“Analysis of the stability factors of Ukrainian banks during the 2014–2017 systemic crisis using the Kohonen self-organizing neural networks”

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ANALYSIS OF THE STABILITY FACTORS OF UKRAINIAN BANKS DURING THE 2014–2017 SYSTEMIC CRISIS USING THE KOHONEN SELF-ORGANIZING NEURAL NETWORKS

Abstract

The article proposes an approach to analyzing reliability factors of commercial banks during the 2014–2017 systemic crisis in the Ukrainian banking system, using the Kohonen self-organizing neural networks and maps. As a result of an experimental study, data were obtained on financial factors affecting the stability of a commercial bank in a crisis period.

It has been concluded that during the banking crisis in Ukraine in 2014–2017, the resource base of a bank was the main factor of this bank stability. The most preferred sources of resources were funds from other banks (bankruptcy rate of 5.7%) and legal entities (bankruptcy rate of 8%), and the least stable were funds from individuals (bankruptcy rate of 28.5%).

The relationship between financial stability and the amount of capital and the structure of bank loans is less pronounced. However, one can say that banks that focused on lending to individuals experienced a worse crisis than banks whose main borrowers were legal entities.

The tools considered in the article (the Kohonen self-organizing neural networks and maps) allow for efficiently segmenting data samples according to various criteria, including bank solvency. The "hazardous" zones with a high bankruptcy rate (up to 49.2%) and the "safe" zone with a low rate of bankruptcy (6.3%) were highlighted on the map constructed. These results are of practical value and can be used in analyzing and selecting counterparties in the banking system during a downturn.

Keywords self-organizing neural network, Kohonen map, crisis, bankruptcy, bank reliability, forecasting

JEL Classification C45, C53, G21, G33

INTRODUCTION

In Ukraine, the banking crisis began in 2014 and continued until mid-2017. The formal end to the crisis can be considered a statement made at the beginning of 2017 by the head of the NBU on the transition to the final stage of cleaning the banking system (National Bank of Ukraine, 2017). For Ukrainian banks, this crisis has become unprecedented in terms of losses. Specifically, out of the 181 banks operating in the country in January 2014, only 77 remained operational by May 2019 (National Bank of Ukraine, 2019).

Since the banking system is closely integrated into the structure of the state, its crisis has resulted in many negative consequences, among which there is a deterioration in the development opportunities of

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economic entities due to the almost complete cessation of lending; growth of social tension due to blocking of deposit funds of the population; mass outflow of funds from turnover, etc.

At the same time, an analysis of the past crisis provides an opportunity not only to obtain unique information about the stability factors of Ukrainian commercial banks in the context of economic collapse, to develop methods for identifying reliable banks and forecasting possible failures, but also to compare the results with the findings on the stability of foreign banks in similar conditions (Lopez-Iturriaga & Sanz, 2015). Together, this will clarify knowledge about the banking system stability and the genesis of crisis phenomena.

1. LITERATURE REVIEW

The traditional approach to analyzing counterparty reliability involves the study of their financial performance indicators. However, when the number of subjects studied increases to many tens or hundreds, it becomes almost impossible to solve the problem within a reasonable period using this method.

One of the existing indirect methods for its solution is the calculation of integral estimates using a certain mathematical function, which characterize, for example, the reliability of a prospective counterparty. Under such a concept, the CAMEL, CAEL, CAMELS, FIMS, and UBSS systems (Meyer & Pifer, 1970; Ivasiv, 2004) were created and subsequently spread in the world practice in the 1970s–1990s.

The global financial crisis, which began in 2008, gave an incentive to new studies on the stability of financial and credit systems. Thus, the idea of creating integral indicators is developed, in particular, by Lerner (2011), Borovskiy and Gatinskiy (2011), Režňáková and Karas (2014). However, the works of these authors have a number of disadvantages:

- a rigidly defined set of weighting parameters in the models;
- the number of analyzed indicators and the complexity of the analytical work remain quite high;
- the complexity of assessing the future development of the entity;
- threshold values between the rating stages are averaged and subjective.

In the context of the research methodology, all of these methods are inductive, that is, developed on the "from the particular to the general" principle. Despite the prevalence of inductive methods in economic research, they have a number of disadvantages due to the multiplicity of causes for economic phenomena and the difficulty of extracting them.

The opposite principle, "from the general to the particular", belongs to a group of deductive methods and was much less common with respect to studying the bank stability until the onset of the global financial crisis (2007 year). Examples of its usage include the cluster-regression analysis of financial indicators based on group method of data handling (Sarycheva & Sarychev, 2013). However, most authors use intelligent techniques as the main analysis tool: support vector machines (Erdogan, 2012), extreme learning machines (Yu et al., 2014), self-organizing neural networks (Lopez & Sanz, 2015; Mints, 2015; Negnevitsky, 2017).

A comparative analysis of the effectiveness of various bankruptcy forecasting methods (Spuchl'akova & Frajtova-Michalikova, 2016; Boyacioglu, Kara & Baykan, 2009) showed that the use of intelligent methods allows one to obtain more reliable forecasts of the financial insolvency of economic entities in general and banks in particular, since it reduces the result subjectivity.

It should be noted that among various data clustering tools, self-organizing neural networks are most often used. Pioneering works in this regard were published at the end of the 20th century (Serrano-Cinca, 1996; Deboeck & Kohonen, 1998; Alam et al., 2000). Their universality is confirmed by their usage during the banking systems analysis in the USA (Lopez-

Iturriaga & Sanz, 2015), Turkey (Boyacioglu et al., 2009), Spain (Lopez-Iturriaga & Sanz, 2017), Middle East and North Africa (Calice, 2014), and the European Union (Sarlin & Eklund, 2013; Iwanicz-Drozdowska, Laitinen & Suvas, 2018).

However, most of these studies mainly focus on predicting the financial results of banks, or the facts of their insolvency. They do not adequately address issues of analyzing bank stability factors. In addition, the situation that developed in the Ukrainian banking system during the 2014–2017 systemic crisis was not yet considered in the literature from this perspective, which determines the relevance of the current study.

2. RESEARCH OBJECTIVE

The aim of the article is to develop an approach to the analysis of the activities of Ukrainian commercial banks in a systemic crisis based on intelligent data clustering techniques (Kohonen maps) and its use to identify factors of banks' financial stability in the times of crisis. This will improve the flexibility and efficiency of analysis, will help accelerate bank reorganization system and increase its stability.

3. RESEARCH METHODS

Clustering belongs to a descriptive group of data mining tasks (Mints, 2017). When solving it, one needs to find patterns in the data array, select a certain number of zones (clusters), and distribute the data among them.

Let's consider the main prerequisites for solving the problem of the banking system clustering.

Let n be the number of banks; m is the number of parameters characterizing their activity. Then the data array S, consisting of indicators characterizing the operation of individual banks in the system, will consist of elements s_{ij}, where $i = \overline{1,n}$; $j = \overline{1,m}$.

The indicator m characterizes the dimension of the input data set. That is, when displaying the current state of the bank as a point in multidimensional space, each of the parameters represents one dimension. Thus, with $m = 2$, the entire array of input data can be located in a two-dimensional coordinate system, on a plane where even the visual allocation of groups of close points is possible. When $m = 3$, it will be necessary to use three-dimensional space, which is more difficult to implement.

The complexity of the clustering problem increases with increasing dimension of the input data. In real data with information on assets, liabilities and capital of Ukrainian banks, $m = 60$ and it is impossible to directly display an array of such a dimension.

To solve the problem of clustering multidimensional data, two main methods are used:

- using formal clustering algorithms;
- displaying the multidimensional input data space to one-dimensional, or two-dimensional one, with subsequent visual analysis and cluster allocation (in this case, formal clustering algorithms can also be used, but they are auxiliary in nature).

The second method is more flexible and illustrative to use. Self-organizing artificial neural networks (Kohonen networks) are used as the main tools in such studies. A two-dimension display of a multidimensional input data array obtained using Kohonen self-organizing neural networks is called a Self-Organizing Map (SOM), or a Kohonen map, and is widely used in economic research (Rashkovan & Pokidin, 2016).

Kohonen map is an array of artificial neurons, the number and location of which correspond to the map cells. Each neuron has a number of inputs corresponding to the dimension of the data. Each input corresponds to a certain weighting coefficient w_m^{xy}, and one output, which can take the value of "0" or "1".

To solve the clustering problems, "learning without a teacher" algorithms are used. In the process of training, examples from the input data sample are sequentially supplied to the input of a neural network. For each example, the learning algo-

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rithm finds a neuron whose weighting coefficients are closest to the values of the input data vector (the winning neuron) and adjusts these values so that the neuron becomes even closer to the example. The weighting coefficients of the neurons closest to the winner are also adjusted, though to a lesser extent. The learning process is repeated until the required level of accuracy, or a certain iteration, is reached.

As a result, if elements accumulated (clusters) were observed in the input data space, then similar clusters will also be observed in the resulting two-dimension display. Moreover, if the objects were nearby in the input data set, then they will also be nearby on the Kohonen map (the opposite is not true in the general case).

The coloring of the cells is an important element of the Kohonen map. The color is assigned to the cell depending on the value of the object's attribute. Moreover, for each attribute, its own map is built.

Kohonen maps can be used to analyze data and search for patterns on them, as well as for forecasting.

When analyzing data, the property of Kohonen maps is used to place similar objects nearby. That is, if a significant number of banks that find themselves on one SOM field went bankrupt in the future, then having highlighted the features of financial reporting common to them, one can find attributes for early diagnosis of financial stability problems.

When forecasting, new data are supplied to the input of the neural network that did not participate in the learning process. The neural network will place them in certain cells of the map, where the data from the training sample are already located. After analyzing these data and taking into account the properties of Kohonen maps to place similar objects next to each other, one can make a forecast of financial stability for banks represented by new data.

To solve this problem, the following software products were used in this study: Microsoft Excel™ (data preparation), Deductor Studio™ (modeling and analysis of results).

4. RESULTS

The analysis of bank stability using self-organizing neural networks involves several stages, which will be discussed below.

Stage 1. *Preparation and preprocessing of the input data sample.*

The research information base is made up of open data of the National Bank of Ukraine (NBU) on assets, liabilities and capital of Ukrainian banks (about 60 items in total) (National Bank of Ukraine, 2019). From the general database, annual data on the balance sheet ratios of banks and information on their work, or facts of license revocation were selected. Balance sheet figures are taken according to the following sections:

1) January 2014 (before the crisis and the massive bank failures);
2) January 2015 (peak of the economic crisis);
3) January 2016 (end of the first wave of bankruptcies);
4) January 2017 (end of the second wave of bankruptcies and stabilization of the banking system).

It should be noted that in January 2016, the National Bank of Ukraine slightly changed the structure of the balance sheet items displayed in the consolidated financial statements. Therefore, additional coordination of data from different periods was required.

To comply with data comparability, instead of the absolute values of the indicators of banking activity, the ratio of the respective indicators to the total value of the bank's assets is taken:

$$p_{i,j-1} = \frac{s_{i,j}}{s_{i,1}}, \quad i = \overline{1,n}; \; j = \overline{2,m}, \tag{1}$$

where n is the number of banks; m is the number of parameters characterizing their activity; s_{ij} is an element of the input value matrix S; and p_{ij} is an element of the normalized value matrix P. The first column of the matrix S is the sum of the bank's assets.

Note that this way of presenting data is not the only one. For example, according to Rashkovan and Pokidin (2016), the input sample consists mainly of calculated indicators characterizing the business models of banks. Lopez-Iturriaga and Sanz (2015), similar to the current article, use relative indicators, but standardize them not only on the value of assets, but also on the amount of capital or the amount of loans, depending on the economic substance of the indicator.

In addition to the normalized balance sheet ratios, the following parameters that fulfill the service function are also included in the input sample:

- the year, to which the data relates;
- information on the fact of the bank's bankruptcy in the near future;
- information on the closing time of the bank, if any, before 2019.

It should be noted that official information provided by the National Bank of Ukraine is sometimes controversial. For example, data on the banking system performance as of January 1, 2016 have no information on banks whose license was revoked later, namely in the first four months of 2016. In such cases, the data was taken from the nearest report where they were present.

Another factor that must be taken into account when creating an input data sample is the reason for revoking a banking license. During the period under review, in addition to insolvency, the reasons for the license withdrawal from banks were as follows:

- being in uncontrolled territory (four banks);
- self-closing (three banks); and
- law violation in the field of financial monitoring (three banks).

Except for the last reason, in other cases, the "bankrupt" label was not set in the line with the bank data. The total sample size was 549 lines.

Stage 2. *Preliminary data analysis using statistical methods.*

Statistical analysis of the input sample is carried out in order to identify emissions, that is, anomalous values that are outside acceptable limits. If this is not done, then the effectiveness of further analysis can be significantly reduced due to the peculiarities of the work of neural network learning algorithms.

Table 1. Statistical analysis of input data characteristics

Source: Developed by the authors.

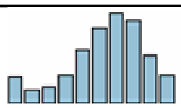
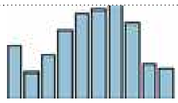
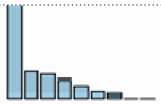
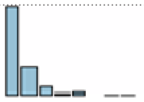
No.	Column label	Statistics: Number of values = 513				
		Histogram	Minimum	Maximum	Average	Standard
12	Loans and customer debts, total		0	0.991076267	0.5738373995	0.2369967493
13	Loans and debts of legal entities, total		0	0.991055805	0.4983580241	0.2480676022
14	including in foreign currency		–0.101010656	0.767642824	0.1555882853	0.1726884517
15	Reserve for impairment of loans and clients debt		–20.96070434	0	–0.1341762336	0.92938949
16	Loans and debts of individuals, total		–0.037305207	0.788363703	0.07547937538	0.1271222111

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Table1 shows a sample of the statistical characteristics of an input data array.

When analyzing emissions, the main feature is the distribution of parameter values presented in Table 1 as a histogram. The minimum and maximum values of the parameters should also be taken into account.

In the absence of emissions and anomalous values of the parameters, the distribution histogram should approximately correspond to one of the distribution laws for random variables, for example, the normal distribution (parameters 12 and 13 in Table 1), the Pareto distribution (parameters 14 and 16 in Table 1), and the uniform distribution or others. As for parameter 15 (Reserve for impairment of loans and clients debt), its distribution is clearly asymmetric. Problems with this parameter are also indicated by its minimum value (–20.9). Given equation (1), this means that one of the banks has reserves almost 21 times higher than the balance sheet amount of assets. Obviously, this situation is not normal and should not be used to cluster data so as not to cause distortion.

The analysis showed that out of 549 lines in the input data, 36 lines contain data outside the interval [–1; 1]. At the same time, only two banks out of all for which this anomaly was observed in 2014–2015 avoided further bankruptcy (Table 2).

Thus, one can conclude that banks with anomalous values of balance sheet ratios have problems with financial stability in most cases. Moreover, this connection is so strong that such banks can be excluded from further consideration as obviously problematic. This will improve the statistical characteristics of the data sample without further processing.

Table 2. Anomalous values of balance sheet ratios of Ukrainian commercial banks in 2014–2015

Source: Developed by the authors.

Year	No.	Bank name	Bankrupt	Data	Reserve for impairment of loans and clients debt	Customer funds, total	Total liabilities	including in foreign currency	Authorized capital	Retained earnings (uncovered loss)
2014	26	RODOVID BANK	0	2016	0.2990719	0.023915	0.596196	0.020151	1.39535	–1.1307
2014	78	KYIV	1	2015	–0.5037935	0.210832	0.62713	0.062243	1.685023	–1.63459
2014	99	KREDYTPROMBANK	1	2015	–0.0043255	0.34597	0.91959	0.639637	2.184311	–2.26212
2014	112	OMEHA BANK	1	2015	0	0.003934	0.390203	0.663506	6.610026	–6.50582
2014	159	DANIEL	1	2014	–1.4328509	1.013707	2.40487	0.474373	0.323363	–1.84727
2014	181	UKRAINSKYI BANK REKONSTR.TA RC	0		–0.0003551	0.00314	0.303495	0	1.01106	–0.34866
2015	21	VIEIBI BANK	1	2014-9	–0.4256711	0.960931	1.624237	0.648219	0.26681	–1.0251
2015	27	RODOVID BANK	0	2016	–0.3454484	0.003945	0.609504	0.02494	1.448687	–1.19874
2015	49	EKSPOBANK	1	2014-9	–0.2326376	0.779024	1.212618	0.307295	0.130169	–0.37666
2015	67	KYIV	1	2015	–0.8170847	0.315918	0.339136	0.110221	2.403109	–2.838
2015	68	MISKYI KOMERTSIINYI BANK	1	2014-9	–20.960704	23.45902	28.76264	13.58776	3.160414	–31.0273
2015	84	BH BANK	1	2014-9	–0.4360523	0.943454	1.244619	0.619234	0.203704	–0.50692
2015	85	KREDYTPROMBANK	1	2015	–0.0294718	0.350105	0.331736	0.391146	2.031481	–2.07314
2015	102	OMEHA BANK	1	2015	0	0.010573	0.902373	0.633405	7.485793	–7.38825
2015	107	BANKKAMBIO	1	2014-9	–1.2535836	1.107161	1.851141	0.778576	0.250723	–1.15984
2015	123	NEOS BANK	0		–0.0357466	0.344516	0.7322	0.281769	0.246335	–1.21656
2015	129	PORTO-FRANKO	1	2014-9	–1.3499269	1.163798	1.998663	0.373403	0.275296	–1.29286
2015	131	BANK DEMARK	1	2014-9	–2.8954154	2.238719	3.063366	0.75611	0.507803	–2.66919
2015	133	LEHBANK	1	2014-9	–0.490151	1.064828	1.248806	0.653929	0.281446	–0.61439
2015	148	AKSIOMA	1	2014-9	–2.5480337	0.375032	1.003878	0.023963	1.775075	–1.83475
2015	157	UKRAINSKYI BANK REKONSTR. TA RC	0		–0.0911815	0.001953	0.340306	0	1.110158	–0.48848
2015	158	MELIOR BANK	1	2014-9	–3.2648135	1.117728	1.126205	1.23E–06	2.241492	–2.38883

Table 3. Statistical characteristics of parameter 15 after eliminating anomalous values

Source: Developed by the authors.

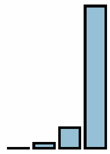
	Column label	Statistics: Number of values = 513			
		Histogram	Minimum	Maximum	Average
15	9.0 Reserve for impairimpairment of loans and clients debt		–0.785769326	0	–0.05735290942

Table 3 shows the characteristics of parameter 15 (Reserve for impairment of loans and clients debt) after the lines containing anomalous parameter values were excluded from the sample.

If one compares the histogram of this parameter in Tables 1 and 3, it becomes evident that the distribution in Table 3 becomes similar to the Pareto distribution. Similar changes are observed in the statistical characteristics of the remaining parameters.

After excluding 36 banks with anomalous balance sheet ratios from the sample, 513 lines remained. Of these, 111 lines contain the "bankrupt" label, which means that the bank with these balance sheet ratios has ceased to be solvent within one year.

Stage 3. *Building Kohonen map construction.*

The process of drawing SOM within the framework of the Deductor Studio analytical platform is carried out interactively, without programming. In this case, it is only necessary to set the basic parameters: the composition and purpose of the data used, Kohonen map parameters, training parameters and settings for the result visualization.

The data used in training include all columns of the input sample, except for service data and information on bank bankruptcy.

After several experiments with different versions of Kohonen maps, their dimension was 8x6, as a compromise, based on the size of the input data sample and the necessary accuracy of clustering.

Training parameters were set based on the requirements for obtaining an accurate result, to the detriment of the speed of training. In particular, the following parameters are set:

- Training epochs: 3000 (default: 500)
- Training rate at the end of learning: 0.001 (default: 0.005)
- Neighborhood function for training: Gaussian (default: bubble)

Let's consider a data analysis procedure using Kohonen maps.

As a training sample, the entire volume of prepared data is taken, that is, the banks' balance sheet ratios for the period from 2014 to 2017. Automatic clustering resulting in four-cluster SOM is shown in Figure 1.

When analyzing the properties of clusters, let's focus on the total number of banks that fell in each of the clusters, as well as on the share of failed banks in this number (see Table 4). Note that the average share of 111 bankrupt banks in a sample of 513 banks is 21.63%.

Table 4. SOM (2014–2017). Analysis of bank reliability by automatically allocated clusters

Source: Developed by the authors.

The cluster's number	Banks total	Including failed banks	Proportion of failed banks, %
0	114	21	18
1	155	37	24
2	165	46	28
3	79	8	10

It follows from Table 4 that cluster 3 includes the most reliable banks. Let us consider the profiles of clusters in order to highlight the specific features of cluster 3 (Table 5).

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Source: Developed by the authors.

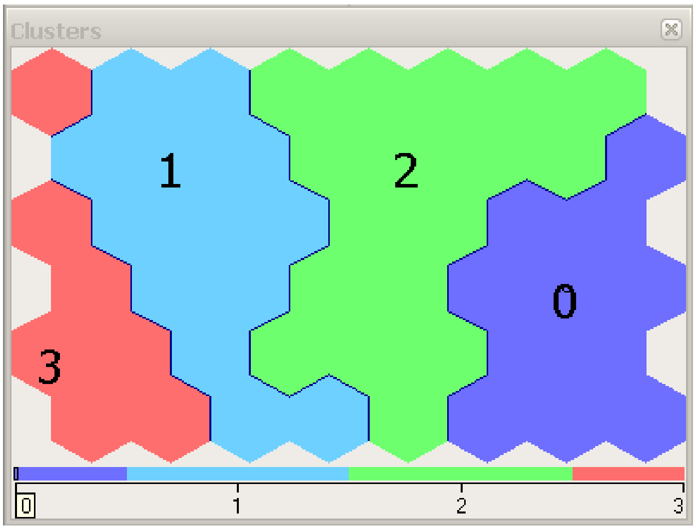


Figure 1. SOM (2014–2017). Automatic clustering

Table 5. SOM (2014–2017). Analysis of the selected clusters' profiles

Source: Developed by the authors.

		Cluster				
		2	**1**	**0**	**3**	**Total**
Fields	**Index**	165 (32.2%)	155 (30.2%)	114 (22.2%)	79 (15.4%)	
Capital total	Importance	100%	100%	100%	100%	100%
	Average	0.1780	0.1505	0.5942	0.1599	0.2594
Authorized capital	Importance	100%	100%	100%	99,80%	100%
	Average	0.1629	0.1405	0.5426	0.1758	0.2425
including Total liabilities in foreign currency	Importance	100%	100%	100%	100%	100%
	Average	0.2460	0.4452	0.0839	0.5832	0.3221
Total liabilities	Importance	100%	100%	100%	100%	100%
	Average	0.8220	0.8495	0.4058	0.8401	0.7406
including funds of individuals total in foreign currency	Importance	42.40%	100%	100%	52.10%	100%
	Average	0.1406	0.2251	0.0366	0.1567	0.1455
funds of individuals, total	Importance	100%	100%	100%	97.80%	100%
	Average	0.3477	0.3589	0.0884	0.2304	0.2754
funds of legal entities, total	Importance	100%	57,80%	100%	99,90%	100%
	Average	0.3351	0.2770	0.1807	0.2134	0.2645
Customer funds, total	Importance	100%	100%	100%	100%	100%
	Average	0.6828	0.6358	0.2691	0.4438	0.5399
including The funds of banks in foreign currency	Importance	100%	87.70%	100%	100%	100%
	Average	0.0291	0.0511	0.0023	**0.2394**	0.0621
The funds of banks	Importance	99.90%	13.90%	100%	100%	100%
	Average	0.0733	0.1102	0.0508	**0.2613**	0.1084
including Total assets in foreign currency	Importance	100%	100%	100%	100%	100%
	Average	0.2098	0.4170	0.0957	0.5554	0.3002
including Loans and debts of legal entities in foreign currency	Importance	100%	100%	100%	100%	100%
	Average	0.0714	0.2163	0.0181	**0.4262**	0.1580
Loans and customer debts, total	Importance	1.30%	33.10%	99.90%	100%	100%
	Average	0.5870	0.5937	0.4777	0.7299	0.5867
Loans and debts of legal entities, total	Importance	98.70%	81.40%	96.00%	100%	100%
	Average	0.4546	0.5292	0.4438	0.6676	0.5075
Funds of individuals on demand	Importance	97.90%	99.10%	100%	99.80%	100%
	Average	0.0688	0.0698	0.0246	0.0390	0.0547

Source: Developed by the authors.

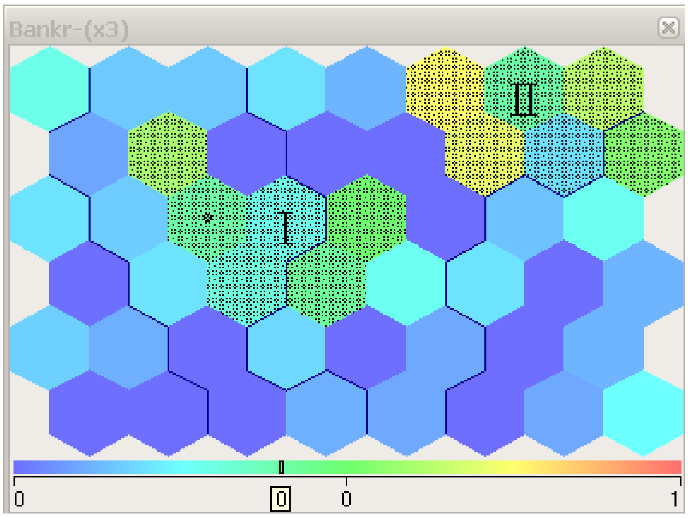


Figure 2. SOM (2014–2017). Local zones on the bank solvency map

The data in Table 5 are arranged in decreasing order of importance for clustering. An analysis of the data shows that the most specific features of cluster 3 are as follows:

- a high share in liabilities of other banks' funds in foreign currency (23.94% relative to the balance sheet currency, compared to the average of the system 6.21% and 5.11% in the nearest cluster);
- a high share in liabilities of other banks in all currencies (26.13%, compared to the average of the system 10.84% and 11.02% in the nearest cluster);
- a high share of foreign currency loans to legal entities (42.62%, compared to the average of the system 15.8% and 21.63% in the nearest cluster).

In addition, it is possible to note a relatively high level of values for items such as:

- total liabilities in foreign currency;
- total assets in foreign currency;
- loans and customer debts, total;
- loans and debts of legal entities, total.

To reduce the article's volume, Table 2 only analyzed the 15 most significant parameters. The analysis of the complete profiles of clusters outside this sample made it possible to further note the high level of deferred tax assets (0.85% at an average of 0.32%) and the low level of securities in the portfolio for redemption (0.9% at an average of 3.5%), as well as a low level of reserves for fund impairment in other banks (–0.065% at an average of –0.455%). Thus, the main difference of a group of banks in cluster 3 is the high proportion of foreign currency transactions conducted with banks and legal entities.

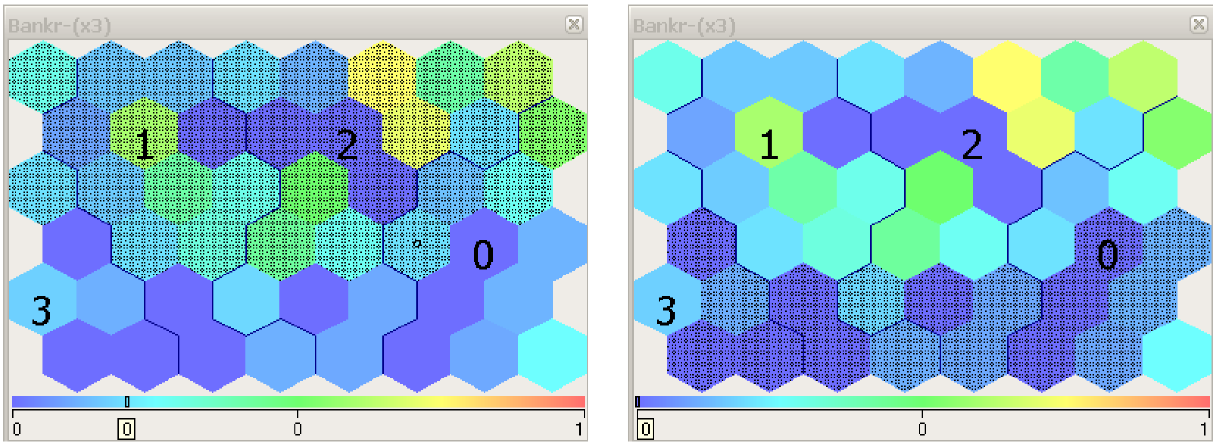
However, automatic clustering does not always allow for finding the best way to divide data into groups. Therefore, the study will further consider a manual method of clustering data on Kohonen maps. Let's consider a map colored according to the average solvency of banks (Figure 2).

The map (see Figure 2) shows two main zones with high concentration of insolvent banks. In zone I, out of 78 banks, 34 were insolvent (43.6%). In zone II, 32 out of 65 banks (49.2%) became insolvent. As can be seen from the figure, none of these zones are completely located in any of the clusters that are automatically allocated.

If we consider the map as a whole, it can be noted that the "safe" zone is located at its bottom, the "hazard" zone is, on the contrary, on the top of the map (Figure 3).

http://dx.doi.org/10.21511/bbs.14(3).2019.08

Source: Developed by the authors.



a) "Hazardous" zone

b) "Safe" zone

Figure 3. SOM (2014–2017). Global zones on the bank solvency map

The marked zones in Figure 3 correspond to the following solvency ratios:

- zone a): 97 banks out of 325 (29.8%) are insolvent;
- zone b): 11 banks out of 174 (6.3%) are insolvent.

Thus, manual clustering made it possible to make bank segmentation more efficient. This Kohonen map can already be used for a preliminary assessment of the financial partners' reliability.

Unfortunately, the Deductor Studio system does not support the ability to build manually selected cluster profiles. Therefore, Kohonen maps built for individual balance sheet items are used to analyze the features of the financial statements of banks with different solvency.

A visual analysis of the full set of Kohonen maps showed that its liabilities structure is closely related to the bank's solvency. The boundaries of the zones on the liabilities maps are predominantly horizontally oriented, which corresponds to the conclusions made earlier about the location of the "hazardous" and "safe" zones.

The remaining balance sheet ratios are statistically weakly related to the bank solvency. Thus, the Kohonen maps of indicators of the authorized capital and structure of loans clearly distinguish zones of varying intensity, the boundaries of these zones are vertically oriented, so they do not have a significant impact on bankruptcy statistics. It can be generally noted, however, that large capital is preferable to small, and loans to legal entities are preferable to personal loans.

Consider Kohonen maps built for selected indicators of bank liabilities (Figure 4).

An analysis of the first two maps (see Figure 4) allows for identifying a cluster of banks with a high level of funds of other banks in liabilities. A cluster of banks borrowing from other banks in foreign currency is even more clearly distinguished. It is in this cluster that a record low level of bankruptcies is observed: four banks out of 70 (5.7%). These banks were Miskyi Komertsiinyi Bank, Bank Demark, Ukrhazprombank, and Finbank.

The "safe" zone also includes banks, in the liabilities of which a large share is accounted for funds of legal entities, especially funds in foreign currency and demand deposits. The bankruptcy rate in the corresponding cluster is 8% (five banks out of 62).

On the contrary, a large share of individuals' funds, regardless of currency and terms, puts the

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Source: Developed by the authors.

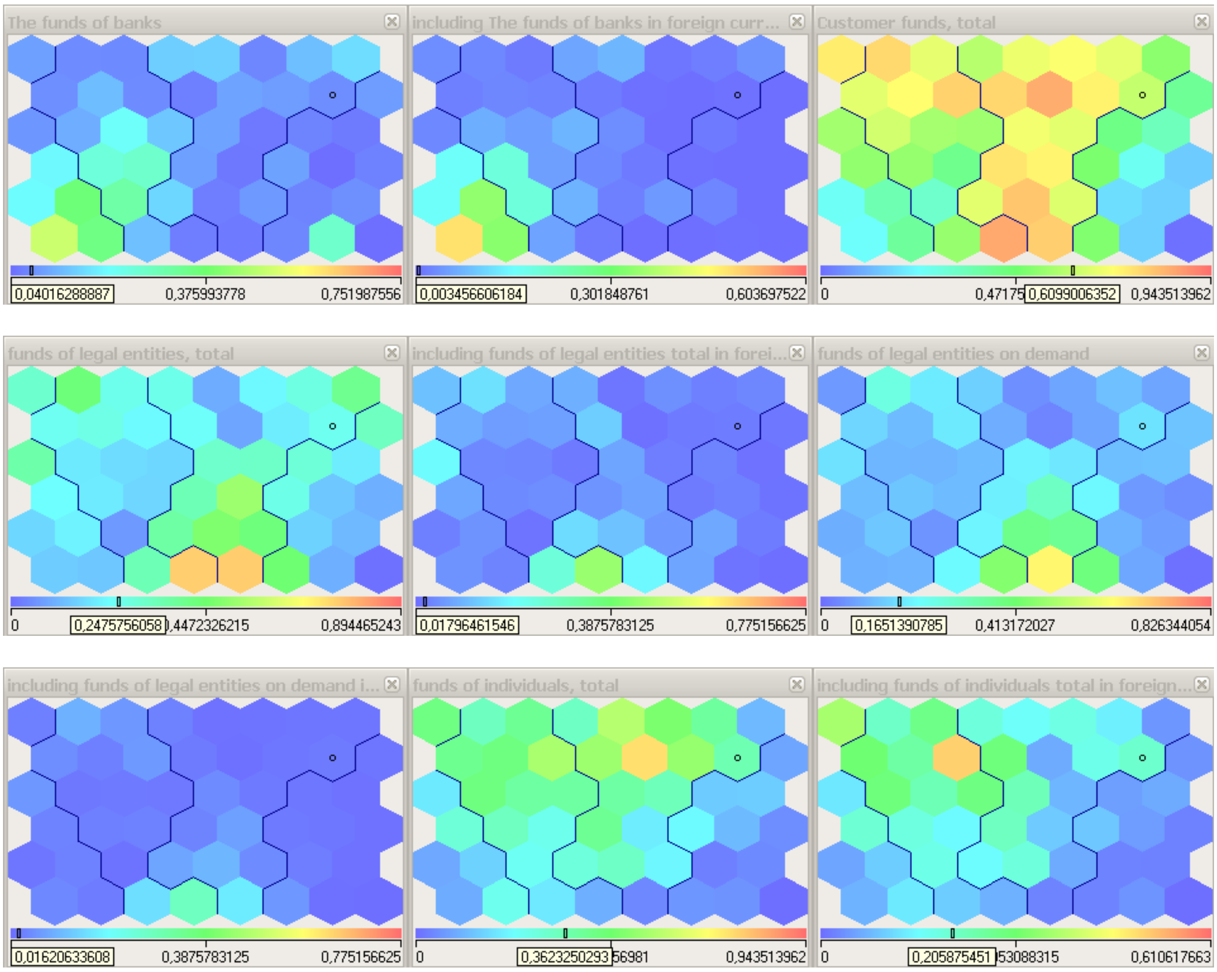

Figure 4. SOM (2014-2017). Kohonen maps for selected indicators of bank liabilities

bank in the "hazardous" zone. Thus, 252 banks were included in the cluster built on the map of "Funds of individuals, total", of which 72 became insolvent (28.5%).

Thus, one can conclude that during the 2014–2017 banking crisis in Ukraine, the bank's resource base was the main factor of its stability. At the same time, the most preferred sources of resources were funds from other banks and legal entities (especially foreign exchange assets), which not only have greater stability, but are usually cheaper. The least stable were banks, the main source of resources of which were expensive and unstable funds of individuals. The connection among financial stability, the amount of capital and the structure of bank loans is less pronounced. However, it can be said that banks that focused on lending to individuals experienced a worse crisis than banks whose main borrowers were legal entities.

Of great interest is the comparison of the reliability factors of Ukrainian banks during the 2014–2017 systemic crisis and the stability factors of banks of other countries in crisis.

Analysis and visualization of US banks failures, conducted on the basis of data for 2002–2012, are the closest scientific research in terms of the pattern of results (Lopez-Iturriaga & Sanz, 2015). Using the Kohonen maps, the authors identified six clusters (groups) in the data structure, of which groups 5 and 6 corresponded to the most reliable banks, and groups 1 and 2 corresponded to the most problematic banks. Analyzing the features of banks in the most stable groups, the authors write that they have lower level of interest expenses, construction loans, provisions, and real state past due and a higher level of deposits compared to groups 1 and 2. Unfortunately, it is not specified whether these are deposits of

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individuals or legal entities, but it is obvious that their stability is their main factor.

Thus, having compared the results of analysis of the stability factors of US banks during the 2007–2009 global financial crisis and Ukrainian banks during the systemic crisis of 2014–2017, one can conclude that in both cases, stability and the cost of resources were the most important factors for the bank sustainability.

The features of the global financial crisis caused a high significance of factors related to the structure of the loan portfolio in the study of US banks. For Ukrainian banks in the period under review, this relationship is weaker, which is due to both the causes of the crisis and the characteristics of the modern Ukrainian economy, when compared to the US economy.

CONCLUSION

In order to analyze the stability factors of commercial banks in a crisis period, the article substantiates the feasibility of using approaches based on the philosophical principle of "from the general to the particular", which is realized through data clustering with subsequent identification of particular features of the clusters obtained.

The tools considered in the article (the Kohonen self-organizing neural networks and maps) allow efficiently segmenting data samples according to various criteria, including bank solvency. The "hazardous" zones with a bankruptcy rate of 43.6% and 49.2% and the "safe" zone with a bankruptcy rate of 6.3% were highlighted on the constructed map.

The main drawback of the proposed approach is the same as for all formal analysis methods: only those factors that are reflected in the financial statements of the bank can be considered. This means that the macroeconomic, political, military, social and similar reasons for the banking system instability cannot be identified without additional research.

Among the advantages of the approach proposed, one can note the use of open data of official reporting, as well as the possibility of formalizing most of the procedures associated with their analysis. This reduces the result subjectivity; high data segmentation (the bankruptcy rates in the "hazardous" and "safe" zones differ almost 8 times); flexibility and universality, which is manifested in the fact that after training the neural network, analysis and clustering of banks can be carried out according to any of the balance sheet items.

Thus, the results of the study allow for clarifying knowledge about the banking system stability and the crisis phenomena genesis. In addition, they are of practical value and can be used in the analysis and selection of counterparty banks during a downturn.

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