loans over 3 years	0.0	274925.2	12267.7	21507.5	0.0	79073.7	12009.4	16164.4	0.0	274925.2	12216.7	20554.7
Loans Overdraft	0.00	49992.78	900.94	2565.83	0.00	17839.09	1170.59	2862.10	0.00	49992.78	954.16	2627.35
Issued interbank loans	0.0	346704.0	15579.4	35339.0	0.0	178547.0	15074.6	25880.6	0.0	346704.0	15479.7	33669.9
Obtained interbank loans	0.0	216073.0	6495.1	19826.0	0.0	122918.7	4917.6	15873.9	0.0	216073.0	6183.7	19112.4

Mean values in the groups have appeared different when constructing 11 clusters by the *k*-means method (Table 8). This fact confirms the validity of the identified clusters existence assumption.

Table 8. Mean values of clusters identified by *k*-means method

Variable	Cluster										
	No. 1	No. 2	No. 3	No. 4	No. 5	No. 6	No. 7	No. 8	No. 9	No. 10	No. 11
Factor 1	0.067	0.049	0.048	0.055	0.030	0.053	0.038	0.005	0.069	0.053	0.088
Factor 2	-0.066	-0.023	-0.001	-0.088	-0.005	-0.045	-0.033	-0.002	0.019	-0.015	-0.156
Factor 3	0.020	0.024	-0.006	0.004	-0.006	-0.046	-0.053	-0.001	-0.013	0.009	0.011
Factor 4	0.023	-0.018	0.009	-0.027	0.002	0.023	-0.069	0.000	0.013	0.002	0.034
Factor 5	-0.009	-0.035	-0.004	0.083	-0.003	-0.015	-0.011	0.000	-0.011	-0.007	0.021
Factor 6	0.008	0.019	-0.010	-0.038	-0.003	0.001	0.015	0.000	-0.024	-0.004	0.005
Factor 7	0.028	-0.028	-0.005	-0.017	0.001	0.011	0.007	0.001	-0.019	0.025	0.040
Factor 8	0.037	-0.004	0.037	0.018	0.013	0.007	0.010	0.002	0.065	0.011	0.052

Factors analysis of variance for clustering by *k*-means method see in Table 9.

Table 9. Factors analysis of variance for clustering by *k*-means method

Variable	Between	*df*	Within	*df*	*F*	Signif.
	SS		*SS*			*p*
Factor 1	0.477313	10	0.109757	825	358.7787	0.0000
Factor 2	0.821892	10	0.238664	825	284.1066	0.0000
Factor 3	0.206719	10	0.216196	825	78.8837	0.0000
Factor 4	0.204741	10	0.108033	825	156.3515	0.0000
Factor 5	0.093620	10	0.117015	825	66.0057	0.0000
Factor 6	0.057426	10	0.055466	825	85.4152	0.0000
Factor 7	0.176608	10	0.108069	825	134.8226	0.0000
Factor 8	0.252934	10	0.131758	825	158.3744	0.0000

Thus, it has been discovered that the most adequate bank clustering based on the *k*-means method and Kohonen neural networks can be traced by division of the banks array into 11 groups. The results of clustering by means of two methods showed the commensurate results, but Kohonen's neural networks have been selected as the main method, which will subsequently enable the available data prediction.

Four business models of credit institutions have been identified despite the universality of banks.

Here is the description of an average representative of the cluster included in the business model.

1. Business model (clusters 1, 2 and 11): an average representative of this group is characterized as the largest bank in the country which has high values of all considered parameters in absolute terms. The bank is mainly focused on the allocation of short-term loans and overdrafts, and is actually not interested in long-term lending. At the same time the funds are being raised for all priority types, but the preference is given to short-term resources. High capitalization and active participation in the interbank lending market are being observed.

It should be mentioned that the cluster includes both the country's largest banks (Sberbank, VTB, Rosselkhozbank etc.) and the small ones (Paritet Bank).

2. Business model (clusters 3, 4, 5 and 9): these banks prefer to allocate resources on a short-term basis (up to 1 year) and overdraft, or to allocate resources on a super long term basis (over 3 years) at the same time neglecting the medium-term lending. Different policy is used for raising funds. The preference is given to short-term (up to 180 days) and medium-term (1 to 3 years) deposits. The capitalization remains at a mean level and the participation in the interbank lending market is average.

The banks of cluster 1 and cluster 4 have the greatest potential for long-term lending to the real sector of the economy. Currently, the banks still have not realized this potential.

3. Business model (clusters 6, 7 and 8): the group mostly includes small banks which prefer to attract medium-term resources (from 1 to 3 years) and allocate long-term resources (over 3 years). These banks take a passive part in the interbank lending market. The banks of the cluster are in close interaction with the real sector of the economy lending on a long-term basis.

4. Business model (cluster 10): The banks can be considered very small in terms of the amount of the resources passing thorough such banks. But the high level of the capitalization with regard to the attracted resources is worth mentioning. The banks are mainly focused on attracting medium-term resources (from 1 to 3 years) and allocating such resources on a short-term basis (up to one year and overdraft) and a super long-term basis (more than 3 years). The banks participate in the interbank lending market, but the granted and obtained amounts are rather small. The banks of the cluster have enough resources for the long-term lending and use these tools to interact with the real sector of the economy.

Let us consider the business models identified for the credit institutions.

5. Description of the results

The banks in the clusters *1*, *2*, *11* prefer to operate on a short-term basis and conduct a conservative policy (Figure 5). The short-term allocation of the resources implies a low risk level of transactions, and the short-term resource attraction means the low cost of the resources. The given bank group prefers to carry out low risk activities with the lowest possible costs, having large amounts of money as well as possibilities to influence the banking sector. Here belong credit institutions with inefficiently excessive amounts of liquid resources. The banks of this group prefer to keep the existing position without associating their activity with the real sector of the economy. Speaking of the large representatives of this group (including the economy forming banks of the country) we observe the inefficient operation results in the chain "Bank – Real sector of economy and Population", while the small representatives of this group are the prototypes of large banks and are founded either as a credit institution of a particular enterprise, or as a means of quick profits earning without any idea to maintain its activities for a long-term time period. Further assessment of the effective amount and allocation of the banks resources in these clusters shall be necessary.

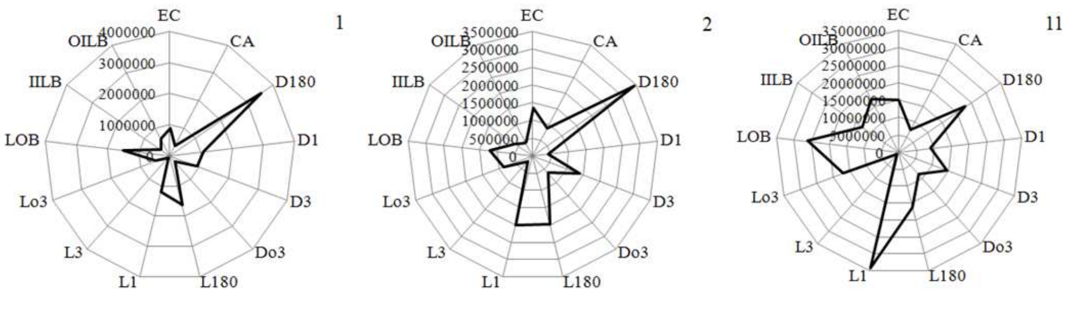


Fig. 5. Mean values of the resources allocation in clusters 1, 2 and 11

On the whole, this business model is characteristic of 389 banks from the whole array. The first cluster includes 34 credit institutions, the second one includes 95 credit institutions and the third cluster includes 260 banks. The credit institutions of the identified clusters include the representatives of the banking sector such as JSC "Sberbank of Russia", JSC "Bank Uralsib"; JSC "Bank VTB", JSC "BankVTB24" JSC "Rosselkhozbank", JSC "MDM Bank", JSC "Bank Zenit", JSC "AKB "Bank Moskvy", JSC "AKB BTA-

Kazan", JSC "Joint Stock Bank "Devon-Credit" (JSC), LLC "Commercial Bank "Intercommerts", JSC "Bank Petrocommerts", CJSC "Raiffeisen Bank", JSC "Rosgosstrakh Bank", CJSC "GE Money Bank", SKB-Bank, Joint Stock Commercial Bank of Commercial Business Promotion.

In respect of clusters *3*, *4*, *5* and *9* banks the imbalance of attracted and allocated resources terms is apparent (Figure 6). When attracting the medium-term resources the banks of this group prefer to allocate them in the assets capable of quick turnover and able to return at least small profits but within ultra short terms, and in the long-term assets capable of high return. These banks are focused on ensuring their own stability rather than on the support of the real sector of the economy. This business strategy could be called a moderate one; however, such imbalances of bank assets and equities terms may have a negative impact on its financial stability during the time of crisis in the economic development.

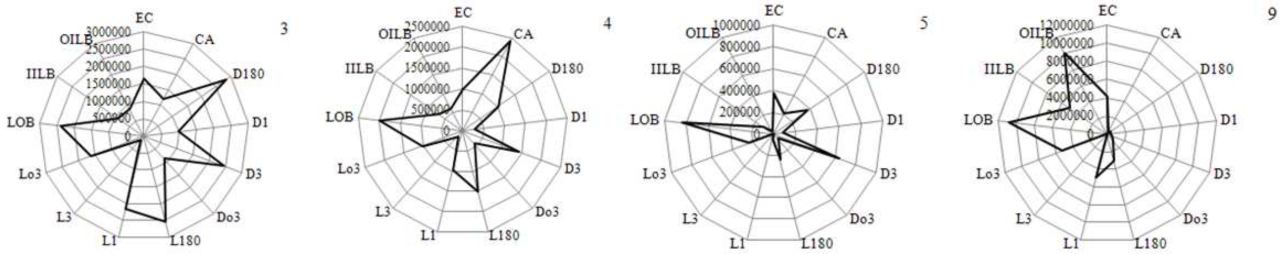


Fig. 6. Mean values of resources allocation in clusters 3, 4, 5 and 9

Altogether clusters *3*, *4*, *5* and *9* include 306 banks; in particular cluster 3 includes 192 credit institutions, cluster 4 includes 62 credit institutions, cluster 5 includes 27 credit institutions and cluster 9 includes 25 credit institutions. The following representatives of this business model shall be mentioned specially: CJSC "Avtogradbank", JSC "Bank Vozrozhdeniye", CJSC "Commercial Bank "Globeks", LLC "Commercial Bank of Economic Development "Bank Kazani", LLC "Vneshprombank", "AKB Spurt" (JSC), JSC "Binbank", JSC "AKB Zarechye", CJSC "Bank "Zerikh", LLC "Tatagroprombank", LLC "Commer-cial Bank "Intercapital-Bank", LLC "RusfinansBank", JSC "Rossiyskiy Bank Podderzhki Malogo I Srednego Predprinimatelstva" (Russian Bank of Small and Medium Size Entrepreneurship Support) (MSP Bank), CJSC "Commercial Bank "DeltaCredit".

The banks of clusters *6*, *7* and *8* conduct an aggressive policy in respect of the liquidity (Figure 7). The credit institutions of this group prefer to allocate the obtained resources in subprime and high-yielding assets, and actively use other banks loans in the interbank lending market as a cushion for their own activities, as such assets can be returned upon a lender's first request and can provide for a stable resource basis capable of ensuring the bank liquidity at any time.

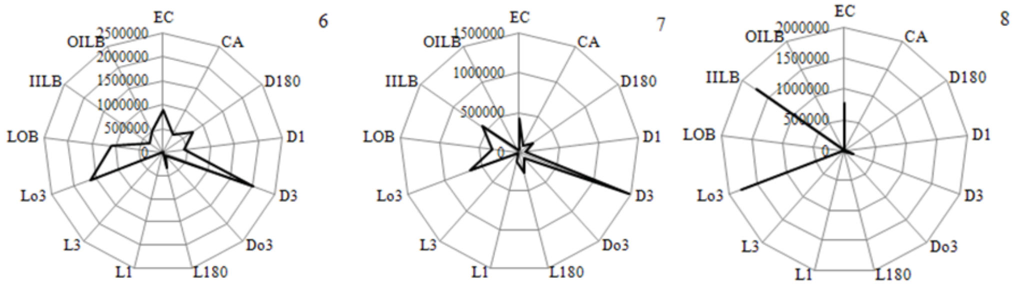


Fig. 7. Mean values of resources allocation in clusters 6, 7 and 8

This strategy may have a negative impact on bank activities under conditions of the economic instability. The banks of these clusters are focused on the interaction with the real sector of the economy.

On the whole, clusters 6, 7 and 8 include 87 credit institutions, and namely 18, 65 and 5 banks respecttively. The list includes LLC "Commercial Bank "BFG-Credit", CJSC "Commercial Bank "Evropeisky Standart", LLC "Commercial Bank "FinTrustBank", JSC "Bank "Purpe", CJSC "Commercial Bank "Evroplan", CJSC "QiwiBank", LLC "OkhaBank".

The strategy of the liquidity management of the cluster 10 banks is similar to that of the cluster 6, 7 and 8 banks with regard to the terms of attracting and allocating the resources (Figure 8). It should be mentioned at this point that the banks of the group 10 have the highest capitalization in relation to the amount of the resources being attracted. Thus, itcan be confirmed that the banks of cluster 10 conduct moderate policy with regard to the liquidity and ensure their activity by high values of their equity that make them reliable and financially stable during crisis in the economic development (it should be noted that the group includes only small banks). The banks of this group are motivated to interact with the real sector of the economy.

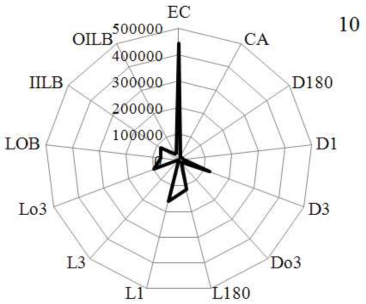


Fig. 8. Mean values of resources allocation in cluster 10

The cluster includes 54 small credit institutions such as LLC "Commercial Bank "Alzhan", CJSC "AKB "Vladicombank", LLC "Commercial Bank "Gefest", CJSC "AKB "Petersburg City Bank", LLC "Commercial Bank "Doris", LLC "Commercial Bank "Makhachkala City Bank", JSC "Commercial Bank "Renta-Bank", JSC " AKB "Severo-Vostochniy Alyans" , JSC "Ukhtabank", LLC "Commercial Bank "Eco-Invest".

Conclusion

At this phase of the work the clustering method has allowed to identify the business models of the credit institutions in the formed groups, to consider the interconnection of the banks in every cluster with the real sector of the economy and suggest possible development ways of this interaction. The hypothesis of the institutional misalignment in the Russian banking system has been confirmed, and we have traced the interaction problem sources between the banking sector and the real sector of the economy during the analysis of the bank business models existing at present.

We plan the further development of effective monetary resources management tools for the insurance of the interaction between the banking sector and the real sector of the economy.

The research work is to be continued in the framework of the developments made by M.Y. Ibragimov and R.M. Ibragimov in respect of the heavy tails theory. It seems possible to apply the theory of heavy tails to the banking sector as alternative stress testing of the identified groups of the credit institutions for their resistance to crisis developments. This will permit to develop an econometric approach to the effective management of the liquidity of the economy as a whole, to consider the monitoring of the banking system not as a separate component that takes into account the issues of the state of the banking sector separately from the other sectors of the economy, but to carry out a comprehensive analysis of the interconnected economic systems. While the current monitoring scheme of the banking system is aimed at processing the available data and short-term forecasting of the banking system condition, the studies will permit to monitor the state and the interaction between the banking sector and the real sector of the economy for the future.

The effective level of the liquidity of the credit institutions in the clusters is to be determined for the efficient interaction with the real sector of the economy and ensuring the banking system stability.

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Appendix

Table 1A. Characteristics of the factors identified upon studying the credit institutions indexes by means of the factor analysis

Factor	Description
Factor 1: Long-term and medium-term lending	The greatest influence is rendered by the following indexes: loans for a period from 180 days to 3 years (short designation (0.66) and medium-term (0.68) loans). This factor indicates the bank activity in the part of short and medium-term loans. That is, the allocation of the available resources on short- and medium-term basis in the real sector of the economy and population.
Factor 2: Equity capital, medium-term deposits and inter-bank loans	The greatest impact has the following indexes: equity (-0.61), deposits from 1 year to 3 years (medium-term resource attraction) (0.51) and interbank loans (-0.73). The bank equity represents the resources of the bank which may also be involved in the turnover and generate profits. In our opinion, this type of resources is to be reasonably referred to the long-term bank resources. Short terms are mostly used as part of the interbank lending; therefore, these resources are referred to the short-term ones.
Factor 3: Long-term lending	The greatest impact has the following indexes: loans over 3 years (long-term loans) (-0.74). This factor indicates the bank activity in the part of the resources allocation on the short-term basis.
Factor 4: Long-term deposits and interbank loans	The greatest impact has the following values: deposits over 3 years (long-term resource attraction) (0.51), interbank loans (-0.77). This factor combines the long-term resource attraction and interbank loans.
Factor 5: Short-term deposits	The greatest impact has the following indexes: deposits up to 180 days (short-term resource attraction) (0.66). This factor indicates the preference on the part of the bank clients to invest for short periods up to six months.
Factor 6: Overdraft lending	The greatest impact has the following indexes: overdraft loans (short-term loans) (0.80). This factor indicates the bank activity in the part of granting short-term loans with a lack of funds on a client's account. Overdraft loan is granted to clients on a contract basis, providing the ability to quickly obtain a loan onto the account; the repayment of the loan shall be effected by the incoming funds.
Factor 7: Short-term deposits	The greatest impact has the following indexes: deposits from 180 days to 1 year (short-term resource attraction) (0.55). This factor indicates the preference on the part of the bank clients to invest for short periods up to a year.
Factor 8: Long-term deposits	The greatest impact has the following indexes: deposits over 3 years (long-term resource attraction) (0.55). The factor indicates the preference on the part of the bank clients to invest for long periods; the client's loyalty to the bank could also be proved.