Measuring systemic liquidity risk in the Russian banking system

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Abstract

The crisis of 2007-2009 has emphasized the importance of systemic risk measurement and regulation. The aim of this paper is to propose an approach to estimating systemic liquidity risk in a banking system and to detecting systemically important banks. The analysis is based on a surplus of highly liquid assets above due payments. Systemic liquidity risk can be expressed as the distance from the current level of the aggregate liquidity surplus to its critical value. The calculations are carried out using simulated empirical distribution of the aggregate liquidity surplus received by employing Independent Component Analysis. Systemic importance of banks is assessed according to their contribution to the variation of the system´s liquidity surplus, for which the covariance principle is employed. The methodology is applied to the Russian banking system. Results reveal the current level of systemic liquidity risk in the system and present the ranking of banks based on their systemic relevance.

Keywords: systemic risk, liquidity surplus, bank, Russia

JEL Classification: G21, G28, P29

1 Introduction

The financial crisis 2007-2009 has brought to the fore the importance of systemic risk analysis and regulation. In April 2009 the leaders of G20 agreed that "…what has also become clear most recently is that this is a systemic crisis which has at its root the build-up of systemic vulnerabilities…" (G20, 2009).

The crisis has also put forward the issue of systemic importance of financial institutions. According to (Bernanke, 2010) "if the crisis has a single lesson, it is that the too-big-to-fail problem must be solved." Identification of organizations - in particular banks of systemic relevance - is a crucial task for assessing financial stability and enhancing macroeconomic supervision.

One of the most serious problems during the downturn was the liquidity shortages in a financial system. Even despite the adequate level of capital many financial institutions found themselves in a tough liquidity situation, which further aggravated the crisis. Thus, analysis and regulation of systemic liquidity risk should be a priority task of the macroprudential supervision.

As of today there is no clear approach to estimating systemic liquidity risk. The appropriate methodologies are still under development and their implementation has some difficulties. Sophisticated mathematical models suffer from model risk. For other approaches the problem is the lack of necessary data. Moreover, the existing methods are discussed mainly in application to developed countries, while, as the recent events have shown, this topic is essential for developing economies as well.

The aim of this paper is to propose an approach to measuring systemic liquidity risk and to identifying systemically important banks. Our research contributes to the current literature in two ways. First of all, it works out a simple and effective methodology which does not rely on assumptions that generate model risk. It employs data from financial statements of credit institutions and does not depend on securities´ prices, which is particularly important for countries with underdeveloped capital markets. Second, the paper fills the gap in the literature with respect to developing countries. In particular, it focuses on the Russian banking system for which systemic liquidity risk was one of the most serious problems during the crisis. However, the approach could be applied in other countries as well.

The paper is organized as follows. Section 2 presents the literature overview. Data and methodology are described in section 3. The major findings are discussed in section 4. Section 5 concludes.

2 Literature overview

2.1 Systemic risk measurement

Systemic risk could be defined as "a risk of disruption to financial services that is (i) caused by an impairment of all or parts of the financial system and (ii) has the potential to have serious negative consequences for the real economy" (IMF/BIS/FSB 2009, p.5). In (ECB, 2010) three forms of systemic risk are distinguished: contagion risk, simultaneous problems of financial institutions due to exposure to common factors and financial imbalances.

There are quite many models and methodologies that cover different aspects of systemic risk. For example, the probability distribution approach and contingent-claim analysis is presented in such papers as (Lehar, 2005), (Segoviano, Goodhart, 2009), (Huang et al., 2011). Within this framework a financial system is considered as a portfolio of financial institutions and potential joint losses and probability of distress are estimated. It should be noticed, that one of the drawbacks of these methodologies is that the stability over time of the joint distribution is assumed. In (Lehar, 2005) the investigation is based on the Merton's theory of option pricing with equity being considered as a call option on bank's assets. The following indicators of systemic risk are used: "systemic risk index based on assets" SIV (probability of bankruptcy[1] of banks whose total assets exceed a particular threshold), "systemic risk index based on number of banks" SIN (probability of bankruptcy of a particular fraction of banks) and the expected shortfall (the value of debt not covered by assets when a bank defaults, it is computed as the value of a put option). The contingent analysis is also employed in (Huang et al., 2009) where systemic risk is considered as an insurance premium against distressed losses. This premium is calculated as the risk-neutral expected value of the losses of a hypothetical debt portfolio (which consists of all banks' total liabilities) in excess of a particular threshold. The risk factors include probability of default (received from the CDS spreads) and asset returns correlations (received from the equity prices data). The idea of the distress insurance premium is close to that of the expected shortfall. In (Segoviano, Goodhart, 2009), in turn, a multivariate density function of the losses for the whole system is constructed. The systemic risk measures include joint probability of distress (JPoD) and the banking stability index (BSI) which measures the "expected number of banks becoming distressed given that at least one bank has become distressed".

[1] Bankruptcy occurs when the market value of bank's total assets becomes less than the face value of bank's debt within the next 6 months.

Systemic risk could also be measured based on interbank market examination. In particular, in (Sheldon, Maurer, 1998) systemic risk is defined as "the likelihood that the failure of one bank will trigger a chain reaction causing other banks linked to that bank through interbank loans to fail, the so-called domino effect." The analysis is carried out for the Swiss banking sector for the period 1987-1995. Interbank lending matrix[2] is constructed using the maximum entropy technique[3]. The authors consider several scenarios and find that in a more realistic one there is no domino effect. However, within a theoretical framework proposed in (Iori et al., 2006) the results confirm that in a heterogeneous banking system the interbank market has the potential to create contagion.

The analysis of systemic risk should also take into account banks´ behaviour during stress events. For example, the herding behaviour could signal systemic difficulties in the sector. In the paper (van den End, Tabbae, 2009) the authors investigate collective actions of banks during the systemic liquidity stress. The research is carried out for all the Dutch banks using monthly balance sheet and cash flow data for the period 2003-2009. In order to assess the herding behaviour of banks an index of extreme response is constructed. It is the number of banks that have made one or more extreme changes (positive or negative) to their balance sheet items. According to the results, the herding behaviour increased during the crisis: the index (based on downward adjustments) was much higher than during the previous years. Another measure, which could also reflect the herding behaviour, is the relative size of a change of some balance sheet items. It shows the creation of common exposures. In particular, during the recent crisis there was a substantial reliance on the central bank financing and the number of banks relying on it increased as well.

One of the most serious types of systemic risk showed up during the crisis 2007-2009 was systemic liquidity risk. In (IMF, 2011) it is defined as "the risk of simultaneous liquidity difficulties at multiple financial institutions". The importance of liquidity risk and its regulation has been emphasized within theoretical setup. For example, modelling the liquidity shock endogenously in (Cao, Illing, 2009) the authors show that additional equity requirements could be inferior with respect to liquidity regulation. Moreover, in the paper (Diamond, Rajan, 2005) it is explained how the contagion of failures could happen due to aggregate liquidity shortages in the system even without depositors' panic.

According to (IMF, 2011) liquidity risk has two main forms: market liquidity risk

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[2] It is constructed for the groups of banks rather than for individual banks. Within each group borrowings are distributed evenly.

[3] It should be noted that according to (Upper, 2011) maximum entropy has several assumptions which make the results biased. In particular, it is assumed that all banks have similar portfolios of interbank credits and loans and do not have claims on themselves. Moreover, the maximum entropy fails to model incomplete structures of the interbank market.

(when an organization is not able to quickly sell its assets without negatively affecting their prices) and funding liquidity risk (when an institution is not able to meet its obligations by raising funds during a short period). Consequently, in the study (IMF, 2011) three measures of systemic liquidity risk, which take into account both market and funding risks, are proposed: a systemic liquidity risk index (SLRI), joint probability of simultaneous liquidity shortfalls based on a systemic risk-adjusted liquidity model, and an effect of an adverse macroeconomic environment on the solvency of multiple institutions based on a macro stress-testing model. SLRI is constructed using the principal component analysis (PSA). The idea is to use the breakdown of the arbitrage relationships on the market. In particular, the violation of arbitrage was considered with respect to interest rate parity, corporate CDS-bond basis, swap spreads, and on-the-run versus off-the-run spreads between 2004 and 2010. The dominant factor, received using the PCA, is interpreted as SLRI. While in order to estimate the joint probability of simultaneous liquidity shortfalls the contingent claim analysis (CCA) is applied. It is based on assessment of the net stable funding ratio[4] (NSFR) proposed by Basel III. The authors construct the market values of ASF and RSF. The present value of RSF is assumed to be a strike price of a put option, while the ASF follows a random walk. The expected loss due to liquidity shortfall occurs when the market value of ASF falls below the market value of RSF. The joint tail risk could then be estimated using the joint probability distribution and applying ES or VaR technique.

Systemic funding liquidity risk can also be analyzed separately. For example, in the study (Drehmann Nikolaou, 2009) a central bank auction is considered and a spread between the submitted bid and the minimum bid rate in the open market is understood as a proxy for funding liquidity risk. The idea behind it is that banks with serious liquidity need bid more aggressively. So, the adjusted bid (AB) for each bank is constructed. It is calculated as the difference between the bank's bid rate and the policy bid rate, multiplied by the bank's bid volume and divided by the total allotment. Then the aggregate proxy for liquidity risk is the sum of all the adjusted bids across banks. The results show that operations during the crisis period become particularly intensive with a substantial increase in levels of the aggregate liquidity risk proxies. The authors also confirm the strong interrelation of funding and market[5] liquidity risks.

In the recent paper (Brunnermeier et al., 2012) it is emphasized that what really matters is the liquidity mismatch of a bank. The authors introduce liquidity mismatch index

[4] It is calculated as the ratio of the bank's available stable funding (ASF) and the required stable funding (RSF).
[5] Market liquidity risk is represented by an index of market liquidity used in (ECB, 2008)

(LMI) which is calculated for a particular time horizon (say, 30 days) as the difference between bank's liquid assets and liquid liabilities. This concept is wider than that of maturity or currency mismatch. All asset and liability items receive liquidity weights which show how liquid a particular item is (for example, cash receives a weight equal to 1, while long-term credits receive much lower weights; the same logic is applied to the liability side of the balance sheet). LMI should be calculated for different scenarios (states of the world) assuming different liquidity weights. Thus, the distribution of the LMI values can be generated and liquidity risk is then assessed using the Value at Risk technique. The estimations could be done for the whole banking system thus receiving a measure for systemic liquidity risk. However, the proposed methodology is quite difficult to implement in practice. There are many types of assets and liabilities and it is rather hard to assign correct liquidity weights especially taking into account the lack of sufficient empirical research in this respect.

The above described systemic risk analysis is close to the examination of liquidity creation by the financial system. The measures of liquidity creation are proposed, for example, in (Berger, Bouwman, 2009). Assets and liabilities including equity are classified into three categories: liquid, semi liquid and illiquid. Each category receives its own weight. The classification is based either on maturity characteristics or on a product type. For example, cash and securities are considered to be liquid, while commercial and industrial loans are assumed to be illiquid under the product type classification. Within the maturity characteristics framework all loans with tenor less than or equal to 1 year are considered to be semi liquid and all the other loans - illiquid. Off-balance sheet items are also included in the calculations. It is assumed that liquidity is created when illiquid assets are transformed into liquid liabilities. Thus, illiquid assets and liquid liabilities receive positive weights 0.5, while illiquid liabilities and liquid assets are weighted by -0.5. Semi liquid assets and liabilities have zero weight. Then all the weighted positions are summed up in order to get the value of liquidity created by a particular bank. The figure for the whole banking system is received by aggregating created liquidity among banks. According to the results for the US banking system, created liquidity doubled during the period 1993-2003 and reached 2.8 trillion dollars in 2003.

An important issue refers to the regulation of systemic liquidity risk. A possible approach is to use the so-called Pigovian tax. It is imposed on activities that generate negative externalities (cf. (Mandal, 2009)). In (Perotti, Suarez, 2011) the authors analyze the effectiveness of the Pigovian tax which is imposed on the short-term funding in a one-period banking system model. Interestingly, they find that it is effective only when banks have different access to credit opportunities. When banks have different risk-shifting incentives the most effective method is to use quantitative instruments (net funding ratio or liquidity coverage ratio).

A more extensive survey with respect to the systemic risk measurement is provided in the study (Bisias et al., 2012). Approaches developed in the literature are an important step forward within the systemic risk analysis and macroprudential regulation. However, as pointed out in (Bisias et al., 2012), most of them have not been tested outside the crisis 2007-2009. Moreover, some methodologies rely on different assumptions and could suffer from model risk. This is shown in the study (Rodríguez-Moreno, Peña, 2011) where the authors conduct an empirical analysis of the several systemic risk measures. The investigation is carried out based on the data of the 20 largest European and US banks. Systemic risk measures include the first principal component received from the banks' CDS spreads, LIBOR spread, SIV and SIN indexes proposed in (Lehar, 2005), CDO (collateralized debt obligation) indexes, JPoD (joint probability of distress) and BSI (banking stability index) proposed in (Segoviano, Goodhart, 2009), and the CoVaR and CoES estimations worked out in[6] (Adrian, Brunnermeier, 2009). In order to understand which measures work better an econometric analysis is employed. A dependent variable is represented by the Influential Events Variable which has dummy nature and indicates important news with respect to the financial crises (such as bankruptcies, stock market falls and etc.). The explanatory variables include the above-mentioned systemic risk measures. An interesting result is that simple indicators perform better than the sophisticated ones. For example, the best indicator of systemic risk for the European market is the LIBOR spread, while the worst one is the CoES measure. For the US economy the best indicator is the first principal component from the banks' CDS spreads.

2.2 SIFI

The issue of systemic risk is closely connected with the systemically important financial institutions problem. There is no clear definition of systemically important banks. According to (ECB 2006, p.131) it is particularly essential to supervise "banking groups whose size and nature of business is such that their failure and inability to operate would most likely have adverse implications for financial intermediation, the smooth functioning of financial markets or other financial institutions operating within the system". On the other

[6] Discussed in section 2.2.

hand, in (Thomson, 2009) it is argued that this concept is not simple and there are several categories of systemic importance. Small banks can be considered as “too many to fail” when they are exposed to common risk factors (cf. (IMF/BIS/FSB, 2009), (Acharya, Yorulmazer, 2007)). It should also be emphasized that a financial institution could become systemically important even if individually it has relatively low risks (Zhou, 2010), (Wagner, Nijskens, 2011).

There are several approaches to identifying SIFIs. The first one is the qualitative assessment. The paper (IMF/BIS/FSB, 2009) provides a set of relevant indicators. To receive a more objective picture the quantitative methods have been developed. In particular, they include an indicator-based methodology, network analysis and assessment of institutions' contribution to systemic risk.

One of the advantages of the indicator-based methodology is that it is based on available data (balance sheet and macroeconomic data) and does not require a lot of assumptions. An example of using such a method is presented in (ECB 2006) and (IMF 2010). This approach has been also proposed for identifying and regulating globally systemically important banks (cf. (BCBS, 2011)) with indicators being size, interconnectedness, substitutability, global (cross-jurisdictional) activity and complexity[7]. All indicators are assumed to have equal weight. Nevertheless, there are several issues with respect to the proposed methodology. First of all, it is not clear why the indicators are weighted equally. Moreover, the proposal does not take into account the issue of liquidity, which was one of the most serious problems during the crisis.

The next possible approach is to analyze interbank network. In this case systemic importance of an institution can be examined from different perspectives: either from the point of view of its influence on other financial institutions through the interbank linkages (cf. (Furfine, 1999)) or from the point of view of its centrality on the interbank market (cf. (Bech, Chapman et al., 2008), (von Peter, 2007)).

The third type of methodologies deals with assessing the institution´s contribution to systemic risk. These methods require a developed financial sector where different types of information are available. Nevertheless, they do not take into account the structure of financial institutions. The interbank interconnectedness is also out of the focus.

The first sub-approach within this type of methodologies is addressed in, among others, (Lehar, 2005), (Segoviano, Goodhart, 2009), (Acharya et al., 2010a), (Zhou, 2010), (Tarashev et al., 2010), (Brownlees, Engle, 2011). The idea is to estimate systemic risk and

[7] All these categories except size include multiple indicators.

then attribute it to individual contributors. All banks are assumed to be exposed to similar risk-factors. In (Lehar, 2005) the risk contribution of banks is considered as their contribution to the volatility of the expected shortfall of the whole banking system. The similar approach is employed in (Acharya et al., 2010) where such a measure as MES (marginal expected shortfall) is constructed. It estimates the bank´s contribution to the system´s expected shortfall. While in (Segoviano, Goodhart, 2009) in order to determine systemic importance of a bank "the probability that at least one bank becomes distressed (PAO) given that a specific bank becomes distressed" measure is proposed. It is extended in (Zhou, 2010) where the author develops a systemic impact index (SII) which estimates how many banks are expected to fail given a failure of a particular bank. The multivariate extreme value theory is employed to deal with the scarcity of extreme events. Though, as pointed out in the paper, the SII approach has one important drawback: it does not estimate if a failure of a bank leads to distress in small or big banks. Thus, the level of systemic importance cannot be determined relying only on this measure. For this purpose a systemic risk index (SRISK) is developed in (Brownlees, Engle, 2011). The key assumption is that capital shortage of an institution affects the whole economy and a significant capital shortfall could be a reason for a distress in the economy. As a result, a systemically important financial institution is considered to be the one with the largest capital shortage (as a percentage of the overall capital shortfall of the institutions under consideration).

Another technique within the first group is to use the Shapley value. This methodology is discussed in (Tarashev et al., 2010). The Shapley value is used to solve the allocation problem in the game theory. In assessing systemic importance of a bank the Shapley value can be used to examine how the overall risk could be attributed to an individual institution. One of the advantages of such an approach is that different measures of systemic risk can be employed. However, when applied to the real world the estimation might be too sophisticated. The Shapley value methodology is also used in (Drehmann, Tarashev, 2011) where the authors propose a generalized contribution approach which takes into account interbank linkages.

Within the second sub-approach the effect of institution´s distress on systemic risk is analyzed. The first paper to discuss is (Adrian, Brunnermeier, 2010). The authors propose such a measure as CoVaR. It is a conditional estimate and the idea behind it is to assess VaR (Value at Risk) for the whole system given a failure of a particular organization. The marginal contribution of this institution can then be received as the difference between VaR given its normal (or median) state and VaR given its distressed condition. CoVaR is a q-quantile of the conditional probability distribution. A similar approach is used in (Chan-Lau, 2010) where the CoRisk measure is introduced. The idea is to examine how default risk of one institution depends on default risk of another institution. For this purpose the quantile regression is run based on panel data, where individual default risk is measured as the expected default frequency[8].

The above mentioned measures could be used for assigning capital requirements. The appropriate example is presented in (Gauthier et al., 2010). In particular, the authors consider component and incremental VaR, the Shapley value and CoVaR. The calculations are carried out for the Canadian banking system based on data of the six largest Canadian banks which hold 90.3 percent of the total assets in the sector. A notable result is that capital reallocation according to all measures of systemic importance reduces the probability of multiple banks' default. The difference in capital allocation as compared to the observed levels of capital can be as much as 50% for an individual bank.

Another approach is proposed in (Acharya et al., 2010b). The authors suggest applying higher deposit insurance premiums to large banks. While in (ECB 2010) a systemic tax is discussed. This is a levy charged to an institution based on its contribution to systemic risk.

The crisis of 2007-2009 has emphasized the importance of SIFIs′ regulation. In the paper (Morrison, 2009) the creation of a systemic risk regulator, which can "seize and stabilize systemically important institutions", is proposed as the most effective way. In the discussion paper (FSA, 2009), in turn, a so-called "living will" concept is considered. It is a recovery and resolution plan which can lower the effect of systemic failures. There are also proposals to restrict the activities of SIFIs (discussed in more detail in (IIF 2010)).

An important drawback in the literature is that most papers focus on developed economies or the global financial market. For example, in (Adrian, Brunnermeier, 2010) the CoVaR model is applied to the US commercial banks, broker dealers, insurance and real estate companies. In (IMF, 2010) the analysis is done to determine systemically important financial sectors in the global arena. In (Segoviano, Goodhart, 2009) the estimation is carried out for the major American and European banks and sovereigns in Latin America, Eastern Europe and Asia. In (Lehar, 2005) the assessment is based on the data of 149 largest international banks.

Moreover, many studies consider theoretical models and provide calculations based on a financial sector model. In (Zhou, 2010) the author considers a banking system consisting of

[8] Calculated and reported by Moody′s KMV

28 US banks. In (Tarashev et al., 2009) and (Drehmann, Tarashev, 2011) the methodology is firstly applied to a hypothetical system and then to the real-world data for only 20 large internationally active financial institutions.

Therefore, it is important to carry out research with respect to systemic risk and SIFIs for developing countries. An essential feature of many developing economies is the underdevelopment of their financial markets. The methodologies based on securities´ prices and spreads are not applicable, while the useful information could be obtained mainly from balance sheets of financial institutions. Thus, it is necessary to work out an approach based on the balance sheet characterises that would allow to avoid making implausible assumptions and would lead to realistic results.

3 Methodology and data

Within our framework systemic liquidity risk means a potential of a system to reach a condition when it is difficult for its elements to find liquidity sources. The term "systemic risk" is applied to the whole system. Its elements may suffer from a systemic event or crisis and contribute to systemic risk. We focus on a banking system which might be considered as a "portfolio" of credit institutions.

The assessment of systemic risk is based on a surplus of highly liquid assets above due payments. The surplus is taken as an absolute or relative value and is calculated at the level of each bank and the whole system at each time point:

Banking system

$S(t) = \frac{\sum_i c_i(t)}{\sum_i o_i(t)}$	$AS(t) = \sum_i c_i(t) - \sum_i o_i(t)$

Individual credit institution

$s_i(t) = \frac{c_i(t)}{o_i(t)}$	$as_i(t) = c_i(t) - o_i(t)$

where at a time point t, S(t) – relative liquidity surplus of the system, AS(t) – absolute liquidity surplus of the system, $s_i(t)$ – relative liquidity surplus of a bank i, $as_i(t)$ – absolute liquidity surplus of a bank i, $c_i(t)$ - highly liquid assets of a bank i, $o_i(t)$ - short term obligations of a bank i.

The absolute surplus of each institution builds input for covariance calculation in order to find systemically important banks (discussed in section 3.2).

Our approach is in a way similar to that proposed in (Brunnermeier et al., 2012) where the liquidity mismatch index (LMI) is introduced (discussed in section 2.1). However, in our framework only short-term (up to 30 days) assets and liabilities are considered. Liquidity weights are not employed as it is difficult to determine which weights could be the most appropriate ones. And systemic liquidity risk is measured in a different way (explained in section 3.1).

3.1 Systemic liquidity risk

The system is in distress at a time point t if S(t) is less than a critical threshold H. Thus, systemic liquidity risk can be expressed as the distance from the current value of the aggregate relative liquidity surplus to its critical level. H is assumed to be equal to 1. According to the Basel Committee requirements each bank has to maintain an appropriate amount of highly liquid assets in order to be able to cover its liquidity needs with the time horizon being 30 days. Hereby, the Basel Committee prescribes to use such a measure as a liquidity coverage ratio which is the ratio of the "stock of high-quality liquid assets" to "total net cash outflows over the next 30 calendar days". This indicator should be more or equal to 1 (cf. (BSBC, 2010)).

However, it is not necessary that all banks have the relative liquidity surplus above 1. For example, foreign owned banks could rely on funds from their parent companies. Then certainly there is no need for such banks to hold excessive liquidity which is rather costly. During stress periods it is highly probable that parent companies support their subsidiaries and provide short-term financing.

In order to express the distance to the critical level in an understandable way, it is proposed to use such a measure as a probability of reaching the critical level. Thus, the probability acts as the measure for systemic risk.

We assume that S varies randomly through the time. The probability that S falls below H can be expressed as the conditional probability P (Mood et al., 1974. p.32):

$$R(S) := P(S \le H \mid S \le \hat{S}) = \frac{P(S \le H \cap S \le \hat{S})}{P(S \le \hat{S})} = \frac{P(S \le H)}{P(S \le \hat{S})}$$

where $\hat{S}$ - current level of the relative liquidity surplus of the system (it is higher than H).

The probability could be calculated based on empirical distribution of the aggregate relative liquidity surplus. However, in our case there are only 60 observations (as we use monthly data for 5 years). In order to have more precise estimations the simulated distribution should be used. For this purpose, we employ an Independent Component Analysis (ICA).

The idea of ICA is the following. First of all, it should be noted that multivariate data can often be explained by the underlying unobserved latent variables (or factors, or independent components). For example, securities´ prices change due to variations in macroeconomic situation, investors´ confidence and other factors that are not directly observed. The possible way to reveal the underlying variables is to use the factor analysis or the principal component analysis (PCA). Nevertheless, they rely on an assumption that factors are normally distributed. In order to avoid this assumption an alternative approach – ICA – could be employed.

The algorithm of ICA is well described in (Hyvärinen, Oja, 2000) and we follow its logic. The underlying factors are assumed to be statistically independent (not just uncorrelated as in PCA) and non-normally distributed. For the purpose of the analysis, the observed variables are centred (that is, sample means are subtracted). The ICA model can be represented as:

$$x = Am\,,$$

where x – vector of n random variables, m – vector of underlying random factors, A – transformation matrix. The only observable data are contained in the random vector x, while A and m have to be estimated[9].

In our framework the vector x consists of 269 random variables (268 banks plus the whole system). For each random variable there are 60 observations (values of the relative liquidity surplus at each time point). The number of underlying factors is chosen to be equal to[10] 30. They are estimated using the statistical program R with the package fastICA[11].

The next step is to find the most appropriate type of probability distribution for each independent component. The fitting is carried out using the statistical program Statistica 10. Kolmogorov-Smirnov and chi-square goodness-of-fit tests are employed in order to find the proper distribution functions. When the distribution type of each factor is known it is possible to use the simulation technique in order to enlarge the number of observations. The simulation is done in the same program Statistica 10. As a result, for each factor 180 000 simulated observations are received.

The simulated data for each independent component and the estimated matrix A are used to get back to the original vector x. Thus, for each bank and for the whole system there are now 180 000 observations of the relative liquidity surplus.

[9] The independent component (or factor) can be obtained after estimating the matrix A and then taking its inverse: $m = Wx$

[10] The number of factors should be less than the number of observations. Moreover, when we use a larger number of factors than 30 it is not possible to make a reasonable distribution fit.

[11] The R code is available from the author upon request.

3.2 Systemically important banks

The potential of the system to fall under the critical threshold H is explained by the variation of S. The larger the variation, the higher the potential is. Systemic relevance of each credit institution is determined by its contribution to this variation.

The risk contribution is calculated based on the covariance principle which is, in turn, based on the Euler capital allocation principle. This is well described in (McNeil et al., 2005).

The approach is widely used for economic capital allocation among sub-portfolios. Within the systemic risk analysis this approach is used in, for example, (Lehar, 2005) where systemic importance of financial institutions is determined based on their contribution to the volatility of the expected shortfall.

According to the definition of the Euler capital allocation principle presented in (McNeil et al., 2005), if there is a risk function, which is positive-homogeneous and continuously differentiable, then the one unit capital allocation would be the following mapping:

$$rc_i = \frac{\partial f(\lambda)}{\partial \lambda_i},$$

where f – risk-measure function, λ_i – weight of a sub-portfolio i in the total portfolio, rc_i – amount of capital allocated to the sub-portfolio i or, in other words, the risk contribution of the sub-portfolio i.

When the risk-measure function is represented by the standard deviation, the capital allocation rule takes the following form:

$$rc_i = \frac{\mathrm{cov}(X_i; X)}{\sqrt{\mathrm{var}(X)}},$$

where X_i – profits and losses generated by the sub-portfolio i, X – profits and losses generated by the total portfolio.

Within our framework the total portfolio is represented by the banking system, while individual banks act as sub-portfolios. We are interested in the banks´ contribution to the variation of the system´s absolute liquidity surplus. Thus, the risk contribution can be expressed in a following way:

$$rc_i = \frac{\mathrm{cov}(as_i; AS)}{\sqrt{\mathrm{var}(AS)}},$$

where as_i – absolute liquidity surplus of a credit institution i, AS – absolute liquidity surplus of the system.

The next step is to examine which banks´ characteristics are relevant determinants of systemic importance. For this purpose the indicators proposed by the Basel Committee (discussed in section 2.2) are considered.

We employ a simple econometric analysis (OLS). As a dependent variable the value of the systemic risk contribution, estimated as described above, is taken. Explanatory variables reflect banks´ size, interconnectedness and complexity[12]. We do not include indicators for substitutability and global activity due to lack of necessary data[13].

3.3 Data

In order to carry out the analysis we use monthly financial statements of the Russian banks for the period January 2007 – December 2011. The largest 268 banks have been selected so that their assets amount to 90% of the total assets in the system. This information is publicly available on the website of the Central Bank of Russia.

For each bank short term assets and liabilities are calculated. Short term assets include cash and cash equivalents, gold, correspondent and current accounts, credits and deposits (to financial and nonfinancial organizations, including deposits held in CBR) up to 30 days, state securities, promissory notes up to 30 days. Short term liabilities, in turn, include credits and deposits (from financial and nonfinancial organizations) with maturity up to 30 days, correspondent accounts, funds from the federal and municipal budgets, debt obligations, deposit and saving certificates as well as promissory notes with maturity up to 30 days.

Bank´s size is expressed as the ratio of bank´s assets over total assets of the sample. Interconnectedness is defined as the ratio of bank´s lending to financial institutions over the sample´s aggregate figure and as the ratio of bank´s borrowings to financial institutions over the sample´s aggregate figure. Complexity is represented by the ratio of bank´s securities held for trading and available for sale over the sample´s aggregate amount. We also consider the level of bank´s retail deposits (expressed as the ratio over the sample´s total amount) in order to reflect bank´s involvement in the economy.

3.4 The history and main characteristics of the Russian banking system

In order to better understand which banks could be of systemic relevance for the Russian banking sector, it is worth examining the history of its appearance and evolution. The banking system in Russia was inherited from the Soviet period after the reforms of 1988-1992

[12] We follow the logic of the Basel Committee in defining these variables, which is described in subsection 3.3.
[13] Moreover, as we focus on the Russian banking system where banks are not globally active, there is no need to account for the cross-jurisdictional activity.

(the period of "shock therapy"). The creation of a two-tiered banking sector in the USSR occurred in 1987 after the introduction of the appropriate legislation[14]. As a result, by the end of 1991 there were 1360 operating credit institutions (cf. (Ekiert, Hanson, 2003)), while at the beginning of 1993 this number reached 1773, 75% of which had very small level of authorized capital (cf. (Lamdany, 1993)). Moreover, the system was rather highly concentrated with 65 banks accounting for 70% of the total assets (cf. (Lamdany, 1993)). The banking sector poorly executed its main function (intermediation of the savings and investments) rather facilitating the embezzlement of the state resources. The main and probably the only source of bank's success was the appropriate political connections.

An interesting feature of the Russian banking system at that time was the monopoly power of the state-owned Sberbank (Savings Bank) on the market of household deposits (cf. (Lamdany, 1993)). All the other banks attracted deposits from non-financial companies. The reason for such a situation dates back to the Soviet times when Sberbank was the only bank for savings of the Russians. Moreover, the Government guaranteed the deposits held only in it. However, the level of household's savings was very low at 6.5% of the total income[15] in 1994 and was decreasing till 1999.

It is important to mention that the difference between Moscow-based and regional banks started to increase significantly from 1993. As pointed out in (Johnson, 2000), a small number of banks managed to create a powerful financial system concentrated in Moscow using connections with high-level state organizations and political parties. Large credit institutions also started to acquire shares of non-financial companies (especially resources and export-oriented enterprises) in 1996 (cf. (Hough, 2001)). This led to creation of financial-industrial groups (FIGs). As described in (OECD, 1997), regulation of such FIGs was difficult as banks, which belonged to those groups, were not required to prepare detailed consolidated financial statements. They could adjust their balances moving assets among affiliated companies.

The 1998 crisis had a significant negative impact on the banks in the system. In particular, it strongly hit the largest ones (cf. (Ippolito, 2002)) which had huge losses on currency forward contracts and government securities (GKO) as well as significant decrease in their deposits (which partly were transferred to the state banks, specifically, to Sberbank[16]).

[14]Resolution of the Council of Ministers No 821 "About the modernization of the banking system in the country and strengthening their influence on the increasing the efficiency of the economy", 17 July 1987; "Law on Cooperation" and the Resolution of the Council of Ministers No 1061 "About the ratification of the charter of the Gosbank USSR", 1988
[15] www.gks.ru, section "Income, expenditures and savings of the population"
[16] According to (Barnard, 2009) in 1999 the share of Sberbank in household deposits was 80%.

Large banks in FIGs also had substantial amount of short term foreign loans an access to which was eliminated after the crisis.

It should be noted that in 1996 an Operational authority for supervision of big and socially important banks ("OPERU-2") was established (cf. (Murichev, Moiseev, 2010)). It covered 14 major banks with 60% of the total assets and 90% of the total deposits of the banking sector. However, the effectiveness of the authority was low: almost all banks under its supervision became bankrupt during the crisis of 1998. As a consequence, it was abolished in 1998.

A notable point is that due to this crisis the state control over the banking system substantially increased and such state banks as Sberbank and Vneshtorgbank significantly expanded their activities (cf. (Lane, 2002)).

After the crisis of 1998 the economy of Russia started to grow quite rapidly at about 6-7% GDP growth rate annually. Therefore, the banking sector also showed relatively rapid growth rates. There were some improvements with respect to the regulation in the banking system (cf. (Barnard, 2009)). Nevertheless, the role of the banking system still remained comparatively limited as regard to intermediating savings and investments especially for small and medium-sized companies (cf. (Fungáčová, Solanko, 2009)). The banking sector remained highly concentrated. Only 50-70 largest banks were important for the whole economy out of more than 1000 credit institutions (cf. (Fungáčová, Solanko, 2009)). And the portion of the state-owned banks was significant (about 50%) with the government interference continuing to rise (cf. (Malle, 2009)).

The crisis 2008-2010 substantially hit the Russian banking system. According to (IMF, 2011) it appeared in two stages. The first one began in the second half of 2008 in the form of liquidity shortages. Funds from non-residents fell substantially starting from September 2008. Moreover, some banks experienced significant deposit withdrawals. The second stage broke out in 2009 in the form of increased credit risk levels. As a result, significant funds were spent to support the Russian banking sector by means of providing state resources to several key financial institutions during the crisis. As described in (IMF, 2011), the support from the CBR was, inter alia, in form of liquidity provision such as guarantees on the interbank market, lending to qualifying banks, wider list of acceptable collateral on repurchase and Lombard operations and others. The lending amount from the CBR was around 12% of the total banking assets at the end of 2008. The support was also provided in form of capital injections the total value of which reached Rub 1.4 trillion (3.5% of GDP) with subordinated loans amounting to Rub 904 billion (2.2% of GDP). Subordinated credits were received by the largest banks including such state-owned banks as Sberbank (Rub 500 billion), VTB (Rub 200 billion) and Rosselkhozbank (Rub 25 billion) (cf. (Golubev, 2009)).

Thus, systemic risk poses a significant threat to the Russian banking system and requires thorough investigation and regulation. The Central Bank of Russia (CBR) is working on implementation of international approaches to the banking regulation. This also refers to systemic risk analysis and macroprudential regulation. A group under the Presidential Council as well as the department at the CBR responsible for systemic risk analysis has been established (cf. (IMF, 2011)). However, the existing mechanisms for assessing systemic risk and regulating systemically important financial institutions are still under development and require further investigation with the proper accounting for the Russian environment.

4 Results

We first analyze the dynamics of the aggregate relative liquidity surplus. According to Fig.1, the banking system experienced severe liquidity problems in May-September 2008 with the lowest point (1.009) in August 2008. The low level of the liquidity surplus in May 2008 was partly due to the mandatory tax and other payments to the budget. This period corresponds to the beginning of the crisis. From May 2008 the stock market started to decline with a significant fall in July 2008 (see Fig. 7 in Appendix).

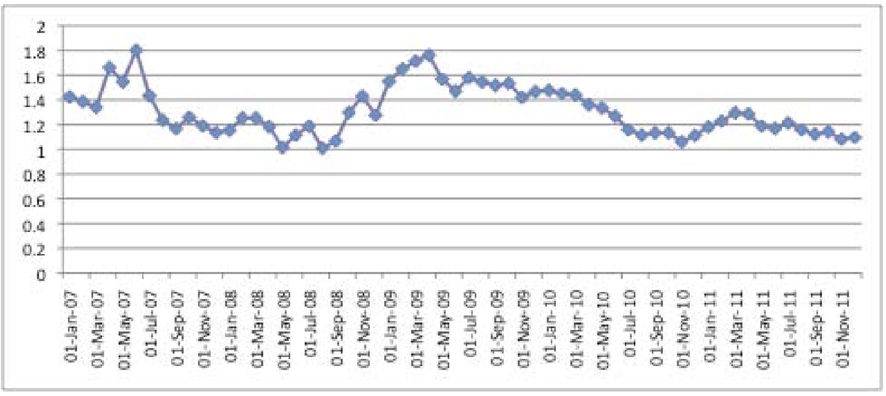

Fig. 1 Relative liquidity surplus of the Russian banking system

Liquidity problems in the system could also be detected looking at the interbank interest rate (Fig. 2). It started to increase from August 2008 reaching a peak in January 2009 and indicating the worsened liquidity situation. At the same time short-term funds from non-residents substantially fell and continued to decrease till the end of 2009 (Fig. 3).

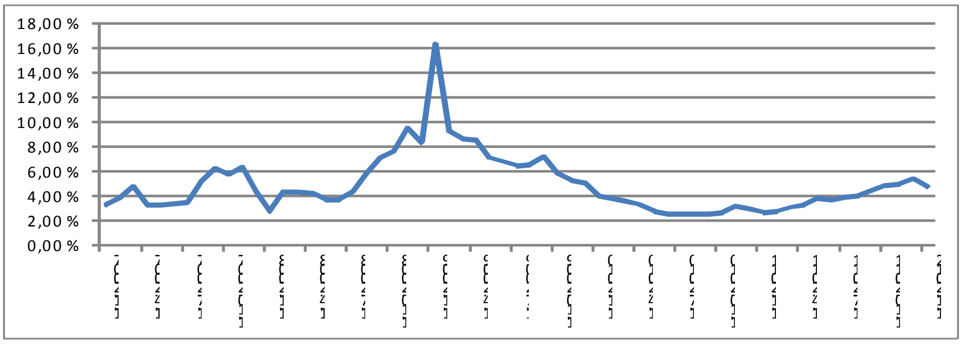

Fig. 2 Average interbank interest rate on a one-day loan in Rubbles

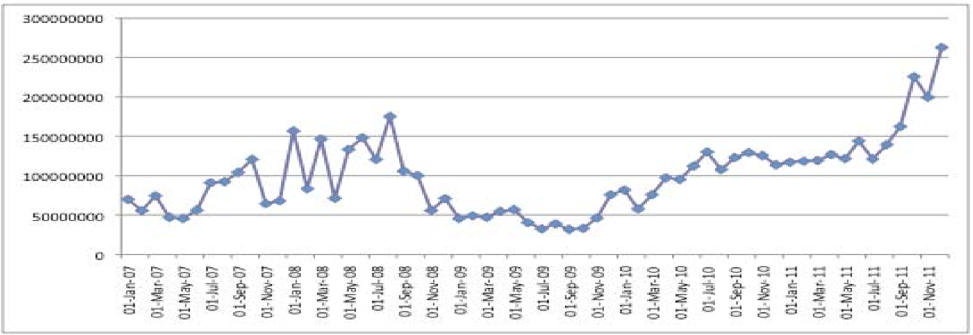

Fig. 3 Short term funds from non-residents (in Rubbles)

In order to restore the stability the government began to provide liquidity support to the banking sector. In September 2008 there was a substantial increase in the short-term funds from the Ministry of Finance (Fig. 4) and overall from the State[17] (Fig. 5). Interestingly, the share of the two largest state-owned banks in the short-term funds received from the State in December 2008 was 38%, while the share of the first 5 main contributors to the liquidity surplus variability (including these two largest state-owned banks) was 55%.

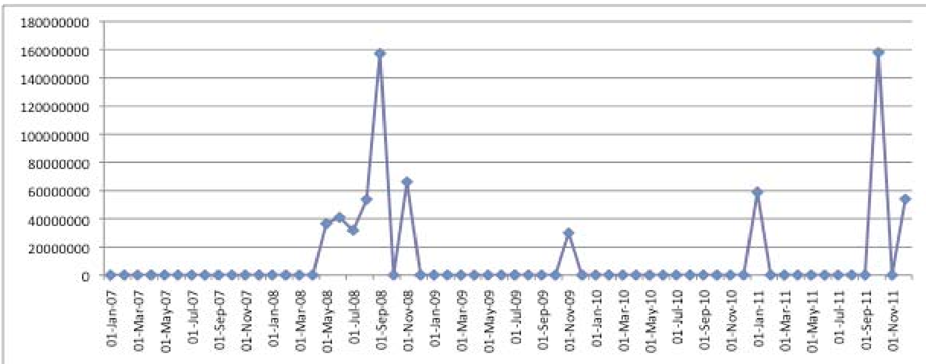

Fig. 4 Short term funds from the Ministry of Finance (in Rubbles)

[17] The support was provided for longer terms as well (cf. (IMF, 2011))

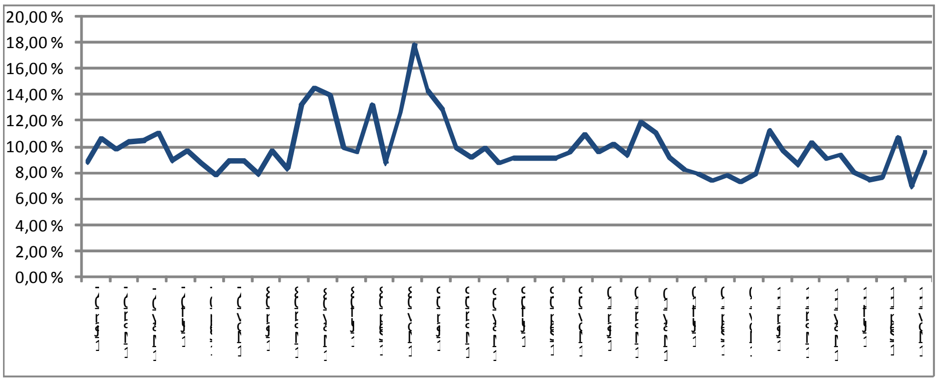

Fig. 5 Overall short term funds from the State (in % of the total banks´ short-term liabilities)

The results of the ICA analysis show that the underlying 30 independent components have the Generallized Extreme[18] and Triangular[19] distributions. Using simulation we receive 180 000 observations for each factor, based on which it is possible to return back to our initial data. Thus, for each bank and for the whole system there are now 180 000 observations. The empirical distribution of the banking system´s relative liquidity surplus is presented on Fig. 6.

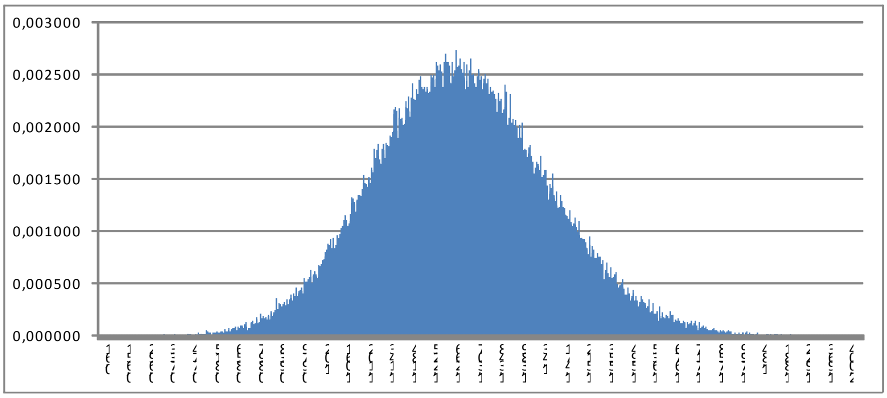

Fig. 6 Histogram of the simulated system's relative surplus

In December 2011 the value of the system´ relative liquidity surplus was 1.096. Therefore, the conditional probability that the surplus reaches its critical level equals to 28% which is high reflecting serious problems in the system.

Now we turn to the analysis of banks´ systemic importance. As it was described in section 3, systemic importance is estimated as the banks´ contribution to the variation of the system's relative surplus during the period under consideration. It should be emphasized that we do not adjust anything for the banks' size. Only the covariance is calculated based on the absolute liquidity surplus, thus, indirectly taking into account the size of a bank.

As a result, we receive a ranking of all the banks based on their systemic importance (see Table 2 in Appendix). Among the first 10 major contributors there are 6 state-owned banks (the largest ones in the system) and 4 foreign-owned banks. These banks are

[18] The description of this type of distribution could be found in (Kotz, Nadarajah, 2000).
[19] The description of this type of distribution could be found in (Forbes, Evans, Hastings, Peacock, 2011).

characterized by rather low levels of the relative liquidity surplus. Some of them often have the liquidity surplus below 1 during the period under consideration.

Interestingly, among contributors there are also banks which have a negative (countercyclical) effect on the system's liquidity level. These banks are characterized by relatively high values of their liquidity surplus (always higher than 1, and at times even more than 5-10).

The regression analysis reveals some important features of the Russian systemically important banks. First of all, systemic relevance has a strong positive correlation with the size of a bank (see Table 1 in Appendix). All the other indicators except the level of retail deposits are insignificant. The level of retail deposits has a negative correlation with systemic importance, which can be explained by the fact that foreign banks with the high systemic relevance rating have relatively low shares of retail deposits.

5 Conclusion

The recent events have shown that liquidity plays a crucial role in aggravating financial instability. Thus, an appropriate measurement of systemic liquidity risk is an important task for the macroprudential regulation.

The paper presents an approach which can be used in order to measure systemic liquidity risk in a banking system and to construct a rating of banks based on their systemic relevance. The proposed methodology can be employed in different countries even without a well-developed capital market. It does not rely on any assumptions that could lead to model risk.

The approach has been applied to the Russian banking system. The findings reveal the relatively high level of systemic liquidity risk in the sector at the end of 2011. The results also present the banks´ rating according to their systemic importance. The main contributors to systemic liquidity risk are the largest state-owned and foreign banks. These banks, especially the state-owned ones, received substantial liquidity support from the State during the crisis. Therefore, stricter requirements for these credit institutions, including tighter capital and liquidity requirements, should be worked out in order to reduce the effect of their problems on the whole economy.

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Appendix

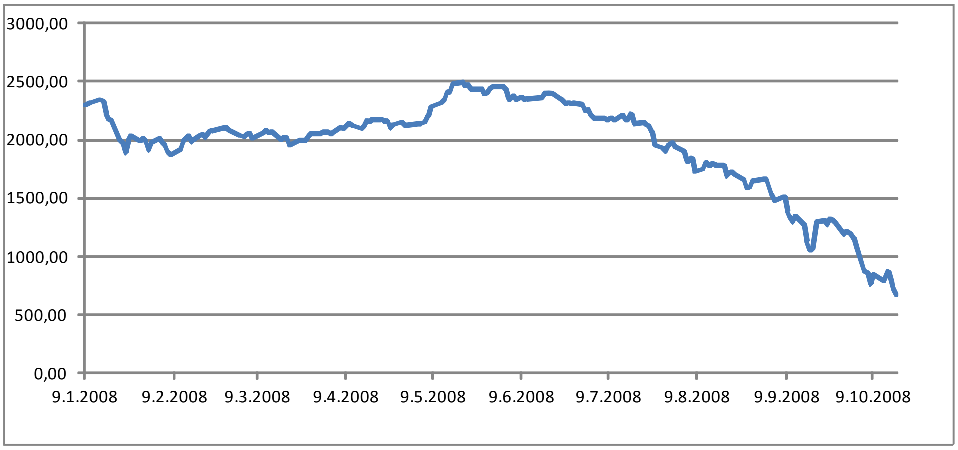

Fig. 7 Dynamics of RTS index

Table 1. The determinants of the banks` systemic importance

Linear regression					Number of obs	268
					F (5, 262)	= 2826.88
					Prob > F	= 0.0000
					R-squared	= 0.9529
					Root MSE	= 0.0041
		Robust				
rc	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
sh_ass	1.225249	0.5163045	2.37	0.018	0.2086151	2.241884
sh_lend	0.0992721	0.0659257	1.51	0.133	-0.0305396	0.2290838
sh_borr	-0.0098114	0.0978668	-0.10	0.920	-0.202517	0.1828943
sh_ret_dep	-0.4119316	0.1535259	-2.68	0.008	-0.7142332	-0.10963
sh_sec	0.1751233	0.1967134	0.89	0.374	-0.2122171	0.5624637
_cons	-0.000291	0.0001512	-1.92	0.055	-0.0005887	6.68e-06

where rc – risk contribution of a bank, sh_ass – ratio of bank´s assets over total assets of the sample, sh_lend - ratio of bank´s lending to financial institutions over the sample´s aggregate figure, sh_borr - ratio of bank´s borrowings to financial institutions over the sample´s aggregate figure, sh_ret_dep – ratio of bank´s retail deposits over the sample´s total amount, sh_sec - ratio of bank´s securities held for trading and available for sale over the sample´s aggregate amount.

Table 2. The rating based on banks´ systemic importance:

Rating	Bank ID	RC	Rating	Bank ID	RC	Rating	Bank ID	RC
1	1481	0,213622	44	2402	0,001829	87	554	0,000668
2	1000	0,169501	45	2225	0,001786	88	3123	0,000665
3	354	0,088781	46	2879	0,001641	89	2551	0,000645
4	2748	0,065149	47	2316	0,001563	90	2586	0,000638
5	3292	0,056218	48	2546	0,001506	91	735	0,000632
6	2272	0,048588	49	2562	0,001504	92	1745	0,000624
7	3251	0,029748	50	3437	0,001457	93	2443	0,000594
8	1	0,02973	51	128	0,001362	94	1376	0,000572
9	3349	0,027645	52	1751	0,001355	95	429	0,000563
10	1623	0,018671	53	2707	0,001352	96	3316	0,000556
11	2275	0,017994	54	197	0,001335	97	324	0,000543
12	2495	0,015928	55	2999	0,00132	98	2913	0,000517
13	1326	0,01535	56	2827	0,001293	99	103	0,00051
14	2557	0,014301	57	3185	0,001259	100	3461	0,000485
15	1776	0,013779	58	3275	0,001214	101	254	0,00048
16	2142	0,011055	59	3137	0,001209	102	2029	0,000465
17	2306	0,009676	60	1581	0,00117	103	2542	0,000463
18	2209	0,008373	61	1574	0,001161	104	2593	0,000459
19	588	0,008242	62	3001	0,00116	105	2998	0,000449
20	1439	0,007927	63	3058	0,001141	106	3269	0,00044
21	323	0,007415	64	3421	0,001113	107	3403	0,000433
22	121	0,006763	65	1637	0,001102	108	843	0,000432
23	3328	0,00607	66	2048	0,001039	109	2764	0,000431
24	328	0,00596	67	2584	0,001025	110	493	0,000427
25	3255	0,0059	68	2914	0,001003	111	2795	0,000419
26	316	0,004978	69	1730	0,000982	112	2997	0,000412
27	2771	0,00448	70	2888	0,000977	113	1885	0,000411
28	3287	0,004301	71	2170	0,000953	114	2208	0,000405
29	3279	0,003934	72	902	0,000903	115	1343	0,000391
30	3064	0,003775	73	2119	0,000891	116	2401	0,000387
31	2766	0,003636	74	2733	0,000817	117	2602	0,000386
32	2590	0,003419	75	3204	0,000807	118	2168	0,000369
33	2412	0,003372	76	3073	0,000773	119	2768	0,000368
34	3431	0,003002	77	3124	0,000771	120	2989	0,000341
35	918	0,002929	78	3016	0,000741	121	3395	0,000332
36	2216	0,002707	79	1961	0,000736	122	2207	0,000328
37	2880	0,002642	80	1810	0,000721	123	2684	0,000303
38	2179	0,002201	81	2307	0,000719	124	2011	0,000302
39	3368	0,002187	82	3261	0,000708	125	2309	0,000286
40	1972	0,002137	83	2618	0,000706	126	1288	0,000284
41	1317	0,002081	84	1966	0,000697	127	84	0,000282
42	2304	0,001925	85	812	0,000691	128	1073	0,00028
43	3390	0,001887	86	1978	0,00067	129	3036	0,000276

Rating	Bank ID	RC
130	3360	0,000273
131	3053	0,000269
132	1319	0,000266
133	249	0,000262
134	880	0,000252
135	3117	0,000251
136	1019	0,00025
137	1307	0,000246
138	3270	0,000245
139	1792	0,000235
140	3138	0,000234
141	1927	0,000227
142	23	0,000191
143	1663	0,000187
144	1975	0,000172
145	2807	0,000169
146	1043	0,000165
147	3161	0,000164
148	2581	0,000162
149	3077	0,000155
150	212	0,000142
151	760	0,000141
152	1616	0,000136
153	2645	0,00013
154	1276	0,000129
155	518	0,00012
156	55	0,000112
157	2555	0,000107
158	3071	0,000106
159	1521	0,000106
160	2103	0,000104
161	1398	0,000102
162	3013	0,000101
163	2816	9,63E-05
164	2524	9,58E-05
165	210	9,57E-05
166	2968	9,46E-05
167	539	8,77E-05
168	2347	8,59E-05
169	2655	8,42E-05
170	2782	7,96E-05
171	2494	7,73E-05
172	2668	7,3E-05

Rating	Bank ID	RC
173	256	7,24E-05
174	1950	7,18E-05
175	2632	6,35E-05
176	3252	6,32E-05
177	3329	6,11E-05
178	1158	5,9E-05
179	435	5,69E-05
180	1557	5,53E-05
181	2576	5,39E-05
182	485	5,17E-05
183	101	4,98E-05
184	5	4,96E-05
185	282	4,93E-05
186	2539	4,8E-05
187	2704	4,75E-05
188	2944	4,72E-05
189	2440	4,54E-05
190	2377	4,29E-05
191	1920	3,28E-05
192	1987	2,63E-05
193	2859	1,6E-05
194	2799	1,25E-05
195	704	1,19E-05
196	2328	1,11E-05
197	1967	9,77E-06
198	777	-1,1E-06
199	1414	-1,8E-05
200	1132	-2,3E-05
201	2755	-2,3E-05
202	2932	-2,5E-05
203	3054	-2,7E-05
204	2960	-3,1E-05
205	2626	-4,3E-05
206	3245	-4,4E-05
207	2867	-4,6E-05
208	1720	-4,7E-05
209	1677	-4,7E-05
210	65	-4,7E-05
211	1659	-5,5E-05
212	52	-6E-05
213	1816	-6,1E-05
214	2110	-6,2E-05
215	1752	-6,5E-05

Rating	Bank ID	RC
216	2269	-7,7E-05
217	2211	-7,8E-05
218	2705	-8,2E-05
219	708	-8,4E-05
220	671	-9,1E-05
221	53	-0,0001
222	2518	-0,0001
223	2956	-0,0001
224	1189	-0,00011
225	2929	-0,00011
226	3052	-0,00013
227	2738	-0,00016
228	1153	-0,00016
229	901	-0,00017
230	2654	-0,00017
231	3407	-0,00018
232	2507	-0,00018
233	963	-0,00019
234	2786	-0,00019
235	3176	-0,0002
236	705	-0,0002
237	2865	-0,00021
238	558	-0,00021
239	3205	-0,00025
240	1242	-0,00025
241	2227	-0,00026
242	1088	-0,00026
243	77	-0,00029
244	3087	-0,0003
245	1573	-0,0003
246	2506	-0,00032
247	3330	-0,00033
248	67	-0,00033
249	2157	-0,00034
250	2647	-0,00034
251	1460	-0,00051
252	948	-0,00051
253	3266	-0,00052
254	410	-0,00059
255	2210	-0,00062
256	912	-0,00078
257	2587	-0,00083
258	3085	-0,00094

Rating	Bank ID	RC
259	2673	-0,00098
260	2176	-0,00108
261	3335	-0,00137
262	1911	-0,00145
263	2312	-0,00148
264	3291	-0,00157
265	514	-0,00198
266	2268	-0,00219
267	107	-0,00283
268	2602	-0,00449