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Application of Neural Network and Simulation Modeling to Evaluate Russian Banks' Performance

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Abstract

This paper presents an application of neural network and simulation modeling to analyze and predict the performance of 883 Russian Banks over the period 2000-2010. Correlation analysis was performed to obtain key financial indicators which reflect the leverage, liquidity, profitability and size of Banks. Neural network was trained over the entire dataset, and then simulation modeling was performed generating values which are distributed with Largest Extreme Value and Loglogistic distributions with estimated parameters providing robust results. Next, a combination of neural network and simulation modeling techniques was validated with the help of back-testing. Finally, we received nine bank clusters that describe the structural performance within the Russian Banking sector.

JEL Classification: C45, C53, G17, G21
Keywords: Banks, Performance, Neural Network, Simulation Modeling

1 Introduction

The application of quantitative techniques in the area of finance became very popular and especially, assessing Bank performance with the use of advances in Operational Research and Artificial Intelligence has received much attention in recent years (Fethi and Pasiouras, 2010). For this paper we used an extensive dataset of 883 Russian Banks for the time period 2000-2010 to assess the performance using ten financial indicators such as Total Assets, Current ratio, Debt-to-Equity (D/E) ratio, Deposits, Total Equity, Earnings, Net Loans, Risk Adjusted Return on Capital (RAROC), Return on Assets (ROA) and Return on Equity (ROE). Next, neural network (Kohonen map) was trained over the entire dataset. Further, to undertake simulation modeling, it is important to consider

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uncorrelated indicators and subsequently we conducted correlation analysis and the final four uncorrelated indicators, which reflect the leverage, liquidity, profitability and size of Banks, were obtained. There is an advantage of our model over the previous models developed within the literature: it is a combination of Artificial Neural Network (ANN) and Simulation Modeling. What it more, back-testing would be performed for a recent dataset. Finally, a robust model was produced which could be applied for future performance predictions.

The rest of the paper is structured as follows: Section II presents a background to the study discussing the context of existing literature and the gap within the Russian Banking sector. Section III discusses the data and methodology of this study. The application of Neural Network with multivariate analysis to support the choice of the dimension of Kohonen map is presented in Section IV. In Section V, the simulation modeling is added to the neural network and the result is discussed. Finally, Section VI concludes this study.

2 Background

Literatures on Bank performance relates to the efficiency, productivity, growth, credit ratings which continues to develop taking into consideration factors such as capitalization, size, profitability, stock returns, market concentration, ownership, events, reforms, etc. (Fethi and Pasiouras, 2010). They argued that whilst determining the efficiency and performance of banks, two approaches of analysis were performed: one is to divide banks into several groups and calculate indicators' averages in order to find the interdependence; the other way was to incorporate factor variables into a second stage analysis. Berger and Mester (1997) using a large dataset of about 6000 US Banks examined three efficiency concepts - cost, standard profit and alternative profit, and found out that these measures are not positively correlated although they might be positively related to some other measures of performance.

Kosmidou *et al.* (2006, p. 192) studied UK Banks performance for the period 1998-2001, concentrating on differences between the performance of domestic and foreign banks that have business in the United Kingdom and have found "*that foreign banks in the UK operate with lower return on equity, net interest revenue/total earning assets, loans/customer and short-term funding as compared to the domestic banks*". The results were opposed to the one obtained by Bonin *et al.* (2005) - Banks from 11 transition countries for the period 1996-2000 and Sturm and Williams (2004) - Australian Banks for the period 1988-2001. They found that foreign banks were more cost-effective and provided better service.

However, Garcia-Cestona and Surroca (2008) while studying Spanish Banks found that state-owned banks were less efficient than those controlled by managers and workers. Contrary to this, Isik and Hassan (2003) reported that state-owned banks have better efficiency levels than the private banks.

In another study on 112 Chinese Banks, Shih *et al.* (2007) used 10 financial ratios to obtain the performance indicators and found that political and economic factors influenced banks' performance. Rao and Tiwari (2008) analysed Indian Banks for the period 2001-2005 and found that the efficiency factor related to a branch is highly correlated to all outputs of the efficiency of a Bank, i.e. assets, deposits, and advances for public sector banks; per branch factor measures the contribution of per branch efficiency in overall efficiency of public sector banks. Further, Ravi *et al.* (2008) presented *"a soft* *computing"* prediction system of bank efficiency based on the sample of 1000 community banks, which used 2-years' (1991-1993) financial information to forecast the coming year's results. As input variables they used 33 numerical and 6 categorical financial indicators related to capital, assets, liabilities, income, expenses and some other bank attributes.

Wu *et al.* (2006, p.109) used Data Envelopment Analysis (DEA) and Artificial Neural Network (ANN) to evaluate the branch performance of 142 Canadian Banks. They concluded that "*the bank branch efficiency is a comprehensive measure…, the relationship between the bank branch efficiency and multiple variables is highly complicated and nonlinear*". Also, Portela and Thanassoulis (2007) found that service quality as an important dimension of efficiency of bank branches has positive correlation to its operational and profit efficiency. DEA determines a weights series to maximize an objective function. Alternatively, ANN determines a weights series to obtain the optimal fitting by means of training dataset observations. It was stated that "*the neural network approach requires no assumptions about the production function (the major drawback of the parametric approach) and it is highly flexible*" (Wu *et al.*, 2006, p.114). Ozkan-Gunay and Ozkan (2007) studying the Turkish Banks with the help of neural networks indicates that the majority of defaults could be foretold beforehand and it could be used to find special signals of possible problems. Contrary to the research of Ravi *et al.* (2008), Ozkan-Gunay and Ozkan (2007) predicted not the efficiency or performance of a bank, but default. Naturally, default prediction would be more accurate, because a number of output variables are determined more clearly.

There are number of studies that compare techniques to assess the performance or predict failures. Alam *et al.* (2000) compared the results derived by the closest hard partitioning of fuzzy clustering and by self-organizing neural networks. As an outcome a specific rating of relative bankruptcy likelihood was prepared. It was shown that both techniques are promissory tools to classify Banks and assess their performance. Kumar and Haynes (2003) explored firms' financial performance data in relation to the credit rating of a debt issue and found out that ANN is superior to the discriminant analysis model as it allows increasing the speed and efficiency of the rating process. In accordance with the results of Alam *et al.* (2000), Wu *et al.* (2006) and Kumar and Haynes (2003), ANNs are better suited to the analysis of a Banking sector, because they are flexible.

Alternatively, Baourakis *et al.* (2007) used a dataset of 1100 UK firms and proposed multi-criteria methodology to rate the credit risk which provided promising results compared to Linear Discriminant Analysis and Ordered Logistic Regression (OLR). Ioannidis *et al.* (2010) compared models in a dataset of 944 Banks from 78 countries that use financial variables only, with those using some extra indicators related to the external factors such as regulatory environment and macroeconomic conditions. Classifying the dataset with UTilités Additives DIScriminantes (UTADIS), ANN, Classification and Regression Trees, k-Nearest Neighbors (k-NN), OLR, Multiple Discriminant Analysis and Stacked Generalization Approach, they found that UTADIS and ANN provided highest average accuracy and the accuracy of classification of models that used the full set of variables (financial ones as well as external factors) was higher.

However, in a study by Mostafa (2009) with 100 Arab banks it was found that neural networks would predict banks' performance successfully as well as traditional statistical methods (e.g. multiple discriminant analysis). While the studies mentioned above compare different mathematical methods, Ho and Wu (2006) with a dataset of 3 Australian banks for a year 2000 compared the Grey Relation Analysis (GRA) to financial statement analysis and found that the GRA approach is better as a reduced number of financial indicators is needed (23 instead of 59).

Within the Russian Banking sector, Gnezditskaia (2003) provided just a descriptive study on Russian Banks, analyzing their profit strategies depending on ownership type, but does not use any mathematical methods of analysis. In a study by Lanine and Vennet (2006), a parametric logit model was used to predict failures from a dataset of year 2004 and there was nothing that could help to understand the determinants of Banks' success. Therefore, there is no research that deals with the entire population of Russian Banks incorporating the Russian Crisis (1998) as well as the Global financial crisis (2008). Furthermore, to the best of our knowledge no previous studies have been found which investigated the changes of the Banking sector's structure over time.

In this study, we try to fill the key missing element in determining the structural performance of Russian Banks with the help of Neural Networks and Simulation Modeling so that the significant indicators could be determined and the model could be used to assess banks' performance in the future.

3 Data

It is mandatory for Banks and Financial Institutions operating within the Russian Federation to submit in a prescribed form to the Central Bank of Russia on an annual basis. Thus, from the database of the Central Bank of Russia a full census data was obtained for this study for the time horizon of 2000-2010. The year 2000 was chosen as the lower frontier as the Russian economy recovered from the financial crisis of 1998. Also, during the period 2000-2007, the average annual GDP was 7% (US$ 6,578 in 2000 and US$ 14,672 in 2007); the real income of the population grew by 11% per year and the foreign-currency and gold reserves increased from US$ 12.45bn to US$ 477.9bn (Rogov, 2008). After 2007, i.e. in the year 2008 the global financial crisis impacted on the Russian economy and there was an imbalance with the economy (Ivanova, 2010).

The period 2000-2010 would represent diverse nature of the Russian economy in which an inclusive structure as well as the performance indicators of Russian Banks could be examined. The dataset of Banks operating within the Russian economy is large - 1279 Banks in the year 2000 and 995 Banks in the year 2010. Moreover, the Central Bank of Russia publishes data in HTML format and not on an appropriate database. Hence, for this study the PHP software was used to download and organize the dataset and SQL queries would be run over with the relevant Operational Research technique to analyze it.

As per previous studies made by Huang *et al.* (2004), Gaganis *et al.* (2006), Ravi *et al.* (2008), Ioannidis *et al.* (2010), Olson and Zoubi (2011), a range of financial ratios and measures were selected for this study which are presented below:

$$ROA = \frac{After - tax\ operating\ income}{Book\ value\ of\ total\ assets}$$

$$ROE = \frac{After - tax\ operating\ income}{Book\ value\ of\ total\ equity}$$

Liquidity is an important figure as it helps to evaluate whether there is sufficient assets to meet liabilities, which is tested by the Current ratio:

$$Current\ ratio = \frac{Current\ assets}{Current\ liabilities}$$

However, this formula has to be adjusted to be used to assess banks' liquidity. The Central Bank of Russia (2004) published directions "On the mandatory banks' ratios" in which it sets rules on the methods of calculation of current assets and current liabilities. For instance, it determines items that are included in current assets. As for current liabilities:

$$Current\ liabilities = Ovt - 0.5 \cdot Ovt^*$$

Ovt – Current liabilities, similar to current liabilities in a general case;
Ovt^* - Deposits of individuals and legal entities (except credit institutions).

Further, the financial strength of a bank or its ability to withstand operating setbacks would be represented by D/E ratio.

$$D/E = \frac{Total\ debt}{Total\ funds}$$

Additionally, to analyze the structural performance of Russian Banks, some absolute measures are needed to compare them in terms of size:

- Assets (total)
- Equity (total)
- Deposits (individuals and legal entities)
- Net income (loss)

All the financial ratios and measures mentioned above can be calculated directly from balance sheet and income statement terms. Also more importantly, the RAROC measure which is to be included in the analysis to represent risk-adjusted return would be calculated as:

$$RAROC = \frac{Earnings - Expected\ loss}{Economic\ capital}$$

Earnings are stated in the income statement. However, because there is no general approach to assess expected losses, the following method would be chosen based on the dataset. The Central Bank of Russia publishes balance sheets and income statements that do not allow the separation of estimates for every group of risk (market, credit, operational, etc.); because of this, an aggregated measure was chosen. Value-at-Risk framework was chosen to asses expected losses. There are a wide range of approaches; generally variance-covariance, historical simulation and Monte-Carlo simulation which could be employed. Unfortunately, none of them is ideal (Sollis, 2009). The variance-covariance approach is usually criticized for normality assumption, but Tan and Chan (2003) concluded that it can still be appropriate. As for historical simulation, this does not have the assumption of normal distribution, but is very sensitive to changes in the size of the sample employed. As a result, it underestimates or overestimates risks (Sollis, 2009). Monte-Carlo simulation, again assumes the normal distribution with corresponding consequences. Because variance-covariance approach is fast and flexible, it will be used to assess expected losses.

$$Expected\ loss = \sigma_{earnin\ gs} \cdot \Phi^{-1}(\alpha)$$

$\sigma_{earnings}$ – Standard deviation of yearly earnings;
$\Phi^{-1}(\alpha)$ – Inverse of the standard normal distribution, confidence level is equal to α.

Because there is a need to calculate a standard deviation, RAROC cannot be calculated for the years 2000 and 2001, so the analysis will be conducted for the period 2002-2010. As for economic capital, this is calculated internally and represents the amount of capital a bank should have to cover any risks. Because it is impossible to obtain the internal information of all the banks for 2000-2010, an assumption of equality of economic capital and equity capital can be accepted. It is necessary to note that as the period 2000-2010 is analyzed, case wise deletion will be performed to obtain a range of banks that existed throughout this period of time. As a result, 883 banks will be analyzed.
As the simulation modeling will be performed, indicators have to independent. To ensure that input variables do not have correlation, a correlation analysis was performed for the 2010 dataset as presented in Table 1. Further, back testing would be performed to validate the model.

Table 1: Correlation Matrix

	Total Assets	Current Ratio	D/E Ratio	Deposits	Total equity	Ear-nings	Net Loans	RAROC	ROA	ROE
Total Assets	1									
Current Ratio	0.00	1								
D/E Ratio	0.03	-0.02	1							
Deposits	0.99	0.00	0.03	1						
Total equity	0.97	0.00	0.01	0.94	1					
Earnings	0.91	0.00	0.00	0.91	0.90	1				
Net Loans	1.00	0.00	0.03	0.99	0.97	0.90	1			
RAROC	0.01	0.00	-0.77	0.00	0.01	0.02	0.01	1		
ROA	0.01	0.11	-0.06	0.01	0.01	0.05	0.01	0.28	1	
ROE	0.01	0.04	-0.57	0.01	0.02	0.07	0.01	0.83	0.54	1

Considering highly correlated indicators we have chosen four indicators such as Current ratio, D/E ratio, Deposits and ROA that are not correlated and could describe the structural performance of Russian Banks. Current ratio stands for liquidity, ROA for profitability, D/E ratio for leverage and Deposits for the size of bank. Input variables were standardized while performing further analysis to exclude the emphasis on dimensionality.

4 Neural Network

Neurocomputing or brainlike computation is an attempt to build computers similar to the human brain that can easily solve non-linear tasks; neural networks try to simulate a human brain and are widely applied in computer science, physics, biology, etc. (Fethi and Pasiouras, 2010). More importantly, they can be applied in finance. Traditionally, there are the following categories of ANNs: signal-transfer, state-transfer and competitive-learning networks (Kohonen, 2001). For the analysis of the Russian Banking sector, it is possible to train neural network to classify banks by performance indicators. Self-organizing maps (SOM), which are competitive-learning networks, are designed to recognize patterns and classify objects; therefore, they could be applied in this study. There are many software packages designed to train ANNs which can be used, additionally, software will be prepared to run trained ANN.

Traditional mathematical methods to classify objects (e.g. multivariate analysis) have difficulties with interpretability of results for further applications. Using the data for the period 2002-2010, an Artificial Neural Network (ANN) is trained - a SOM (Kohonen map). There are four continuous inputs indicators for the neural network which are the same as presented in Section III. From the sample of 883 banks the training sample size is taken as 80% (707 banks), and test sample size as 20% (176 banks). To get dimensions of the Kohonen map, a multivariate analysis has been performed. Moreover, multivariate techniques could help to reveal any problems related to correlation among the variables. Firstly, a factor analysis will be performed as an attempt to reduce the number a variables.

Table 2: Eigenvalues

Eigenvalues Extraction: Principal components				
	Eigenvalue	% Total - variance	Cumulative - Eigenvalue	Cumulative - %
1	1.139118	28.47795	1.139118	28.4780
2	1.017849	25.44622	2.156967	53.9242
3	0.963345	24.08363	3.120312	78.0078
4	0.879688	21.99220	4.000000	100.0000

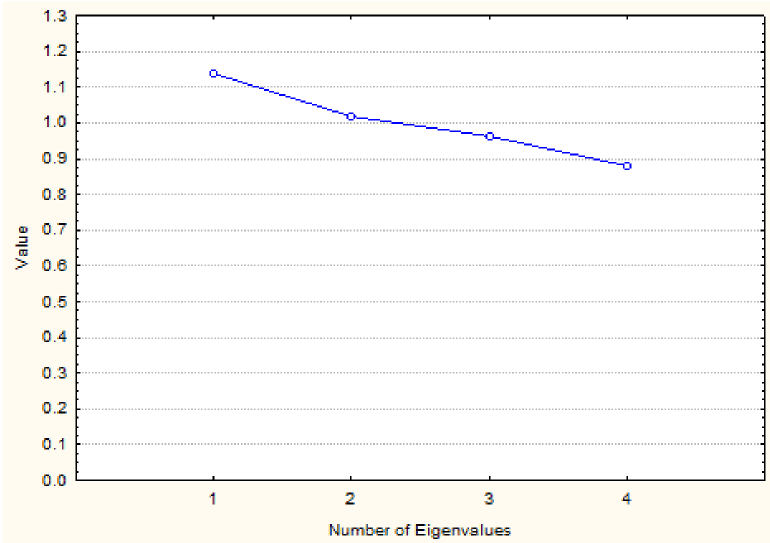

Figure 1: Plot of Eigenvalues

As can be seen, reducing the number of input variables to 3 will lead to losing as much as 22% of variance, i.e. the choice of indicators was eligible. Secondly, to get dimensions for the Kohonen map, hierarchical clustering will be performed by grouping objects into clusters in a nested sequence of clusterings and using tree diagrams. As a distance measure, Euclidian distance is chosen as it assumes that variables are homogeneous. The next step is selecting algorithm of hierarchical clustering (amalgamation rule). Ward's method assumes the similarity between 2 clusters is equal to the sum of squares over all variables and because it minimize within-group variation. Therefore, these four indicators are appropriate for the current study.

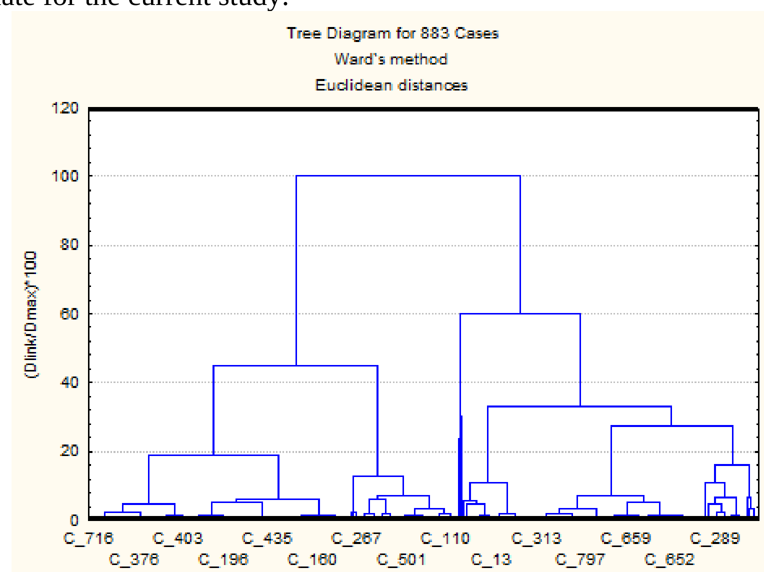

Figure 2: Tree Diagram

9 clusters were selected by considering the minimum joining distance to be 20% and the analysis of variance (ANOVA) as presented in Table 3 demonstrated that these clusters differ significantly.

Table 3: Analysis of Variance (ANOVA)

	Analysis of Variance					
	Between - SS	df	Within - SS	df	F	signif. - p
Current Ratio	875.6663	8	6.3337	874	15104.42	0.00
D/E Ratio	794.4606	8	87.5394	874	991.49	0.00
Deposits	791.8707	8	90.1293	874	959.86	0.00
ROA	773.8196	8	108.1804	874	781.47	0.00

Further, the topological height and width of the Kohonen map are 3 and 3; these dimensions provide 9 clusters that correspond to the results of hierarchical clustering. Training of network as presented in Table 3 illustrates that the general prediction error is 2.1% (0.1% in the training sample and 10% in the test sample) which is an acceptable result for ANN.

Table 4: ANN Summary

		Summary of active network		
Index	Network name	Training error	Test error	Training algorithm
1	SOM 4-9	0.001275	0.100291	Kohonen 1000

The derived Kohonen map structure is presented below:

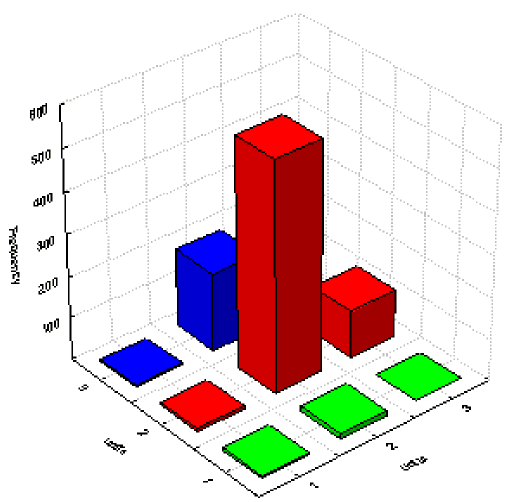

Figure 3: Kohonen Map

Table 5: Kohonen Map

Frequency spreadsheet
Network: SOM 4-9
Samples: Train, Test

	1	2	3
1	7	13	1
2	6	551	113
3	3	188	1

These nine clusters can be ordered and presented in more human-transparent way as in Figure 4:

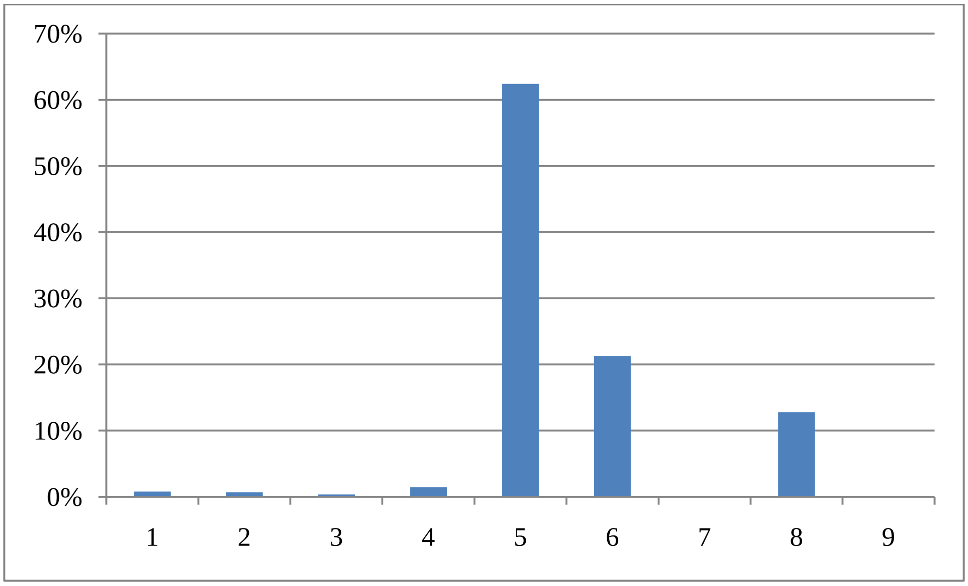

Figure 4: Russian Banks Classification

Table 6: Descriptive Statistics of Clusters (Deposits are measured in Russian Rubles)

Clusters	No. of Banks	Current Ratio		D/E Ratio		Deposits		ROA	
		MEAN	STDEV	MEAN	STDEV	MEAN	STDEV	MEAN	STDEV
1	7	1.92	0.15	9.09	3.54	1.7 tn	2.2 tn	0.05%	2.73%
2	6	11.44	19.57	2.48	3.03	0.7 bn	1.5 bn	-14.7%	6.61%
3	3	2.08	2.07	2.22	2.83	1.3 bn	2 bn	-58.3%	6.34%
4	13	2.03	0.23	8.47	2.97	243 bn	67 bn	0.78%	1.31%
5	551	3.48	13.06	4.24	2.22	3 bn	7 bn	0.63%	1.09%
6	188	2.05	0.34	11.82	4.84	18 bn	25 bn	0.31%	1.15%
7	1	15.70	N/A	1.69	N/A	0 bn	N/A	14.02 %	N/A
8	113	17.59	123.37	2.77	2.37	5 bn	14 bn	4.54%	2.34%
9	1	1.15	N/A	184.53	N/A	2 bn	N/A	-3.30%	N/A
TOTAL	883	5.01	45.45	5.95	7.48	23 bn	238 bn	0.77%	4.21%

Table 7: Members of Clusters

Clusters	Number of Banks	Members
1	7	Gazprombank, VTB, Alfabank, Sberbank, VTB24, Bank Moskvy, Rossijskij Selskokhozyajstvennyj Bank
2	6	Severo-Zapadnyj Alyans Bank, PotentsialBank, Razvitiya Predprinimatel'stva Bank, Ist Bridzh Bank, Assignatsiya, Mezhbankovskij Kreditnyj Soyuz
3	3	Tarkhany, Transportnyj investitsionnyj Bank, Bazis-Tsentr
4	13	UniCreditBank, MDM Bank, Rossiya, Sankt-Peterburg Bank, Vozrozhdenie, TransKreditBank, NOMOS Bank, Rosbank, Uralsib Bank, Citibank, AK Bars, Promsvyazbank, Raiffeisen, etc.
5	551	Energobank, AMI Bank, Bank Russkij Standart Bank, Dojche Bank, TSentroKredit, Bank Sibir, GUTA-Bank, Maksimum Bank, Aldanzolotobank, YAroslavskij Zemel'nyj Bank, Solid Bank, Obedinennyj Razvitiya Bank, Snezhinskij Bank etc.
6	188	ROSINTERBANK, Ural'skij Bank Rekonstruktsii i Razvitiya, Surgutneftegazbank, SDM Bank, VUZ Bank, BIN Bank, LOKO Bank, TRAST, ZENIT, Bank Sos'ete ZHeneral' Vostok, KIT Finans Investitsionnyj Bank, Bank24, etc
7	1	VUDP Vostok
8	113	HomeCredit and Finance Bank, Rusfinans Bank, Sovkombank, Bank Venec, Simbirsk Bank, FINAM, DzhiI Mani Bank, OTP Bank, Promsvyazinvestbank, Balakovo Bank, Severnaya Kazna Bank, OTKRYTIE Bank, etc.
9	1	Bashinvestbank Bank

62.4% (551 out of 883) of the Russian banks put together a single largest cluster. Banks in this cluster has slightly less than average values for all factors; this is the majority of the banking sector with average amounts of assets and slightly less than average profitability. Solid Bank, Snezhinskij Bank and Obedinennyj Razvitiya Bank are examples of this cluster. Based on weight matrix; the software was prepared, which allows making custom predictions of the structural performance of Russian banks. This software automates calculations based on trained ANN which allows assessment of the performance of a single bank. Using this model, an analysis of five banks which were not considered in the primary analysis was performed, because they were established later than 2000 and the results are presented in Table 8.

Table 8: ANN Custom Predictions

Name of bank	Cluster	Activation
Bank Severnyj Morskoj Put	8	0.031923273
Renessans Kapital Bank (Renaissance Capital)	5	0.016667566
BNP PARIBA Bank	8	0.022427821
Pervyj Obedinennyj Bank	5	0.016322698
Morgan Stjenli Bank (Morgan Stanley)	6	0.006972652

Morgan Stjenli (Morgan Stanley) Bank was classified as a member of Cluster 6, i.e. it is a medium-sized bank which performance is below average. Severnyj Morskoj Put Bank and BNP PARIBA Bank gained higher ratings, as they have better values of liquidity and profitability indicators. Finally, Renaissance Capital Bank and Pervyj Obedinennyj Bank got the results that can be compared with the majority of banks, i.e. appropriate profits –

medium rating. What is more, the model can be used to assess the structural performance for the future period, which could help to reveal the changes in the structure of the Russian Banking sector with the help of simulation modeling.

5 Simulation Modeling

To perform simulation modeling there is a need to accept a precondition that the system is a randomized probabilistic, in our case – the Russian Banking sector. As mentioned above, 4 chosen indicators (D/E ratio, ROA, Deposits and Current ratio) are assumed to be independent; otherwise simulation modeling would demonstrate non-interpretable results. Further, the distributions of these indicators would be examined as below.

D/E ratio: To ensure we have the most appropriate distribution for the future simulation modeling a dataset was checked against the range of distributions: Normal, Lognormal (3-parameter), Gamma (3-parameter), Exponential (2-parameter), Smallest Extreme Value, Largest Extreme Value, Weibull (3-parameter), Logistic, Loglogistic (3-parameter). For D/E ratio it was derived that Largest Extreme Value distribution fits better than others.

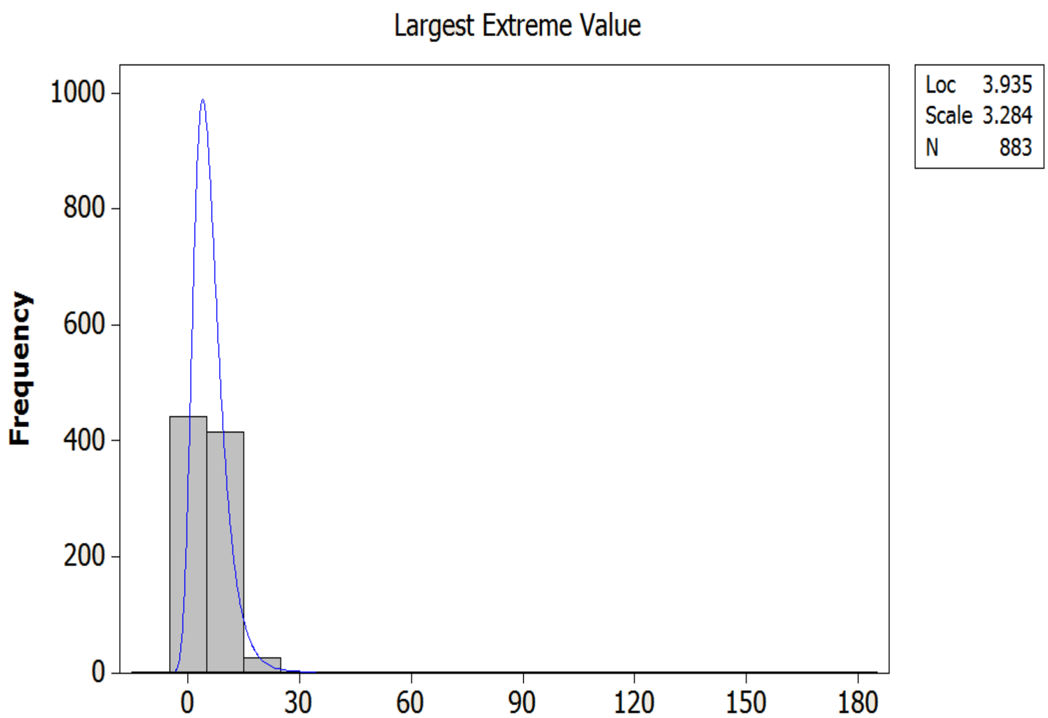

Figure 5: Histogram of D/E Ratio

Additionally, Anderson-Darling test was performed to test the goodness of fit of the largest Extreme Value distribution (as presented in Figure 4) and the results obtained (AD=2.146) suggest that D/E ratio can be described by the distribution. Finally, D/E ratio is distributed with Largest Extreme Value distribution with location parameter is equal to 3.935 and scale parameter is equal to 3.284.

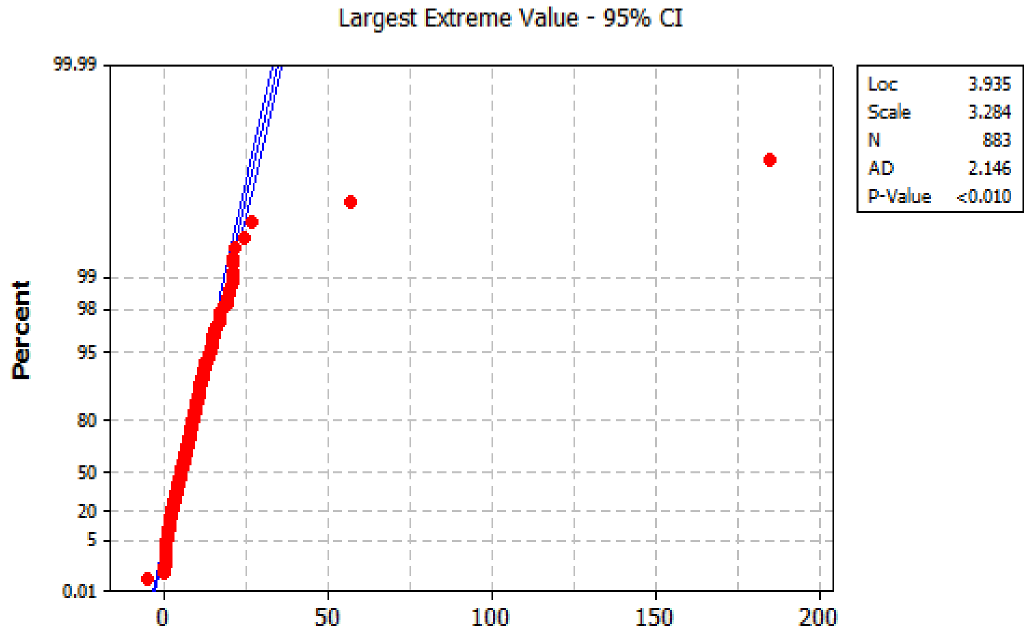

Figure 6: Probability Plot of D/E Ratio

ROA: Similarly, the analysis of ROA was performed and the results obtained suggest that ROA is distributed with loglogistic distribution with following parameters: location – 6.24, scale – $2.132 \cdot 10^{-5}$ and threshold - -512.7.

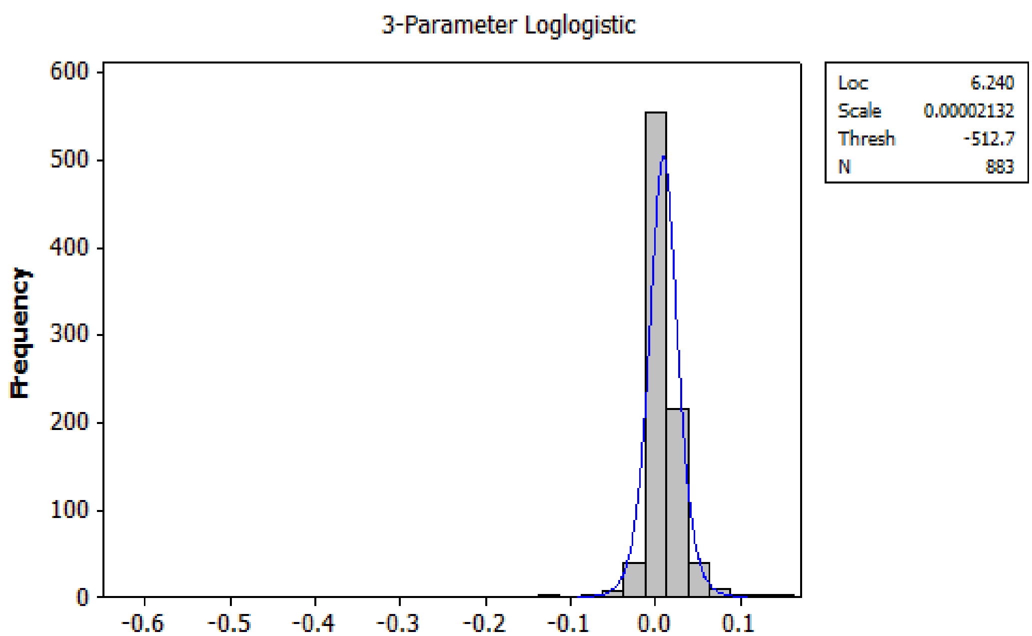

Figure 7: Histogram of ROA

Deposits: In the same way, the analysis of the value of Deposits was performed. It was found that Deposits is distributed with loglogistic distribution with following parameters: location – 14.32, scale – 1.111 and threshold - -936.4.

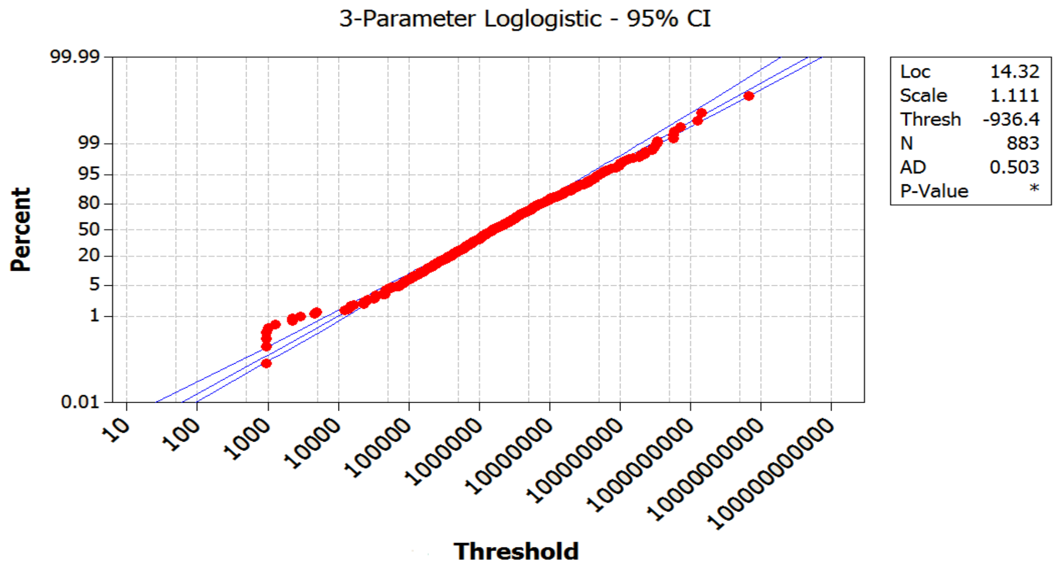

Figure 8: Probability Plot - Deposits

Current ratio: Finally, it was found that Current Ratio can be describe with loglogistic distribution with following parameters: location – 0.8586, scale – 0.1974 and threshold - -0.03465

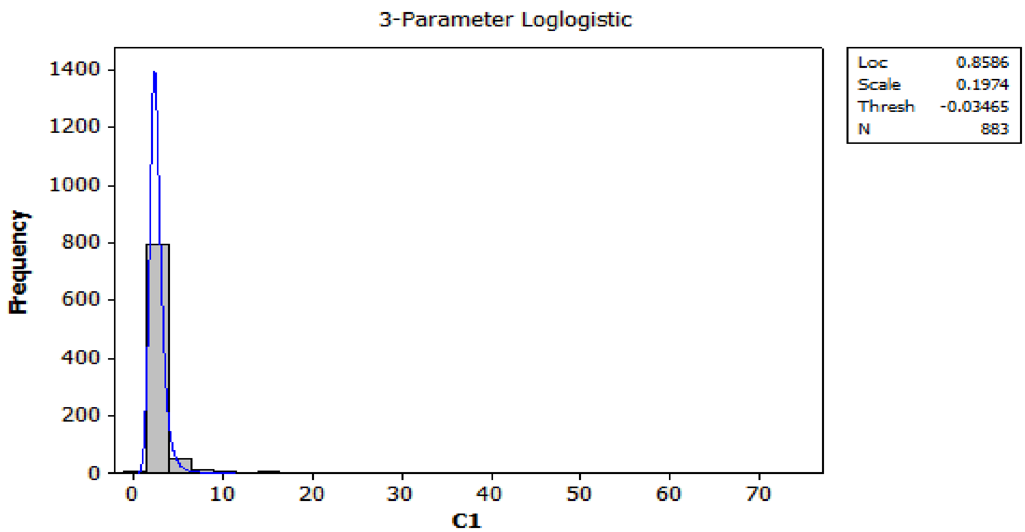

Figure 9: Histogram of Current Ratio

Simulation Modeling: Whilst simulation modeling is being executed, a back-testing is performed to ensure that the approach is reliable. We generated 88300 values for 4 input indicators based on a dataset for 2009: Current Ratio, D/E Ratio, Deposits and ROA, under the assumption they would reflect the real structure of the Russian Banking sector. Applying the trained neural network generated cases distributed among 9 clusters; we obtain the results as presented in Table 9 and Figure 10.

Table 9: Back-testing of the Model

Clusters	2009	Modelled for 2010	2010
1	0.57%	0.02%	0.79%
2	1.81%	0.05%	0.68%
3	0.11%	0.00%	0.34%
4	0.79%	2.63%	1.47%
5	77.92%	70.82%	62.40%
6	9.51%	17.21%	21.29%
7	0.23%	0.00%	0.11%
8	8.95%	9.27%	12.80%
9	0.11%	0.00%	0.11%

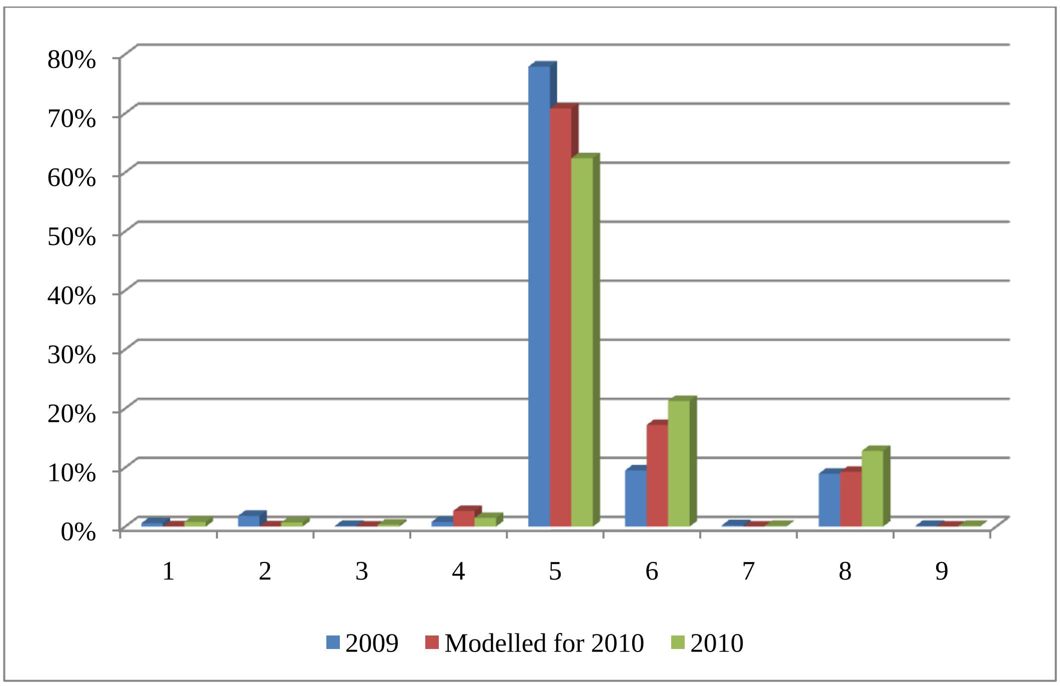

Figure 10: Back-testing of the Model

Further, comparing the real data for 2010 and modeled ones, it can be seen that the employed approach could help to recognize structural changes within the Russian Banking sector. For instance, neural network recognized that on the modeled data there

are 70.82% of Banks in the 5th cluster (it stands for the majority of banks with slightly below average values of input variables) whereas there were 77.92% of Banks in 2009. This demonstrates a negative trend, i.e. the model predicted the decline in number of banks in 5th cluster. In fact, the real data indicates that there are 62.4% of banks in the 5th cluster. The model recognized a direction of this change. Similarly, it recognized the direction of changes in number of banks in following clusters: 2, 4, 6, 7, 8. Thus, 6 of 9 changes in clusters were recognized correctly, 3 of 9 changes were not recognized, but the share of these clusters is very low. This demonstrates the reliability of the model.
Next, the data was modeled based on a dataset of 2010, thereby, predicting the changes within the Russian Banking sector in 2011 and the neural network will be run to classify these cases:

Table 10: Modelled Data for 2011

Clusters	Modelled for 2011	2010
1	2.12%	0.79%
2	14.88%	0.68%
3	0.00%	0.34%
4	0.80%	1.47%
5	61.60%	62.40%
6	7.09%	21.29%
7	0.00%	0.11%
8	13.50%	12.80%
9	0.00%	0.11%

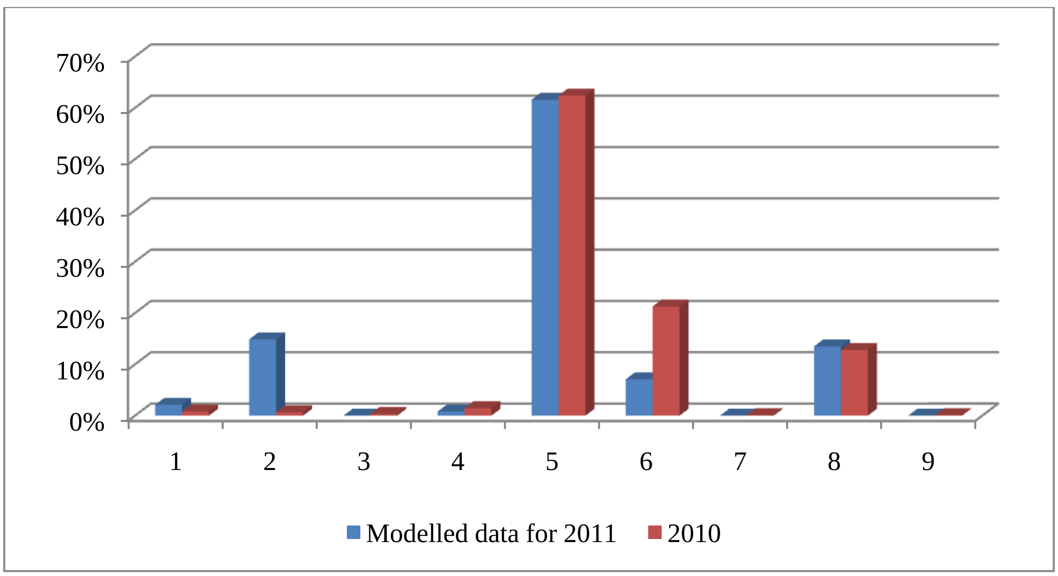

Figure 11: Modelled Data for 2011

As it can be seen in Figure 11, there is a decline predicted in the number of banks in Cluster 6 and vice versa; also an increase predicted in the number of banks in Cluster 2. Cluster 6 stands for slightly below-average banks in terms of structural performance, as it was demonstrated above, Morgan Stanley Bank is one of them and Cluster 2 stands for

not-successful banks, i.e. the model predicted deterioration of performance of the Russian Banks.
To summarize, we demonstrate that our model produces reasonable results which could be applied for further estimation of the structural performance within the Russian Banking sector by incorporating the following four indicators: D/E ratio (which signifies leverage), ROA (which reflects profitability), Deposits (which stands for the size) and Current ratio (as a measure for liquidity).

6 Conclusion

We develop a combination of neural network and simulation modeling to assess and analyze the Banks performance within the Russian Banking sector. The dataset used for this operational research techniques were 883 banks covering a time horizon from 2002-2010 in which the ANN was trained. As a result, four uncorrelated indicators: D/E ratio, ROA, Deposits and Current ratio were obtained. We believe that the ANN is able to automate calculations which allow the assessment of the structural performance of Russian Banks.
Further, we apply the four indicators into a simulation model in which back-testing was performed to ensure that the approach is reliable. The model predicts that number of non-successful Banks in Russia would increase by the means of "below-average" group in 2011. The outcomes from this modeling exercise indicated that reasonable results were produced which could further be applied to estimate structural performance in terms of leverage, liquidity, profitability and size. In future, there is a scope of developing this study by incorporating factor analysis to obtain non-correlated factor scores that stands for a larger number of indicators. Additionally, the indicators that we used are not dynamic and this could be the way for further research.

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