Master in Finance Program

NEKN02 Master Essay I

Stress-testing of the Russian Banking Sector: Contingent Claims Analysis Approach

by

Anna Kulakova

Supervisor: Associate Professor Birger Nilsson

Lund University School of Economics and Management

Lund, Sweden

June 2019

Abstract

This study aims to perform stress-testing of the Russian banking sector with a focus on credit risk measures derived by using contingent claims analysis, an extension of Black-Scholes and Merton option pricing theory. Risk exposure indicators are linked to a number of macroeconomic variables that describe global and domestic economic and financial development. To reduce the dimension of the dataset, principal component analysis is applied. The derived factors of financial stability, economic growth, and interest rates together with credit risk measures are used in vector autoregressions so as to draw impulse response functions, which allows for stress-testing of the analyzed banks by estimating the effect of adverse and severe adverse shocks to the factors specified by 95% and 99% VaR. Stress test analysis revealed that shock to the economic growth factor shows more persistence compared to the financial stability factor. Surprisingly, shock to the interest rates factor resulted to be insignificant at a chosen lag length. The results also suggest high degree of banks' heterogeneity, which complicates a derivation of a parsimonious model suitable for the whole system. While international banks are barely affected by the proposed shocks, domestic banks, regardless of their size, may react rather strongly to the financial stability and economic growth shocks – to the point of reaching distress level within several months after the adverse event.

Keywords: credit risk, stress-testing, contingent claims analysis, Merton model, vector autoregression, impulse response function, principal component analysis.

Acknowledgements

I would like to express my gratitude to Associate Professor Birger Nilsson, my thesis supervisor, for his constructive comments and valuable suggestions during the research process.

List of abbreviations

CBR The Central Bank of the Russian Federation, Bank of Russia

CCA Contingent claims analysis

CPI Consumer price index

DD Distance to default/distress

IRF Impulse response function

NPL Non-performing loans

OFZ Federal loan bond

PCA Principal component analysis

PD Probability of default

VAR Vector Autoregression

VaR Value-at-Risk

List of bank abbreviations:

BSPG Bank Saint-Petersburg

RAI Raiffeisenbank

ROSB Rosbank

SBER Sberbank of Russia

UCG UniCredit Bank

USBN Uralsib bank

VTB VTB Bank

Table of Contents

1. Introduction

Before the global financial crisis, the application of stress-testing techniques was largely limited to individual companies that used them for internal risk management purposes. However, the crisis that emerged from the excessive risk-taking of major financial institutions exposed some deficiencies in the financial regulation, leading to the introduction of Basel III. It was shown later that the severity of the crisis was mainly caused by its unexpected nature and some of its repercussions could have been avoided or mitigated given a more extensive use of stress tests (Quagliariello, 2009). Since that time, stress-testing for banks has become relatively well established worldwide. Now, macroprudential stress tests are used by financial regulators to assess banks' resilience to the adverse economic conditions so as to possibly identify the vulnerabilities of the banking sector.

This may be especially relevant to the case of Russia that currently faces a rather turbulent economic situation that negatively affects the stability of the financial system. In this regard, financial stability implies that the financial system is able to survive and perform its key functions when faced with unfavorable economic developments. Imposed external economic sanctions on Russian credit institutions in 2014, which restricted their access to some attractive foreign financial markets, resulted in overall instability of the financial sector so that some key performance indicators of the Russian banks still show a negative trend. Along with this, fragmentary nature of the Russian banking sector, high vulnerability of banks' operation models to the external shocks, and their low adaptability to the changing macroeconomic environment increase the relevance of stress-testing analysis for the Russian banking sector.

Banking systems are exposed to different types of risk. However, credit risk, resulting from inability of an obligor to meet their contractual obligations, i.e. make debt payments, is considered to be of the utmost importance, especially for the emerging economies (Fungáčová & Jakubík, 2013). Thus, this study aims to assess the exposure of the Russian banking sector to credit risk by using the contingent claims analysis (CCA) approach. This method is based on the estimation of the probability that an entity (in our case, banks in Russia) defaults on its obligations. It is based on the combination of balance-sheet and market data, which makes up one of the main advantages of this approach. While risk indicators derived from the bank balance sheet data (non-performing loans, for instance) tend to be rather static, risk measures based on market data can not only be calculated at a higher frequency but also reflect the forward-looking expectations of the market (Gray & Walsh, 2014).

After deriving a credit risk measure of the Russian systemically important banks by using the CCA methodology, we proceed to assess how changes in macroeconomic and financial variables affect it by specifying macroeconomic shocks. The Central Bank of the Russian Federation (Bank of Russia, CBR) regularly assesses the stability of the banking sector by using macroprudential stress-testing. However, the applied methodology is somewhat limited as argued by the IMF (2016). In the latest stress-test, the CBR macroeconomic scenario modelling is based on changes in four main parameters: oil price, GDP growth, CPI, and growth of fixed capital investment (Bank of Russia, 2018). This study expands this list by including some other internal (inflation, unemployment, MOEX index, production index, etc.) and external (USDRUB, US Treasury rate, S&P500 index, etc.) factors. Since the dataset of used variables is rather extensive, principal component analysis is used to decrease its size. Then, VAR models are estimated for each bank by using the obtained risk measure and macroeconomic factors, which are later used to derive impulse response functions so as to assess how macroeconomic shocks affect banks' risk measures. Importantly, stress-testing will include two specifications of shocks – adverse and severe adverse events, which are based on 95% and 99% VaR estimates, respectively.

Overall, the aim of this research is twofold. First, this paper contributes to the existing academic literature on the topic of stress-testing by implementing a relatively uncommon contingent claims analysis method to estimate the credit risk exposure of the Russian banking sector. Second, it develops the currently used stress-testing methodology of the main Russian financial sector regulator by using a different measure of risk exposure and identifying some other risk factors that may potentially affect the banking system. So, the main research question is which macroeconomic factors Russian banks are exposed to the most.

The main objectives include: 1) to investigate the main theoretical frameworks and methodologies of the stress-testing of banks; 2) to use the CCA methodology and derive credit risk measures of the Russian banks; 3) to evaluate the resilience of the chosen Russian banks to main macroeconomic risks by carrying out sensitivity and top-down stress-testing analysis.

The paper is structured as follows. In Section 2, the main sources of literature on the topics of contingent claims analysis and stress-testing are covered. Section 3 provides some description of the Russian banking sector, which is necessary to support some of the assumptions made in later chapters. Then, in Section 4, after providing some background theory on contingent claims analysis, we proceed directly to the qualitative analysis – estimation of the default probabilities of the chosen banks in Russia. Section 5 deals with stress-testing of the Russian banking sector, starting with a derivation of macroeconomic risk factors by using PCA and analysis of their effect on the banks' credit risk measure by implementing VAR models and impulse response functions. Finally, after discussing the limitations of the conducted research and providing some suggestion for its further development in Section 6, some conclusions are drawn based on the obtained results.

2. Literature review

Performing a stress test on the banking sector poses two main challenges – the first one deals with the choice of an appropriate risk measure, the second one is connected to the macroeconomic shocks simulation and the stress test *per se*. Thus, in this section two corresponding groups of literature sources will be covered, after providing a brief history of macroprudential stress-testing practices' development.

Still, it is necessary to particularly mention two sources. The first one is the article by Dale F. Gray & James P. Walsh (2014) published in "A Guide to IMF stress-testing" (Ong, 2014). In the paper, they carry out the stress-testing of Chilean banking system using the contingent claims analysis approach. This thesis mainly follows the methodology laid out by the authors, although some adjustments were made to account for the differences in the economy as a whole and in the banking sector of Russia compared to those of Chile. The second source is the book "Stress-testing the banking system: Methodologies and applications" by Mario Quagliariello (2009) which provides a general methodology and main frameworks for bank stress tests.

2.1. Development of macroeconomic stress-testing practices

Stress tests as a risk management tool have been used by various credit institutions since 1990s; however, at first, they were considered as a supplementary tool in evaluating bank's trading or credit activities (Blaschke et al., 2001). The formalization of stress-testing practice began in 1996 with the introduction of Market Risk Amendment to the Basel Accord. Later, in 2004 with the emergence of Basel II, banks were recommended to conduct stress tests on the capital requirements, which, however, served only as guidelines for the bank risk management and was not universally implemented (Basel Committee on Banking Supervision, 2009). So, stress tests were mainly applied at the micro level and in general were relatively simple (Blaschke et al., 2001), but in the early 2000s financial regulators started to consider the possibility of using them as a part of macroprudential regulation framework (Committee on the Global Financial System, 2000).

In 1999, the IMF and World Bank initiated Financial Sector Assessment Program (FSAP) so as to analyze the stability and soundness of a country's financial sector. Since the introduction of FSAP, more than 350 financial sector assessments have been conducted. Besides, many central banks (although mainly in the developed countries – Spain, Sweden, Canada, Denmark, etc.) have been developing their own macroprudential stress-testing methodologies and regularly communicating the assessments' results to the public (Baudino, 2009). However, prior to the financial crisis, stress tests were considered rather uninformative and did not encourage appropriate policy actions from the financial regulators (Čihák, 2007). Nevertheless, system-wide applications of stress tests have encouraged the development of more holistic methodologies and frameworks based on the lessons learned from the crisis.

In 2009, the Basel Committee published stress-testing principles that addressed major weaknesses of the used methodologies that were made evident by the financial crisis. Having acknowledged the integral role of stress-testing techniques within more recent risk management frameworks, these principles were reviewed and updated by the regulator almost 10 years later in "Stress-testing principles" (Basel Committee on Banking Supervision, 2018). These principles are essentially high-level guidelines for financial regulators and large internationally active banks so each entity develops and calibrates the applied stress tests to their own needs. Nevertheless, since the emergence of Basel III, stress-testing established itself as a one of the major tools of the macroprudential policy.

2.2. Risk exposures of the financial system

One of the primary practical issues a researcher should address while conducting stress tests deals with selecting an appropriate risk measure to be stressed and connecting it to the risk factors that are likely to affect it. This decision is usually based on the scope of the research comprising a set of institutions and portfolios (Sorge & Virolainen, 2006). Ideally, a macroeconomic stress test should be conducted on the whole financial system. However, in practice, such test is almost impossible to implement due to significant increase in the model complexity and lack of necessary data. The most common approach is to subject a part of the financial system to stress-testing – it can be a pension fund or an insurance company but the most common one is a banking sector given its apparent importance to the financial stability (Borio et al., 2012). In case of Russia, for instance, banking assets constitute around 85-90% of total assets of the financial system; for comparison, in the USA and China it is approximately 55%, in Brazil – around 60% (Dzhagityan, 2016). So, by assessing the stability of the Russian banking sector, it would be possible to extrapolate the obtained results to the whole financial system.

Generally, a suitable risk measure should meet two main requirements (Čihák, 2007): (1) the chosen variable should be relatively easy to interpret as a measure of the soundness of the analyzed financial system, and (2) it should be possible to credibly connect it to risk factors. Most of risk metrics are based on aggregate and accounting data including non-performing loans (NPL), risk-weighted assets, loan loss provisions, level of indebtedness, banks' capital, profits and their components, etc. (for detailed analysis of advantages and disadvantages of these metrics refer to Čihák (2007) and Quagliariello (2009)). They are usually linked to some rather typical macroeconomic factors. For example, Blaschke et al. (2001) connect GDP, nominal interest rates, inflation, and shifts in trade structure to NPL to total assets ratio. However, in case of using aggregated data, it is implicitly assumed that all the analyzed banks, regardless of their size and strategies, have the same level of risk exposure. To address this issue, Quagliariello (2007) tried to account not only for macroeconomic factors (including GDP, stock indices, interest rates, and spreads) but also for idiosyncratic ones (total bank assets, credit growth, capital-to-asset ratio, etc.) that resulted to have a significant impact on Italian banks' loan loss provisions.

One of the alternatives to stress-testing models based on balance-sheet data is contingent claims analysis that allows to derive a credit risk measure, relating it to future values of assets in relation to debt payments. This approach is based on the estimation of the probability that the bank (or any other institution) defaults on its obligations. The theoretical framework was laid out by Dale F. Gray with some co-authors (see, for example, Gray & Malone, 2008; Gray et al., 2007; Gray & Jobst, 2010).

Given that CCA constitutes an extension of the Merton model (1974), it manages to capture nonlinearities, which is considered as one of the advantages of this approach. Although the linear dependence between the economic variables is a quite common assumption in macroeconomic modelling and forecasting, it is only valid under normal economic conditions. However, by using stress tests, one analyses the economy in extreme market situations when non-linear relationships between the variables may be significant (Quagliariello, 2009). It was shown, for instance, by Drehmann (2005), who applied the

Merton model to estimate credit risk exposures of the UK banks and found significant non-linear and non-symmetric impact of macroeconomic factors on credit risk. Another advantage is that CCA/Merton model approach uses market value of equity, which is forward-looking and is available at a high frequency. However, this method requires a lot of data and is rather computationally demanding (Sorge, 2004).

2.3. Main approaches to stress-testing of the financial system

Stress test of the banking sector can be performed in two main ways – top-down or bottom-up. While in the first approach the same assumptions and models are applied to all the analyzed banks, the latter is more tailored to the specifics of each credit entity. Thus, the top-down method is used mainly by central banks and other regulatory institutions, and bottom-up method is employed by individual banks. The advantage of top-down approach is that it allows for comparison across different entities, the disadvantage is that some of the idiosyncratic information may be lost due to data aggregation (Kapinos et al., 2015).

A much less common approach is so-called reverse stress-testing when researchers try to identify the magnitude of macroeconomic shock that will result in banks' distress (Breuer et al., 2009; Glasserman et al., 2015). Although it is unlikely that this method will find a wide application in regulatory stress-testing due to interpretation and implementation challenges, it still can be used as a supplementary tool in scenario modelling (Baudino et al., 2018).

Any stress test comprises a set of exogenous shocks that may threaten the stability of the financial system. Jakubík & Sutton (2011) identify two main ways of specifying adverse shocks – sensitivity tests and scenario analysis. Under the first approach, only one risk factor is shocked so it is relatively easy to implement in practice. However, sensitivity tests tend to lack plausibility since it is unlikely that under adverse economic conditions only a single variable undergoes negative changes. Thus, they argue that scenario modelling where several key macro variables are shocked together tends to generate more plausible results.

Regardless of how many macro variables drive the shock, one should specify a time horizon over which the effects of an adverse scenario are analyzed. Since it may take a long time for these effects to be realized (especially in case of credit risk analysis), practitioners often choose a horizon from one to three years (Jakubík & Sutton, 2011).

Having decided on the risk factor, it is necessary to design macroeconomic scenarios, i.e. decide on the severity of the shocks and how fast the economy will recover from it. Quagliariello (2009) suggests that the simulation of the shocked variables should depend on the baseline scenario, which can be based on simple forecast using historical data. While historical data is, by definition, backward-looking so it can become less relevant to the analysis because of market structural changes, it is the most intuitive approach. As for adverse shock, it can be calibrated based on the largest past change in the macroeconomic variable or on historical conditional or unconditional variances (Sorge, 2004). This way, it would be possible to obtain severe but rather plausible scenarios – what happened in the past, could possibly recur.

Another method of scenario modelling is based on Value-at-Risk (VaR). The magnitude of simulated shock is defined by either historical simulation or parametric approaches to VaR estimation. In many credit and market risk models, risk factor is assumed to be normally distributed. Although this approximation is rather useful and can be applied to many situations, it may not be appropriate because of fat-tails inherent to financial data. However, non-normality assumptions may lead to higher probability and, thus, underestimation of the stress event risk (Isogai, 2009). Besides, if the aim of a stress test is to assess more extreme scenarios, VaR may not be appropriate since it tends to ignore events at the end of the tail. So, sometimes a worst-case scenario approach is applied.

Overall, the research in the field of macroprudential stress-testing is quite extensive. There are no commonly accepted methods but there are some key issues to consider while defining the applied stress-testing methodology. As argued by Drehmann (2008), the design of the model and used econometric instruments should depend on the objectives of the stress test.

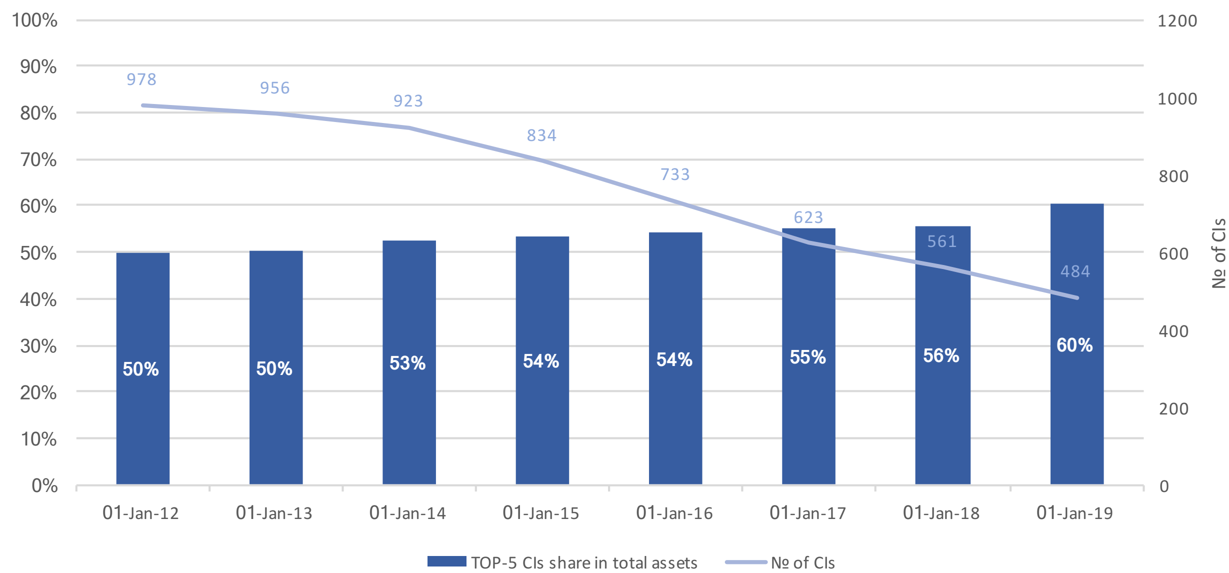
3. Characteristics of the Russian banking sector

Before proceeding to a more quantitative analysis, it is necessary to provide some information about the banking sector of the Russian Federation. According to the Central Bank of Russia, as of March 2019, the banking system of the Russian Federation consists of 478 operating credit institutions with banking license — 435 of them are banks and the remaining 43 are classified as non-bank credit institutions. In total, they account for RUB 91 trillion (or approx. EUR 1.25 trillion) the banking sector assets, which is roughly commensurate with the GDP of Russia. Around 70% of banking assets are loans; liabilities mainly consist of private deposits and deposits from non-financial corporations (approx. 25% each).

In 2018, the Central Bank of Russia approved the latest list of systemically important banks consisting of 11 credit institutions that are shown in Appendix A. Overall, they account for more than 70% of the assets of the Russian banking sector. The shares of the two biggest banks, Sberbank and VTB, equal 31% and 15% respectively, while TOP-5 banks constitute 61% of the total assets. This measure of banking industry concentration is equal to the average readings among the EU countries (Bank of Russia, 2018).

Still, the sector shows a clear tendency to consolidation as can be seen from Figure 1. The number of banks started to decrease significantly in 2014 following the CBR policy aimed at recovery of the Russian banking system in response to some negative changes in the external political and economic environment – oil price plunge negatively affected the economic growth of the country (that experienced a slowdown prior to it) and imposed sanctions restricted credit entities' access to international financial markets. While state ownership continues to prevail in the Russian banking sector, small regionally important banks that operate in monoidustrial cities tend to hinder the CBR's efforts to further consolidate the sector (IMF, 2016).

Figure 1. Banking sector concentration and number of operating credit institutions (CIs) in Russia

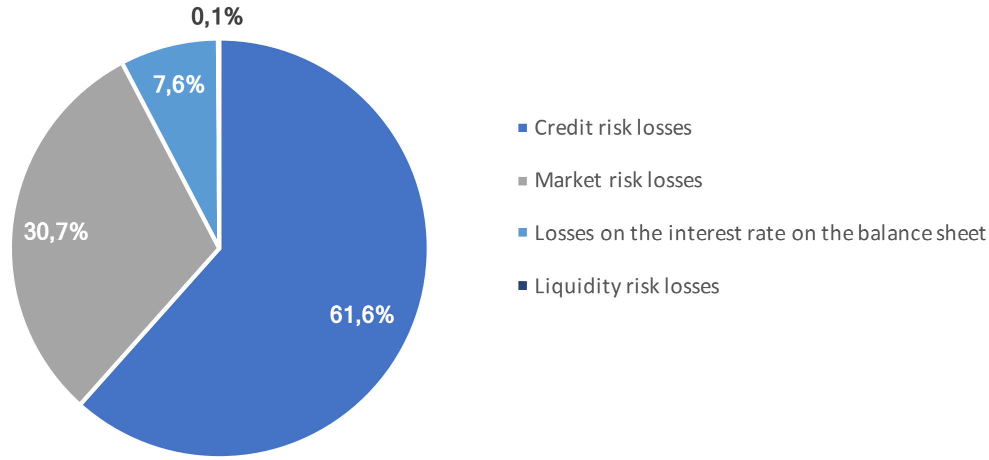


Source: Bank of Russia, Author.

Within the IMF's Financial Sector Assessment Program, Russia, as one of the 25 jurisdictions with systemically important financial sectors, has to be assessed every five years. According to the latest assessment that was carried out in 2016, the key vulnerability of the Russian banking sector is the asset quality leading to significant credit losses, while market and liquidity risks appear to be contained (IMF, 2016).

The CBR also carries out the macroprudential stress test of the Russian banking sector on a regular basis since the early 2000s. The methodology was enhanced in 2015 when the Bank of Russia started to implement Basel III regulation. However, the applied methodologies are still somewhat limited under the existing legislation so the IMF recommended the CBR to further develop its macroprudential stress-testing practices (IMF, 2016). The latest available results of the CBR stress test (based in the data from 2017) are similar to the ones of the IMF – the banks are more prone to the credit risk, followed by the market risk, as can be seen from Figure 2. For comparison, the stress test carried out using the data from 2016 showed a significantly larger share of credit losses accounting for more than 85% of total losses of the banking sector (Bank of Russia, 2017).

Figure 2. Bank losses by risk type in case of stress event



Source: (Bank of Russia, 2018).

Overall, the Bank of Russia is immersed in driving the process of the banking system recovery following the events of the economic and political turmoil of 2014. Still, although there have been some considerable developments in the banking system regulation and banks' risk management, there is still room for improvement. Considering a crucial role of loans in banks' assets and their relatively poor quality, credit risk seems to outweigh other types of risk of the Russian banking system. Therefore, the usage of credit risk as a focus of this research so as to assess the stability of the Russian banking sector is justified.

4. Estimation of Russian banking sector default probability with Contingent Claims Analysis

4.1. Background theory and methodology

Contingent claims analysis can be considered as a generalization of the option pricing theory developed by Black & Scholes (1973) and Merton (1974). A contingent claim is defined as a financial asset whose future payouts depend on the value of another underlying asset; in other words, these payoffs depend on the realization of some uncertain future events. So, a contingent claim is viewed as an option that gives the right to buy (a call option) or sell (a put option) the underlying asset at a strike price within a specified period. While option pricing methodology (and, consequently, the CCA approach) can be applied to different types of contingent claims, in this paper it is used to analyze the credit risk of the banking sector in Russia.

The contingent claims approach is based on three main principles (Gray et al., 2007): (1) the value of liabilities is derived from assets; (2) liabilities have different priority level (senior and junior claims), and (3) assets follow a stochastic process. Denote A_t as the value of an asset at time t. The asset return follows the process:

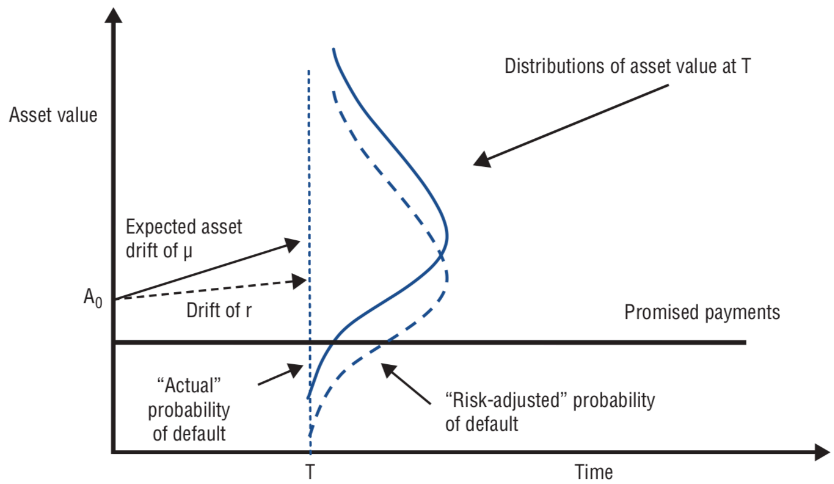
$$\frac{dA_t}{A_t} = \mu_A dt + \sigma_A dZ_t \tag{1}$$

where μ_A is a drift term (set equal to the average return), σ_A is a standard deviation of the asset return per unit of time, and dZ_t is a stochastic component representing an uncertainty in the future development of the asset value – it is basically a random walk process where the variance of the asset returns is assumed to be proportional to time. In a continuous time, this process is called a geometric Brownian motion, where the diffusion term dZ_t represents a differential increase to a Wiener process, $dZ_t = \varepsilon\sqrt{t}, \varepsilon \sim N(0,1)$. This stochastic differential equation can be solved for the A_t given the asset value at time zero:

$$A_t = A_0 * \exp\left[\left(\mu_A - \frac{\sigma_A^2}{2}\right)t + \sigma_A \varepsilon \sqrt{t}\right], \varepsilon \sim N(0,1) \tag{2}$$

The stochastic nature of any company's assets can be shown as a probability distribution at some horizon T (Figure 3). An entity defaults if the value of its assets A_t falls to or below some distress barrier that corresponds to the value of the promised debt payments, B_t. More precisely, it is the value of risky debt, usually calculated as a sum of short-term debt and half of the long-term debt (Gray & Malone, 2008; Antunes & Silva, 2010).

Figure 3. Distribution of asset value and estimated PD



Source: (Gray & Walsh, 2014).

Liabilities are seen as claims (or *contingent claims*) on the firm's uncertain assets so they may be used for asset value estimation. Thus, default risk is driven by the uncertain changes in the assets' value in relation to the firm's liabilities. The probability of default (PD) can be calculated as:

$$\mathrm{PD}_0 = \Pr(A_t \leq B_t) = \Pr\left(A_0 * \exp\left[\left(\mu_A - \frac{\sigma_A^2}{2}\right)t + \sigma_A \varepsilon \sqrt{t}\right] \leq B_t\right) \tag{3}$$

It is possible to rearrange this formula of default probability so that a stochastic component of the asset return, ε, is less or equal to a negative value of distance to default (DD):

$$\mathrm{PD}_0 = \Pr\left(\varepsilon \leq -\frac{\ln\left(\frac{A_0}{B_t}\right) + \left(\mu_A - \frac{\sigma_A^2}{2}\right)t}{\sigma_A\sqrt{t}}\right) = \Pr\left(\varepsilon \leq -DD_0\right) \tag{4}$$

The larger the distance to default is, the smaller is the probability that the analyzed entity will default. Since the random component has a standard normal distribution, the probability of default can be rewritten as $PD = N(-DD)$. This is an "actual" probability of default. It is possible to estimate a risk-neutral PD if μ_A is set equal to the risk-free rate r_f, this way eliminating asset risk premium, which results in a higher probability of default, as can be clearly seen from Figure 3.

The main challenge of implementing the Merton model in practice is that A_0, σ_A, and μ_A are not directly observable. Within Merton/CCA framework, a risk-neutral PD is assumed so $\mu_A = r_f$ (Gray & Malone, 2008); however, the estimation of the market value of assets and the corresponding volatility is not that straightforward. One way of doing this is by solving a system of two equations. The first one is the Black-Scholes formula for call option (Black & Scholes, 1973) but it will be used in reverse – the market value of equity will be used as an input in the equation. The second one is derived from Itô's lemma (Gray & Malone, 2008). The system looks as following:

$$\begin{gathered} E_0 = A_0 N(d_1) - B_t e^{-rt} N(d_2) \\ E_0 \sigma_E = A_0 \sigma_A N(d_1) \end{gathered} \tag{5}$$

where $d_1 = \frac{\ln\left(\frac{A_0}{B_t}\right) + \left(r + \frac{\sigma_A^2}{2}\right)t}{\sigma_A \sqrt{t}}$ and $d_2 = d_1 - \sigma_A \sqrt{t}$, E is the market value of equity and σ_E is the corresponding volatility (standard deviation), B is the value of risky debt. By solving this system, one obtains the implied value of assets and its volatility that are later used as inputs in default probability calculation in the Merton model.

4.2. Data collection and applied methods

CCA is quite data-intensive – it combines market and balance sheet data. To calculate the probability of default using the Merton model, one needs risk-free rate, market value of a firm's assets and its annualized volatility (that are not observable directly but can be estimated using the market capitalization of the banks), and value of debt.

The Black-Scholes model uses risk-free rate as an input in the equation. However, the sovereign debt of Russia is far from AAA and it only recently has been upgraded from a 'junk' status. In this study, a fixed 5 percent rate was used, following Gray & Walsh (2014) assumption.

The daily data on market capitalization was obtained from Bloomberg for 7 years, from January 2012 to December 2018. This period is chosen so as to capture the banking sector development several years prior to the sanctions imposed in 2014. The volatility was estimated by using a simple GARCH(1,1) model, which is the most common technique to obtain conditional second moments (Sorge & Virolainen, 2006). While market capitalization can be obtained on daily basis, value of debt is obtained from a bank's balance sheet and it is available only at a monthly or quarterly frequency. So, daily volatility estimates were later transformed to monthly values by taking an average over each month and then annualizing them (since the Merton model requires an annualized standard deviation of the market value of equity as an input).

In academic literature, there are different ways of estimating the distress barrier. Pesaran et al. (2006) assumed that a firm defaults if its asset value decreases by a certain percentage in a quarter, which is determined by the firm's credit rating. This way, they managed to implement the Merton model by using only two variables – market capitalization and credit ratings. Altar et al. (2014) assumed that distress barrier equals some percentage share of bank's total liabilities. However, it is rather difficult to justify such decision regarding the distress level. The most common approach is to sum a short-term debt and half of the long-term debt, which was used by Gray & Walsh (2014). They calculated the distress barrier by summing banks' demand deposits and 50% of the senior debt plus time and saving deposits.

While it is possible to obtain the amounts of demand, time, and saving deposits as well as of senior debt from Bloomberg, the total values do not seem to match the amounts directly reported by banks to the Bank of Russia (which is likely to be attributed to differences in accounting principles), and they are available only on quarterly basis. Thus, the amounts of short- and long-term deposits were obtained in the following way from the Bank of Russia website.

Each credit entity on monthly basis provides the CBR with special accounting/balance sheet reporting forms that are later published on the website of the Bank of Russia. Data on deposits and senior debt was gathered from the form 101. Deposits that are made for a period of less than 1 year (including current accounts, deposits for a term of less than 90 days, from 91 to 180 days, and from 181 days to 1 year) are considered to be short-term. Respectively, long-term deposits are comprised of the deposits made for a term of more than 1 year.

Although debt value can be gathered for every bank registered within the Bank of

Russia, market value of equity can be obtained only for listed banks. The banking sector of Russia is characterized by a significant government participation, and not all the systemically important banks are listed on the stock exchange. The two biggest banks, Sberbank and VTB, are listed as well as Rosbank and Credit Bank of Moscow, which, however, went public only in 2015. Its inclusion in the analysis is bound to increase the complexity of an already rather complicated modelling process. Besides, 3 year monthly observations may not be enough for VAR estimation. Therefore, this bank was not included in the analysis.

This sample is hardly sufficient to evaluate the stability of the banking sector and identify main risk factors. Therefore, it was extended by including unlisted banks – UniCredit Bank and Raiffeisenbank that are subsidiaries of the corresponding public banking groups. The importance of including these banks, which have a more international exposure, is to see whether they are affected by different risk factors, compared to the listed Russian banks. The market capitalization of the affiliated banking groups was used as a proxy for the market capitalization of their subsidiaries in Russia by making an adjustment corresponding to the share of the balance-sheet equity of the analyzed subsidiary in the total balance-sheet equity of the banking group. Then, the proxy of the equity volatility was estimated by using the average between the volatility of the market capitalization of the banking group and the volatility of the Russian banking sector measured as asset-weighted average of the listed banks' market capitalization volatility. Similar approach was used by Altar et al. (2014) who performed stress tests on the Romanian, Bulgarian, and Hungarian banking sectors and faced the same problem of somewhat insufficient sample of listed banks.

Then, having the aim of the research in mind, two regionally important banks, Uralsib and Bank Saint-Petersburg, were included in the analysis as well. Although they are not considered as systemically important, they are among top-20 largest banks in Russia. This way, the research covers three groups of banks: (1) large systemically important banks that are likely to be exposed to domestic as well as foreign risk factors, (2) international banks largely affected by external or global risk factors, and (3) regionally important banks that are active mainly in the domestic market. In total, the sample of the Russian banks consists of 7 banks corresponding to 53% of the banking sector assets.

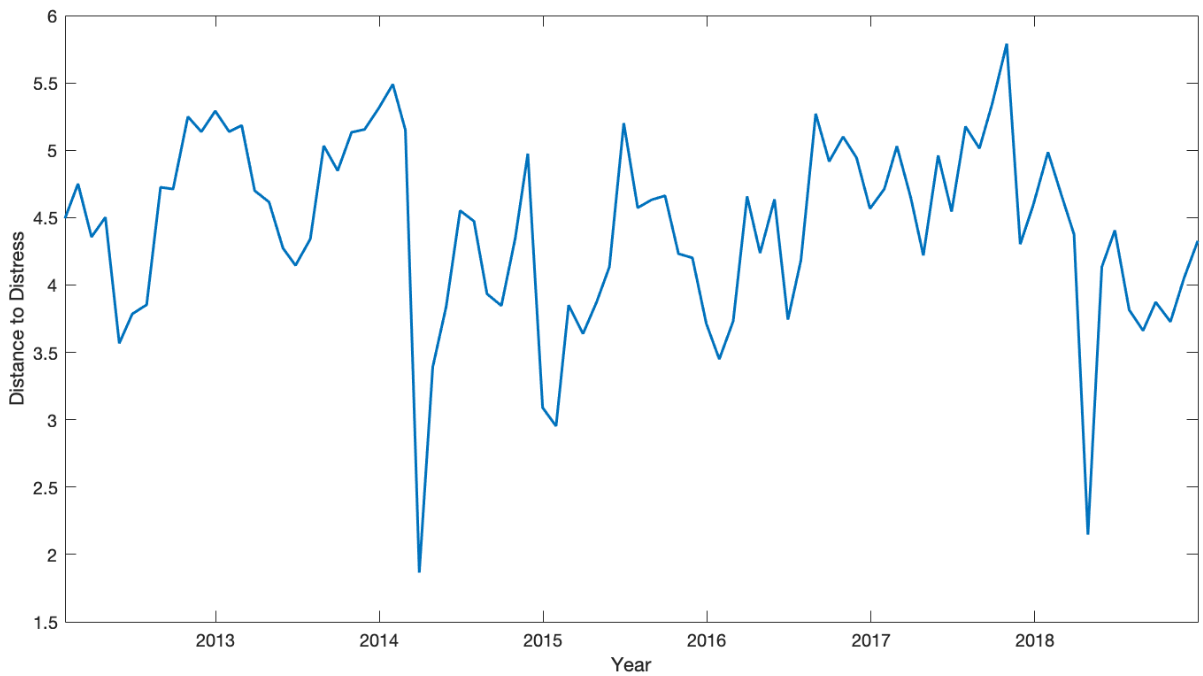
4.3. Default risk indicators of the Russian banking system

As described in the methodology laid out in Section 3.1, the Merton model allows to derive a time series of risk measures – distance to default (DD) and probability of default (PD). It is necessary to mention that in case of risk estimation of banks (especially systemically important ones) if implied assets value falls below a distress barrier, it does not mean that the credit entity will default – central banks and other regulators are likely to take some actions (bailing-out, for instance) to avoid huge fiscal costs caused by bank default (Chan-Lau & Sy, 2006). That is why distance to default rather means distance to distress that is a level below which a regulator will intervene and save the bank.

Figure 4 shows the development of distance to distress measure over the analyzed period of the Russian banking system. It was estimated by summing market capitalization and debt of all the analyzed banks and using the obtained values as inputs in the Merton model. Basically, these banks were treated a one "big bank". In Appendix B, DD time series of every analyzed bank separately are provided.

From Figure 4, we may see that DD of the Russian banking system was rather volatile over the analyzed period. The most severe and sharp shock occurred in March 2014, when foreign sanctions were imposed, followed by a 2-year period of increased risk. The next two relatively huge plunges happened in the beginning of 2015 and 2016, which corresponds to periods of ruble depreciation and low oil prices. The second half of 2016 and 2017 were marked by a reduced risk in response to gradually growing oil prices. The latest significant drop in April 2018 corresponds to an increased political tension between Russia and the USA, which is largely driven by higher risk of Sberbank, as can be seen from Appendix B.

Figure 4. Distance to distress of the Russian banking system

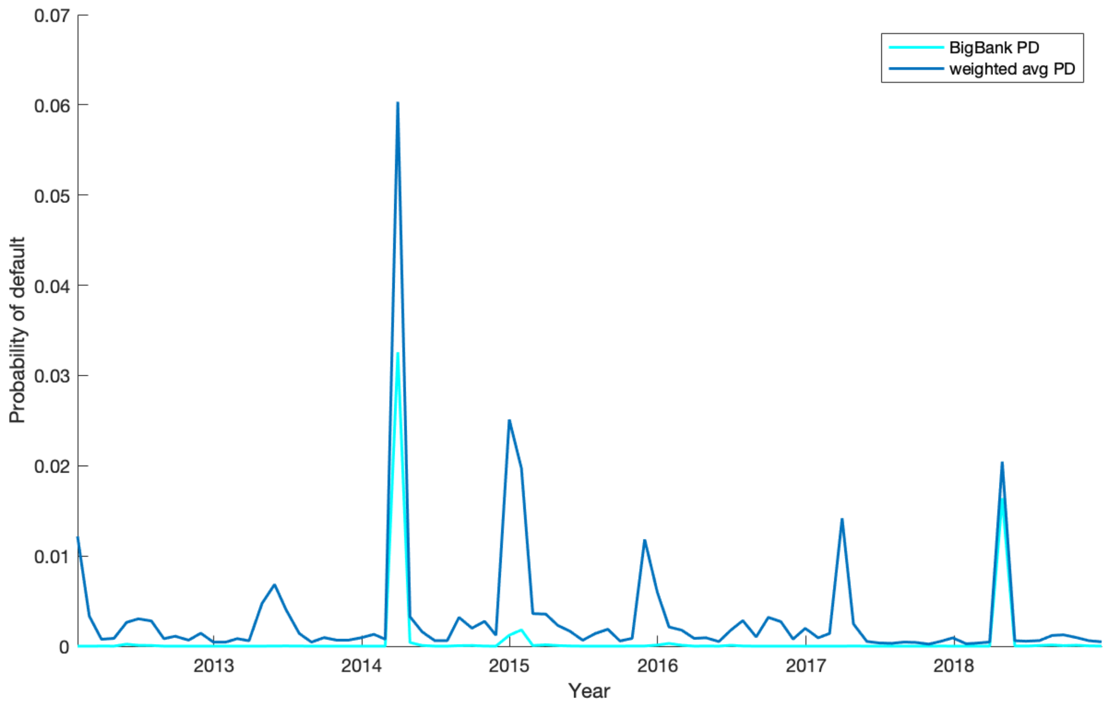


Source: Author.

Having obtained values of DD, it is possible to estimate PD for each analyzed credit entity. It is a cumulative probability estimated over a certain period (in our case, one year) that a bank will default. Importantly, it is a risk-neutral PD, which is bound to be lower compared to the real-world default probability. Still, the changes observed in the calculated PDs are pretty demonstrative. Appendix C shows PD time series for each analyzed credit entity individually.

As in case with DDs, a cumulative PD for a "big bank" was calculated, which is shown in Figure 5. This risk measure peaked in March 2014, and the second largest risk increase happened in April 2018. Over the remaining period, default probability was close to zero. However, considering the sample of banks and respective weights of Sberbank and VTB, risk exposures of smaller banks are likely to be lost in this aggregated "big bank" PD. Therefore, asset-weighted average default probability was included as well (Figure 5, light blue line). It was calculated by multiplying banks' PD by their share in the total assets of the analyzed banks and summing them up. This resulted in higher default probabilities, especially during the turbulent periods. While an aggregate PD is more suitable for assessing the risk exposure of banking system as a whole, an asset-weighted PD is better for indicating whether an individual credit entity may suffer distress.

Figure 5. Probability of default of an aggregated "big bank" and asset-weighted average default probability



Source: Author.

Several years prior to the sanction period, default risk of the banking system was somewhat lower compared to more recent periods that were also more volatile – risk measures tended to vary in a broader range. Besides, huge banks remained rather stable, experiencing relatively severe distress only as a result of deteriorated political relations with foreign partners. Overall, credit risk of the Russian banking system seems to be responsive to political tensions as well as oil price decrease and subsequent national currency depreciation. However, the analyzed banks are heterogeneous, as can be seen from Appendices B and C; thus, they are likely to be affected by different risk factors. In the next Section, the relationship between default risk of the chosen Russian banks and some macroeconomic variables, that are likely to affect it, will be investigated.

5. Stress-testing of the Russian banking sector

5.1. Connecting credit risk exposure to macroeconomic variables

The choice of the right risk factors that may threaten the stability of the financial system is not straightforward. It depends on the peculiarities of the banks comprising the financial system. While for the domestically active banks internal factors – such as unemployment, interest rate, or inflation – may be considered of higher importance, large banks that are active on foreign loan markets are more likely to be affected by external or global risk factors – exchange rates, commodity prices, etc. (Quagliariello, 2009). Given the rationale behind the choice of the banks in the sample and peculiarities of the Russian economy, three groups of macroeconomic factors were analyzed: (1) internal economic development: unemployment rate, consumer price index (CPI), industrial production index; (2) internal financial market development: 1-year OFZ bond (Federal Loan Bonds of Russia) and OFZ spread, MOEX (Moscow Stock Exchange Index); (3) global economic development: USDRUB, oil price (Urals), S&P500 return, 1-year Treasury rate. Importantly, the choice of macroeconomic variables was limited to those that are available at least on a monthly basis. The full list of used macro variables with respective notations and sources are provided in Appendix D.

Before proceeding to shock modelling, a simple sensitivity analysis of banks' risk measures to the chosen macroeconomic variables was conducted. To assess whether these macroeconomic variables have any effect on banks' credit risk exposure, a stepwise regressions with backward elimination were run on each bank's log-returns on implied assets (estimated with the Merton model earlier) against the whole set of macro variables that were either transformed to log-returns or left without changes if already were expressed in percentage points. With every step, the least significant independent variable was eliminated, until the remaining ones became significant at a chosen level (in this exercise, 10% significance level was chosen). The results of stepwise regressions are shown in Table 1.

Table 1. Stepwise regression result for macroeconomic variables

	Return on Implied Assets						
	Sberbank	VTB	Rosbank	Bank SPB	Uralsib	UniCredit Bank	Raiffeisenbank
Intercept	-0.192	-0.317	-0.122	-0.139	-0.169	-0.003	0.005
	(-3.371)	(-4.050)	(-2.175)	(-3.115)	(-3.327)	(-0.417)	(1.608)
CPI	0.009						
	(2.146)						
MOEX	0.175	0.161			0.0014		0.177
	(3.386)	*(2.126)*			*(3.734)*		*(1.662)*
OFZ_1year				-0.124		-0.194	
				(-2.006)		*(-4.448)*	
OFZ_1year (change)		0.195			-0.082		
		(2.773)			*(-4.173)*		
OFZ_sread	0.005						
	(2.207)						
Production	0.106	0.164	0.111	0.129	0.059		
	(4.006)	*(4.434)*	*(2.231)*	*(3.257)*	*(3.740)*		
SP500						0.543	
						(2.450)	
Tbill_1year (change)	0.031						
	(2.414)						
Unemployment	1.364	2.622					
	(1.954)	*(2.712)*					
Urals				-0.111		-0.208	
				(-2.691)		*(-2.414)*	
USDRUB	0.990	0.312	0.274			0.409	0.397
	(2.118)	*(4.262)*	*(3.061)*			*(2.723)*	*(4.477)*
Adj. R-squared	0.365	0.452	0.144	0.193	0.184	0.243	0.188
F-stat	7.750	14.517	7.909	10.803	9.141	9.769	10.517

Source: Author.
Note: the coefficients shown are the ones that are jointly significant at 10% significance level; corresponding t-statistics are in parentheses.

As we can see from the table, only for 1 out of 7 banks adjusted R-squared is higher than 40%, for one bank it is around 35%, and all the remaining ones are in the range of 15-25%. It may not be considered as an extremely satisfactory result, but it is indeed rather adequate for proceeding with further research. It also implies that a more tailored set of variables might be needed to account for higher explanatory power of the regressions. Still, all the regressions are significant at 5% significance level.

Most of the used macroeconomic variables are significant for Sberbank and VTB. Given their position as the two largest banks accounting for more than 45% of the banking system assets, it should be expected that they tend to co-move with the whole economy and have significant relationships with factors determining its development (production index, unemployment, MOEX index, USDRUB exchange rate). Other banks have a smaller number of significant coefficients, which may suggest that their credit risk is explained by more idiosyncratic factors.

As for macroeconomic variables, USDRUB exchange rate and industrial production index resulted to be significant for 5 banks, followed by MOEX stock index which is significant for 4 banks. Surprisingly, oil price is significant only for 2 banks, which may suggest that the effect of oil price change becomes evident with some lag. Credit risk is not directly affected by commodity prices, rather this effect is translated through changes in disposable income of households and financial performance of businesses. S&P500 index is significant for UniCredit bank as expected since it has the largest exposure to foreign markets. Interest rates show low levels of significance, which is rather surprising since banks' performance and risk exposure are likely to be directly affected by them. For example, 1-year OFZ rate may be considered as a proxy for the CBR key rate (Russian analogue of the US Federal Reserve rate) that affects overall level of interest rates (on deposits, loans) in the economy and inflation. Thus, the key rate increase may lead to worsening of loan portfolio quality due to more expensive loans. However, as in the case with oil prices, changes in the key rate may have a delayed effect on banks' credit risk exposure. This may also be a reason for a relative insignificance of CPI. Still, every chosen factor seems to have at least some effect on the banks' implied assets.

5.2. Dimensionality reduction with principal component analysis

Since some of the used variables are correlated, which is bound to impede VARs' estimation later, principal component analysis (PCA) was applied in order to address a possible collinearity problem and reduce the dimension of the used dataset, which is crucial in this case as the series consist of only 84 observations. In short, this procedure applies an orthogonal transformation to correlated variables so as to create a set of nearly uncorrelated principal components. PCA is designed in such a way that the components are derived in a descending order of importance – the first principal component is a linear combination of variables with the maximum explained variance, and each succeeding component has the highest possible variance of all combinations of variables that is orthogonal to the preceding principal component.[1] Given the idea behind PCA, some of the last derived principal components will account for a small increase in variance of the original variables so that it would be possible to discard these last factors without losing much information.

In this paper, PCA was applied to the full set of macroeconomic variables specified in previous sub-sections. Kaiser-Meyer-Olkin test measure resulted to be 0.686, which is somewhat higher than a recommended threshold of 0.6 for sampling adequacy; and Bartlett's test results strongly rejected the null hypothesis that correlation matrix of the analyzed variables is an identity one. So, PCA should produce rather plausible factors. Ultimately, 11 principal components were derived that explain the total variance of the analyzed variables. The first three factors were chosen since they have initial eigenvalues larger than 1 and account for 74.7% of variation of the macroeconomic variables (Appendix E). Then, a varimax rotation method was applied to these factors. It maximizes the correlation between the variables and factors, leading to high factor loadings for a relatively small number of variables, which simplifies further interpretation of the components. The results of the PCA with varimax rotation are shown in Table 2.

Table 2. Factor loadings after varimax rotation

	Factor 1 **Financial (in)stability**	Factor 2 **Economic growth**	Factor 3 **Interest rates**
Urals	**-0.912**	-0.323	0.044
OFZ_spread	**-0.897**	-0.072	-0.032
OFZ_1year	**0.846**	-0.180	0.376
USDRUB	**0.836**	0.485	0.002
SP500	0.422	**0.830**	-0.032
MOEX	0.425	**0.786**	-0.241
Unemployment	0.260	**-0.765**	-0.196
Production	0.195	**0.738**	0.155
OFZ_1year (change)	-0.174	0.055	**0.853**
CPI	0.313	-0.455	**0.582**
Tbill_1year (change)	0.138	0.139	**0.421**

Source: Author.
Note: Numbers in blue indicate factor loadings greater than 0.5 (in absolute value).

[1] More on the topic of PCA and types of rotations can be found in, for example, Jolliffe (2002).

The first factor includes USDRUB, OFZ rate and spread, and oil price. These variables seem to describe the financial stability (or rather instability) of the Russian economy. This component is driven by USDRUB exchange rate and oil price, that historically have high negative correlation, given the importance of oil as the main export item of the country. USDRUB has a positive correlation with the factor, which means that depreciation of ruble against dollar is associated with higher values of the factor. Then, OFZ rate tends to co-move with the derived factor, while the OFZ spread has a negative correlation with it.

The second factor seems to be linked to the economic growth. Production index, returns of S&P500 and MOEX stock indices are included with a positive sign while unemployment rate shows a negative sign. Also, CPI has a relatively high factor loading and goes into the component with a negative sign, which somewhat surprising since economic growth usually entails increase in inflation. Still, during a part of the analyzed period Russian economy suffered from stagflation driven by sanctions and national currency depreciation.

The last factor deals with interest rates. It weighs strongly change in OFZ rate followed by positive changes in CPI and in the US Treasury rate. As sensitivity analysis showed, these variables were significant only for several banks. Hence, this factor is likely to have low explanatory power in the further analysis. Still, these macroeconomic variables may be crucial for explaining risk exposure of banks (as explained earlier), so it was not omitted from the analysis.

Overall, 3 components were derived from the chosen 11 variables that explain around 75% of the variance. Using these factors instead of separate variables allows us to account for most of the variance while applying a universal model to all banks.

5.3. Vector Autoregression models and Impulse Response Functions

Having derived the macroeconomic factors, we proceed to estimate vector autoregression (VAR) models. VAR can be considered as a generalization of AR process with more than one variable influencing the dependent one. Formally, VAR(p) model can be defined as (Lütkepohl, 2005):

$$y_t = \upsilon + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, t = 0, \pm 1, \pm 2, \ldots \quad (6)$$

where $y_t = (y_{1t}, y_{2t}, \dots, y_{Kt})'$ is a $K \times 1$ random vector, $\upsilon = (\upsilon_1, \upsilon_2, \dots, \upsilon_K)$ is $K \times 1$ vector of intercepts, A_i is a $K \times K$ coefficient matrix, and $u_t = (u_{1t}, u_{2t}, \dots, u_{Kt})'$ is a K-dimensional innovation process. Basically, within VAR(p) framework, a certain variable at time t depends not only on its own lagged values (like in AR process) but also on the p lagged values of other variables included in the model.

VAR models were estimated for every analyzed bank in Russia and each specification included four variables: returns on implied assets, and previously derived factors (that were calculated by multiplying every variable by a corresponding factor loading). Note that the financial stability factor was multiplied by a negative one. The rationale is that it will facilitate the interpretation of the negative shocks since the initial values of the factor related more to financial *instability* which, by definition, corresponds to negative economic environment. Then, although implied asset values, estimated with the Merton model, do not directly measure banks' risk exposure, they seem to produce more plausible results compared to DD. Implied assets value is used to derive these risk measures, so the results of VAR estimation should be similar (Gray & Walsh, 2014). Log-returns of each of the banks' implied assets were calculated, resulting in 83 observations for each entity. The returns seem to be stationary under the augmented Dickey-Fuller test.

The main challenge of VAR estimation is in choosing the appropriate number of lags. For this purpose, Akaike (AIC) and Bayesian (Schwarz, BIC) information criteria were calculated for each bank for VAR models with up to 4 lags. One should choose a specification that minimizes information criteria. In case they point to different specifications, results with the minimum BIC will be preferred since it tends to penalize large number of parameters more severely compared to AIC. The information criteria were pointing out to either 1 or 2 lag specifications. Specifications with 2 lags for most of the banks showed the lowest values of information criteria; thus, VAR(2) models were used in the analysis. Table 3 provides the results of VAR models in a rather condensed manner – it shows which coefficients resulted to be significant (at 5% level) and with which sign.

Table 3. VAR(2) estimation results

	Return on implied assets						
	Sberbank	VTB	Rosbank	Bank SPG	Uralsib	Raiffeisen	UniCredit
Assets (t-1)	+	+	+	-	-	+	+
Assets (t-2)	no	no	-	-	-	no	+
Factor1 (t-1)	+	+	+	+	no	+	+
Factor1 (t-2)	no	no	-	no	no	no	no
Factor2 (t-1)	+	+	+	no	+	no	no
Factor2 (t-2)	no	no	no	no	no	no	no
Factor3 (t-1)	no	+	no	no	no	no	no
Factor3 (t-2)	no	no	no	no	no	no	no
Adj. R-sqr	0.315	0.298	0.517	0.259	0.298	0.2192	0.2391

Source: Author.
Note: "no" means that the coefficient is not significant at 5% level, + or - indicate the sing of a coefficient that is significant at 5% significance level.

Estimation of VAR allows us to derive impulse response functions so as to see how shocks to each of the factors affect the value of bank's implied assets. Gray & Walsh (2014) argue that IRFs estimated with factors, which should be orthogonal by construction, have an advantage over the ones calculated with separate macro variables, that may affect each other. For example, the impulse response of the implied assets to financial stability factor will show the impact of shock only to this factor while other factors will be kept constant. In Appendix F.1-F.7, the IRFs for banks' response to shocks of each of the three factors as well as their own assets are provided.

First of all, a shock to banks' own assets leads to positive impulse in most cases. For big systemically important banks, the response seems to persist for 2-3 months after the shock. For comparison, Gray & Walsh (2014) in their analysis of Chilean banking system showed a much higher persistence – most of the shock effects dissipated within 8 months. However, Russian banking system during the analyzed period is characterized by extremely high volatility and risk that is partly explained by some political factors not directly affecting fundamental economic indices. So, a relatively short persistence of the shock is rather justified.

A shock to the financial stability factor is positive and significantly different from zero for 4 out of 7 banks. In the sensitivity analysis, all of them had significant coefficients with either Urals price or USDRUB. Sberbank, being the largest bank in Russia, is affected by the overall stability of the economy and, besides, has a relatively significant proportion of foreign currency loans, so its loan portfolio is affected by exchange rate. The same goes for Bank Saint-Petersburg that is active on the currency market. Finally, the importance of financial stability and especially ruble exchange rate for two subsidiaries of international banking groups – UniCredit and Raiffeisenbank – is quite clear.

Shock to economic growth factor seems to be significant for Russian systemically important banks and Uralsib. As it was shown previously, these banks are significantly affected by industrial production index (used as a proxy for GDP growth), MOEX, and unemployment. This result was expected for Russian systemically important banks, given their large exposure to the domestic market (compared to Raiffeisenbank and UniCredit Bank) and high importance for the overall economy. While Uralsib is not considered to be systemically important by the Bank of Russia, it indeed has a crucial importance for the Ural-Siberian region.

Finally, the coefficients for the third factor (interest rates) are not significant in most of the models (except for VTB), as was expected. Still, VAR models of higher lags that were run on implied asset return with only the third factor included showed a significant coefficient at the third lag for some banks. It supports a previously mentioned idea that effects of interest rate changes may be delayed. It may be advisable to estimate VAR model of higher lags (3 and above), but it will may lead to overfitting. Also, considering a relatively small number of observations, increasing the number of parameters in VAR models hardly seems a worthwhile pursuit.

5.4. Specification of macroeconomic shocks

Derivation of impulse response functions allows us to analyze how the chosen risk measures of the Russian banking sector react to some defined macroeconomic shocks. In the following sections, the effect of three shocks will be estimated: Urals oil price decrease (as part of the financial stability factor), drop of MOEX stock index (as part of the economic growth factor), and a positive change in the OFZ rate (in the interest rate factor).

There are various ways of specifying the magnitude of shocks, as was described in the literature review section. In this research, Value-at-Risk (VaR) measure was used to create adverse and severe adverse shocks corresponding to $VaR_{0,95}$ and $VaR_{0,99}$, respectively. A parametric approach to VaR calculation was applied by assuming a normal distribution of losses, $L \sim N(\mu, \sigma)$. In this case, VaR can be obtained by the following formula:

$$VaR_{\alpha}(L) = \mu + \sigma * z_{\alpha} \tag{7}$$

where z_{α} is a z-score of a normal distribution. This formula was applied to daily returns of the shocked variables over the whole analyzed period of 8 years. Then, the daily values of 95% and 99% VaR were multiplied by square root of 21 so as to transform them to monthly values. This way, we obtained VaR estimates to specify the shocks of the chosen variables (Table 4). Then, the obtained VaR values were multiplied by the corresponding factor loadings in order to obtain the final value of the shock, which was used as an input to IRFs.

Table 4. Specification of shocks

	Daily VaR	Monthly VaR
Urals oil price (shock to Financial stability factor)		
VaR 95%	-3.26%	-14.93%
VaR 99%	-4.60%	-21.08%
MOEX index (shock to Economic growth factor)		
VaR 95%	-1.81%	-8.32%
VaR 99%	-2.58%	-11.83%
OFZ rate (shock to Interest rates factor)		
VaR 95%	2.57%	11.79%
VaR 99%	3.63%	16.63%

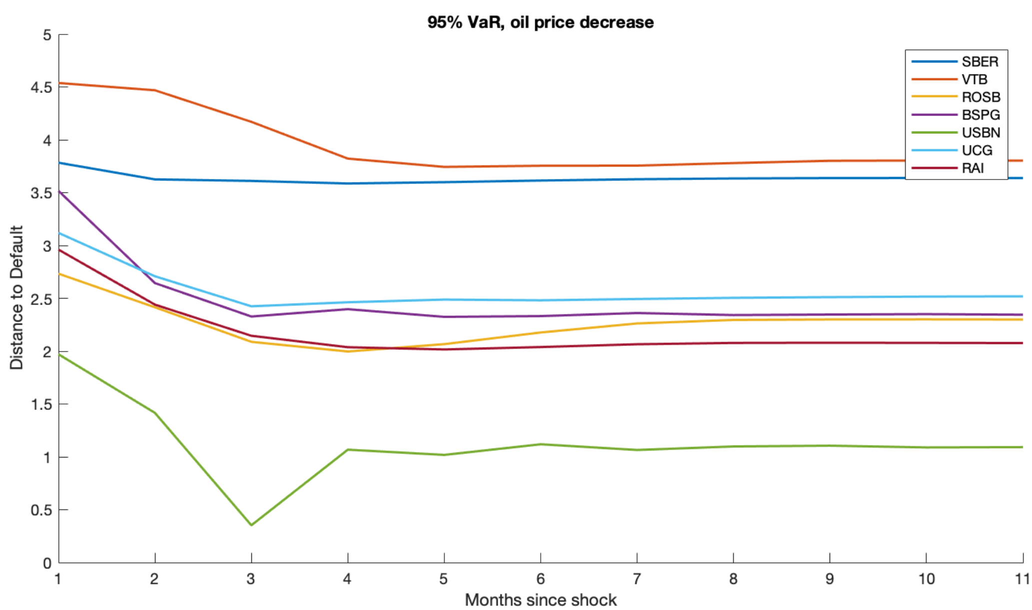
Source: Author.

We obtained the value of log-returns on implied assets for every bank for 11 months after the shock. They were used to calculate implied asset values over the estimation period. This way, it is possible to estimate DD for each bank using the asset values derived from IRF. Other inputs in the DD formula, including asset volatility, value of debt, and risk-free rate, were assumed to be constant and equal to the last available observation (December 2018). Importantly, this is bound to lead to overestimation of DD (and, thus, underestimation of PD) since asset volatility is likely to increase during turbulent periods which is the idea behind stress tests.

5.5. Stress-testing results: Financial stability factor

Figure 6 shows the effect of an adverse shock to the financial stability factor (estimated by 95% VaR oil price decrease). As we can see from the graph, DD decreased in the first months after the shock for every bank, however, DD reaches its lowest point in 3 or 4 months. As for the systemically important banks, DD of VTB decreased over the first 3-4 months by 0.5 showing only a small recovery, Sberbank was hardly affected by the change, and DD of Rosbank was gradually decreasing for four months but recovered to almost pre-shock values by the end of the year. International banks, Raiffeisenbank and UniCredit, showed similar dynamics – a drop of 0.5-1 units by the 4th month followed by a modest recovery. Bank Uralsib was severely affected by the change – DD almost reached zero in the first 3 months after the shock and then bounced back by the amount equal to one third of the fall in the next period.

Figure 6. DD response to Financial stability factor shock: Oil price decrease (95% VaR)

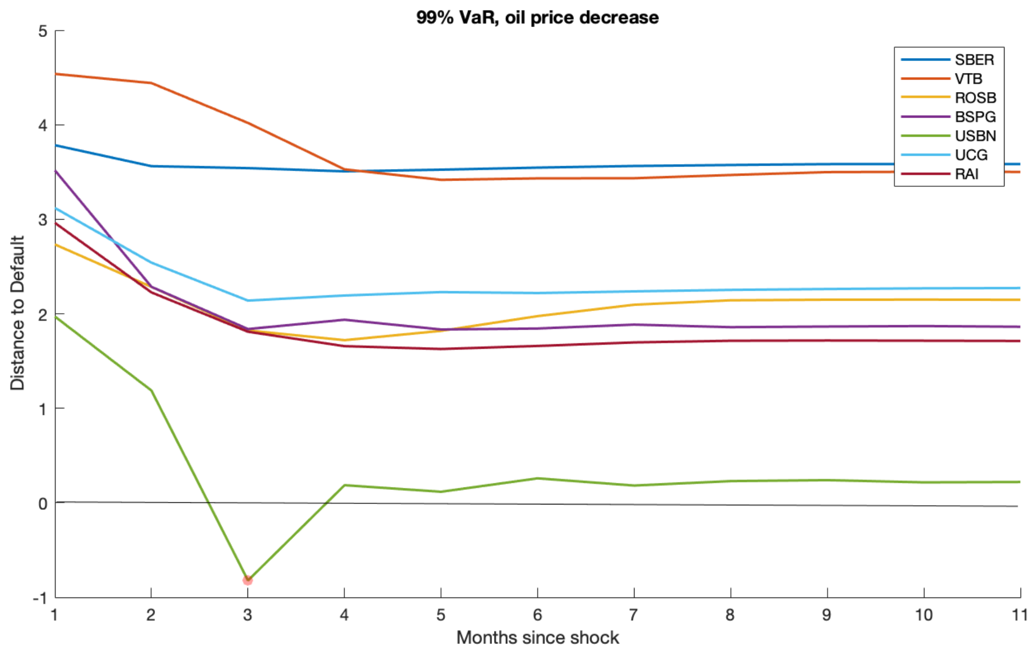


Source: Author.

In severe adverse shock to the financial stability factor (Figure 7), determined by 99% VaR Urals price decrease, the banks' response is similar to the adverse shock in overall dynamics and magnitude for some banks – Sberbank, Rosbank, Bank Saint-Petersburg, UniCredit and Raiffaisen. DD of VTB showed a more significant decrease – by around 1 unit.

Uralsib was severely affected by the shock to the point of reaching negative values of DD. This bank historically had a fairly low DD compared to other banks. Still, the response of DD of Urialsib to financial stability factor shock is extremely high.

Figure 7. DD response to Financial stability factor shock: Oil price decrease (99% VaR)



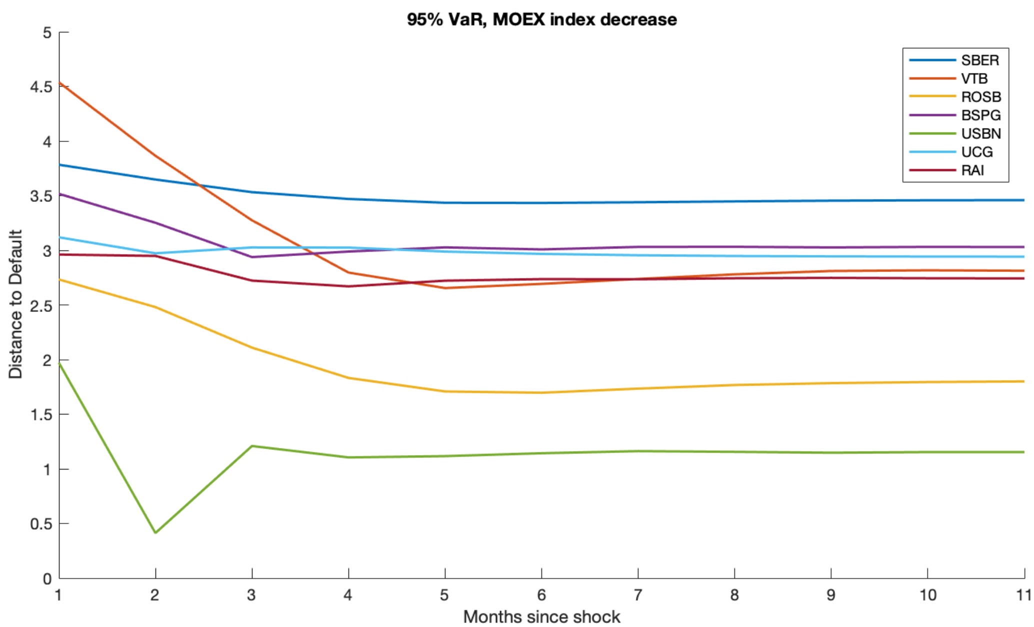
Source: Author.

Banks reacted rather differently to the proposed shock. The results suggest that the analyzed banks do not reach default point except for one bank, which should be closely monitored by the regulator. Also, the shock has a somewhat long-lasting effect, and most banks show an extremely modest recovery starting around the 5th month after the shock.

5.6. Stress-testing results: Economic growth factor

Figure 8 provides the development of DD of the analyzed banks in Russia under an adverse shock to the second factor based on the MOEX stock index drop. The peak of the shock happens during the 3rd - 5th month, which is slightly longer than for the financial stability factor shock. Sberbank is affected by the shock only slightly but DD of VTB and Rosbank decreased by more than 1 unit during the first 5 months. UniCredit and Raiffaisenbank risk increased for 2-3 month after the shock but they almost completely recovered by the end of the year. So, they were barely affected by the factor, determined mainly be domestic economic growth. DD of Uralsib plummeted after the first month following the negative economic growth shock. However, it recovered by around half of the decrease amount in the next period.

Figure 8. DD response to Economic growth factor shock: MOEX index decrease (95% VaR)

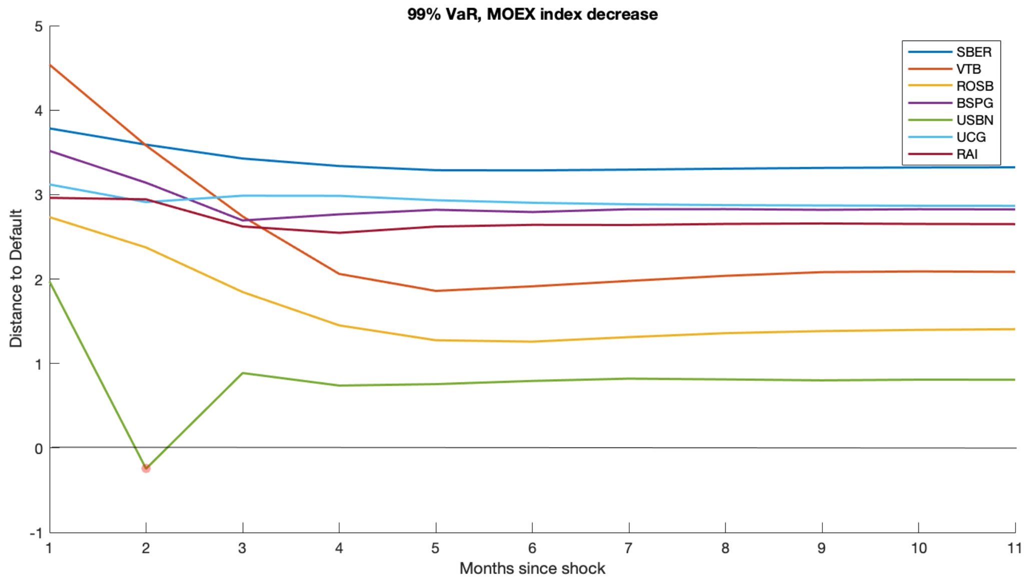


Source: Author.

Again, a severe adverse shock effect on DD is similar to the one generated by an adverse shock, as seen in Figure 9. The magnitude of the shock is quite the same for Sberbank, Bank Saint-Petersburg, UniCredit and Raiffaisenbank; they remain relatively unaffected by the changes. Uralsib, as in the case of financial stability shock, reaches distress point rather quickly – during the second month after the shock. Also, it is the only bank with such rapid response to the proposed turmoil. VTB, surprisingly, was affected the most – DD decreased by around 2 units in the first five months.

Overall, a shock to the economic growth factor seems to have more persistence compared to the financial stability one, which is expected since fundamental macroeconomic indices take more time to change and take effect. The regulator is recommended to monitor closely systemically important banks (except for Sberbank but including Uralsib) since they seem to be severely affected by the economic growth shock.

Figure 9. DD response to Economic growth factor shock: MOEX index decrease (99% VaR)



Source: Author.

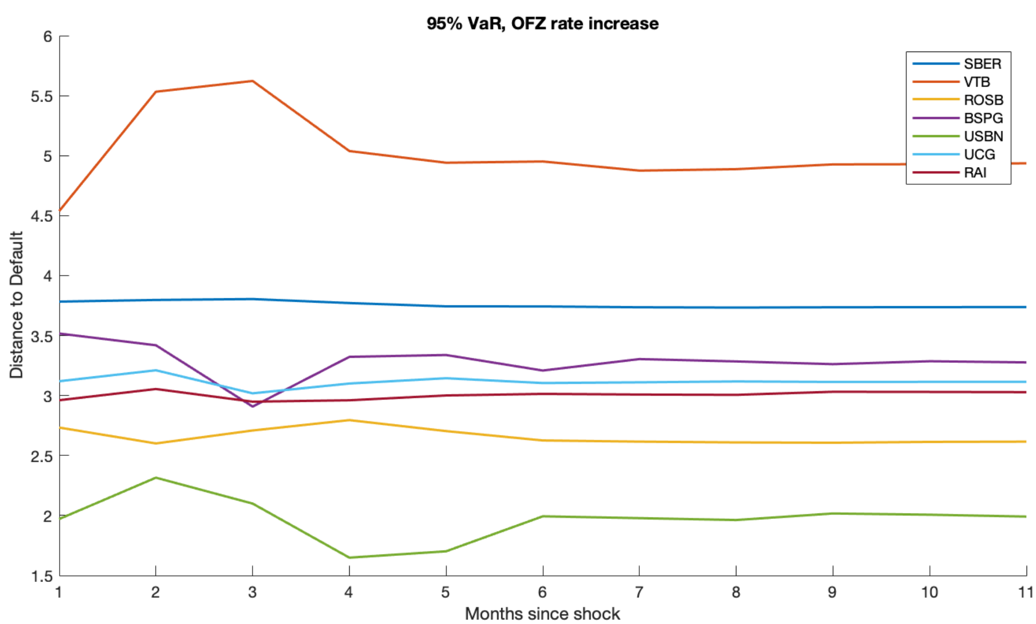
5.7. Stress-testing results: Interest rates factor

Finally, an effect of a shock to interest rates factor driven by OFZ rate increase was analyzed. OFZ, or Federal loan bonds, rate can be considered as a proxy for key interest rate, set by the CBR. The increase in this rate is associated with higher risk – for example, in 2014, in response to sanctions, the key rate was increased from 5.5% to 17% by the end of the year in order to contain the inflation risk. Higher level of key rate leads to higher loan interest rates, which may lead to worsening of the credit portfolio of banks. That is why, a positive shock to this variable was specified.

Still, changes in this factor may not have an immediate effect on the banks' credit risk. As it was shown earlier, 2-lag specification of VAR was not enough to capture this effect for most of the banks and interest rate factor coefficients were not significant. Hence, the results obtained in this section may lack reliability. Nevertheless, they may give a general overview of how credit risk measures react to interest rate shock.

Figure 10 shows banks' response to 1-year OFZ rate increase determined by 95% VaR. Sberbank was not significantly affected by interest rate factor change in contrast to VTB that showed a rather rapid growth of around 1 unit of DD in the first three months after the shock, followed by a drop to almost pre-shock levels in the next month. The result is rather unexpected since an increase in the key rate should lead to lower DD through worsening of banks' loan portfolios. The reason for this is not clear. Most likely, in case of higher loan interest rates, banks tend to conduct more rigorous assessment of potential borrowers resulting in improvement of loan portfolio quality in the first months. However, in a longer term, people may not have enough resources to service the loan taken at a higher interest rate, which may result in higher NPL negatively affecting bank credit risk. Uralsib showed a dynamic similar to VTB. UniCredit and Raiffeisenbank were affected by the change only slightly and reverted to their pre-shock values in 4 months. Rosbank and Bank Saint-Petersburg showed periods of growing and declining DD measures for half a year after the shock before stabilizing at their pre-shock levels.

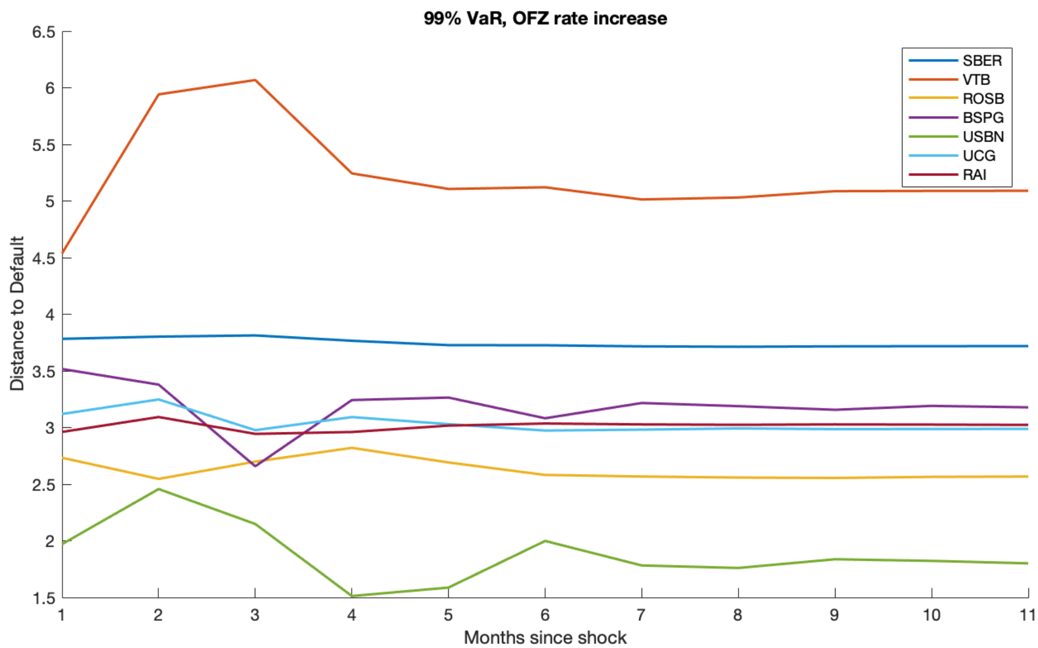
Figure 10. DD response to Interest rates factor shock: 1-year OFZ rate increase (95% VaR)



Source: Author.

Severe adverse shock (Figure 11) produced larger changes in DD measure. Still, neither of the banks defaulted or showed a considerably lower DD after the turmoil produced by the shock. Overall, some results are indeed rather difficult to interpret, as expected. Still, it is possible to notice that domestic banks are more affected by interest rates shock, compared to the international banks. As for Sberbank, it was hardly affected by any of the analyzed shocks (although it showed some decline in DD in the second factor shock specification). It is likely that the reason for this may be the size of the bank and its value of implied assets which is more than 15% higher than the value of risky debt.

Figure 11. DD response to Interest rates factor shock: 1-year OFZ rate increase (99% VaR)



Source: Author.

6. Limitations and areas of future research

One of the main limitations of the research deals with a relatively insufficient sample of banks. As it was stated earlier, the analysis covers banks that correspond to less than 55% of total banking sector assets. Still, while the expansion of the sample is certainly possible, it is hardly worthwhile and requires a lot of resources. There are around 500 credit institutions in the banking system of Russia but the majority of them are rather small. Every credit institution starting from the 24th biggest bank (ranked by assets) accounts for less than 0,5% of total banking assets in the system.

Then, the results of a sensitivity analysis showed that used macroeconomic variables explain a relatively small share of variance, which implies that some important factors were not included. At the same time, heterogeneity of the analyzed banks is unlikely to allow for a larger number of factors that may influence their credit risk exposure. Nevertheless, the research may be extended by checking whether some macroeconomic variables may influence the credit exposure of the banks with lags of higher order.

Furthermore, the analysis only covers the credit risk but the financial system is exposed to different kinds of risk – namely, market risk, counterparty credit risk, or liquidity risk that are slowly gaining momentum in the academic literature (Borio et al., 2012). It is possible to integrate credit risk analysis with some other risk exposures – for example, include a possible domino effect. For the analysis of the stability of the system as a whole, this effect of counterparty credit risk may be crucial especially if the sector has significant interbank lending. Still, some researchers suggest that this kind of risk is of secondary importance (Elsinger et al., 2006).

Moreover, one of the limitations is a lack of realism in CCA/Merton model default estimates – for example, it produces risk-neutral probabilities, a constant risk-free rate and normal distribution of the asset returns are assumed, which does not really reflect reality (Gray & Walsh, 2014). These drawbacks can be addressed by adjusting the model[2], which will increase its complexity but is likely to produce more plausible results. This research may also be extended by using estimated by CCA credit risk measures in other models – namely, Moody's KVM – so as to derive more plausible estimates of default probability.

[2] Some possible adjustments are described in Gray & Malone (2008).

7. Conclusion

The present study investigates credit risk exposure of the Russian banking sector with an aim to identify major macroeconomic factors that may threaten its stability by performing top-down stress test. While a substantial proportion of literature on the topic of bank stress-testing deals with balance-sheet credit risk models, this study focuses on contingent claims analysis that allows to derive forward-looking estimates of credit risk exposure, based on market data. To the best of author's knowledge, this is the first paper to apply this method to the banking sector of Russia. The banks included in the analysis can be divided into three groups: large domestic systemically important banks, subsidiaries of international banking groups, and regionally important smaller banks.

The development of derived CCA risk measures correspond to a general economic context of the country: a period of gradually improving health of Russian banking sector was interrupted by a rapid growth of credit risk as a result of imposed economic sanctions on Russian credit entities in 2014. While large systemically important banks remained relatively stable over the analyzed period, smaller banks showed a higher level of credit risk exposure contributing to the banking sector default probability increase.

Then, the potential effect of macroeconomic risk variables on the CCA risk measures were assessed by running stepwise regressions. The results showed that large banks are significantly affected by most of the variables describing economic development of the country, while only several coefficients resulted to be significant for smaller banks suggesting that their variance may be explained by some idiosyncratic factors.

By using PCA, these variables were further transformed into three factors: financial stability, economic growth, and interest rates. Together with log-returns on implied assets of banks, they were later used as inputs into VAR models, allowing for derivation of IRFs. The results vary considerably across the entities. Banks show a relatively short persistence of the shock to their own assets – for systemically important banks the response persists for 2-3 months, for other banks it is around 1 month. A shock to financial stability factor resulted to be significant for international banks, economic growth factor is more likely to influence domestic systemically and regionally important banks. Surprisingly, a shock to interest rates factor resulted to have almost no effect on banks' credit risk. However, it is likely that changes to this factor may become evident with some lag.

Finally, using derived IRFs, some stress-tests were conducted specified by 95% and 99% VaR corresponding to adverse and severe adverse shocks. The shocks of the derived factors were driven by oil price decrease, decline of MOEX index, and increase of OFZ rate (proxy of the key rate). CCA measures of Sberbank were largely unaffected by any of the shocks. It is likely explained by the size of the bank and the value of its implied assets compared to the value of debt. VTB and Rosbank responded rather similarly to the first two shocks (although in case of VTB the magnitude was much larger) but not to the interest rate factor. UniCredit and Raiffeisenbank, subsidiaries of international banking groups, were slightly affected by the shocks (maximum drop correspond to around 0.5 units of DD) and tended to move together. Bank Saint-Petersburg, although being one of the regionally important banks, showed dynamics similar to international banks' one. Finally, Uralsib responded strongly to the first two shocks, reaching default level in severe adverse scenarios.

Based on these results, we may suggest that the financial regulator should focus on domestic banks since the exposure to internal risk factors is much higher compared to more international ones. While Sberbank remains stable under the proposed shocks, VTB, despite being the second largest bank, tends to react quite strongly to all the shocks. The magnitude of Rosbank response is rather small but in case of extreme shocks it may suffer some distress. Uralsib reached distress level under the proposed scenarios of financial stability and economic growth shocks, which is a cause for concern given its regional importance for the Siberian region and rather turbulent economic situation in the country.

There are several limitations to the study – relatively insufficient sample of banks and dataset of macroeconomic variables, lack of integration with other risk measures, and some drawbacks intrinsic to the chosen credit risk model. Nevertheless, these limitations may be addressed by further developing the model, but it will require a lot of resources and lead to a substantial increase in the model's complexity.

References

Altar, M., Altar-Samuel, A.-N., & Marcu, I. (2014). Measuring Systemic Risk Using Contingent Claims Analysis (CCA). *Romanian Journal of Economic Forecasting, 17* (4), 22.

Antunes, A. R., & Silva, N. (2010). An Application of Contingent Claim Analysis to the Portuguese Banking System. *Banco de Portugal Financial Stability Report*, 141-152.

Bank of Russia (2017). *Banking Supervision Report 2016*. Moscow: Central Bank of the Russian Federation.

Bank of Russia (2018). *Banking Supervision Report 2017*. Moscow: Central Bank of the Russian Federation.

Basel Committee on Banking Supervision (2009). Principles for sound stress testing practices and supervision: BIS Basel.

Basel Committee on Banking Supervision (2018). Stress testing principles: Bank for International Settlements.

Baudino, P. (2009). Use of macro stress tests in policy-making. In M. Quagliariello (Ed.), *Stress-testing the banking system: methodologies and applications* (pp. 117-129): Cambridge University Press.

Baudino, P., Goetschmann, R., Henry, J., Taniguchi, K., & Zhu, W. (2018). *Stress-testing banks – a comparative analysis* (Vol. No 12): Bank for International Settlements.

Black, F., & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy, 81*(3), 637-654.

Blaschke, W., Majnoni, G., Jones, M. T., & Peria, M. S. M. (2001). Stress Testing of Financial Systems : An Overview of Issues, Methodologies, and FSAP Experiences. [Journal Issue]. *IMF Working Papers* (88).

Borio, C., Drehmann, M., & Tsatsaronis, K. (2012). *Stress-testing macro stress testing: does it live up to expectations?* (Vol. No 369): Bank for International Settlements.

Breuer, T., Jandacka, M., Rheinberger, K., & Summer, M. (2009). How to Find Plausible, Severe, and Useful Stress Scenarios. *International Journal of Central Banking, 5*(3), pp. 205 - 224.

Chan-Lau, J. A., & Sy, A. N. R. (2006). *Distance-to-Default in Banking: A Bridge Too Far?* (Vol. WP/06/215): International Monetary Fund.

Čihák, M. (2007). *Introduction to Applied Stress Testing* (Vol. No. 07/59): International Monetary Fund.

Committee on the Global Financial System (2000). Stress Testing by Large Financial Institutions: Current Practice and Aggregation Issues. Basel, Switzerland: Bank for International Settlements.

Drehmann, M. (2005). *A market based macro stress test for the corporate credit exposures of UK banks:* Bank of England.

Drehmann, M. (2008). Stress tests: Objectives, challenges and modelling choices. *Sveriges Riksbank, 2.*

Dzhagityan, E. (2016). Bazel' III v Rossii: sinhronizaciya reformy regulirovaniya na fone sistemnyh riskov? [Basel III in Russia: Regulation Reform Aligning amid Systemic Risks?]. *Russian Journal of Money and Finance, 7*, 47-58.

Elsinger, H., Lehar, A., & Summer, M. (2006). Risk Assessment for Banking Systems. *Management Science, 52*(9), 1301-1314.

Fungáčová, Z., & Jakubík, P. (2013). Bank Stress Tests as an Information Device for Emerging Markets: The Case of Russia. *Czech Journal of Economics & Finance, 63*(1), 87-105.

Glasserman, P., Kang, C., & Kang, W. (2015). Stress scenario selection by empirical likelihood. *Quantitative Finance, 15*(1), pp. 25-41.

Gray, D. F., & Jobst, A. A. (2010). New Directions in Financial Sector and Sovereign Risk Management. *Journal of Investment Management (JOIM), First Quarter 2010*.

Gray, D. F., & Malone, S. W. (2008). *Macrofinancial Risk Analysis*. Chichester, West Sussex, England: Wiley.

Gray, D. F., Merton, R. C., & Bodie, Z. (2007). *New framework for measuring and managing macrofinancial risk and financial stability*: National Bureau of Economic Research.

Gray, D. F., & Walsh, J. P. (2014). Factor model for stress-testing with a contingent claims model of the Chilean banking system. In L. L. Ong (Ed.), *A guide to IMF stress testing: methods and models* (pp. 387-406): International Monetary Fund.

International Monetary Fund (2016). *Russian Federation. Financial System Stability Assessment* (Vol. No. 16/231). Washington, D.C.

Isogai, T. (2009). Scenario design and calibration. In M. Quagliariello (Ed.), *Stress-testing the Banking System: Methodologies and Applications* (pp. 68-79): Cambridge University Press.

Jakubík, P., & Sutton, G. (2011). Thoughts on the proper design of macro stress tests *Macroprudential regulation and policy* (Vol. 60, pp. 111-119): Bank for International Settlements.

Jolliffe, I. T. (2002). *Principal Component Analysis* (2 ed.): Springer-Verlag New York.

Kapinos, P., Mitnik, O., & Martin, C. (2015). *Stress Testing Banks: Whence and Whither?* (Vol. No. 2015-07): FDIC Center for Financial Research.

Lütkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis* (1 ed.): Springer-Verlag Berlin Heidelberg.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of finance, 29*(2), 449-470.

Ong, L. L. (Ed.). (2014). *A guide to IMF stress testing: methods and models*. Washington, D.C.: International Monetary Fund.

Pesaran, M., Schuermann, T., Treutler, B.-J., & Weiner, S. M. (2006). Macroeconomic Dynamics and Credit Risk: A Global Perspective. *Journal of Money, Credit and Banking, 38*(5), 1211-1261.

Quagliariello, M. (2007). Banks' riskiness over the business cycle: a panel analysis on Italian intermediaries. *Applied Financial Economics, 17*(2), p. 119-138.

Quagliariello, M. (2009). *Stress-testing the banking system: methodologies and applications*: Cambridge University Press.

Sorge, M. (2004). *Stress-testing financial systems: an overview of current methodologies* (Vol. No 165). Basel, Switzerland: Bank for International Settlements.

Sorge, M., & Virolainen, K. (2006). A comparative analysis of macro stress-testing methodologies with application to Finland. *Journal of Financial Stability* (2), 113–151

Appendices

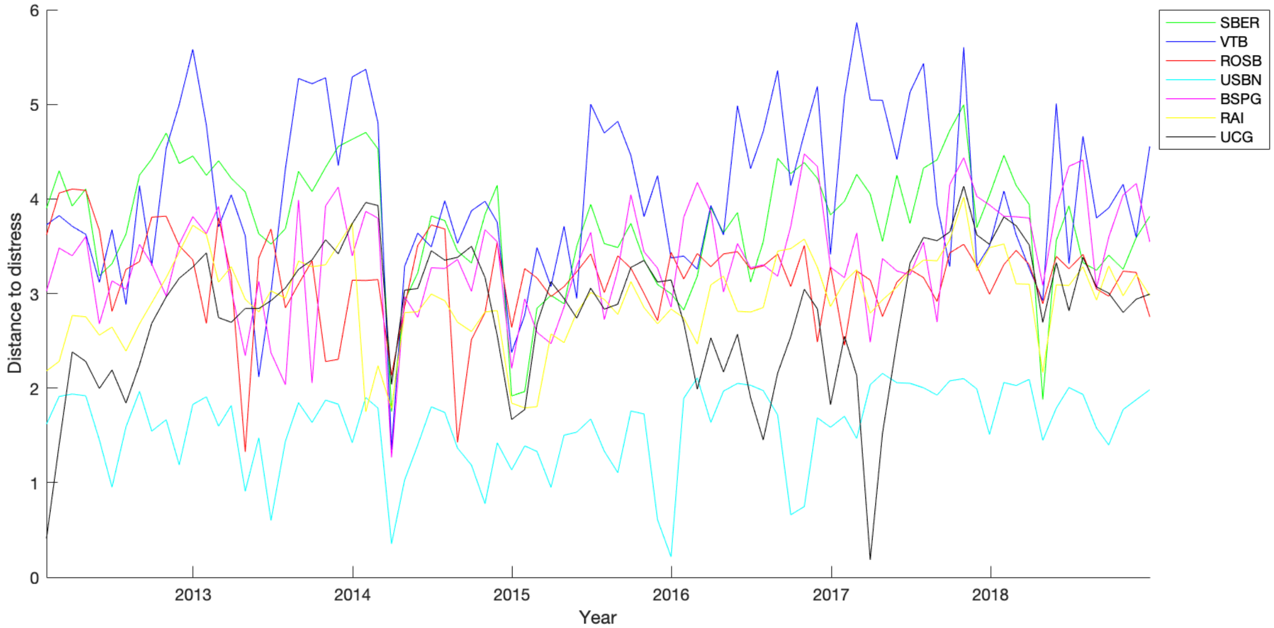
Appendix A. List of systemically important banks of Russian Federation and their corresponding shares in the total assets of the banking sector

Bank	Assets as of March 2019, mln RUB	EUR*	% to Total
Sberbank	28 357 072	389 467	31%
VTB	13 941 984	191 484	15%
Gazprombank	6 274 991	86 183	7%
Russian Agricultural Bank	3 381 847	46 448	4%
Alfa-Bank	3 290 037	45 187	4%
Credit Bank of Moscow	2 167 418	29 768	2%
Bank Otkritie	2 157 395	29 630	2%
Promsvyazbank	1 605 991	22 057	2%
UniCredit Bank	1 448 183	19 890	2%
Raiffeisenbank	1 171 341	16 088	1%
Rosbank	1 068 247	14 672	1%
Total systemically important banks	**64 864 505**	**890 874**	**71%**
Remaining credit institutions	26 067 008	358 014	29%
Total	**90 931 512**	**1 248 888**	**100%**

**FX rate EUR/RUB (13 Apr 2019) = 72.81*

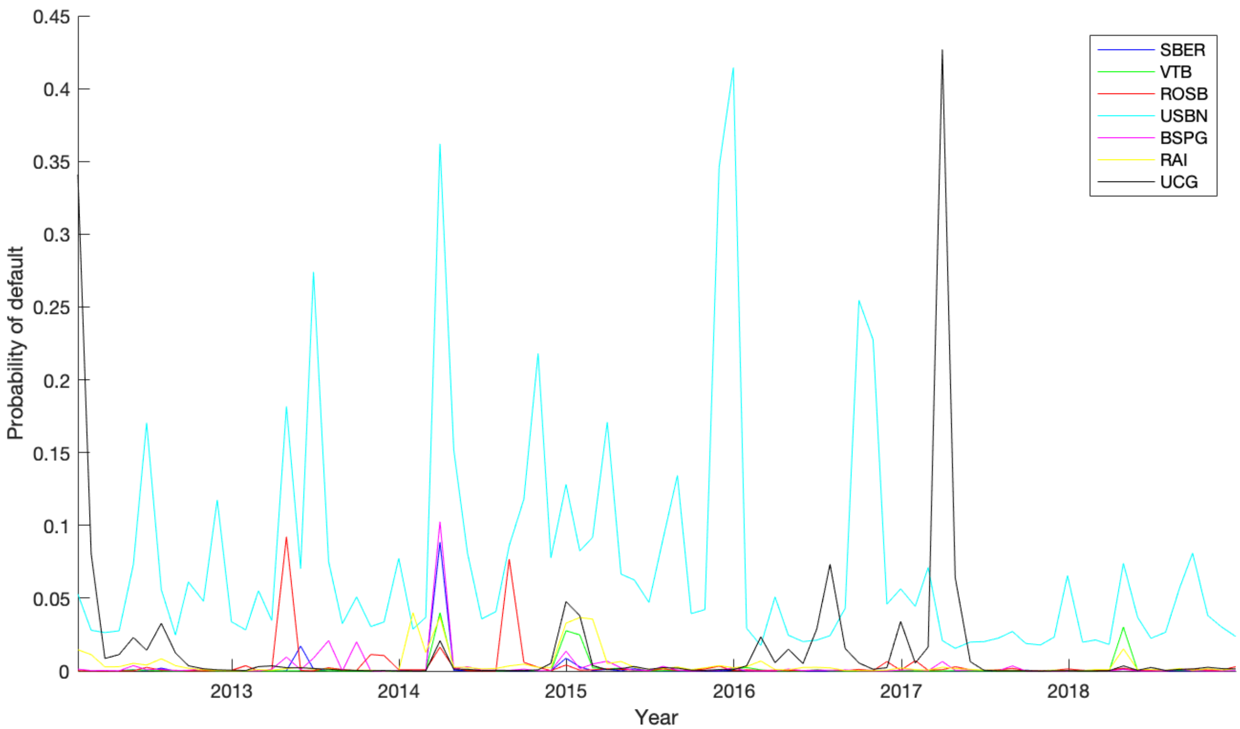
Source: Bank of Russia, Author.

Appendix B. Distance to distress of analyzed banks in Russia



Source: Author.

Appendix C. Default probability of analyzed banks in Russia



Source: Author.

Appendix D. List of macroeconomic variables

Notation		*Description*	*Source*
1	Tbill_1year	US Treasury 1-year rate - percentage change	DataStream
2	SP500	Return on the S&P500	DataStream
3	MOEX	Return on the MOEX Russia Index (Russian stock market benchmark)	DataStream
4	Urals	Price on Urals oil (Russian export oil mixture)	DataStream
5	USDRUB	USDRUB exchange rate	DataStream
6	CPI	Consumer Price Index	Russian Federal State Statistics Service
7	Unemployment	Unemployment rate	Russian Federal State Statistics Service
8	Production	Industrial production index, seasonally adjusted (proxy for domestic economic growth)	Euromonitor International
9	OFZ_1Y	Russian Federal Loan Bond (OFZ) rate	Bank of Russia
10	OFZ_1Y (change)	Russian Federal Loan Bond (OFZ) rate - percentage change	Bank of Russia
11	OFZ_spread	Russian Federal Loan Bond (OFZ) spread (difference between 1Y OFZ and 10Y OFZ)	Bank of Russia

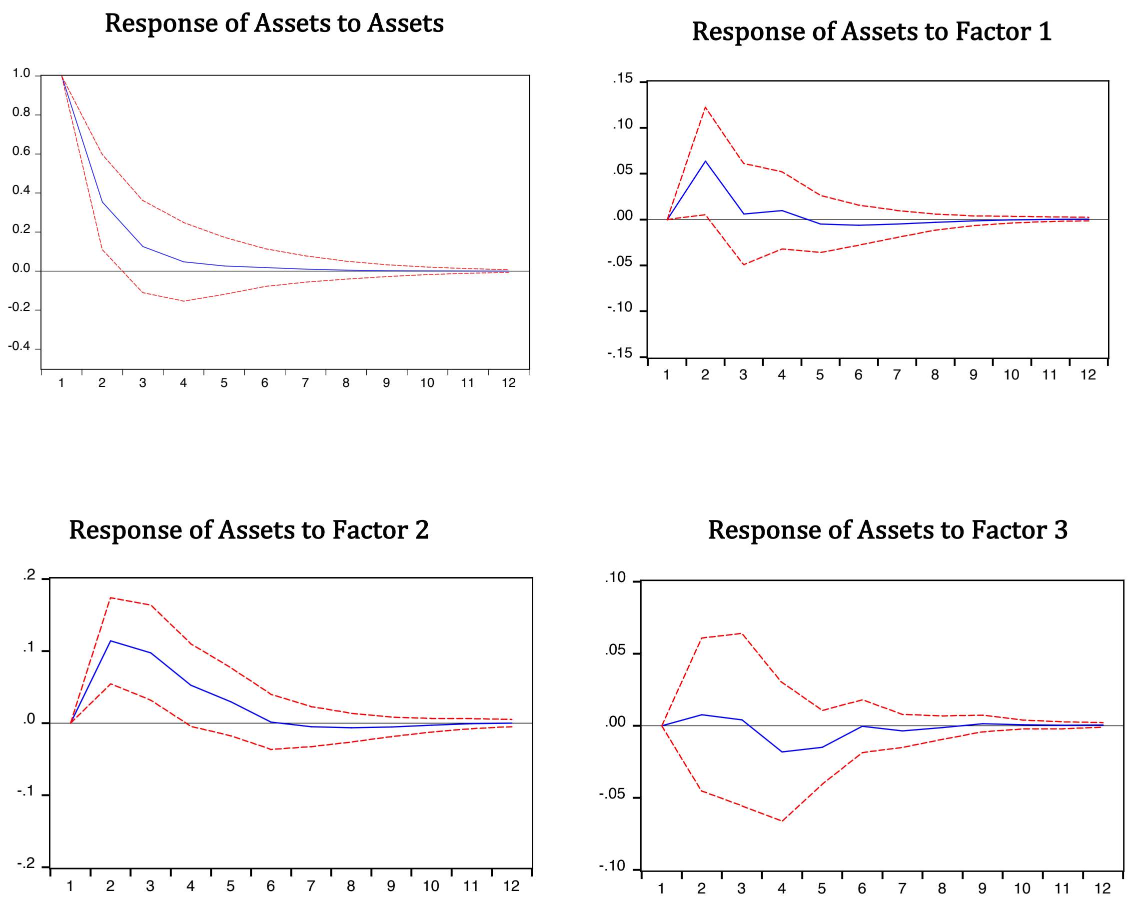
Appendix E. PCA results: Total Variance Explained

	Initial Eigenvalues		
Component	Total	% of Variance	Cumulative %
1	**4.507**	**40.977**	**40.977**
2	**2.320**	**21.094**	**62.071**
3	**1.388**	**12.619**	**74.689**
4	0.984	8.943	83.633
5	0.566	5.144	88.777
6	0.456	4.150	92.927
7	0.393	3.572	96.498
8	0.178	1.622	98.120
9	0.124	1.126	99.246
10	0.064	0.584	99.829
11	0.019	0.171	100

Source: Author.

Appendix F.1: IRF to one unit innovations (Sberbank) for 12 periods

Sberbank

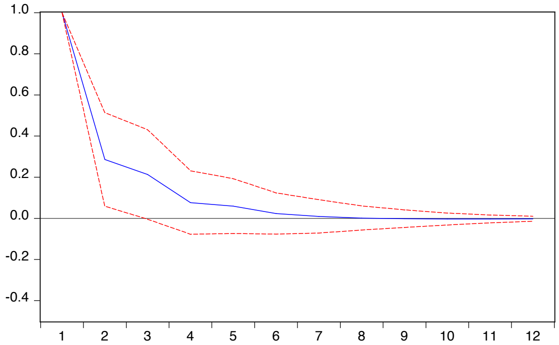


Source: Author.
Note: Bounds represent $\pm\ 2\ S.E.$

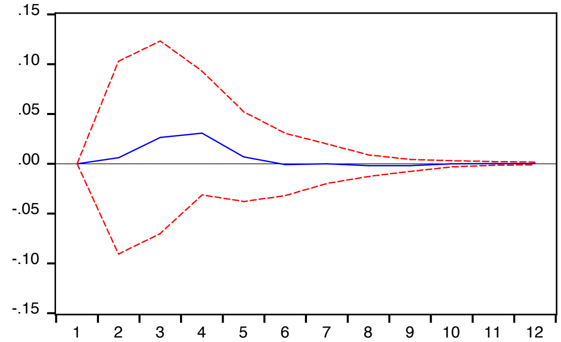
Appendix F.2: IRF to one unit innovations (VTB) for 12 periods

VTB

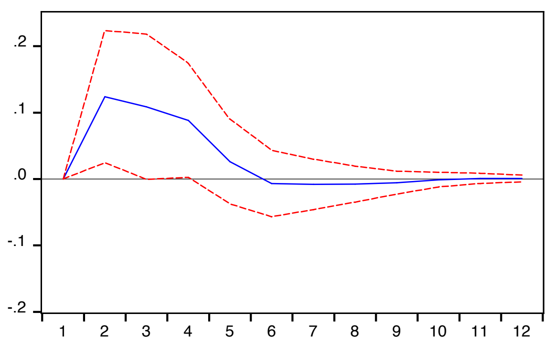
Response of Assets to Assets



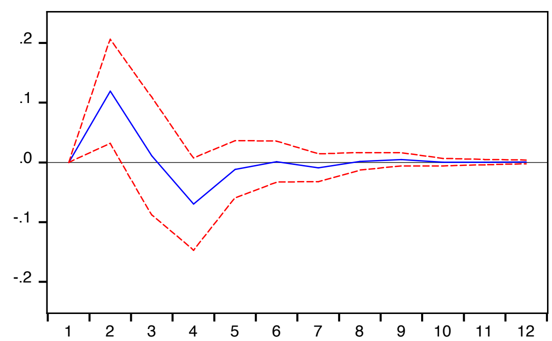
Response of Assets to Factor 1



Response of Assets to Factor 2



Response of Assets to Factor 3

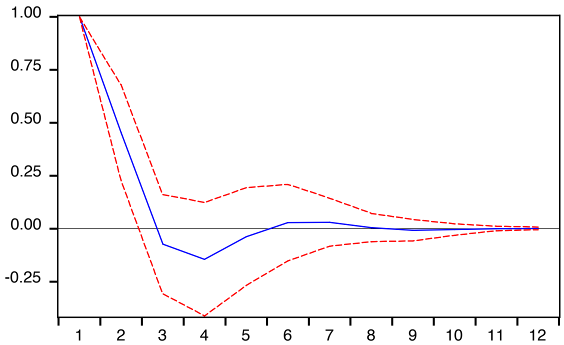


Source: Author.
Note: Bounds represent $\pm 2\ S.E.$

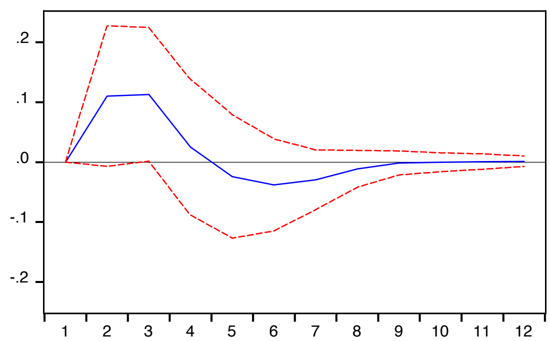
Appendix F.3: IRF to one unit innovations (Rosbank) for 12 periods

Rosbank

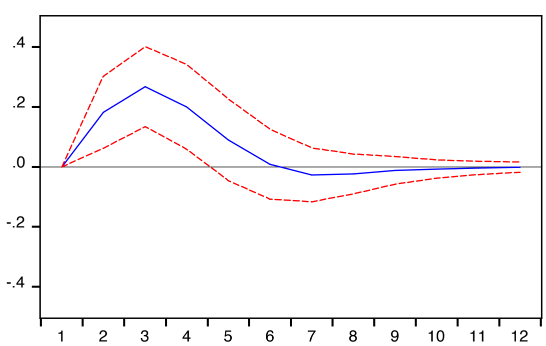
Response of Assets to Assets



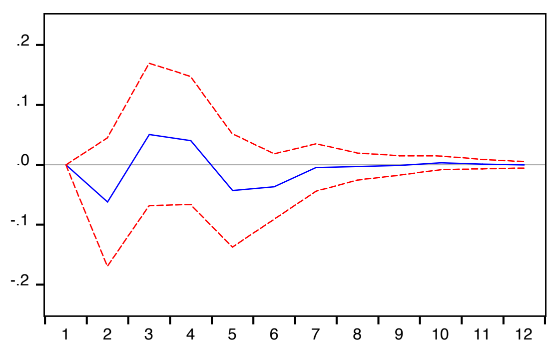
Response of Assets to Factor 1



Response of Assets to Factor 2

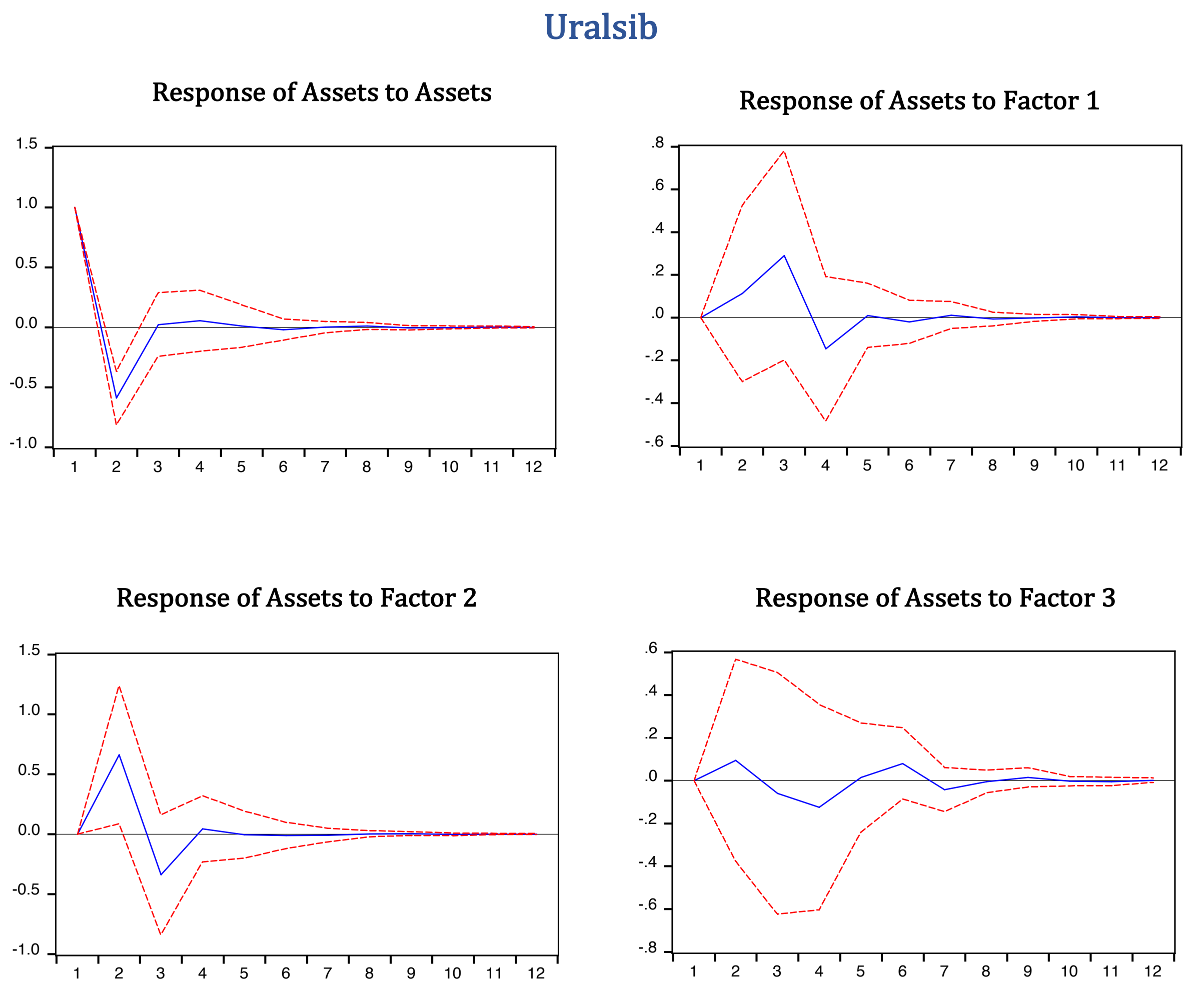


Response of Assets to Factor 3



Source: Author.
Note: Bounds represent $\pm 2\ S.E.$

Appendix F.4: IRF to one unit innovations (Uralsib) for 12 periods

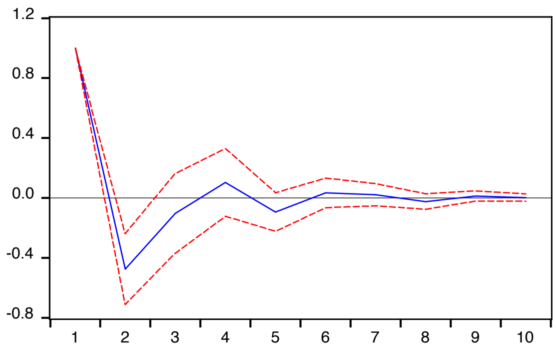


Source: Author.
Note: Bounds represent $\pm$ 2 $S.E.$

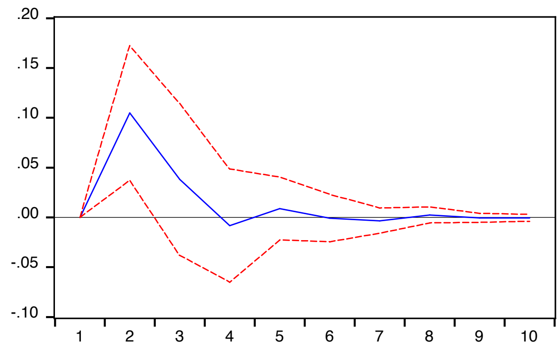
Appendix F.5: IRF to one unit innovations (Bank Saint-Petersburg) for 12 periods

BSPG

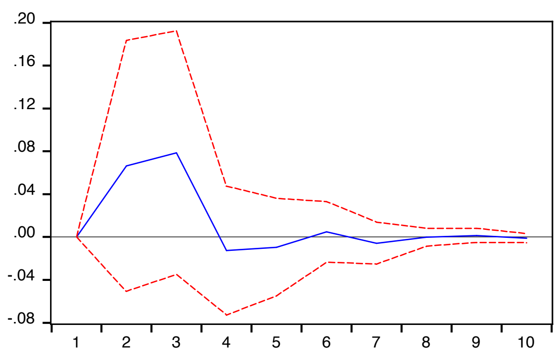
Response of Assets to Assets



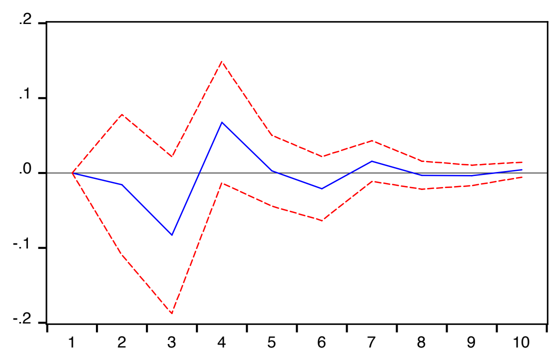
Response of Assets to Factor 1



Response of Assets to Factor 2

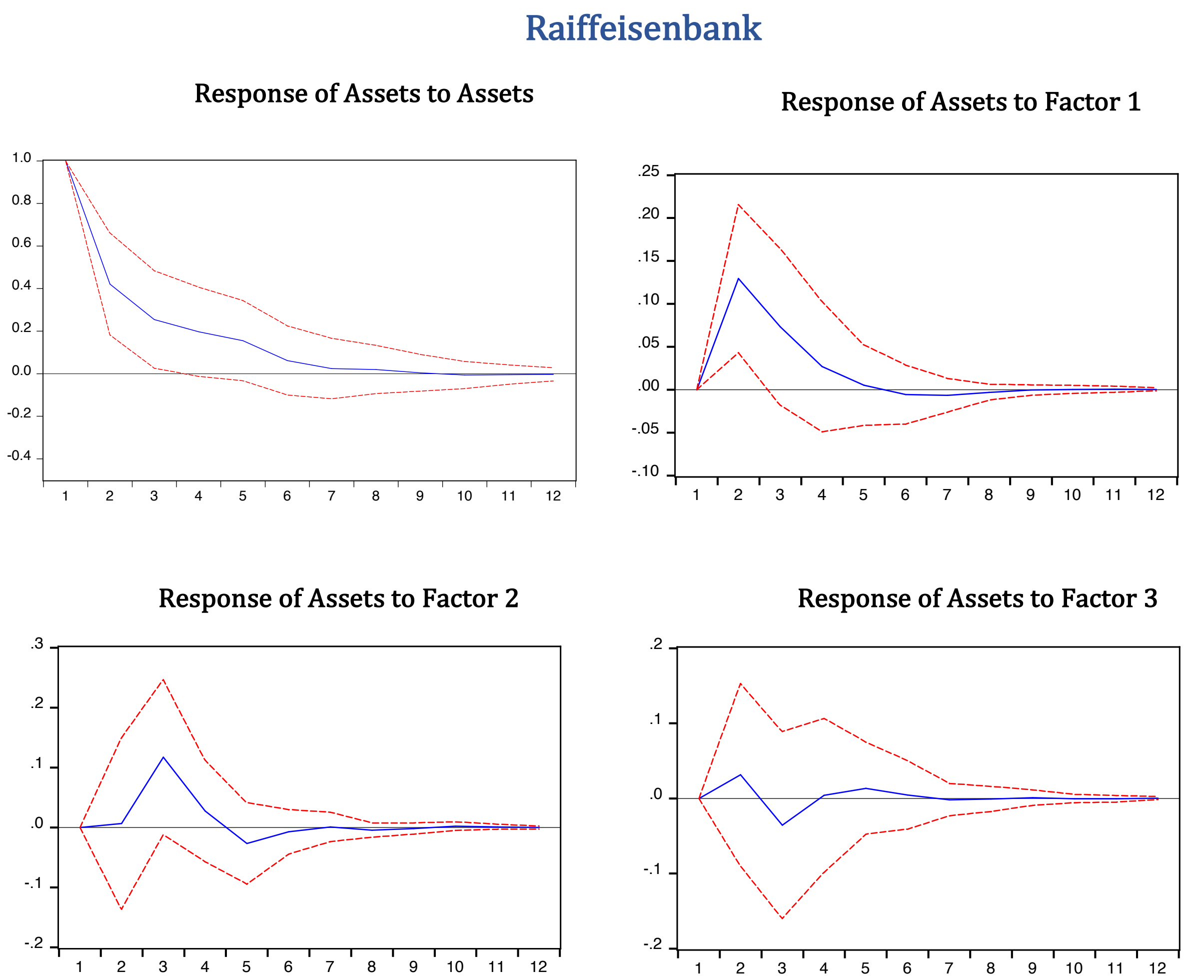


Response of Assets to Factor 3



Source: Author.
Note: Bounds represent $\pm\, 2\ S.E.$

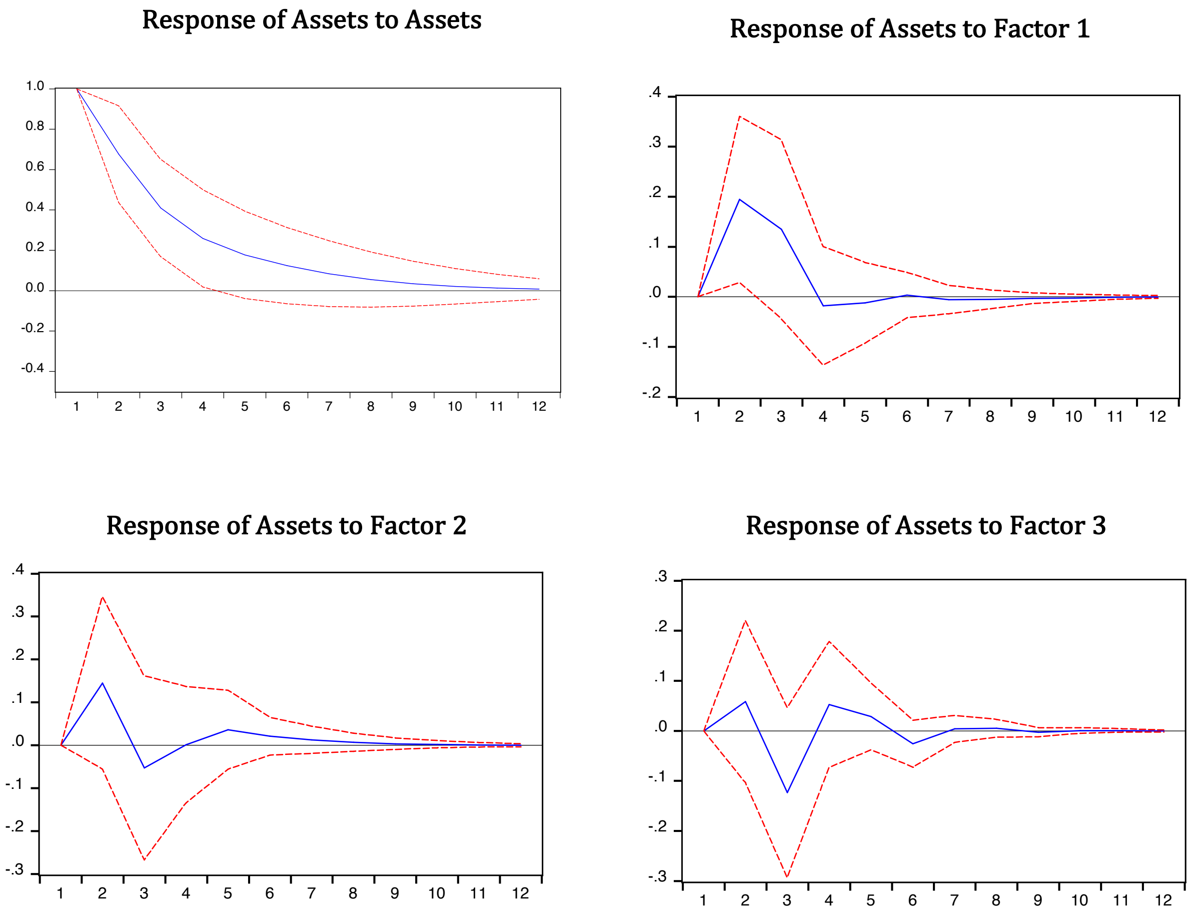
Appendix F.6: IRF to one unit innovations (Raiffeisenbank) for 12 periods



Source: Author.
Note: Bounds represent $\pm$ 2 *S.E.*

Appendix F.7: IRF to one unit innovations (UniCredit Bank) for 12 periods

UniCredit



Source: Author.
Note: Bounds represent $\pm 2\ S.E.$