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Irina Andrievskaya

Measuring systemic funding
liquidity risk in the Russian
banking system



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Abstract

The 2007–2009 global financial crisis demonstrated the need for effective systemic risk measurement and regulation. This paper proposes a straightforward approach for estimating the systemic funding liquidity risk in a banking system and identifying systemically critical banks. Focusing on the surplus of highly liquid assets above due payments, we find systemic funding liquidity risk can be expressed as the distance of the aggregate liquidity surplus from its current level to its critical value. Calculations are performed using simulated distribution of the aggregate liquidity surplus determined using Independent Component Analysis. The systemic importance of banks is then assessed based on their contribution to variation of the liquidity surplus in the system. We apply this methodology to the case of Russia, an emerging economy, to identify the current level of systemic funding liquidity risk and rank banks based on their systemic relevance.

Keywords: systemic risk, liquidity surplus, banking, Russia

JEL Classification: G21, G28, P29

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1 Introduction

The 2007–2009 global financial crisis brought to the fore the importance of systemic risk analysis and regulation. In April 2009, the report of the G20 working group noted: “...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). Moreover, the crisis placed a spotlight on the issue of systemically important financial institutions. In his testimony to the US Congress, Federal Reserve Chairman Ben Bernanke observed: “If the crisis has a single lesson, it is that the too-big-to-fail problem must be solved” (Bernanke, 2010). Thus, identification of organizations, particularly banks of systemic relevance, is a crucial task for assessing financial stability and enhancing macroeconomic supervision.

The liquidity shortages seen in the financial system are particularly notable as e.g. Lopez-Espinosa et al. (2012) suggest short-term wholesale funding is the most important determinant of a bank’s contribution to global systemic risk. It seems reasonable therefore, that analysis and regulation of systemic liquidity risk should take priority in macroprudential supervision. Particularly deserving of greater scrutiny is systemic funding liquidity risk, or the “system-level maturity mismatch” (Fender, McGuire, 2010), which is the component of systemic liquidity risk that tends to skyrocket during a crisis.

Approaches have long existed for estimating funding liquidity risk at the level of the individual bank (e.g. Sundararajan et al., 2002). Even so, there is no generally accepted methodology for assessing funding liquidity risk at the level of an entire financial system. Efforts to rectify the situation include the works of Aikman et al. (2009), Drehmann and Nikolaou (2012) and Brunnermeier et al. (2012). Aikman et al. (2009) integrate funding liquidity risk in a RAMSI model,¹ but restrict their analysis to the liability side of bank balance sheets. Brunnermeier et al. (2012) note, however, that what really matters in assessing liquidity risk is the liquidity mismatch among asset and liability items. They propose measuring this mismatch explicitly by applying liquidity weights to all asset and liability items, and then examining the distribution of the difference between total liquid assets and liquid liabilities. Unfortunately, it is not clear how one should determine the appropriate liquidity weights apart from maturity, especially in the midst of a global financial crisis. Drehmann and Nikolau (2012) offer a more implementable approach. For now, it is

¹ Risk Assessment Model for Systemic Institutions.

sufficient to note that they use proxies that allow identification of troubled banks in periods when the banking system faces serious funding pressures, but these proxies do not lend themselves to explicit measurement of a particular level of systemic funding liquidity risk.

To overcome these drawbacks, we focus on the short-term maturity mismatch taking into account its stochastic nature and propose a measure of the level of systemic funding liquidity risk. We use data from financial statements of credit institutions and consider the surplus (absolute and relative) of highly liquid assets above highly liquid liabilities as defined below at the level of an individual bank and an entire banking system. Independent Component Analysis (ICA) is used to derive the simulated distribution of the aggregate relative liquidity surplus. Systemic risk is understood as the distance between the current value for the aggregate relative liquidity surplus and its critical level, measured as the probability of reaching this critical level. The absolute liquidity surplus, in turn, builds the input for identification of systemically important banks using the standard Euler capital allocation principle.

This paper attempts to contribute to the current literature in two ways. First, we offer a straightforward empirical approach to measuring systemic funding liquidity risk and identifying systemically important banks. While we build on the methodology proposed in Brunnermeier et al. (2012), there are a few notable differences. We consider only short-term assets and liabilities (up to 30 days) without applying any liquidity weights to make our approach more implementable. Systemic risk in our framework is understood as distance to a critical level rather than the difference between liquid assets and liquid liabilities. Identification of systemically important banks is based on their contribution to the variation of the aggregate liquidity surplus rather than an absolute value for the bank's liquidity mismatch. Unlike Brunnermeier et al. (2012), who confine themselves to discussion of a theoretical setup, we apply our methodology to a real-world case.

The second aspect of our study worth mention is that it focuses on the banking system of an emerging economy. The Central Bank of Russia (CBR) is currently working on implementation of international approaches to banking regulation, making this study quite topical. The CBR is interested in systemic risk analysis and macroprudential regulation, and a working group under the Presidential Council as well as the department at the CBR responsible for the systemic risk analysis has been established (IMF, 2011a). However, the existing mechanisms for assessing systemic risk, including systemic funding liquidity risk, and regulating systemically important financial institutions are still under de-

velopment and require further work that includes a proper accounting of the Russian environment. Thus, the results presented in this paper hopefully provide a first step in designing such mechanisms.

The paper is organized as follows. Section 2 presents the relevant literature in more detail. Our methodology is described in section 3. Section 4 is devoted to the empirical implication and describes the data we use and the major findings of our estimations. Section 5 concludes.

2 Literature overview

Systemic risk can 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).

One approach to estimating overall systemic risk uses probability distribution and contingent-claim analysis (e.g. Lehar, 2005; Segoviano and Goodhart, 2009; and Huang et al. 2009). Here, the financial system is considered as a portfolio of financial institutions for which potential joint losses and probability of distress are estimated. A drawback of these methodologies is that joint distribution is assumed to be stable over time.

Overall systemic risk can also be measured by examining the interbank market. Sheldon and Maurer (1998) provide an empirical investigation; Iori et al. (2006) take a theoretical tack. Another possibility is to analyze bank behaviour such as herding during stress events that might signal systemic difficulties in the sector. It is explored by van den End and Tabbae (2009).

Systemic liquidity risk was a dominant concern during the 2007–2009 crisis. The IMF defines the problem as “the risk of simultaneous liquidity difficulties at multiple financial institutions” (IMF, 2011b, p. 78). The IMF further notes that liquidity risk has two forms: market liquidity risk, where the organization is unable to sell off assets quickly without negatively affecting their prices, and funding liquidity risk, where the institution is unable to raise funds during a short period in order to meet its obligations (IMF, 2011b). Consequently, the IMF proposes three measures of systemic liquidity risk to take into account both market and funding risks, i.e. employing a systemic liquidity risk index (SLRI, based on the breakdown of the arbitrage relationships on the market), determining the joint

probability of simultaneous liquidity shortfalls based on assessment of the net stable funding ratio (NSFR) proposed in Basel III,² and calculation of the effect of an adverse macro-economic environment on the solvency of multiple institutions based on a macro stress-testing model.

In their recent paper, Brunnermeier et al. (2012) emphasize that the bank's liquidity mismatch is really what matters in creating systemic liquidity risk.³ The authors introduce a liquidity mismatch index (LMI) calculated for a particular time horizon (say, 30 days) as the difference between bank's liquid assets and liquid liabilities. All asset and liability items receive liquidity weights to indicate the liquidity of a particular item. LMI should be calculated for different scenarios (states of the world) with different liquidity weights, so the distribution of LMI values can be generated and liquidity risk assessed using the Value-at-Risk (VaR) technique. In principle, it might be possible to make estimations for the whole banking system to achieve a measure for systemic liquidity risk. However, the proposed methodology is difficult to implement at such scale. There are many types of assets and liabilities and it is a non-trivial task to assign correct liquidity weights, especially given the lack of empirical research in this area.

Drehmann and Nikolaou (2012) lay out a more implementable empirical approach to estimate liquidity funding risk based on a central bank auction. The spread between the submitted bid and the minimum bid rate in the open market is used as a proxy for funding liquidity risk. (The intuition here is that banks with serious liquidity needs can be expected to bid more aggressively.) From this spread, the adjusted bid (AB) for each bank 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. The aggregate proxy for liquidity risk is the sum of all the adjusted bids across banks. The results show that operations during a crisis period become particularly intense with a substantial increase in levels of the aggregate liquidity risk proxies. The authors also confirm the strong interrelation of funding and market liquidity risks.⁴ Unfortunately, the proposed methodology does not allow for estimating the level of systemic funding liquidity risk and overlooks the fact that not all banks have easy access to central bank financing. Thus, the systemic nature of the funding liquidity risk is not fully taken into account.

² Calculated as the ratio of the bank's available stable funding (ASF) and required stable funding (RSF).

³ This analysis is close to the examination of liquidity creation by the financial system (e.g. Berger and Bouwman, 2009).

There is also the issue of identifying “systemically important” financial institutions. For starters, there is not even agreement as to what a systemically important financial institution (SIFI) is. The ECB asserts that it is 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” (ECB, 2006, p.131). However, small banks *en masse* also rise to this SIFI criteria when they are “too many to fail” and exposed to common risk factors (see IMF/BIS/FSB, 2009; Acharya and Yorulmazer, 2007).

There are several approaches to identifying SIFIs. The first is the qualitative assessment. IMF/BIS/FSB guidelines (2009) provide a set of relevant indicators. Recently, quantitative methods have been developed that include an indicator-based methodology, network analysis and assessment of institution’s contributions to systemic risk.

Indicator-based methodologies have the advantage of drawing on available data (balance sheet and macroeconomic data) and only requiring a small set of assumptions.⁵ However, it is not always clear how to weight the indicators.

Another possible approach is to analyze the interbank network. Here, the systemic importance of an institution is examined either from the point of view of its influence on other financial institutions through the interbank linkages (e.g. Furfine, 1999) or from the point of view of its centrality on the interbank market (e.g. Bech et al., 2008; von Peter, 2007).

The third approach involves assessing the institution’s contribution to systemic risk. These methods require a developed financial sector where various types of information are available. They do not take into account the structure of financial institutions, and largely discount the interconnectedness of the banking community. There are two broad sub-approaches. The first is to estimate systemic risk and then attribute it to an individual contributor as all banks are assumed to be exposed to similar risk factors (e.g. Lehar, 2005; Segoviano and Goodhart, 2009; Acharya et al., 2010; Zhou, 2010; Tarashev and Drehmann, 2011; and Brownlees and Engle, 2011). In the second sub-approach, the effect of an institution’s distress on systemic risk is analyzed directly. The major contributors here are Adrian and Brunnermeier (2010) and Chan-Lau, (2010).

⁴ Market liquidity risk is represented by an ECB index for market liquidity (ECB, 2008).

⁵ For examples of such methods, see ECB (2006), IMF (2010) and BCBS (2011).

A more extensive survey with respect to the systemic risk measurement and SIFI identification is provided in Bisias et al. (2012). All these approaches have advanced systemic risk analysis and macroprudential regulation. However, as pointed out in Bisias et al. (2012), most are limited to the crisis period of 2007–2009. Moreover, they rely on varied assumptions and do not necessarily provide reliable results. Rodríguez-Moreno and Peña (2011) conduct an empirical analysis of several systemic risk measures and make the interesting finding that simple indicators perform better than sophisticated ones.⁶ For the European market, the best indicator of systemic risk is the LIBOR spread and the worst is the CoES measure (proposed in Adrian and Brunnermeier, 2010). For the US economy, the best indicator is the first principal component of bank CDS spreads.

Another drawback of existing models is the fact that they have been developed with a focus on advanced economies or the global financial market, and many studies consider theoretical models and provide calculations based on a financial sector model. In other words, there is a gap in empirical research on systemic funding liquidity risk in the case of emerging economies.

3 Methodology

An essential feature of many developing economies is the underdevelopment of their financial markets. Methodologies based on securities prices and spreads are inapplicable, so information must be obtained mainly from balance sheets of financial institutions. Consequently, it is necessary to work out an approach based on the balance sheet characteristics that avoids implausible assumptions and yields realistic results.

Although systemic funding liquidity risk was one of the most significant components of systemic risk of the recent crisis, there is, as noted above, still no generally accepted measure for estimating it. Thus, we propose a straightforward method for assessing the level of systemic funding liquidity risk in a banking system using accessible information. The idea here is to use bank-level data to create a measure of aggregate liquidity sur-

⁶ 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 (Adrian, Brunnermeier, 2009).

plus of a system. As mentioned earlier, this methodology follows the lead of Brunnermeier et al. (2012), but dispenses with liquidity weights and considers only short-term assets and liabilities. This approach we shall see is fairly efficient in detecting and assessing liquidity difficulties in a banking sector.

Within our framework, systemic funding liquidity risk means the potential of a system to reach a condition when it is difficult for its elements to find liquidity sources. The term “systemic risk” is all-encompassing, but elements may suffer from a systemic event or crisis and contribute to systemic risk. We treat “banking system” here as a “portfolio” of credit institutions.

The assessment of systemic funding liquidity 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 , $S(t)$ is the relative liquidity surplus of the system, $AS(t)$ is the absolute liquidity surplus of the system, $s_i(t)$ is the relative liquidity surplus of a bank i , $as_i(t)$ is the absolute liquidity surplus of a bank i , $c_i(t)$ represents the highly liquid assets of a bank i and $o_i(t)$ stands for the short-term obligations of a bank i .

The measure of systemic funding liquidity risk is derived from the simulated distribution of the aggregate relative liquidity surplus (received using ICA analysis). The absolute liquidity surplus of each institution builds the input for covariance calculations to identify systemically important banks.

3.1 Systemic liquidity risk

The system is in distress at a time point t if $S(t)$ is less than its critical threshold (H). Thus, systemic funding 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 equal 1. Under Basel Committee requirements, each bank is required to maintain an appropriate amount of highly liquid assets to cover its liquidity needs for 30 days. For this purpose, the Basel Committee suggests using a liquidity coverage ratio, i.e. 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 greater than or equal to 1 (BSBC, 2010).

However, it is not necessary that all banks have the relative liquidity surplus above 1. For example, foreign-owned banks may rely on funds from their parent companies. Moreover, holding excessive liquidity can be costly for banks. Therefore, within our framework the threshold is applied at the level of the whole banking system.

To express the distance to the critical level in an understandable way, we propose a measure of the probability of reaching the critical level. Here, that 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):

$$R(S) := P(S \leq H | S \leq \hat{S}) = \frac{P(S \leq H \cap S \leq \hat{S})}{P(S \leq \hat{S})} = \frac{P(S \leq H)}{P(S \leq \hat{S})},$$

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

While probability can be calculated based on empirical distribution of the aggregate relative liquidity surplus, more precise estimations require a simulated distribution. For this purpose, we employ Independent Component Analysis (ICA).

Before delving into the deeper part of the ICA discussion, please note that multivariate data can often be explained by the underlying unobserved latent variables (or factors, or independent components). For example, securities prices change with fluctuations in macroeconomic conditions, investor confidence and other factors not directly observed. While it is possible to reveal the underlying variables through factor analysis or principal

component analysis (PCA), they inherently rely on the assumption that factors are normally distributed. To avoid this assumption, we use the alternative ICA approach.

Following with well-described ICA algorithm of Hyvärinen and Oja (2000), our 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 (i.e. sample means are subtracted). Thus, our ICA model can be represented as:

$$x = Am ,$$

where x is the vector of n random variables, m is the vector of underlying random factors and A is the transformation matrix. The only observable data are contained in the random vector x , while A and m have to be estimated.⁷ For the purpose of our analysis, all the calculations are carried out in the statistical program R with the package `fastICA`.⁸

The next step is to find the most appropriate type of probability distribution for each independent component. The fitting is carried out using the Statistica 10 software. Kolmogorov-Smirnov and chi-square goodness-of-fit tests are employed to find the proper distribution functions (see Panik, 2005). When the distribution type of each factor is known it is possible to use the simulation technique to enlarge the number of observations. The simulation is also performed with Statistica 10. Finally, our simulated data for each independent component and the estimated matrix A are used to get back to the original vector x .

3.2 Systemically important banks

The potential of the system to fall below the critical threshold H is explained by the variation of S . The larger the variation, the greater the potential. 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, in turn, is based on the Euler capital allocation principle. This is well described in McNeil et al. (2005).

⁷ The independent component (or factor) can be obtained after estimating the matrix A and then taking its inverse: $m = Wx$.

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

In defining the Euler capital allocation principle McNeil et al. (2005) state that if there is a risk function that 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 is the risk-measure function, λ_i is the weight of a sub-portfolio i in the total portfolio, rc_i is the amount of capital allocated to the sub-portfolio i (i.e. 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:

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

where X_i represents profits and losses generated by the sub-portfolio i and X stands for the 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. As we are interested in the contribution of banks to the variation of the system's absolute liquidity surplus, the risk contribution can be expressed as:

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

where as_i is the absolute liquidity surplus of a credit institution i and AS is the absolute liquidity surplus of the system. \square

The next step is to examine which bank characteristics are relevant determinants of systemic importance. For this purpose, we consider several indicators proposed by the Basel Committee,⁹ and employ a simple econometric analysis (OLS). The value of the systemic risk contribution (estimated above) is used as a dependent variable. Explanatory

⁸ The R code is available from the author upon request.

⁹ These indicators are used by BCBS (2011) to detect global systemically important banks.

variables reflect bank size, interconnectedness and complexity. Lacking the necessary data, we do not include indicators of substitutability and global activity.¹⁰

4 Empirical application

4.1 Data

In performing our analysis for Russia, we use the monthly financial statements of the Russian banks for the period January 2007–December 2011. The largest 268 banks have been selected; their assets amount to 90% of the total assets in the system.¹¹

The liquidity surplus is calculated on the base of each bank's short-term assets (c_i) and liabilities (o_i) up to 30 days. Following the CBR's own logic,¹² we define these short-term items with slight modification due to data availability.¹³ These bank-level balance sheet data are typically available in all emerging economies, but there may be slight discrepancies over which asset and liability items should be included in the calculations, especially when there is a better access to the balance sheet data (e.g. by bank supervisory authorities). In any case, the concept remains the same.

Short-term assets here comprise cash and cash equivalents, gold, correspondent and current accounts, credits and deposits (to financial and nonfinancial organizations, including deposits held by the CBR) up to 30 days, state securities and promissory notes up to 30 days. Short-term liabilities, in turn, include credits and deposits (from financial and nonfinancial organizations) with maturities 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 maturities up to 30 days.

Table 1 below presents descriptive statistics for the relative liquidity surplus. At the level of the whole banking system, the relative liquidity surplus is above 1 throughout

¹⁰ Here, we focus on the Russian banking system. As banks are not globally active, there is no need to account for the cross-jurisdictional activity.

¹¹ This information is publicly available on the website of the Central Bank of Russia.

¹² The CBR has established several liquidity ratios to regulate bank liquidity positions. In particular, it requires that banks calculate their ratios of instant liquidity (N2, which characterizes a bank's risk of losing liquidity during one operational day), current liquidity (N3, which characterizes a bank's risk of losing liquidity during 30 operational days) and long-term liquidity (N4, which characterizes a bank's risk of losing liquidity during 365 or more operational days).

the period under consideration. The minimum of 1.009 was reached in August 2008, while the maximum of 1.802 was observed in June 2007. If we consider all banks separately, the values of the relative liquidity surplus vary substantially with minimum levels often well below 1.

Table 1 Descriptive statistics: Relative Liquidity Surplus

| | Mean | Std. Dev. | Min | Max |
|-----------|-------------|-------------|-------------|-------------|
| System | 1.313483245 | 0.19813466 | 1.009004406 | 1.801845367 |
| All banks | 2.445995387 | 4.017038024 | 0.012859692 | 163.0827358 |

In order to enlarge the number of observations for the relative liquidity surplus we employ ICA calculations with the vector x consisting 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 30.¹⁴ For each independent factor, 180,000 observations are simulated. Thus, we get 180,000 observations for each bank and the whole system.

For our regression analysis, we define the following. Bank size is the ratio of a bank's assets over total assets of the sample (sh_ass). Interconnectedness is defined as the ratio of a bank's lending to financial institutions over the sample's aggregate figure (sh_lend) and as the ratio of a bank's borrowings from financial institutions over the sample's aggregate figure (sh_borr). Complexity is the ratio of a bank's securities held for trading and available for sale over the sample's aggregate amount (sh_sec). We also consider the level of a bank's retail deposits (expressed as the ratio over the sample's total amount (sh_ret_dep)) to reflect the bank's level of involvement in the economy.

Table 2 below presents the summary statistics for the above-described variables.

¹³All the items we include are considered to be liquid (for the time horizon up to 30 days) by the CBR. The modification refers to the fact that the list of items used by the CBR is wider due to better access to the necessary data.

¹⁴The 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.

Table 2 Summary Statistics: Regression Analysis

| Variable | Mean | Std. Dev. | Min | Max |
|------------|------------|-----------|---------|----------|
| sh_ass | 0.00373172 | 0.0199050 | 0.00000 | 0.290500 |
| sh_lend | 0.00372649 | 0.0155957 | 0.00000 | 0.176900 |
| sh_borr | 0.00372724 | 0.0264278 | 0.00000 | 0.418600 |
| sh_ret_dep | 0.00372873 | 0.0314767 | 0.00000 | 0.509800 |
| sh_sec | 0.00372910 | 0.0245488 | 0.00000 | 0.374500 |

4.2 Major findings

In analyzing the dynamics of the aggregate relative liquidity surplus, we should start by noting that Russia's financial crisis was a two-stage affair (IMF, 2011a). The first part began in the second half of 2008 with the appearance of liquidity shortages. Funds from non-residents fell substantially starting in September 2008. This can be seen in our data on short-term liabilities; short-term funds from non-residents substantially fell in August 2008 and continued to decrease through to the end of 2009 (Figure 4 in Appendix). Some banks also experienced significant deposit withdrawals.

Liquidity problems in the system in the second half of 2008 are also reflected in interbank rates (Figure 5 in Appendix). Interbank rates started to rise in August 2008 and peaked in January 2009.

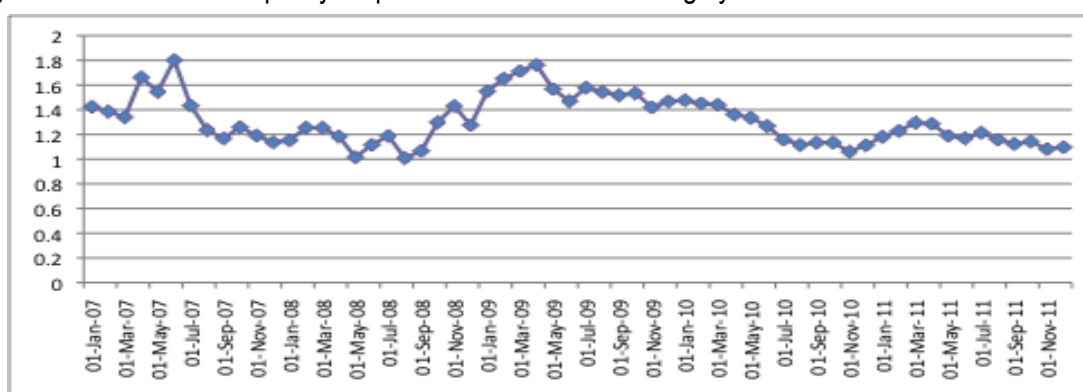
The second stage of Russia's financial crisis manifested in 2009 in the form of rising credit risk. The government was forced to prop the banking sector by channelling state resources to the banking sector and the wider economy via several key financial institutions.¹⁵ Some of this liquidity support provided by the government to the Russian banking system shows up in our data. In September 2008, for example, there was a substantial increase in short-term funds provided by the Ministry of Finance (see Figure 6 in Appendix) and the state (see Figure 7 in Appendix). Interestingly, the share of the two largest state-owned banks in the short-term funds received from the state in December 2008 was 38%,

¹⁵ By the IMF's own assessment (IMF, 2011a), support from the CBR was provided in forms that included liquidity provision such as guarantees on the interbank market, lending to qualifying banks, as well as an expanded list for acceptable collateral on repurchase and Lombard operations, etc. 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 1.4 trillion roubles (3.5% of GDP) with subordinated loans amounting to 904 billion roubles (2.2% of GDP). Subordinated credits went to the largest banks

while the share of the top five main contributors to the liquidity surplus variability was 55% (the list of the main contributors is presented in Table 4).

The dynamics of the aggregate relative liquidity surplus (that we constructed) confirm the tight liquidity situation in the banking sector in the second half of 2008. Our results (Figure 1), however, also reveal that banking system was experiencing severe liquidity distress as early as May 2008 and was at its most acute (1.009) already in August 2008. This is confirmed by the CBR in its overview of the Russian banking sector in 2008 (CBR, 2008). May 2008 corresponds to the beginning of the crisis and the emergence of serious liquidity problems in the Russian banking system. The stock market went into decline at this point and experienced a significant drop in July 2008 (Figure 3 in Appendix).

Figure 1 Relative liquidity surplus of the Russian banking system



Now we turn to the analysis of the systemic funding liquidity risk measure. Note that the results of the ICA estimations show that the underlying 30 independent components have Generalized Extreme¹⁶ and Triangular¹⁷ distributions. As there are 180,000 observations for each factor, there are also 180,000 observations for the whole system. The simulated distribution of the banking system's relative liquidity surplus is presented in Figure 2.

including state-owned Sberbank (500 billion roubles), VTB (200 billion roubles) and Rosselkhozbank (25 billion roubles) (see Golubev, 2009).

¹⁶ A description of this type of distribution appears in Kotz and Nadarajah (2000).

¹⁷ A description of this type of distribution appears in Forbes et al. (2011).

Figure 2 Histogram of the simulated system's relative surplus

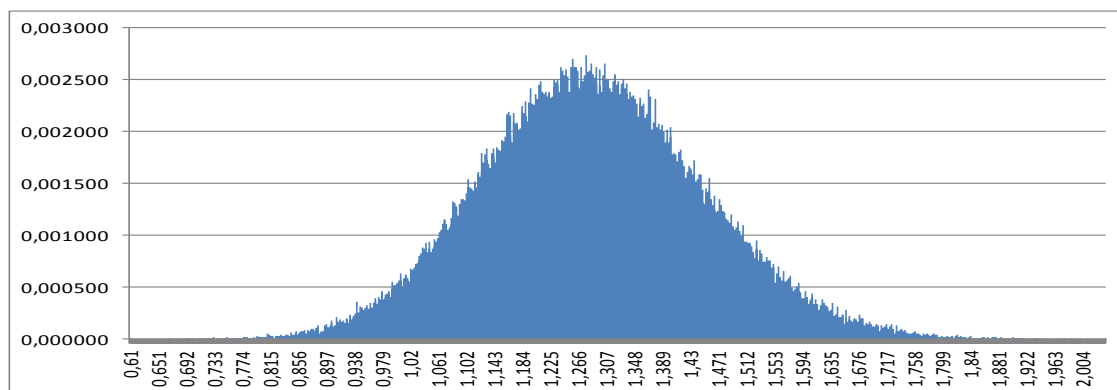


Table 3 contains the relevant summary statistics. The value of the mean is virtually the same as it was using our initial data. The simulated distribution is characterized by a slight skewness to the left and rather thin tails (as shown by the negative value of the kurtosis).

Table 3 Summary statistics: Relative Liquidity Surplus

| Mean | Std.Dev. | Min | Max | Skewness | Kurtosis |
|-------|------------|------|------|--------------|----------|
| 1.325 | 0.41323843 | 0.61 | 2.04 | -4.73993E-14 | -1.2 |

This distribution allows us to estimate the level of systemic funding liquidity risk. For example, in December 2011 the value of the system's relative liquidity surplus was 1.096. Thus, the level of systemic funding liquidity risk can be expressed as:

$$P(S \leq 1 | S \leq 1.096) = \frac{P(S \leq 1)}{P(S \leq 1.096)} = 0.2817$$

The conditional probability that the surplus will fall to the critical level (i.e. the systemic funding liquidity risk) equals 28%. This is a relatively high level of funding liquidity risk and reflects serious problems in the system.

It is important to emphasize that the CBR was well aware of the decreasing level of liquidity in the banking sector in the final four months of 2011. It responded by providing additional liquidity support to the banking sector (CBR, 2011). Our measure simply allows expressing of the liquidity situation in a more formal way, characterizing the degree

of liquidity difficulties in the sector in a manner that is potentially useful in macroprudential regulation.

We now move to examination of the systemic importance of individual banks. As it is described in subsection 3.2, systemic importance is estimated according to the bank's contribution to the variation of the system's liquidity surplus during the period under consideration. It should be mentioned that we do not adjust for bank size here. However, covariance is calculated based on the absolute liquidity surplus (thus indirectly taking bank size into account).

Using our methodology, we obtain a ranking of all banks based on their systemic importance. Table 4 presents the top ten major contributors, a group that includes six major state-owned banks (Sberbank, VTB, Gazprombank, Bank of Moscow, Russian Agricultural Bank and VTB 24), three foreign-owned banks (Raiffeisenbank, Rosbank and UniCredit Bank) and a privately owned domestic bank (Promsvyazbank).¹⁸

Table 4 Top ten banks ranked by systemic importance (RC = risk contribution)

| Ranking | Bank ID | Bank name | RC | Relative surplus: Mean | Relative surplus: Std. dev. |
|---------|---------|---------------------------|-----|------------------------|-----------------------------|
| 1 | 1481 | Sberbank | 21% | 1.07 | 0.19 |
| 2 | 1000 | VTB Bank | 17% | 1.65 | 0.61 |
| 3 | 354 | Gazprombank | 9% | 2.18 | 1.55 |
| 4 | 2748 | Bank of Moscow | 7% | 1.78 | 0.77 |
| 5 | 3292 | Raiffeisenbank | 6% | 0.96 | 0.41 |
| 6 | 2272 | Rosbank | 5% | 1.61 | 0.65 |
| 7 | 3251 | Promsvyazbank | 3% | 1.31 | 0.41 |
| 8 | 1 | UniCredit bank | 3% | 0.61 | 0.23 |
| 9 | 3349 | Russian Agricultural Bank | 3% | 2.19 | 0.92 |
| 10 | 1623 | VTB24 | 2% | 1.03 | 0.46 |

These banks are characterized by relatively small liquidity surpluses. Some dip repeatedly below 1 during the period under consideration, most notably the foreign-owned banks Raiffeisenbank and UniCredit bank, which can turn to their parent companies for liquidity.

¹⁸ The full list is available from the author by request.

For Russia's state-owned banks, the liquidity surplus averages above 1, but also varies considerably (especially for Russian Agricultural Bank and Bank of Moscow).¹⁹

Interestingly, 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 (consistently above 1, and sometimes in the range of 5–10). These banks are typically quite small and privately owned domestic banks. They cannot rely on a parent company and lack ready access to government support. Thus, they retain excess liquidity as insurance against liquidity difficulties in the system.

The regression analysis reveals some interesting features of the Russian systemically important banks. First, systemic relevance has a strong positive correlation with the size of a bank (see Table 5 and Table 6 in Appendix). All the other indicators besides 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 a high systemic relevance rating have relatively low shares of retail deposits.

In 2011, the CBR started to consider the issue of systemically important banks (CBR, 2011). Our suggested approach here could be incorporated into the broader macroprudential effort to detect such banks. Although we deal with only funding liquidity risk here, it is a component that significantly influences overall financial stability. Thus, the biggest contributors to variation in system liquidity deserve particular attention from regulators.

5 Conclusions

Recent events highlight the crucial role liquidity plays in financial instability and the need for appropriate measurement of systemic liquidity risk in macroprudential regulation.

This paper presented a straightforward approach for measuring systemic funding liquidity risk in a banking system and constructing a rating of banks based on their systemic relevance. The proposed methodology is also suitable for countries that lack well-developed capital markets. Using bank-level balance sheet data, it effectively detects and measures the level of funding liquidity difficulties in the banking sector.

¹⁹ At the end of June 2011, the Bank of Moscow received a massive 395-billion-ruble bailout from the authorities to prevent its collapse.

Here, our approach was applied to the Russian banking system, which experienced a high level of systemic liquidity risk in banking sector in late 2011. Our results show the large state-owned and foreign banks were the major contributors to fluctuation in system liquidity. These banks (especially the state-owned banks) 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 in place before the crisis hit to reduce the impact of liquidity problems on the economy as a whole.

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Appendix

Figures

Figure 3 RTS index performance in 2008

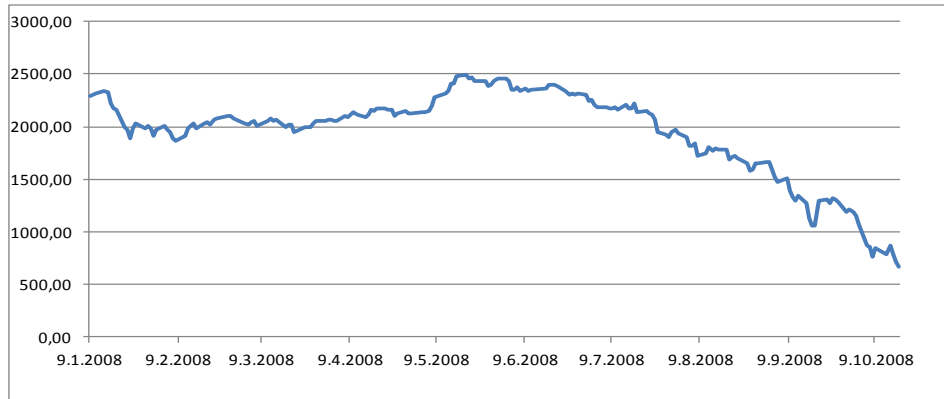


Figure 4 Short-term funds from non-residents (in roubles)

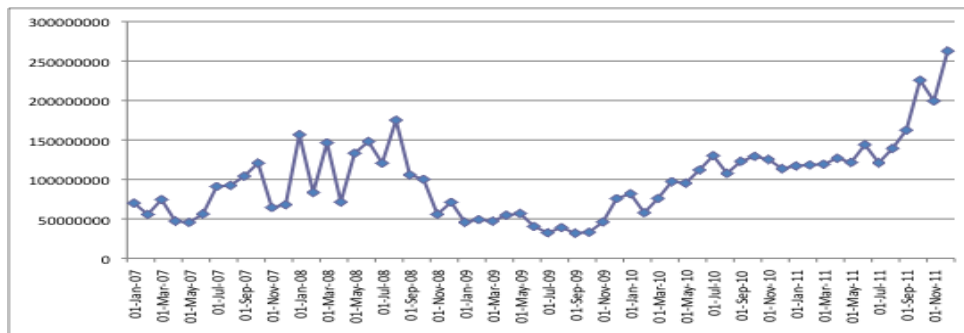


Figure 5 Average interbank interest rate on a one-day rouble loan

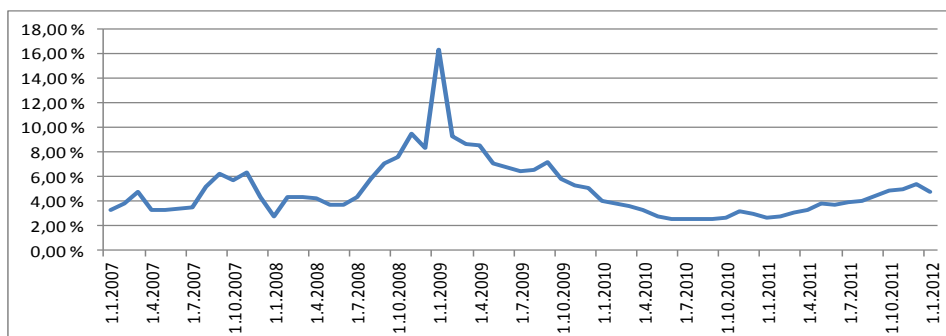


Figure 6 Stock of borrowing at Ministry of Finance short-term funds rate (roubles)

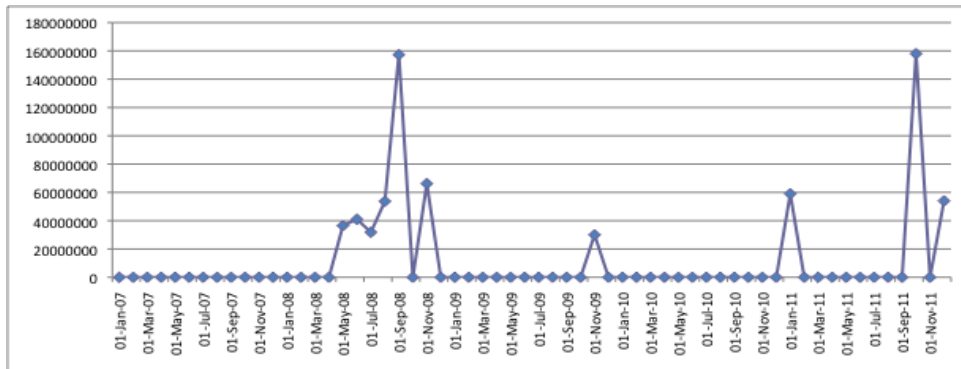
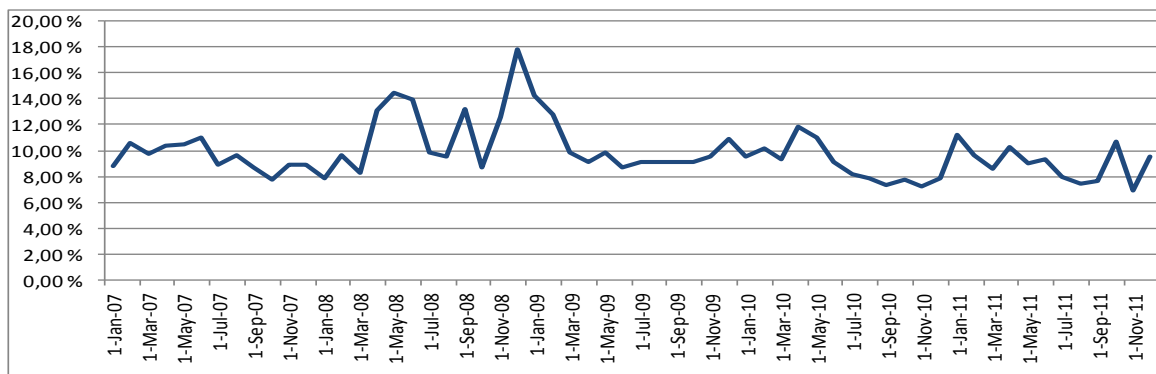


Figure 7 Overall short-term state-provided funds (% of total bank short-term liabilities)



Tables

Table 5 Determinants of a bank's 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 the bank's assets over total assets of the sample, sh_lend = ratio of the bank's lending to financial institutions over the sample's aggregate figure; sh_borr = ratio of the bank's borrowings to financial institutions over the sample's aggregate figure; sh_ret_dep = ratio of the bank's retail deposits over the sample's total amount; sh_sec = ratio of the bank's securities held for trading and available for sale over the sample's aggregate amount.

Table 6 Regression with statistically significant variables only

| Linear regression | | | | | Number of obs. | 268 |
|--------------------------|------------|---------------|--------|-------|----------------|------------|
| | | | | | F(2, 265) | =10983.32 |
| | | | | | Prob > F | = 0.0000 |
| | | | | | R-squared | = 0.9493 |
| | | | | | Root MSE | = .00422 |
| | | Robust | | | | |
| rc | Coef. | Std. Err. | t | P>t | [95% Conf. | Interval] |
| sh_ass | 1.462882 | 0.0662064 | 22.10 | 0.000 | 1.332524 | 1.593239 |
| sh_ret_dep | -0.4119848 | .0360319 | -11.43 | 0.000 | -0.4829301 | -0.3410396 |
| _cons | -0.0001912 | .0001798 | -1.06 | 0.289 | -0.0005451 | 0.0001628 |

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