Charles University in Prague

Faculty of Social Sciences
Institute of Economic Studies

MASTER THESIS

Estimation of Bank Runs probability in the context of Deposit Insurance implementation in Russia

Author: **Bc. Ecaterina Danila**

Supervisor: **Roman Horváth, Ph.D.**

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature.

Prague, June 1, 2013

Signature

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Finally, I take the opportunity to express my gratitude to my parents and Pavel for their love and support.

Abstract

This thesis empirically investigates the bank runs probability cases over the period 2005-2011 on Russian banking market and, simultaneously, tests the hypothesis of influence of bank-fundamental factors and macroeconomic conditions on the decision of depositors to withdraw their funds from banks. Methodologically, was conducted a logit econometric model to test our assumptions. We find evidence on both *bank-fundamentals*, such as high debt ratio, rising real interest rates, small asset size, and *macroeconomic conditions*, such as high inflation, and sharp increases in the real exchange rates, to influence on bank runs. In addition, the thesis analyzes the significance of deposit insurance implementation in avoiding bank runs. Moreover, we compare if the newly adopted deposit insurance diminished the credibility of the depositors in the state-controlled banks compared with private banks, thus, increasing the amount of investments to private banks. Finally, based on our approach, the method identifies a run on Russian deposit market during quarter four of 2008 year; however we would not characterize it as a severe run because it did not touch all banks but more as a partial one (approx. 1/3 of banks from the system were affected).

Keywords	bank runs, deposit insurance, Russia, logit

Author's e-mail	ecaterina.danila@yahoo.com
Supervisor's e-mail	roman.horvath@gmail.com

Table of Contents

List of Tables

List of Figures

Acronyms

DIS	Deposit Insurance System
DIA	Deposit Insurance Agency
CBR	Central Bank of Russia
ROA	Return on Assets
NPL	Non-performing Loans
CAR	Capital Adequacy Ratio
GDP	Gross Domestic Product
AIC	Akaike Information Criterion
ROC	Receiver Operating Characteristic
RUB	Russian Ruble
EUR	Euro
USD	United States Dollar

Master Thesis Proposal

Author:	**Danila Ecaterina**	Supervisor:	**PhD. Roman Horváth**
E-mail:	ecaterina.danila@yahoo.com	E-mail:	roman.horvath@gmail.com
Phone:	+420774100176	Phone:	222112317
Specialization:	Economics and Finance	Defense Planned:	June 2013

Proposed Topic:

Estimation of Bank Runs probability in the context of Deposit Insurance implementation in Russia

Topic Characteristics:

My research will be focused on testing the probability of bank runs on Russian banking system. The most influential theories on bank runs stress that occurrence of bank runs can be caused by panic effects (based on Diamond and Dybvig Model, 1983), bank-fundamental factors, or macroeconomic conditions. Thus, the main aim of this research will be studying Russian depositors' behavior after the implementation of deposit insurance scheme in Russia and understanding forces that make depositors to come and withdraw their money from bank.
Also, I will analyze the role deposit insurance policy plays in the performance and stability of run-prone Russian banking sector and as well try to test if DIS scheme can have even an adverse side effect.
I will also attempt to empirically verify my model. For the model I am going to use data from Central Bank of Russia, World Bank Data Base and other valuable sources on Russian market.

Hypotheses:

H1: Weak bank-fundamental factors may lead to the withdrawal of depositors from that bank, thus causing a bank run phenomena.
H2: Weak macroeconomic conditions may lead to bank deposit withdrawals from banking system of that country.
H3: The deposit insurance implementation helps avoid exposure to bank runs.

Methodology:

I will rely on a logit econometric model in order to test my hypotheses. By examining over 900 banks from Russian banking industry, I am going to demonstrate which factors – bank fundamentals or macroeconomics – can lead to a bank run and also if the deposit insurance scheme implemeted in 2004 is the first-best optimum in preventing bank runs.

Outline:

1. **Theoretical Frameworks:**
   - 1.1. Reflections on Bank Runs Theories
   - 1.2. Literature Review on Bank Runs and Deposit Insurance
   - 1.3. Characteristics of Russian Banking system
2. **Methodology and Model:**
   - 2.1. Logit model and hypothesis
   - 2.2. Description of varaibles and model
3. **Empirical Results:**
   - 3.1. Discussion on tested hypothesis
   - 3.2. Analysis of factors influencing bank runs
   - 3.3. Results interpretation

Core Bibliography:

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Author

Supervisor

Chapter 1

Introduction

Bank runs along with the banking crisis are considered to be one of the most severe global phenomena during the last decades. A run on a bank might cause financial instability and stimulate banking crisis because banks typically hold only a fraction of customers' deposits in cash and a situation of an excessive and unexpected deposit withdrawal would threaten bank's solvency. Moreover, a run on a single bank can evolve into runs on the whole banking system, hence causing contagion and leading to bank crisis. According to Laeven and Valencia (2007), during 1970-2007 were identified around 42 bank runs around the globe, including Russia, the country of interest in our research. The importance of analysis and prevention of exposure to massive deposit withdrawals is additionally confirmed by the current Cyprus financial crisis that might lead Europe to a new bank run risk. Consequently, a good understanding of the bank runs mechanism is not only crucial for the bank supervision, but also important for understanding the recent crisis episodes (Zhu, 2001). Several techniques have been used by the policymakers during history to prevent the effects of bank runs, through the most recent being considered the deposit insurance technique. Although deposit insurance policy might guarantee the value of capital, it also might imply less monitoring by depositors, which allows banks to hold riskier portfolios and cause moral hazard issues. Thereby, an optimal protecting policy against banks runs is yet to be found.

In this thesis, our primary objective is to estimate the underlying driving forces of bank runs and answer to the following relevant questions. How and why the depositors are determined to run on a bank? Also, we would like to test whether deposit insurance implementation helps avoid exposure to bank runs?

According to the existing literature, most empirical studies distinguish between two types of bank runs: *information-based* bank runs, correlated with the bank

fundamentals or macroeconomic fundamentals, and panic-based bank runs in which there are no fundamental factors. The panic-based theory is related to the classical work of Diamond and Dybvig (1983), where depositors run to extract their money for non-economic reasons, such as herd behavior. However, in this thesis we will focus on the second type of bank runs that are expected to happen when bank fundamentals and the economy as a whole are in bad state - the information-based bank runs.

As the country of interest, to test our theories and hypothesis on the depositors' incentives to run on a bank, was selected Russia. For Russia, the estimation of factors that may cause a bank run is particularly relevant in the view of the high vulnerability of the domestic financial sector. Also, Russian deposit market is an ideal environment to test for bank runs in connection with the new law on deposit insurance, implemented in 2004. Therefore, in this paper we aim to test for significance of the impact of bank-fundamentals and macroeconomic factors on the exposure of Russian banking sector to bank runs. Particularly, we are interested in the post-deposit implementation period as we would like to examine, also, how Russian depositors responded to the introduction of the deposit insurance scheme. Simultaneously, we are interested to analyze the evolution of the reliance of depositors on the state-controlled banking sector as we expect the introduction of deposit insurance to lead to a decrease in the amount of deposits in state-controlled banks.

We consider the analysis of bank run exposure for Russian deposit market an important research for future policies improvement. The thesis contributes to the economic research in this area by analyzing the banks' institutional deficiencies, as well as the macroeconomic issues that can cause a run on Russian banks. Besides testing the factors that may lead to run on Russian banks, this study will also investigate the efficiency of deposit insurance as a policy against deposit withdrawals. As the most appropriate econometric technique for this purpose was selected the logistic regression which allows for a binary outcome, in our case presence or absence of a run.

The thesis is structured as follows. The Chapter 2 comprises the literature review on bank runs and deposit insurance conducted so far, as well as a detailed description on the main characteristics Russian banking system specifics and the new law on deposit insurance. Chapter 3 represents the methodological section where are presented the hypothesis aimed to be tested in this research together with a description of the applied econometric model. Chapter 4 provides the results and a sharp discussion of the empirical results and the explanatory factors that cause bank

runs. The concluding remarks are in Chapter 5. The references list and the Appendix can be found at the end of the research.

Chapter 2

Theoretical Background

2.1 Chapter Overview

This chapter presents a comprehensive review on the existing bank runs literature mainly focusing on the studies on the determinants of bank runs and the role of deposit insurance scheme in preventing deposit withdrawals. Additionally, it includes section 2.5 that provides detailed explanation on the main characteristics of the Russian banking system and the introduction of the compulsory deposit insurance scheme in Russia. The description is followed by an illustration of the main changes in deposits' amount pre- and post- adoption of deposit insurance law.

The final section of this chapter is devoted to the comparison of the empirical evidence applied in the existing researches and description of the specifics – original contribution - of the model built in this thesis.

2.2 Literature Review on Bank runs

Kaufman (1988), in his paper *Bank runs: causes, benefits and costs*, defines a run on a bank as a phenomenon where a large number of depositors, fearing that their bank will be unable to repay their deposits in full and on time, simultaneously try to withdraw their funds immediately. It is important to highlight that the banking sector may be exposed to bank runs due to the fact that banks issue liquid liabilities but invest in illiquid assets. This provision of liquidity insurance, as describes Zhu (2001), may come at the risk of losses due to a panic-based bank run. The reason is that if all depositors at once demand their withdrawals, the bank will not be able to serve all of them and will fail. Moreover, a run on an individual bank may also affect

other solvent institutions or even the banking system as a whole. Neuberger (1991) stress that if a run starts at one bank and can spread to others, it imposes costs not only on the bank in question but also on the other banks. The size of this negative externality determines the costliness of bank runs and the desirability of encouraging depositor discipline.

Back in the history, bank runs were an important economic phenomenon. United States experienced before the mid of 1930s severe bank runs where the number of bank failures averaged over 2000 per year (Samartin, 2002). Another significant example is the run on Argentinean banks in 2001 that resulted in a temporary closure of the banking system. Russia Federation, the country of interest for our paper in testing bank runs exposure, experienced as well a partial run in 2004 (Guta Bank and Alfa Bank) and 2008 (Globex). Other countries experiencing bank runs during global financial crisis 2007-2008 were U.K. with a run on Northern Rock that end up for bank being nationalized and the collapse of the U.S. investment bank Bear Stearns in 2008 – event described by economists as being fundamentally similar to a run on a bank. Thus, taking into account the historical importance of bank runs and the costly adverse effects caused by them, it is important to understand why they occur and which implemented policies are effective to deal with them. In this sense, there are several economic theories to explain the occurrence of bank runs.

One of the most influential theories on bank runs is the panic-based effect theory. Friedman and Schwartz (1963) have provided substantial insights into defining particular panic episodes of the 1930s United States crises as bank runs. They come with the argumentation that panics originate from the lack of confidence on the banking sector, for e.g. bankruptcy of a big bank or loss of confidence in the local currency. A valuable contribution to the panic-based theory was added by the Diamond and Dybvig (1983) paper which presents a model where a run on a bank is a rational response to agents' beliefs due to asymmetric information.

The model shows how banks' combination of illiquid assets and liquid liabilities – the deposits that consumer have the right to withdraw at any time - may lead to a self-fulfilling panic[1] among depositors. Diamond and Dybvig affirm that any bank

[1] The term *self-fulfilling prophecy* was coined by Robert Merton (1948) as defining "a false definition of the situation evoking a new behavior which makes the originally false conception come true". The term self-fulfilling prophecy was used by Diamond and Dybvig to describe a run on a bank caused by panic effects.

may suffer a massive withdrawal - it is enough for the individuals to believe that other depositors will run at that bank too.

There is as well empirical evidence suggesting that bank runs are not random events. Calomiris and Gorton (1991) contest the Diamond and Dybvig theory on panics by analyzing what types of events or beliefs would lead to panics and eventually bank runs by combining the self-fulfilling prophecy and the fact that panics can be caused by depositor revisions in the perceived risk of bank debt when they are uninformed about bank asset portfolio values and receive adverse news about the macro economy. The panic view on the bank runs origin was as well discussed in the papers of Alen and Gale (1998) and Calomiris and Mason (2003) interpreting the self-fulfilling prophecy as contagion in the bank runs context. Calomiris state that liquidity problems and depositor runs were the reason of drove of the economically solvent independent banks into insolvency in the times of Great Depression.

In addition to the panic-induced deposit withdrawal theory, there is empirical evidence suggesting that bank-fundamental factors, and in some cases both macroeconomic conditions and fundamental factors are on the origins of bank runs. The bank-fundamental and macroeconomic conditions are widely discussed in our paper as they stay at the base of our method to identify the probabilities of occurrence of bank runs for the Russian banking system during 2005-2011.

One stream of the literature on bank runs develops an empirical analysis on the role of bank fundamentals in the bank runs exposure. Chari and Jagannathan (1988), Calomiris and Gorton (1991), Duffoo, M.A. (2004) argue that sudden deposit withdrawals during the crisis periods represent an informed market response to observable weaknesses in individual financial institutions, traceable to ex-ante bank characteristics as asset risk, solvency, liquidity, and profitability. Simorangkir (2011), by using a dynamic panel data model, investigate the determinants of bank runs and bank crises in Indonesia during 1997-1998. He shows empirically that both bank financial performance (ROA, NPL ratio affect bank run; while CAR ratio has an opposite influence on bank runs) and macroeconomic variables (high exchange rate volatility, inflation and real interest rates on deposits) increase the probability of bank runs in Indonesia.

Demirgüç-Kunt and Detragiache (1998) conducted a research on the determinants of banking crises using a dataset of a combination of developed and developing countries from 1980-1994. The multivariate logit model used by them demonstrated that weak macroeconomic environments are closely related to the emergence of

banking crises, especially low GDP growth rates, high inflation, and high interest rates.

On the other hand Kindleberger (1978), Allen and Gale (1998), and Zhu (2001) state that banking crises are part of a cycle that affects the financial sector which in turn becomes highly leveraged when a downturn occurs due to an increase in the non-performing loans, leaving banks unable to pay depositors because majority of their creditors cannot repay their loans. In sum, what explain a bank run are bank-fundamentals - real shocks and insolvency problems as the causes of depositors' panics.

Graeve and Karas (2008) investigate the Russian deposit market during 2002-2007, finding evidence that both panic and the informational-based views can lead to bank runs. However, the same authors continue their research and quantify the effects of the two main theories of bank runs in another paper (2010) for the same sample and same period by incorporating cross-sectional heterogeneity into structural VARs and find that the panic view bank runs for Russia are much more important than the information-based. The authors believe that it is important from a regulatory point of view to know that depositors may punish banks for bad behavior in normal times – oriented by bank-fundamentals; it is quintessential to acknowledge, however, that they may not make that distinction during a financial crisis – and therefore be conducted by panics.

2.3 Policy implications applied in preventing bank runs during history

As Chu (2003) mentions in his paper, the bank runs are bad signs of financial instability being costly and economically inefficient because they interrupt financial intermediation and adversely affect economic activity and growth. Thus, it is important for the state to implement the correct policies in order to maintain and promote the financial stability and to prevent the arising bank runs due to asymmetric information and self-fulfilling prophecies.

Against a panic-driven bank run the following policy responses were applied during history: *suspension of convertibility of deposits* (bank does not allow to be withdrawn more than a fraction of deposit), *taxation on short-term deposits*, *capital requirements*, and *deposit insurance schemes*. First two are more things of the past due to their negative effects, while deposit insurance and provision of liquidity

facilities are widely applied till present. Zhu's (2001) investigations demonstrate that suspension of convertibility of deposits is inefficient in preventing runs because it can't distinguish between those with true liquidity needs and those who are running on the banks. The author also accentuates the negative effect of taxation on short-term deposits; policy that implemented can affect both the quantity and composition of early withdrawals, thus introducing investment distortions into the economy. On the other side, the last two policies, capital requirements measures and deposit insurance, as well experience many shortcomings. With regards to the capital requirements, the global regulatory standard Basel 3 was established to improve the banking regulations, especially with reference to the capital adequacy. However, this policy is hard to be maintained by the banks. The deposit insurance is also facing issues due to the moral hazard problems. A more detailed review on the costs and benefits of deposit insurance as a policy against bank runs is presented in chapter 2.4.

Alternatively, when bank runs are based on fundamentals, should be applied regulations related to market discipline factor. For example, Graeve and Karas (2008) suggest imposing constraints on bank behavior or applying government recapitalization.

2.4 Literature Review on the Deposit Insurance from perspective of policy implication against Bank Runs

Deposit insurance is a guarantee up to a certain amount, often provided by a government agency, to protect bank depositors as well as the bank itself from likelihood and severity of bank runs during a financial crisis. By 2011, the International Association of Deposit Insures (IADI) counts 111 countries that have instituted some form of explicit deposit insurance up from 12 in 1974. Also, IADI mention another 41 countries that are studying or considering the implementation of an explicit deposit insurance system. The United States was the first country to introduce in 1933 a national deposit insurance system and from its experience we can deduct that any country that adopts a deposit insurance scheme must confront with the destabilizing effects of this policy on the banking sector of that country.

Deposit insurance design varies across countries. As Demirgüc-Kunt and Kane (2002) mention in their study on deposit insurance around the globe, an optimal worldwide blueprint is not likely to be found. The authors remark that depending on

each country in part, the account coverage varies from unlimited guarantees to tight coverage limits: on one hand, Russia, Japan, Mexico, and Turkey promise 100 percent depositor coverage, while countries like Chile, Switzerland, and U.K. cover only an amount of deposits that is actually less than their per capita GDP as they state.

Also, the empirical researches encounter different results on the impact of deposit insurance schemes on bank risk taking behavior. One stream of empirical studies has found that deposit insurance reduces bank risk (Karels and McClatchey 1999; Gropp and Vesala, 2001; Cull, Senbet, and Sorge, 2005). Also, Diamond and Dybvig (1983) consider in their paper deposit insurance to be an efficient policy to avoid socially undesirable bank runs. However, an additional paper of Cull, Senbet, and Sorge (2002), focused on the examination of cross-country data, suggests that DIS has a negative impact on financial development and growth in long run, except in countries with strong legal and regulatory institutions. Thus, the introduction of DIS needs to be accompanied by a strong regulatory scheme, otherwise, the new policy my lead to the financial system deterioration.

On the other hand, another stream of empirical studies has shown that deposit insurance can create moral hazard, encourage banks to take high risks, and reduce the incentives of depositors to monitor banks (Demirgüc-Kunt and Detriagache, 2002; Cooper and Ross (2002), Laeven, 2002). For example Chu (2003), by studying 52 countries over the period 1996–2007, finds that the higher the deposit insurance coverage, the more severe the banking crisis is. He empirically demonstrates that higher coverage tends to undermine market discipline and aggravate the moral hazard problem associated with deposit insurance. Thus, their effectiveness in promoting banking stability in the long term should not be taken for granted. Chernykh and Cole (2011) examine the impact of implementation of deposit insurance in Russia. Their results suggest that even the DIS had the effect of leveling the playing field between state-controlled banks and private; there were strong evidence of the increase in moral hazard.

Another research on the moral hazard was provided by the Demirgüc-Kunt and Huizinga (2004) on a cross-country sample, including Russia, suggesting as well that explicit deposit insurance reduces required deposit interest rates, while at the same time it lowers market discipline on bank risk taking.

It is very important to highlight that the effectiveness of deposit insurance as a policy against bank runs depends also on the established coverage rate. Many researchers have stressed that partial deposit insurance has a better effectiveness than

full deposit insurance. Ioannidou and Dreu (2006), by testing the deposit insurance on the Bolivian banking sector, showed that when the coverage rate is more than 60 percent, market discipline is significantly reduced and it is completely eliminated when the coverage rate reaches 100 percent. Additionally, some papers emphasize the importance of client-bank relationship on bank runs. According to Iyer and Puri (2008) analysis, the collapse of a major bank in India in 2001 lead the depositors to run on a solvent bank, unrelated to the collapsed bank. Their findings suggest that deposit insurance is only partially effective in preventing bank runs and accentuate that depositors with longer relationships and those who have availed of loans from a bank are less likely to run during a crisis.

As a concluding remark on the studied literature review, we can state that deposit insurance represents a frequent policy implication implemented by countries nowadays. However, the conducted econometric researches present it only being partially effective in preventing bank runs, or even having serious adverse effects on the banking system. As a major concern to be taken into account is that deposit insurance may reduce the incentives of depositors to monitor and discipline their banks. Coupled with weak regulatory and supervisory systems, this could lead to huge costs, both for taxpayers and for the economy more generally, from exacerbating and prolonging crises (Ioannidou and Dreu, 2006). Thus, the major challenge for the policymakers is to create such a deposit insurance scheme that protects the financial system from systemic bank runs without reducing market discipline.

2.5 Characteristics of the banking sector in Russia

The main characteristics of the Russian banking system are: domination of state-controlled banks on the market, existence of banks that have strong linkage with financial industrial groups, predominance of many tiny banks with a low share in the total sector activity, and the lack of foreign competition. The banking sector is considered to be of small size, very concentrated (first 30 banks account more than 2/3 of market), and have a short-term nature of banking operations. **Table 1** from Annex summarizes some general information in numbers about the banking sector in Russia during 2001-2011.

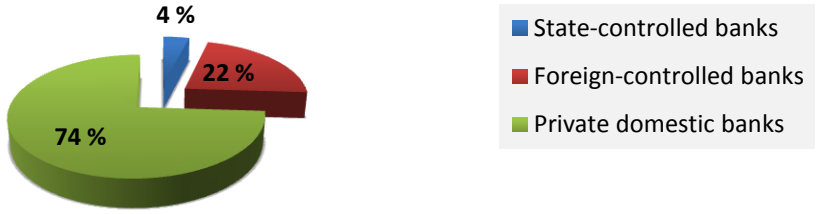
Before 1980s the Gosbank was the controlling institution in the Soviet Union's banking system, which combined the role of a central bank and a commercial bank by carrying out a variety of lending, holding deposits activities, monitoring population

payments and currency issue. In the late 1980s, with the implementation of *Law on Cooperatives* in 1988, the first non-state banks were formed. Chowdhury (2003), in his paper on the banking reform in Russia, mentions that as part of the economic reforms, the country moved away from the strictly centralized control of the mono-bank system to a relatively more diversified and functionally more specialized two-tier system. According to the author, the central banking functions were vested with Gosbank (from 1991 named Central Bank of Russia), while commercial banking functions were performed by five specialized institutions: Sberbank (savings), Vneshtorgbank (foreign trade), Promstroibank (industrial lending), Agroprombank (agricultural lending), and Zhilsotsbank (housing). However, only with the adoption of Federal Law 395-1 (02.12.1990) *On Banks and Banking Activity*, the development of the banking system started to take shape. In the process of privatization of the government property many private banks emerged, together with the so-called *oligarchy* and large financial industrial groups (e.g. Gazprombank). Meanwhile, many small regional banks emerged; mostly those had very strong ties with the local governments and companies. The major banks as Sberbank and Vneshtorgbank still remained under the government control (Gorshkov, 2012). This situation stands till present, where government remains to be the major shareholder of the banks with the dominant position on the market.

Even though, at first glance, the total number of state-controlled banks is a small percentage in the total market share (see **Figure 1**), most of the small banks, also called *pocket banks*, do not operate as normal credit institutions, but rather are serving a single company or act as treasuries for financial-industrial groups and large corporations (Ippolito, 2002). Moreover, the majority of the private banks are so small that World Bank (2002) research classified less than 250 banks from Russia to have capital exceeding the EU established minimum capital requirements. Foreign banks presence is still considered relatively low in Russia to influence the market[2].

[2] *Russian banking sector has received limited foreign investment compared to other East European and Baltic States. In these countries, foreigners now control over half of the banking market; while Russian banks remain in the hands of the government and private domestic companies, themselves usually controlled by a handful of oligarchs* (Chowdhury, 2003).

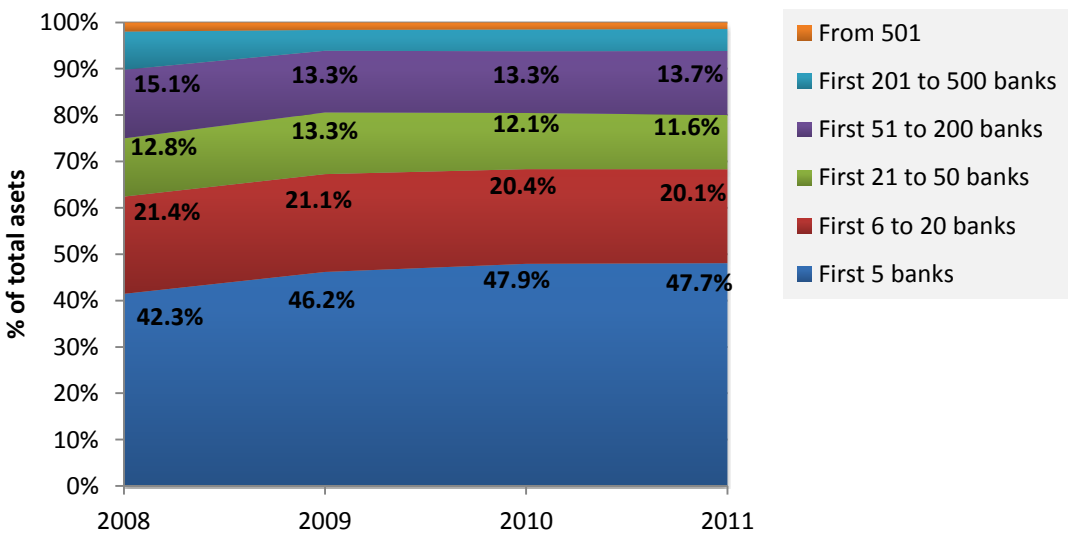
Figure 1: Russian banks by ownership type, % of market share (2011)



Source*:* Author's computations based on Central Bank of Russia data and A. Vernikov Paper on state-controlled banks in Russia.

As of the beginning of 2011 year, the CBR states 1012 credit institutions holding banking license in Russia. According to Gorshkov (2012), the peak of the number of banks was in 1995 when there were 2273 banks operating on the market. This number is gradually decreasing along the years (see evolution of the number of banks for 2001-2011 in **Table 16** from Appendix A). However, when compared with the number of banking institutions in other countries the number of banks in Russia is still excessive. Despite the large number of institutions operating in the country, the first 5 banks prevail with a concentration of assets around 47% of the market (see **Figure 2**), providing evidence that the structure of the banking sector is strongly concentrated.

Figure 2: Concentration of assets in the Russian banking sector

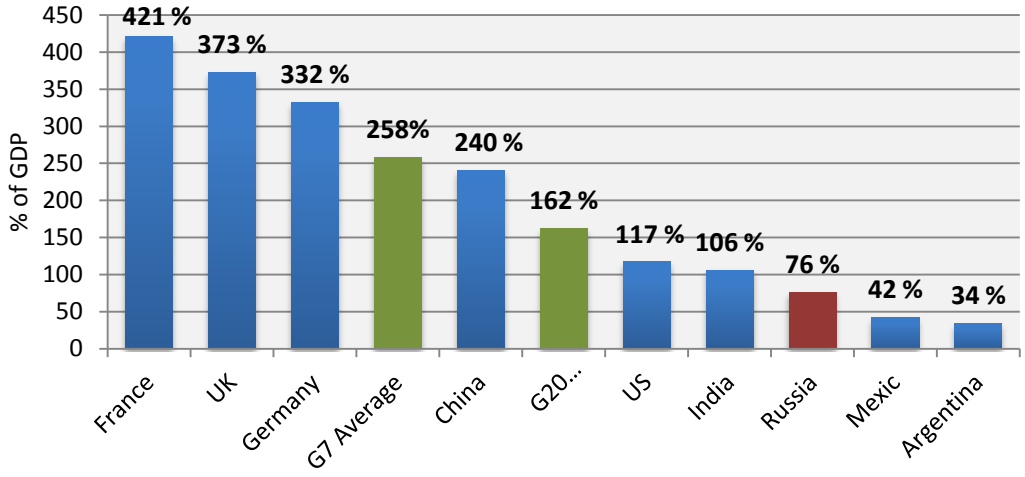


Source: Author's computations based on Central Bank of Russia data

All five top banks (Sberbank, VTB, Gazprombank, Russian Agricultural Bank, Bank Moskvy) are state-controlled banks. The biggest state-controlled bank and the leader on the market is Sberbank and in terms of volume of activity (e.g. in 1998 Sberbank's share of private deposits reached a peak of 80% of total market) and number of branches across the country. One fourth of branches are Sberbank branches (see Table 16 from Appendix A).

Although the Russian banking system has gone through many transformations, it is still very weak and of small size in terms of industry sector. **Figure 3** represents the banking sector's total assets as a percentage of GDP for 2011 year. In 2011 the total assets as percentage of GDP was 76%. Corresponding figures are over 100% for countries as France (421%), UK (373%), and China (240%). The credit to private sector as percentage of GDP of 46.8% for 2011 is as well lower when compared with France (116%), UK (188%), US (193%), China (127%).

Figure 3: Total Banking Sector Assets as % of GDP (2011)



Source: Author's computations based on Central Bank of above mentioned countries.

Note: For the evolution of the percentage of assets over GDP and percentage of credit to private sector over GDP ratios for 2001-2011 years please see **Table 16** from Appendix A.

According to Barnard and Thomsen (2002), the continued underdevelopment and weakness of the Russian banking system reflects the fundamental remaining problem of lack of trust: of the population in banks, of banks in borrowers, of foreign counterparties in Russian banks, and of banks in each other. This is one of the reasons why Russians prefer to keep their savings under *mattresses* rather than in bank deposit accounts. Camara and Montes-Negret (2006), in their paper on the *Deposit*

insurance and banking reform in Russia, mention a survey made in 2006 by VTsIOM indicating that 70 percent of Russians have not had a savings account in the past eight years, either because they had no money or simply because they did not trust the banks.

In **Table 4** are represented the ratio of the total household deposits as a percentage of GDP is only 22% as of 2011. The amount of household deposits as percentage of population's income is only 31% for 2011.

Table 1: Household Deposits as percentage of GDP (sector liabilities, population Income).

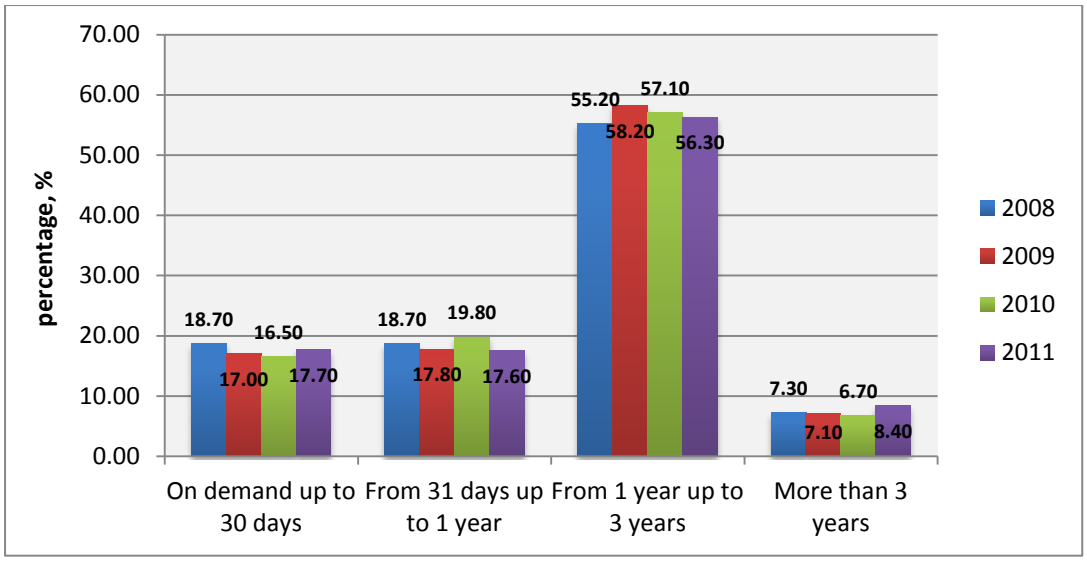
	2005	2006	2007	2008	2009	2010	2011
Household Deposits (billion rubles):	1980.8	2761.2	3809.7	5159.2	5907.0	7485.0	9818.0
as % of GDP	11.6	12.8	14.2	15.5	14.3	19.3	22.1
as % of the banking sector liabilities	27.9	28.5	27.3	25.6	21.1	25.4	29.0
as % of income of the population	18.0	20.0	22.0	24.2	23.4	26.3	31.3

Source: Author's computations based on Central Bank of Russia data.

Also, although the average of deposit interest rate is considered to be high in nominal terms, thus should be attractive for depositors (see **Table 16** from Appendix A), when you take inflation into account it is still low. For the changes in deposit interest rates as well as the overview of the changes in the GDP, inflation, and M2 during 2006-2011 please see **Figure 10** and **Figure 11** from Appendix A.

Specific for Russian banking system is the fact that household deposits are legally required to be available on demand, regardless of contractual maturity. This inability to attract long term liability limits credit expansion (Chowdhury, 2003). From **Figure 4** we can observe that the largest share in the household deposits in terms of maturity in 2011 hold the deposits with terms longer than one year that make banking operations for Russian banking sector to have a short-term nature. Gorshkov (2012) also highlight the bank system inability to execute the function of converting deposits into investments, imposing companies to issue bonds or attract capital from foreign markets instead. Thus, the banking system is still far from playing the role that it should in intermediating savings and investment.

Figure 4: Structure of deposits of individuals, depending on the term (in %)



Source: State Corporation Deposit Insurance Agency.

On the base of the crisis of depositors confidence in the Russian banking system lie as well the systemic problems from: 1994 (rubble collapse), 1995 (liquidity crisis in the interbank market when a large number of banks failed), 1998[3] (government's default on its ruble bonds and subsequent ruble devaluation; many depositors lost their savings) and 2004 – where Graeve and Karas (2008) mention a severe bank run at the beginning of 2004 where several large banks suffered from deposit withdrawals (e.g. Guta Bank and Alfa Bank). Since 1992, as a consequence of these crises, more than 2000 Russian banks have been liquidated or have vanished (Karas, Schoors, Weill, 2008). The Financial Crisis of 2007-2008 reached Russian market as well. In 2008 several Russian banks failed due to liquidity issues related to US credit derivatives. According to *Stratfor*'s article with a very meaningful name, *Russia: A Bank Run and Fears of a Repeat*, the Russian bank *Globex* barred customers from withdrawing money from their accounts on October, 15 in the first bank run of the current global economic crisis spreading to other Russian banks panic mode.

Given the large number of private depositors who have lost their savings in Russian bank crisis, state came with the introduction of compulsory deposit insurance scheme in order to improve confidence in the country's banking system. Before,

[3] *On September 3, 1998, during the 1998 Russian financial crisis, private accounts at the SBS-Agro and MENATEP banks, Inkombank, Promstroibank, Most Bank, and Moscow Business Bank were frozen. Depositors at these banks were given the opportunity to transfer their money to the Sberbank at the rate of 9.33 rubles/US dollars* (Chowdhury, 2003).

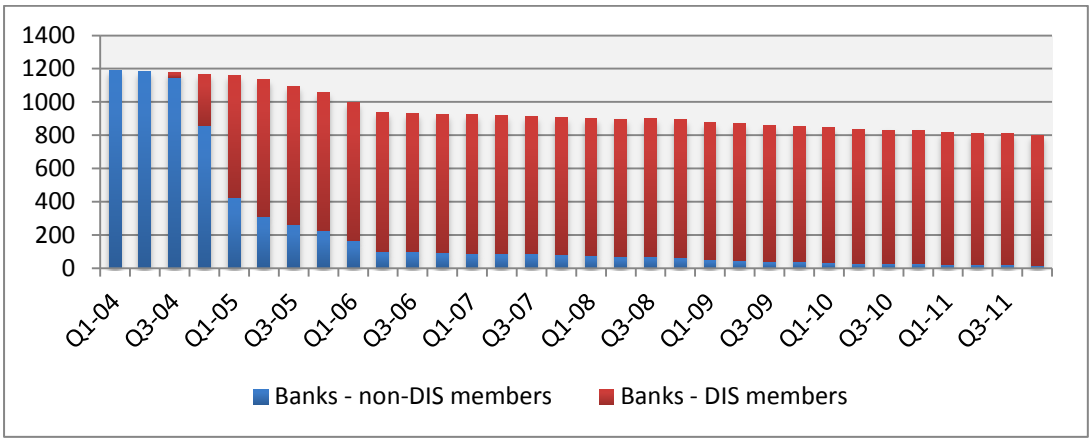
Sberbank was the only bank that enjoyed consumer confidence because of the deposit insurance guarantee provided by the state. With a 100 percent covered government guarantee, the Sberbank's deposit market share at that time was 63 percent from total deposits. This distorted market competition conditions and created incentives for future moral hazard.

The Federal Law *On Insurance of Household Deposits in Banks of the Russian Federation* was adopted by the State Duma on 28.11.2003. Tompson (2004) mentioned that took more than a decade for the law to be approved by the Duma. The objectives of this Federal Law are: (i) to protect the rights and legal interests of depositors of the Russian Federation, (ii) to strengthen confidence in the Russian Federation's banking system, and (iii) to encourage attraction of household savings mobilization in the banking system of the Russian Federation. The law only covers deposits of physical persons, excluding corporate and inter-bank deposits. In 2004 the limit of cover was up to 100 000 RUB. Foreign currency-denominated deposits are covered (up to 100 000 RUR equivalent), payable in rubles, and converted at the foreign exchange rate determined by the CBR. The state-controlled Sberbank did not participate in the deposit insurance scheme at that stage, but will join it only starting with January 2007. In August 9, 2006 the coverage was increased till 190 000 RUB, while from March, 26 2007 the coverage limit increased up to 400 000 RUB. The last amendment to the law was made in the fall of 2008, increasing the coverage limit at 100 percent of deposits up to but not more than 700 000 RUB (Federal Law of 13.10.2008 N 174-FZ).

Simultaneously, in January 2004 was created the Russian Deposit Insurance Agency (DIA) whose primary responsibilities were: determining the deposit insurance premium, receiving payments from registered banks, making pay-outs to depositors in case of bank failures, managing the Deposit Insurance Fund, and administering bankruptcy proceedings to liquidate insolvent banks (Camara, Montes-Negret, 2006).

Specific for Russian banking system is that banks entered into the deposit insurance at different points in time rather than all at once. **Figure 5** presents how many banks were accepted by the CBR quarterly during 2004-2011.

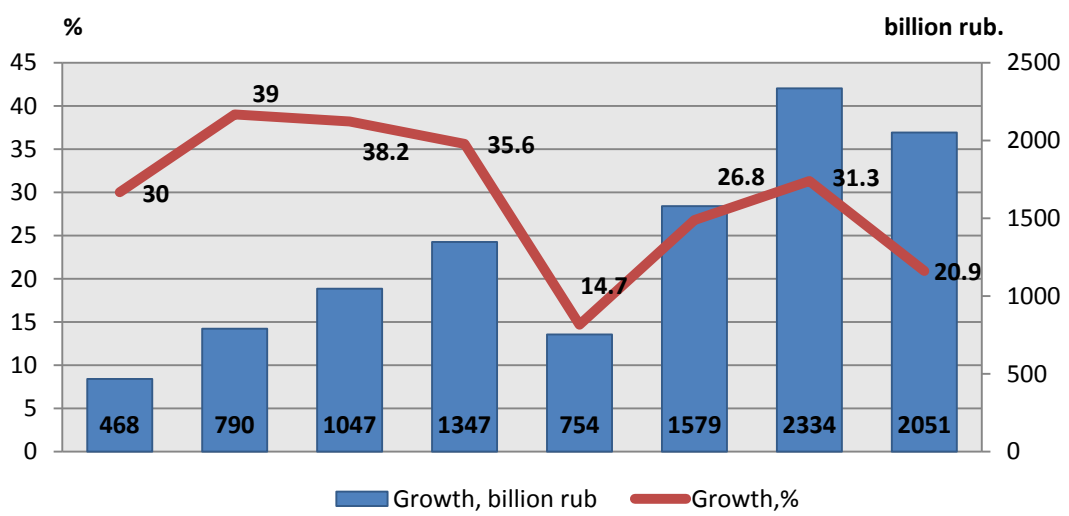
Figure 5: Number of banks licensed by CRB to take deposits: DIS member and non-DIS members.



Source: Author's computations based on Central Bank of Russia, State Corporation Deposit Insurance Agency data

Currently, under the protection of DIA are 895 banks - participants in the system (as of June, 2012), including: operating banks licensed to work with individuals - 787; operating credit institutions before taking deposits, but lost the right to attract individuals' funds -11; banks in liquidation – 97. The DIA fund's size is currently 193 billion rubles. The main sources of the DIA's funds are state fees (7.9 billion rubles.), banks' insurance premiums and income from the investments of the fund.

Figure 6: Growth of household deposits during the period of 2004-2011

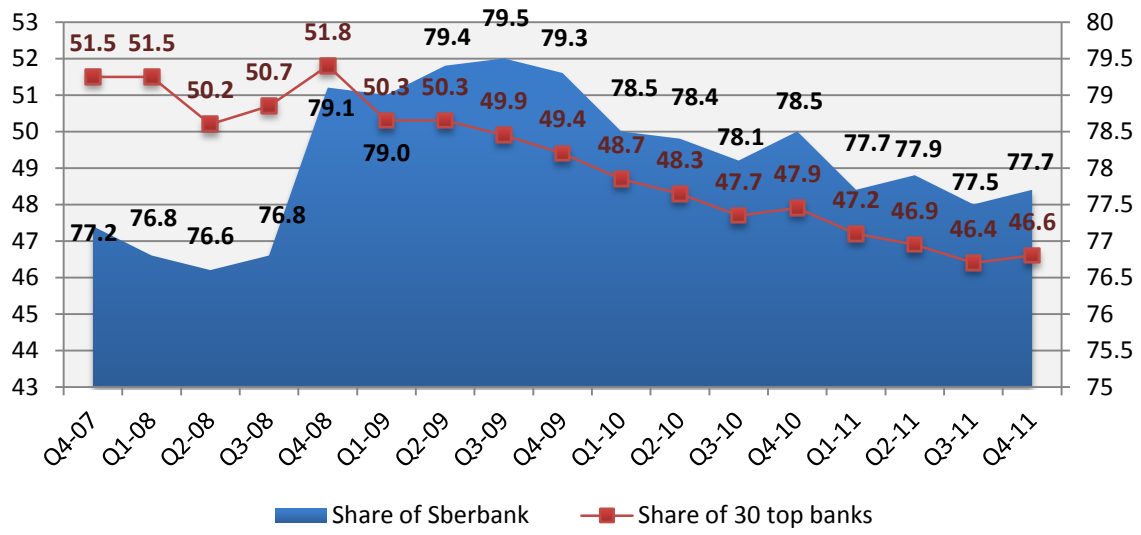


Source: State Corporation Deposit Insurance Agency.

The insurance premiums are paid by banks on a quarterly basis. The premium rates are established by the DIA and currently constitute 0.1 percent of the average

size of the insured household deposits in the bank for the corresponding quarter. **Figure 6** shows that as a consequence of DIS there is a subsequent growth in the amount of deposits. Although private deposit collection is growing, it remains far behind corporate lending. As previously mentioned, Sberbank was the only bank that was enjoying consumer confidence because of the deposit insurance guarantee provided by the state before 2004. After mandatory DIS implementation for all Russian banks, Sberbank was initially exempted and kept its full state guarantee until January 2007, when it finally joined the new deposit insurance scheme. Other regulatory advantages of Sberbank (for e.g. lower required reserves on ruble deposits) were also abolished (Karas, Schoors, Weill, 2008).

Figure 7: **Share of Sberbank and 30 top banks in total deposit market (in %)**



Source: State Corporation Deposit Insurance Agency.

This ensured that Sberbank's share of private deposits gradually fell during the last years. However, the amount of deposits is still considered to be at a very high level (see **Figure 7**). During 2005-2011 Sberbank's shares are at the level between 50% and 45% from the total share of the 30 top banks on the market.

Considering the current weakness of the Russian banking system, Camara and Montes-Negret (2006) stress that is surprising that over 80 percent (more than 90 in the present) of all Russian banks have been so easily admitted under the deposit insurance system and that the number looks to grow further. As a concluding remark, I would like to highlight that an ample number of researches provide convincing evidence that state decision to implement deposit insurance to weak bank institutions

may increase moral hazard risk. Thus, DIS is not yet a guarantee of bank stability and absence of bank runs.

2.6 Review of Empirical Literature on Bank Runs and Deposit Insurance

There are two main directions in the econometrical studies on depositors' behavior with the purpose to check for the probability of bank runs occurrence. The first, stress on the existence of market discipline and its effectiveness on the deposit market (Semenova, 2007; Demirgüc-Kunt and Huizinga, 2004), as well as on the impact of deposit insurance schemes on bank risk-taking behavior and the exposure to moral hazard (Chernykh and Cole, 2011; Gropp and Vesala, 2001; Demirgüc-Kunt and Detriagache, 2002; Laeven, 2002). The econometric model applied in most of these papers is based on a continuous function[4]. Thus, the dependent variable specific for this model is unlimited and continuous, and usually is represented by the change in the amount of deposits.

The second type of econometric researches are focused on the study of factors that lead to the outflows of deposits from banks and under what categories these factors can be classified: panics-based, bank fundamentals, or macroeconomic factors as well as what is the probability of occurrence of bank runs (or crises) under these factors (Solntsev and Mamonov, 2012; Simorangkir, 2011; Graeve and Karas, 2008, 2010; Iyer and Puri, 2008). The specific econometric model used in these papers is based on a discrete function where the dependent variable takes value between 0 and 1. Authors usually use a logit (probit, tobit) model to test for bank run probability[5].

The aim of our paper is to study the depositors' behavior after the implementation of deposit insurance scheme in Russia and understand what forces made depositors to come and withdraw their money; with other words, what is the probability of bank

[4] Exception: Demirgüc-Kunt and Detriagache (2002) who estimate a logit probability model to test how deposit insurance increase bank fragility.

[5] Exception: Simorangkir (2011) who uses a panel data model to test for bank runs and Graeve and Karas (2008, 2010) who identify bank runs by incorporating a cross-sectional heterogeneity into structural VARs.

run for Russian banks. Therefore, our research is closer to the second type of econometric researches.

A detailed comparison of the models used in the discussed econometric papers concerning bank runs and deposit insurance is presented in **Table 2**.

Table 2: Related Empirical Studies on Bank Runs and DIS

Data	Paper	Model Used	*
Country-level	Chernykh, Cole (2011)	continuous function	Russia
	Simorangkir (2011)	continuous function	
	Graeve, Karas (2008 and 2010)	continuous function	Russia
	Iyer and Puri (2008)	discrete function (probit)	
	Semenova (2007)	continuous function	Russia
	Ioannidou, Dreu (2006)	continuous function	
	Gropp and Vesala (2001)	continuous function	
	Demirgüc-Kunt and Detriagache (2002)	discrete function (logit)	
Cross-country level	Berger, Turk-Ariss (2011)	continuous function	
	Solntsev and Mamonov (2011)	discrete function (tobit)	Russia
	Demirguc-Kunt and Huizinga (2004)	continuous function	

Source: Author's computations

(Note) * Research includes Russia

Table 2 shows that the most recent econometric researches in this area that includes Russian market as Chernykh, Cole (2011), Graeve, Karas (2008 and 2010), Semenova (2007), and Solntsev and Mamonov (2011). Only Solntsev and Mamonov (2011) use a binary choise model to test their assumptions. Specific for our model, we take only one country – Russia – for e.g. Solntsev and Mamonov used for their analysis 20 countries (e.g. Belgium, Czech Republic, Republic of Moldova, Russia, Estonia, Argentina, etc.) with a very different economic development and banking system structure. We consider by taking only Russia to keep the specifics of the country and decrease the error in estimating probability of bank runs. Additionally, our research tests the effectiveness of DIS scheme in Russia, which is an important element in estimating bank run probability. We consider the utilized reliable data from multiple sources and the unique combination of variables to bring an original contribution to the research of bank runs in Russian banking industry and offer an important breakthrough at the empirical level.

Chapter 3

Empirical Investigation

3.1 Chapter Overview

This chapter describes the theoretical and empirical methodology used to test the probability of bank runs on Russian banks during 2005-2011. Additionally, it provides detailed explanation of variables employed in the model as well a theoretical background on the logit model used to test our hypotheses.

3.2 Assumptions and Hypotheses

Following the discussion on bank runs literature review from Chapter 2, the occurrence of bank runs can be caused by panic effects, bank-fundamental factors, or macroeconomic conditions. Before building our hypotheses, it is useful to highlight the difference between the concept of run and failure. A run on a bank by the depositors not always leads that bank to failure. Thus, our main interest for this research is to only investigate what motivates depositors in Russia to run on a bank without investigating further probability of failure on those banks.

The first two hypotheses focus on testing the effect of bank-fundamentals and, respectively, macroeconomic conditions in a bank run. For the hypotheses to hold is assumed the dependent variables related to these factors to be significant. A detailed explanation on the variables is provided in section 3.6.

H1: Weak bank-fundamental factors may lead to the withdrawal of depositors from that bank, thus causing a bank run phenomena.

H2: Weak macroeconomic conditions may lead to bank deposit withdrawals from banking system of that country.

Our third hypothesis focuses on the panic-induced deposit withdrawal factor. One of the main policy implications against panic-based withdrawals is considered to be the deposit insurance scheme. Considering the deposit insurance law implementation in 2004, the panic effects on deposit withdrawals should not be expected for the Russian banks which entered the deposit insurance. Third hypothesis is intended to test this assumption.

H3: The deposit insurance implementation helps avoid exposure to bank runs.

Before DIS implementation, in the last 20 years, in Russia were identified three banking crises – in 1994, 1995, and 1998 where depositors suffered substantial losses (Chernykh and Cole, 2010). Also, Karas and Graeve (2008) identify in their research one severe bank run at the beginning of 2004 where several large banks suffered from deposit withdrawals. However there are few researches testing the probability of bank runs for the 2005-2011 periods (after DIS implementation). The aim of this study is to complete the empirical literature on bank runs on Russian banking system for post-insured period and test how beneficial was the decision of DIS policy regulation.

3.3 Data description

The dataset used for our research comprises observations made from a sample of over 900 commercial banks in Russian Federation over the period 2005-2011, quarterly basis. The choice of explanatory variables is based on the existing theoretical and empirical literature on Bank Runs discussed in Chapter 2. The quarterly bank data have been taken from the database of the financial information agency Interfax[6]. The source of data for the calculation of the list of *Interfax-100* is the so-called form 101 (Balance Sheet turnover) and form 102 (Profit and Loss Statement), published on the website of the Russian Central Bank. **Table 3** contains the information on the number of banks per quarter included in our model. The sample of data limits only to banks holding the license to attract household deposits.

[6] The Statistical database of Interfax /*Interfax-100. Russian Banks/* covers available bank data starting with only 2005 year, reason why our research is limited to the study of the period after deposit insurance implementation in 2004.

The monthly *Bulletins of Central Bank of Russia* provides the information on the license type that holds each commercial bank in Russia. The last source used to collect the data on each bank entry into the deposit insurance system is provided by the Deposit Insurance Agency (DIA). Specific for Russian banking system are the different points in time banks entered into the new DIS. The number increased gradually and not all at once which, in our opinion, represents an advantage in testing how DIS implementation influenced Russian banking system.

Table 3: Number of banks included in the sample per quarter

	All banks*	Insured	Uninsured	State-controlled	Foreign	Private-domestic
2005 q4	824	682	142	26	39	759
2006 q1	812	562	250	25	33	754
2006 q2	814	568	246	26	34	754
2006 q3	891	613	278	25	37	829
2006 q4	937	653	284	27	41	869
2007 q1	925	651	274	27	40	858
2007 q2	927	652	275	27	39	861
2007 q3	921	651	270	27	40	854
2007 q4	914	656	258	27	42	845
2008 q1	932	678	254	27	45	860
2008 q2	924	672	252	27	45	852
2008 q3	922	680	242	25	45	852
2008 q4	901	673	228	26	43	832
2009 q1	897	617	280	21	42	834
2009 q2	902	689	213	25	47	830
2009 q3	895	689	206	27	47	821
2009 q4	886	689	197	27	47	812
2010 q1	895	706	189	28	47	820
2010 q2	888	708	180	28	46	814
2010 q3	877	709	168	28	47	802
2010 q4	872	706	166	28	47	797
2011 q1	864	705	159	28	48	788
2011 q2	860	706	154	27	48	785
2011 q3	851	707	144	28	47	776
2011 q4	836	703	133	28	46	762

Source: Author's computations.

Note: (*) Total number of Russian banks with license to attract private deposits at the beginning of each period is mentioned in Table 1 from Annex.

The gathered panel bank-specific data is unbalanced because some banks failed, merged (in our sample if bank merged, the resulting bank is taken as *new*) or were founded during the sample period. The reason of taking unbalanced data was to cover as many banks as possible. Also, according to Central Bank requirements towards

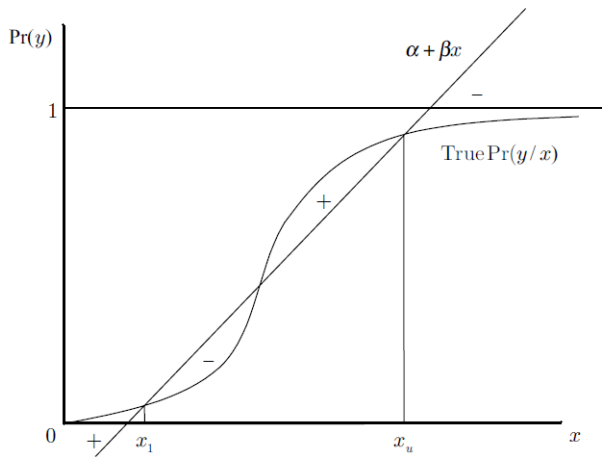
commercial banks, reporting the information to central banks is obligatory. However, public reporting on the official site of CBR is voluntary – reason why not all the banks grant CBR to disclose their data.

Depending on the ownership, the Russian banking system comprises state-controlled, foreign, and private-domestic banks. To identify state-controlled banks, was used the list build on the basis of A. Vernikov paper, *Government Banking in Russia: Magnitude and New Features* (2011). The list of foreign banks was taken from the CBR site. Our research is also based on macroeconomic variables. The sources used for identification of these variables were the *World Bank database* – for GDP growth data and unemployment; Central Bank of Russia's *Quarterly Inflation Review* – for inflation rate, exchange rate of EUR/RUB, and exchange rate of USD/RUB. A logit model in a panel data framework was applied for testing our hypotheses. The detailed description of the model is provided in the following sections.

3.4 The Logistic Regression

The logistic regression is used for the prediction of the probability of occurrence of an event by fitting data into a logistic function. Logit distribution is an S-shaped distribution function (see **Figure 8**), which is similar to the standard-

Figure 8: Linear Probability Model



Source: Baltagi. *Econometrics*

normal distribution but easier to work with in most applications (the probabilities are easier to calculate)[7].

The dependent variable for the logit model is binary as the outcome we are interested in is not a continuous variable but a binary outcome. For example, the logit model is suitable when you want to analyze whether an event occurred or not – in our thesis we are interested to test if a bank run occurred on Russian banking system during the analyzed period or not. In order to construct the model, we assume that an unobservable variable Y* determines the value of the observable dependent binary variable Y, e.g. as follows:

$$Y_i f(x) = \begin{cases} 1, & Y_i^* < 0 \\ 0, & Y_i^* \geq 0 \end{cases} \tag{3.1}$$

The unobservable variable Y* depends on banks' characteristics as well as on an error term, in the following way:

$$Y_i^* = \beta x_i + \varepsilon_i \tag{3.2}$$

where β is parameters' vector, x_i - vector of the values of explanatory variables for the i-th bank and ε_i is the error term. The distribution of ε_i is assumed to be logistic Λ. This implies that the probabilities of bank run and non-bank run are equal to:

$$\mathrm{P}\,(Y_i = 1|x_i) = \Lambda(x_i\beta) = \frac{\exp(x_i\beta)}{1 + \exp(x_i\beta)} \tag{3.3}$$

$$\mathrm{P}\,(Y_i = 0|x_i) = 1 - \Lambda(x_i\beta) = 1 - \frac{\exp(x_i\beta)}{1 + \exp(x_i\beta)} \tag{3.4}$$

One issue with this model is the probability P_i on the left-hand-side that has to be between zero and one, while the linear predictor $x_i\beta$ on the right-hand-side can take any real value, thus there is no guarantee that the predicted values will be in the correct range unless complex restrictions are imposed on the coefficients. A simple solution to this problem is to transform the probability to remove the range restrictions, and model the transformation as a linear function of the covariates by moving probabilities to the *odds*, defined as the ratio of favorable to unfavorable cases[8].

[7] The information on the logistic regression described in section 3.4 was based on the descriptions of logit model from Baltagi (2008), Maddala (2001), Majer (2010) and www.appstate.edu

[8] Princeton University research site: data.princeton.edu, *Logit models for binary data*

$$odds_i = \frac{P_i}{1 - P_i} \tag{3.5}$$

As an alternative to odds in interpreting logit coefficients comes marginal effect. The analysis of Marginal Effects in logit regression requires that we examine:

$$\frac{\partial y_i}{\partial x_j} = \frac{\partial F(x_i\beta)}{\partial x_j} = \frac{\partial F(x_i\beta)}{\partial x_i\beta} \times \frac{\partial x_i\beta}{\partial x_j} = F'(x_i\beta)\beta_j = f(x_i\beta)\beta_j \tag{3.6}$$

However, the *odds ratios* are preferred to marginal effects as the interpretation of the logit coefficients is usually more intuitive with odds ratios. The parameters of logit model are usually estimated with the maximum likelihood estimation.

$$L = \prod_{i=1}^{N} F(x_i\beta)^{y_i} (1 - F(x_i\beta))^{1-y_i} \tag{3.7}$$

The log-likelihood function is:

$$\ln L = l = \sum_{i=1}^{N} [Y_i \ln F(x_i\beta) + (1 - Y_i) \ln(1 - F(x_i\beta))] \tag{3.8}$$

The higher the likelihood function, the higher the probability of observing the dependent variable values in the sample.

To test for statistical significance of independent variables can be used the Wald test (analogous to the t-test in linear regression) - the ratio between the square of the regression coefficient and the square of the standard error of the coefficient, asymptotically distributed as a chi-square distribution:

$$\text{Wald} = \frac{\beta_j^2}{SE_{\beta_j}} \tag{3.9}$$

where the H_0 for the test is $\beta_j = 0$

To measure the overall performance of the model, as goodness of fit for our logit regression, there are designed several pseudo-R^2 measures that have been developed specifically for models where dependent variable takes only two values y.

- **McFadden's R^2**:

$$\text{McFadden's } R^2 = 1 - \frac{\ln L_{UR}}{\ln L_R} \tag{3.10}$$

where L_{UR} and L_R correspond to likelihood functions of the unrestricted and restricted model.

- **Percentage (proportion) of correct predictions**: number of total predictions/total number of observations - assumes that if the predicted probability is greater than or equal to 0.5 then the event is expected to occur and not occur otherwise.

3.5 Dependent variable

According to the general definition, a bank run happen when the financial institution suffers a large withdrawal of deposits because customers believe that the financial institution is or exist the probability to become insolvent. As we are interested to investigate the factors that motivates depositors in Russia to run on a bank, our dependent variable (observable variable) is expected to be *Bank Run*. As unobservable variable is identified the quarterly percentage changes in deposits for bank i.

Our formulation of dependent variable Y_i takes 1 in the period when there was a bank run, and 0 in all other periods in the bank i. Thus, the essence of the values of unobservable variable, for example, equal to 1, is defined as the decrease in the quarterly percentage change in deposits higher than 10%.

3.6 Independent variables

Based on the literature review on Bank runs, our explanatory variables were splited into two main categories: financial bank performance variables and macroeconomic variables. Bank-level variables serve as a proxy for bank liquidity, risk, profitability and solvency of the analyzed banks. While the macroeconomic variables represent how the banking system is influenced by changes that the economy experiences over time.

- **Capital Adequacy Ratio**

This ratio, measured as capital to total assets, has been developed as a measure of bank solvency that helps to protect depositors and promote the bank stability and efficiency. Capital serves as a buffer for unexpected losses incurred on the bank's

assets. The higher the capital ratio, the less likely it is that losses will hurt the depositors. The amount of equity indicates how much the value of the assets may decline before the position of depositors and other creditors is jeopardized (Lanine, Vennet, 2005). Hence, the higher the ratio the more reliable the bank is considered to be. It is expected to be a significant determinant of bank runs, fact confirmed by numerous empirical studies (Gangopadhyay and Singh, 2000), McCulloch and Yu, 1998) show that if there is an adequate equity level with a bank, then depositors have an assurance and panic runs can be avoided).

- **Debt ratio**

The debt ratio is a measure of bank's leverage. A high debt ratio for a bank means the inability to meet its financial obligations, thus this could be a problem if many depositors start to demand their deposits back. The dependent variable debt ratio is calculated as the ratio of total liability over total assets.

- **Return on Assets (ROA)**

An indicator on how profitable the bank is relative to its total assets. A high ROA is associated with strong and healthy banks, which should decrease the probability of bank run. Return on Assets ratio was used as a measure of resilience against bank runs in many empirical studies (Lanine, Vennet, 2005; Simorangkir, 2011).

- **Bank size – log of Assets**

This variable characterizes the size of the bank. We can assume that larger banks have a higher level of confidence for Russian depositors, therefore, the higher the bank, the lower the probability of bank runs.

- **Deposits interest rate**

If deposit interest rates rise, it will become more attractive to make deposits in the bank rather than spend as you will get a better rate of return from saving your money. On the other side, there is empirical evidence (Kraft and Galac, 2007) showing that high deposit interest rates were used as a source of funding for risky banks, and had important negative external effects on healthy banks, thus making a strong contribution to the banking crisis.

Also, it is essential to highlight the importance to take the real interest rate as a dependent variable and not the nominal in order to capture the real growth. The real interest rate is nominal interest rates minus inflation.

Gunsel (2008) stress that high real interest rates would signal an impending liquidity problem in the financial system that would indicate deterioration in commercial bank loan portfolios and is also potentially to result in a slowdown in the rate of economic growth. In such an environment banks are faced with increasing financial and credit risks. Hence, in such circumstances it is expected that an increase in interest rates would serve to increase the probability of bank run due to deterioration of bank fundamentals.

According to Domaç and Peria (2003), high real interest rates can reduce banks' profits or produce losses. Additionally, the author mention that increasing interest rates make loan repayments harder for debtors and adversely affect banks by increasing non-performing loans, thus, contributing to systemic banking sector problems.

Initially was planned to be tested as well the **NPL** – non-performing loans variable. However, due to the unavailability of data for this variable in the Interfax data base it was excluded from the test.

- **Inflation**

We can assume that a higher inflation would lead to economic uncertainty and greater tendency for bank runs. According to Fisher theory, an increase in prices can influence a decrease in deposit attractiveness as the consumption in this period needs more funds. Thus, high inflation tends to be associated with an increase in the probability of banking sector distress. Gunsel (2008), in his research on micro and macro determinants on bank fragility, mentions that sudden changes in inflation can have a negative impact on interest rates and deterioration of bank capital (expansion in non-performing loans) and collateral values, and also weaken bank balance sheets.

- **GDP growth rate**

According to Demirgüç-Kunt and Detragiache (2002) the declining GDP growth rate as well as a high inflation (variable described above) rate would increase the likelihood of bank failures. Including GDP growth variable in the model would help not only to capture the effect of general level of economy at a given time, but also to take into account the impact of the crisis without the necessity to enter for this another separate variable.

Economic analysts argue that banking crises are commonly preceded by a significant contraction in real GDP growth. Thus, an increase in the GDP growth rate is negatively related to the probability of failure.

- **Exchange rate**

For this model was taken the RUB/USD exchange rate and the RUB/EUR exchange rate. These variables can be analyzed from two perspectives. First, they characterize the alternative ways to invest savings. For example, with RUB fall, value deposits denominated in domestic currency become less attractive than deposits denominated in foreign currencies. As a consequence, the value of deposits in domestic currency decreases relative to that of foreign currency. On the other hand, Semenova (2007) in her paper draws attention to the fact that the deposits include as well deposits in foreign currency and according to the accounting standards they are converted into rubles to be reflected in balance sheets. So the influence of exchange rates is also expressed in changes in their value in rubles (the interest payment include those paid for deposits in foreign currency as well).

Domaç and Peria (2003) also mention the government dilemma regarding exchange rate fluctuations when analyzing 95 developed and developing countries' exchange rate policies. The authors argue that if the government pegs the exchange rate, banks can suffer self-fulfilling runs motivated by investors' fears that others will run first and exhaust bank's reserves, while if the government allows the exchange rate to float, banks and firms will be affected by the currency mismatch problem.

In the model are also included **Institutional Variables** as:

- **Deposit Insurance Dummy**

The information from the Deposit Insurance Agency related to the dates of admittance to DIS allow us to construct a dummy variable that equals 1 from the quarter bank entered deposit insurance and 0 otherwise. Thus, DIS dummy variable helps us identify what banks in the Russian banking industry benefited from the introduction of the deposit insurance system.

- **Ownership Dummy**

Russia's banking system is dominated by state-controlled banks. The *Economist* in 2011 states that Sberbank, the biggest bank, holds 54% of deposits, calling the banking industry of Russia *in the shadow of giants*.

In order to better capture the degree of changes in deposits depending on the type of ownership we introduced a dummy that helps us identify the state-controlled banks. This variable is equal to 1 if the bank is a state-controlled bank and 0 otherwise. Under the state-controlled are included the directly state-owned banks or

banks whose primary owner is public corporations or regional authorities. As mentioned in chapter 3.3, the list of state-controlled banks was formed on the basis of A.Vernikov paper as CBR does not provide any such list on their site.

- **Demographic Dummy**

To distinguish between private-domestic banks and foreign-controlled banks, we introduced an additional dummy variable that identifies from the sample which is the foreign-controlled banks. Thus, the dummy equals to 1 if there is a foreign bank and 0 otherwise.

Table 4 reports the data descriptive statistics as means, standard deviations, and definitions for our independent variables.

Table 4: Descriptive statistics (entire sample of banks)

Variable	Obs	Mean	Std. Dev.	Min	Max
Debt ratio	22072	0.957	0.103	0.81	0.92
Capital Adeq.	22072	9.961	4.338	1.585	82.09
ROA	22072	0.467	0.449	-5.687	5.317
logASSETS	22072	14.618	1.809	7.703	23.07
Inflation	22167	11.008	2.425	7.390	15.16
GDP Growth	22167	7.257	0.570	-10.400	7.90
RUB/USD	22167	26.795	2.020	2.824	32.11
RUB/EUR	22167	40.121	2.762	3.653	44.89
Real interest r.	22167	4.382	0.477	1.557	5.30
dState	22167	0.030	0.171	0	1
dForeign	22167	0.049	0.215	0	1
dDIS	22167	0.754	0.430	0	1

Source: Author's computations in Stata.

Given the assumption that Russian depositors' trust more state banks, we divided banks in 3 samples *state-controlled, foreign-controlled,* and *private-domestic* banks for a deeper analysis of bank-fundamentals variables. **Tables 5**, **6**, and **7** report the data descriptive statistics bank-fundamentals variables divided on all three categories. The data suggest the mean for size of assets and the mean for profitability ratios to be higher in the state-controlled sample, confirming the dominance of state banks in Russian banking sector.

Table 5: Descriptive statistics (state-controlled sample of banks)

Variable	Obs	Mean	Std. Dev.	Min	Max
Debt ratio	666	2.599	0.526	1.06	2.77
Capital Adeq.	666	8.757	5.132	2.84	63.88
ROA	666	11.031	8.680	0.01	18.59
logASSETS	666	16.992	2.415	12.30	23.07

Source*:* Author's computations in Stata.

Table 6: Descriptive statistics (foreign-controlled sample of banks)

Variable	Obs	Mean	Std. Dev.	Min	Max
Debt ratio	305	1.121	0.065	1.06	1.37
Capital Adeq.	305	21.534	12.619	8.36	90.34
ROA	305	2.467	2.338	-5.68	6.27
logASSETS	305	16.132	2.234	10.13	22.14

Source: Author's computations in Stata.

Table 7: Descriptive statistics (private-domestic sample of banks)

Variable	Obs	Mean	Std. Dev.	Min	Max
Debt ratio	20324	0.962	0.216	0.92	8.3
Capital Adeq.	20324	11.089	5.865	1.58	92.12
ROA	20324	0.473	0.401	-3.77	4.83
logASSETS	20324	14.456	1.661	7.70	20.63

Source: Author's computations in Stata.

3.7 Methodology

Based on the hypotheses stated in section 3.2, the estimated model is as follows:

$$Y_{it} = \alpha + \sum_{k=1}^{K} \beta_k \, (BF_k)_{it-1} + \sum_{h=1}^{H} \beta_h \, (MACRO_h)_{it-1} + Instituional\ Factors + \varepsilon_{it}$$

i=1…N, represents a cross-sectional unit

t=1…T, represents quarterly time series (the time effect)

k=1…K, represents a specific explanatory variable from BF_{it}

h=1…H, represents a specific explanatory variable from $MACRO_{it}$

Y_{it} stands for Bank runs measured by unobservable variable Y_{it}^{*} - quarterly percentage change in deposits; BF_{it} stands for vector of bank fundamentals factors of the bank i; and $MACRO_{it}$ stands for the vector of macroeconomic factors that influence the depositors' decisions.

Also, our explanatory variables will be lagged by one period as it is expected that the factors' value in period t to be dependent on the values of other factors in period t-1. The list of dependent variables included in each vector is presented in **Table 3.3** together with the expected sign for each variable in part.

Table 8: Independent variables Expected Signs

Variable name	Symbol	Formula	Expected sign (prob.of run)
Bank fundamentals variables			
Capital Adeq.Ratio	CAR	Capital/Total Assets	-
Debt Ratio	DebtR	Total Liabilities/ Total Assets	+
Return on Assets	ROA	Net Income/Total Assets	-
Bank Size	logASSETS	Log(Total Assets)	-
Deposits interest rates	RDIR		+/-
Macroeconomic variables			
GDPgrowth	GDP_GR		-
Inflation	INFL		+
Exchange Rate	RUB_USD		+/-
	RUB_EUR		+/-

Source: Author's computations.

Chapter 4

Results and Interpretation

4.1 Chapter Overview

This chapter provides the empirical results based on the model described in the methodology section from chapter 3. The empirical results are interpreted and analyzed in order to verify the hypothesis validity. The analysis includes a complete correlation analysis between variables, a wide description of results on each section of variables in part, and the tests applied to proof model veracity. Based on the main findings of this chapter, we build our conclusion and discussion paragraphs regarding the bank runs prevention in Russia.

4.2 Estimation of Results

As previously mentioned in Chapter 3, our empirical investigation on bank runs is based on a logistic model. We aim to test the three formulated hypotheses by running the model in the STATA statistical software. As we are interested to identify the factors that lead to the occurrence of bank runs for Russian banks during 2005-2011, it is worth to mention that in the context of analysis of causal processes it is specific that some factors' value in period t to be dependent on the values of other factors in period t-1. Thus, in order to avoid simultaneity problems we lag all explanatory variables by one period, apart from bank assets for which we take log in order to measure bank size.

Also, before we run the logit model we must test for colinearity. Multicolinearity is a specific phenomenon when the explanatory variables are highly correlated between each other, reason which could lead us to invalid results. Therefore, in order to evaluate the interaction of our independent variables we performed two correlation matrices: one for all our explanatory variables and another for their lags t-1. The

results in **Table 9** and **Table 10** show no statistically significant evidence of high correlations between variables that could bias our results.

Table 9: Correlation Matrix between bank-fundamentals variables

Variable	DebtR	CA	ROA	logASSETS
DebtR	1.0000			
CA	0.1097	1.0000		
ROA	0.0359	0.5322	1.0000	
logASSETS	-0.0909	-0.2393	-0.0618	1.0000

Source*:* Author's computations in Stata.

Table 10: Correlation Matrix between macroeconomics variables

Variable	INFL	GDP_GR	RUB_USD	RUB_EUR	RDIR
INFL	1.0000				
GDP_GR	-01078	1.0000			
RUB_USD	-0.3481	-0.6601	1.0000		
RUB_EUR	-0.0283	-0.7921	0.7525	1.0000	
RDIR	0.2102	-0.8367	0.3963	0.6620	1.0000

Source: Author's computations in Stata.

However, when taking the relevant lags, we can notify a higher presence of correlation between our variables (see **Table 11** and **Table 12**). For example, there is high correlation between bank-fundamentals variables as on the base of their calculation formula there is asset component. Regarding macroeconomics variables, we notified a higher correlation between GDP growth variable and inflation variable, as well as inflation and exchange rates lags.

Table 11: Correlation Matrix between bank-fundamentals variables lags

Variable	lagDebtR	lagCA	lagROA	logASSETS
lagDebtR	1.0000			
lagCA	0.5462	1.0000		
lagROA	0.0445	0.0506	1.0000	
logASSETS	-0.1015	-0.0263	-0.1435	1.0000

Source: Author's computations in Stata.

Table 12: Correlation Matrix between macroeconomics variables lags

Variable	lagINFL	lagGDP_GR	lagRUB_USD	lagRUB_EUR	lagRDIR
lagINFL	1.0000				
lagGDP_GR	0.7207	1.0000			
lagRUB_USD	0.6318	0.5806	1.0000		
lagRUB_EUR	-0.6380	-0.6552	-0.1495	1.0000	
lagRDIR	-0.2424	-0.2328	-0.1949	0.3137	1.0000

Source: Author's computations in Stata.

Moreover, we attempt to minimize any existing correlation and bias among our explanatory variables by running various combinations of variables that we incorporated in four sets of regression equations (see **Table 13**). Of the macroeconomic indicators, EUR and USD exchange rates are closely related and, thus, they do not use them together in the models. Similarly, GDP growth and inflation were separated within the four existing models in order to avoid close correlation. Of the financial indicators, since the formula of calculating all four bank-fundamentals variables is based on bank's assets value, we performed the regressions on each parameter separately in order to avoid multicollinearity in our model specifications.

Table 13: Results of the Logit Analysis of Determinants of Bank Runs

Variables	Model 1	Model 2	Model 3	Model 4
Bank-fundamentals Variables				
lagDebtR	1.011 (0.072)	-	-	-
lagCA	-	0.053*** (0.000)	-	-
lagROA	-	-	0.220* (0.029)	-
logASSETS	-	-	-	-0.242*** (0.000)
Macroeconomic Variables				
lagINFL	0.082*** (0.000)	-	-0.054* (0.014)	-
lagGDP_GR	-	0.446*** (0.000)	-	0.374*** (0.000)
lagRUB_USD	-	-	0.159*** (0.000)	-

lagRUB_EUR	-	0.020*	-	0.035***
		(0.025)		(0.000)
lagRDIR	-	-	0.752***	
			(0.000)	
Institutional Variables				
dState	-	-1.356***	-1.166*	-0.936***
		(0.000)	(0.012)	(0.000)
dForeign	0.365	-	-	-
	(0.097)			
dDIS	-0.205	-1.004***	-1.055***	-0.921***
	(0.064)	(0.000)	(0.000)	(0.000)
Constant	-2.143***	-5.797***	-7.769***	-1.916**
	(0.000)	(0.000)	(0.000)	(0.004)
Model Statistics				
Wald Chi2	24.53	271.40	126.07	382.61
Pseudo R2	0.012	0.056	0.055	0.069
Log likelihood	-969.43	-6459.32	-1793.49	-6391.37
No. of Obs.	1452	17613	3971	17686
LR chi2	23.53	776.67	211.52	959.67
AIC	1.342	0.734	0.907	0.723

Source: Author's computations in Stata

Note: (1) ***, **, * indicate significance at the 1, 5, and 10 percent level;
(2) values in the parentheses indicate the p-value; for more information regarding the results of the model, see Appendix B

The findings suggest that the great majority of the independent variables are statistically significant and can be explained as follows:

- **Bank-fundamentals Characteristics**

The findings on the debt ratio indicate that banks with a high debt ratio are more likely to be exposed to bank runs. In our model we find debt ratio positively related with our dependent variable, having a p-value of 0.079. The results agree with those obtained by Gunsel (2008), Graeve and Karas (2008), Duffoo (2004), and Semenova (2007).

The result on ROA profitability measure is positive, with the p-value of 0.029 and statistically significant at 10% level. Regarding the potential interpretation of this indicator of net profits to total assets, it can be noted that a growing trend is the

expression of positive results. However, an exaggerated growth might be, as well, the expression of an excessive risk to the bank, thus, this explaining the positive sign of the coefficient for our model results.

Regarding the capital adequacy ratio, the coefficient was positive and, thus, not in the line with the expectations as it was assumed that the higher the ratio the more reliable the bank is considered to be. However, the coefficient is statistically significant with a p-value of 0.000. An explanation against the positive sign can be the limited information that depositors hold on the performance of the bank in which they hold their deposits. Moreover, the results suggest that depositors pay more attention to the interest rate, debt ratio, bank size, and earnings, therefore, not being sensitive to the bank shareholder's equity to total assets ratio. This result is consistent with the previous findings in Simorangkir (2011) paper on the determinants of bank runs in Indonesia where the CA also did not play an important role in depositors' behavior compared to other indicators of financial performance as ROA, NPL that showed a high significance.

Measure of bank size is negative and statistically significant at 1% level. These results suggest that larger banks experience a lower probability of bank run as they enjoy depositors' confidence. Thus, the probability of bank run is lower for the "too-big-to fail" banks. This result is consistent with the previous findings of Graeve and Karas (2008), Chernykh and Cole (2011), Gunsel (2008), and Duffoo (2004).

- **Macroeconomic Characteristics**

The findings suggest that inflation rate indicator has positive parameter estimates, and is statistically significant at 1% level, thus, indicating that an increase in inflation is associated with the bank runs exposure. The increase in inflation has a negative impact on interest rates, which in turn increase the cost of funds to the debtor. As a consequence this may lead to the expansion of non-performing loans, decrease in deposit attractiveness, and leave Russian banking system more vulnerable to a bank run. These results agree with the obtained by Simorangkir (2011), Gunsel (2008), Heffernan (2003), and Demirgüç-Kunt and Detragiache (2002).

The results for the GDP growth rate in our model appear to be contrary to the expectation in empirical literature. According to the results from our model, bank runs are not sensitive to GDP growth rate due to coefficients having a positive sign but still being statistically significant. Following the literature, we would expect that a declining GDP growth rate, succeeded by a reduction in economic activity would increase the credit risk and probability of default on loans, thus leading banking

system to distress. However, the conflicting sign of coefficients in our case might suggest that changes in deposits were not sensitive to GDP growth for Russian case. These results are consistent with the previous findings of Heffernan (2003) who used real GDP growth rate together with other macroeconomic variables to test for significance against bank failures in a group of European banks. In Hefferman's case, as well, the coefficients on all the variables had the expected sign except for real GDP growth rate.

Regarding the real interest rate, our findings suggest the lagRDIR variable is positive and statistically significant at 1% level. It was hard to predict the interest rate influence on our dependent variable as from one point of view it is expected that an increase in the interest rate on deposits would attract Russian depositors to invest their money in that banks, while on the other hand, what in short run may lead to an increase of deposits in long run may increase the probability of failure of the bank as attracted deposits may be used as a source of funding for risky investments. Thus, it is highly probable that a bank with sharply increasing interest rate that invested in risky investments may fail to pay the customers' deposits plus interest in the end, fact that would lead to a bank run. These results are in agreement with the research conducted by Gunsel (2008), Demirgüç-Kunt and Detragiache (1998, 2002) researches. For example, Gunsel's findings support the view that an increase in the real interest rate in the past increased bank fragility in North Cyprus during 1984-2002. In the model run by us the interest rate variable is positive and statistically significant with a p-value of 0.000.

Exchange rate variables also significantly influence bank runs. The variables RUB_USD and RUB_EUR were separated when running the models in order to avoid multicollinearity. It was observed that exchange rates are positive and statistically significant at 1% significance level. Thus, devaluation of ruble may lead to a massive withdrawal of deposits by the customers. It is worth to mention that over 80% of household deposits are local currency deposits. Till 2008, the ruble showed a long-term appreciation, which encouraged accumulation of local currency deposits. However, after Russia was affected in 2008 by global financial crises, the ruble lost around 30% of its value in some months. The ruble is significantly influenced by oil and gas prices on the global market, and thus, the depositors face two risks on losing their money: inflation and uncertainties in the ruble. As a consequence a fall in ruble, showed by the positive sign of the coefficient in our four models, can determine the customer to run on the bank. This result is consistent with the previous findings of Gunsel (2008), Duffoo (2004), and Heffernan (2003).

Based on the above results, we can conclude that Hypothesis 1 and Hypothesis 2, stating that *weak bank-fundamental factors / weak macroeconomic conditions may lead to the withdrawal of depositors from that bank, hence, causing a bank run phenomena,* hold.

- **Institutional Variables**

Apart, our objective is to test for the importance of the deposit insurance implementation (Hypothesis 3), classified as an institutional variable in our model. According to the results, there is a negative correlation between deposit insurance and bank runs. This is indicated by the negative sign and significant coefficients the DIS dummy received in all four models we run. The findings suggest that Russian banking industry benefited from the introduction of the deposit insurance system, and thus lowered the probability of bank runs. Based on the revealed results, we can conclude that Hypothesis 3, *deposit insurance implementation helps avoid exposure to bank runs*, holds. This investigation is consistent with Graeve and Karas (2008) results, where authors demonstrated that during 1999-2007 Russian non-insured banks experienced a drain in deposits, while insured banks did not suffer large deposit outflow. Moreover, the author state that insured group of banks experienced a deposit inflow.

Additional evidence supporting the credibility of Russian depositors in the insurance mechanism represents the *Sberbank credibility* – the only bank before 2004 with a full state guarantee – reason that permitted to this state bank to enjoy consumer confidence for a long period of time. Moreover, with the DIS implementation by the majority of banks, the state bank still maintains its leadership position. This credibility is also reflected in our results on the ownership and demographic dummies. The negative sign of the ownership dummy in our models stress that state-controlled banks dominate on the market, having a higher confidence from consumers than private banks have (see **Table 13**).

On the other hand, there is also interesting to mention that when comparing domestic banks with foreign banks, the positive correlation of demographic dummy with our dependent variable demonstrates that Russian customers trust more to invest their money into a domestic bank than a foreign one. However, this factor may be interpreted from another point of view that some foreign banks' main activity in Russia is not in attracting deposits, but rather serving a single company or large corporation. Still, there are foreign bank with a high performance in Russia is considered Raiffeisen Bank, which holds on the fifth place in 2012 Interfax ratings on household deposits amounts. Other competitive foreign banks operating in Russia

are UniCredit Bank, Rosbank (Société Générale Group), Citibank, and Deutsche Bank.

Finally, in order to assess the quality of the model, we will analyze a group of Model Statistics presented in **Table 13**.

The overall measure of how well the model fits is given by the likelihood parameters. **Table 13** presents a listing of the log likelihoods resulted from our four run models. The log likelihood for iteration 0, LL_0, is a model with no predictors, when there are no explanatory variables in the model - only the constant term is included. We are interested in the last log likelihood, reported as LL_M, because the iteration stops when the model is said to have converged. As we mentioned in chapter 3, a good model is one that results in a high likelihood of the observed results. Consequently, the higher the likelihood function, the higher the probability of observing dependent variable values in the sample, thus, Model 1 and Model 3 seems to have the most suitable log likelihood ratios in our case. Also, the log likelihood is used in the likelihood ratio chi-square test to check whether all regression coefficients β's are equal to zero versus the alternative that at least one did not, similar to the F-test for OLS regressions. The LR chi2 results on our models are presented in Table **13**. The Model Chi-Square statistic is used to determine if the overall model is statistically significant and the Prob > chi2, which for all our four models represents 0.000, indicates that all of the specification models are highly significant (see **Appendix B**).

Regarding the pseudo-R^2 results, they cannot be interpreted independently or compared across datasets in order to analyze how well the model is explained by the independent variables as in the OLS regressions; they are considered to be valid and useful in evaluating multiple models predicting the same outcome on the same dataset. Thus the value of this ratio will not be taken as a valuable measure of quality for our model.

For our logit regression, we assess the quality of the model based on the results of the Model chi-square and the AIC criteria. According to Gunsel (2008), the purpose of Akaike Information Criterion (AIC) is to compare the model with different degrees of freedom and eliminate the model specification when irrelevant explanatory variables are added into the regression. Therefore, we prefer a model with a lower AIC to one with a high AIC. From **Table 13**, Model 2 and Model 3 are selected to be optimal.

Other way to assess goodness of fit for logit regressions in stata represents the classification tables. This command shows you how many cases were predicted correctly and incorrectly, where cases with probabilities ≥ 0.5 are predicted as having the event and a negative outcome otherwise.

Table 14: Classification tables (correctly and incorrectly predicted results of the model)

Model 1			
Classified	**True**		**Total**
	D	**~D**	
+	70	60	130
-	521	801	1322
Total	591	861	1452
Correctly Classified			59.99%

Model 2			
Classified	**True**		**Total**
	D	**~D**	
+	0	11	11
-	2312	15290	17602
Total	2312	15301	17613
Correctly Classified			86.81%

Model 3			
Classified	**True**		**Total**
	D	**~D**	
+	1	6	7
-	732	3232	3964
Total	733	3238	3971
Correctly Classified			81.42%

Model 4			
Classified	**True**		**Total**
	D	**~D**	
+	8	14	22
-	2311	15353	17664
Total	2319	15367	17686
Correctly Classified			86.85%

Source: Author's computations in Stata

Note: entire output, including sensitivity and specificity, see Appendix B;

The Classification **Table 14** shows that, for example, in model 1 we have a total of 130 variables classified as 1. For 70 of the observations this corresponds to the true value, but for 60 of the observations it does not. We have assigned value 0 to 1322 observations, which turned out to be correct for 861 of the observations. Consequently, in total we correctly classified 59.99% of observations for our first model. Thus, from the results of the Classification **Table 14**, we can conclude that from Model 1 we predicted correctly 59.99% of the cases; Model 2 - 86.61% of the cases; Model 3 – 81.42% of the cases; Model 4 – 86.85% of the cases.

Other indices of interest might represent the sensitivity and specificity measures that help us measure the performance of our models. At the base of sensitivity calculation stays the false negative rate, see classification table. From our four models, a higher sensitivity ratio has Model 1 with a proportion of 11.84% of actual positives which are correctly identified as such. However, a perfect predictor would be a 100% ratio. For specificity the probability is calculated based on the false positive rate from classification table, thus, measuring the proportion of negatives

which are correctly identified as such. Model 2 has the best specificity ratio, 99.93%. The plots of sensitivity and specificity for each of four models as well as their value in the classification table see **Appendix B**.

Finally, the performance of our models can be as well evaluated by the receiver operating characteristic (ROC) curve, a plot of specificity versus sensitivity generated by varying the cut point. For ROC the area of interest is under the curve that helps us measure the predictive power of the model. The range is 1 for a perfect test and less than 0.5 otherwise. To compare the areas under the ROC curve for four different models is possible by using the logistic linear predictors and the roccomp command. The area under the curve is not significantly different for our four models, see **Table 15**. All four have a ROC area around 0.68.

Table 15: Receiver operating characteristic ratios

		ROC		Asymptotic Normal	
	Obs	**Area**	**Std.err.**	**95% Conf. Interval**	
Model 1	3137	**0.6890**	0.0130	0.66349	0.71459
Model 2	3137	**0.6834**	0.0129	0.65803	0.70874
Model 3	3137	**0.6834**	0.0129	0.65803	0.70874
Model 4	3137	**0.6890**	0.0130	0.66349	0.71459

Source: Author's computations in Stata

From the results of the logistic analysis, we can conclude that our four estimated models do not differ significantly in results. However, we would highlight Model 2 and Model 4 as having one of the best significant estimation coefficients, a high goodness-of-fit, significant Prob > chi2 as 0.000. Also, Model 2 has the best AIC ratio.

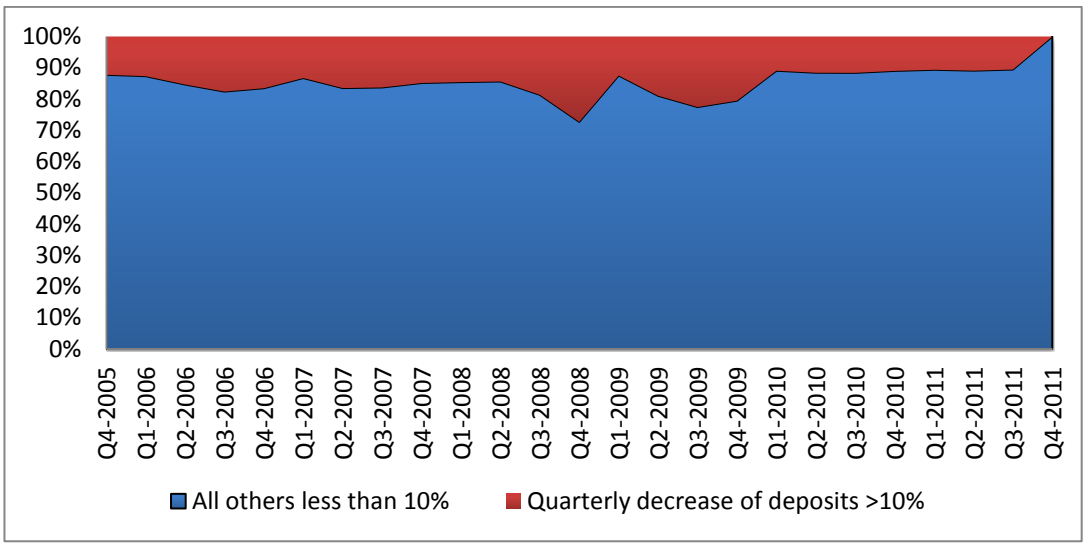
4.3 Discussion on the results

Based on the results from the logistic regression, we can conclude that the estimated model proved the assumptions about our three built hypothesis. From these tests, we can conclude that weak bank fundamentals together with fragile macroeconomic factors contribute to the bank runs in Russian deposit market, and variables as inflation, real interest rate, exchange rate, debt ratio, bank size, ROA are important explanatory variables to our model. However, some of the model variables as capital adequacy and GDP growth proved to be insignificant and have a controversive sign. Also, the deposit insurance influence efficiency in prevention of

bank runs is proved through our DIS dummy significance. Additional evidence supporting the credibility of insurance mechanism, as well as trust of depositors in state banks, is provided by other two dummy variables included in the model, ownership and demographic dummies.

With regards to the model quality, we can affirm that our four models proved a high significance with a 0.000 Prob > chi-square and over 86% correctly predicted cases according to the classification.

Figure 9: Percentage of banks in the sample with decrease in deposits over 10% for 2005-2011 quarterly



Source: Author's computations based on sample data

However, when analyzing the percentage of cases whether or not the country's banking system experiences a depositors' run, defined as 10 percent drop in total outstanding deposits during quarter, we did not identify severe bank runs cases. As presented in **Figure 9**, there is a significant drop in the percentage of deposits in last quarter of 2008 and 2009 year that confirms our expectations about a run in 2008 (Globex – Financial Times, 2008). Therefore, we may conclude that our analysis identified a partial run for 2008, not of high proportions, estimating around 28% of bank sample. Also, it is worth to mention the significant decrease in deposit withdrawals for 2011 year. The reason might be a better regulation from the DIS Agency and the deposit insurance guarantee itself.

Chapter 5

Conclusion

The aim of this thesis is to examine the factors behind the decision of depositors to withdraw their funds from banks and simultaneously to test the effect of deposit insurance on bank runs during 2005-2011 period on Russian banking market. Methodologically, we have used a logit econometric model to test our assumptions.

Based on the existing empirical literature and recent theories of bank runs and banking regulation, we have determined the main bank-fundamental factors and macroeconomic conditions factors that are important in determining the bank fragility against runs as capital adequacy, debt ratio, ROA, bank size, inflation, GDP growth rate, exchange rate, and real interest rate. The empirical results confirm that both financial and macroeconomic indicators have a high significance in our model. The findings suggest that drain in deposits in Russian banks is associated with specific factors such as high debt ratio, rising real interest rates, small asset size, as well as high inflation, and sharp increases in the real exchange rates (RUB/USD, RUB/EUR). Regarding the indicators of financial performance as capital adequacy, ROA, as well as GDP growth rate macroeconomic factor, which were not in line with expectations due to a conflicting positive sign but still statistical significant for our model, we consider the reason of results might be due to limited customer information taken from published bank financial statements.

Another interesting fact is related to the deposit insurance scheme adopted by Russia in 2004. In addition to understanding the forces that make depositors to come and withdraw their money from bank our research is also focuses on testing on Russian depositors' behavior after the implementation of deposit insurance scheme in

Russia. Estimation results of our deposit insurance dummy, created to test our third hypothesis, confirms that implementation of insurance mechanism helps avoid exposure to bank runs in Russia.

Finally, we wanted to test if deposit insurance adoption had an impact on the changes in the degree of deposit amounts from different types of banks: state-controlled, foreign-controlled, and private-domestic banks. The newly adopted deposit insurance might diminish the comprehended safety by the depositors in the state-controlled banks compared with private banks, thus, increasing the amount of investments to private banks. However, the findings suggest that state banks still maintain their leadership position for depositors' credibility, a bank run being associated more with the private banks than with the state-controlled once.

With regards to the identification of bank runs cases, our model was designed to identify a run in case of a decrease of more than 10 percent in bank deposits per quarter. From our sample analysis, during 2005-2011 years a significant drop was identified in the 2008 year, quarter 4, when 27.11 percent of the cases were recognized as a run on the particular banks; this percentage represents more than 1/3 of banks from the entire system. As a conclusion, we can state that during the end of 2008 was identified a run on Russian deposit market, however we would not characterize it as a severe run because it did not touch all banks but more as a partial one. The findings coincide with the official reports on the financial crisis where Russian officials' state that a major drop began in October, 2008 and continued in November–December[9]. During October, 2008 Globex (the first Russian bank to experience a sharp run on deposits during the crisis) and dozens of other Russian banks have reported a sharp rise in withdrawals and account closures, thus confirming our findings.

Overall, we can conclude that the estimated logit econometric model proved a high significance with a 0.000 Prob > chi-square and over 86% correctly predicted cases according to the classification. The method can contribute to a better understanding by regulators, policy makers, and bank supervisors of bank runs phenomena and the factors that can influence its inception in order to prevent the

[9] Russia confirms recession to come. BBC News. December, 2008

future bank failures. However, we do not exclude possible extensions on the topic. For further investigation, we might focus on increasing the time period of sample (available data before DIS implementation would be of great value); add more financial variables as non-performing loans, interest rates per bank; also, contrast the episodes of runs from perspective of deposit drains versus perspective of changing the deposits from an insolvent bank or uninsured bank to a solvent or insured one. The model, obtained results, and interpretation were based on my understanding of the model and knowledge background and a further research is more than welcome.

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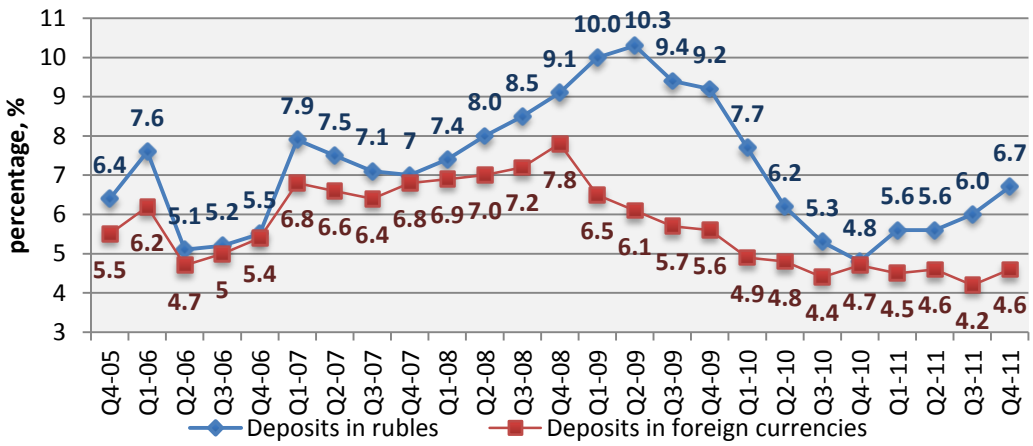
The Federal Law on **Insurance of Household Deposits in Banks of the Russian Federation**

Appendix A

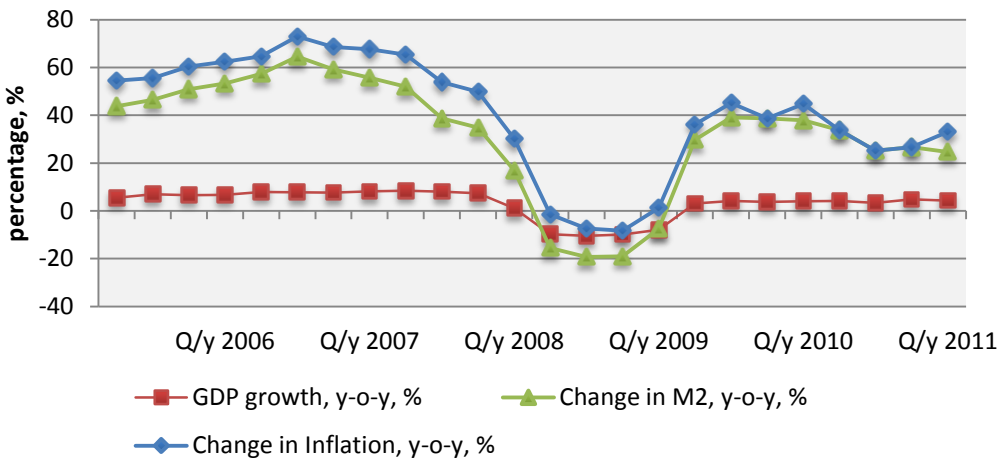
Russian Banking Sector

Figure 10: Interest rates dynamics for deposits with term higher than 1 year



Source: Author's computations based on DIA data.

Figure 11: Changes in the GDP, Inflation, and M2 during 2006-2011



Source: Author's computations based on CBR and World Bank data.

Table 16: General overview on the Russian banking sector

Data as at start of period (01.01)	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
Number of credit organizations	2124	2001	1826	1666	1516	1409	1345	1296	1228	1178	1146
with banking license	1311	1319	1329	1329	1299	1253	1189	1136	1108	1058	1012
license to attract private deposits	1239	1223	1202	1190	1165	1045	921	906	886	849	819
license to conduct foreign currency operations	764	810	829	845	839	827	803	754	736	701	677
general license	244	262	293	310	311	301	287	300	298	291	283
license for operations with precious metals	163	171	175	181	182	184	192	199	203	203	208
Foreign credit organizations with banking license	130	126	126	128	131	136	153	202	221	226	220
fully foreign owned	22	23	27	32	33	41	52	63	76	82	80
50 to 100% foreign owned	11	12	10	9	9	11	13	23	26	26	31
Included in the register of banks participating in the DIS	-	-	-	-	739	930	924	909	893	859	832
Total number of branches of existing credit organizations	3793	3433	3326	3219	3238	3295	3281	3455	3470	3183	2926
of which branches of Sberbank	1529	1233	1162	1045	1011	1009	859	809	775	645	574
of which branches of fully foreign owned banks	7	9	12	15	16	29	90	169	242	241	203
Total banking sector assets as % of GDP	n/a	35.3	38.3	42.3	41.7	44.8	51.9	60.5	67.9	75.9	76
Domestic credit to private sector as % of GDP	16.8	18.0	21.2	24.3	27.5	32.5	38.8	42.2	46.2	44.9	46.8
Deposit interest rate (%)	5	5	5	4	4	4	5	6	9	6	n/a
Lending interest rate (%)	18	16	13	11	11	10	10	12	115	11	9

Source: Central Bank of Russia, State Corporation - Deposit Insurance Ag

Appendix B

Logit Estimation: Stata Output

Model 1:

```
. logit br  lagDEBTR dforeign ddis lagINFL

Iteration 0:   log likelihood = -981.19969
Iteration 1:   log likelihood = -969.44475
Iteration 2:   log likelihood = -969.43706
Iteration 3:   log likelihood = -969.43706

Logistic regression                             Number of obs     =       1452
                                                LR chi2(4)        =      23.53
                                                Prob > chi2       =     0.0001
Log likelihood = -969.43706                     Pseudo R2         =     0.0120

------------------------------------------------------------------------------
          br |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    lagDEBTR |   1.010516   .561892     1.80   0.072    -.0907716    2.111804
    dforeign |   .3650439   .219967     1.66   0.097    -.0660836    .7961713
        ddis |  -.2055855   .1109651   -1.85   0.064     -.423073    .011902
     lagINFL |    .082239   .0219677    3.74   0.000     .0391831    .1252949
          _cons |  -2.143009   .5985215   -3.58   0.000    -3.31609   -.9699285
------------------------------------------------------------------------------

. fitstat

Measures of Fit for logit of br

Log-Lik Intercept Only:      -981.200   Log-Lik Full Model:          -969.437
D(1447):                     1938.874   LR(4):                        23.525
                                        Prob > LR:                     0.000
McFadden's R2:                 0.012   McFadden's Adj R2:             0.007
Maximum Likelihood R2:         0.016   Cragg & Uhler's R2:            0.016
McKelvey and Zavoina's R2:     0.020   Efron's R2:                    0.016
Variance of y*:                3.359   Variance of error:             3.290
Count R2:                      0.600   Adj Count R2:                  0.017
AIC:                           1.342   AIC*n:                      1948.874
BIC:                       -8596.295   BIC':                          5.598
```

Model 2:

```
. logit br  lagCA lagGDP lagRUBEUR dstate ddis

Iteration 0:   log likelihood = -6847.7149
Iteration 1:   log likelihood = -6492.8044
Iteration 2:   log likelihood = -6459.6916
Iteration 3:   log likelihood = -6459.3306
Iteration 4:   log likelihood = -6459.3294
Iteration 5:   log likelihood = -6459.3294

Logistic regression                             Number of obs     =      17613
                                                LR chi2(5)        =     776.77
                                                Prob > chi2       =     0.0000
Log likelihood = -6459.3294                     Pseudo R2         =     0.0567

------------------------------------------------------------------------------
          br |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       lagCA |   .0528269   .0047331    11.16   0.000     .0435502    .0621037
     lagGDP |   .4462577   .0507221     8.80   0.000     .3468442    .5456712
  lagRUBEUR |   .0202338    .009031     2.24   0.025     .0025334    .0379342
     dstate |  -1.355569   .2641778    -5.13   0.000    -1.873348   -.8377904
       ddis |  -1.003544   .0468649   -21.41   0.000    -1.095397   -.9116903
      _cons |  -5.796943   .6486998    -8.94   0.000    -7.068371   -4.525514
------------------------------------------------------------------------------

. fitstat

Measures of Fit for logit of br

Log-Lik Intercept Only:    -6847.715     Log-Lik Full Model:         -6459.329
D(17607):                  12918.659     LR(5):                        776.771
                                         Prob > LR:                      0.000
McFadden's R2:                 0.057     McFadden's Adj R2:              0.056
Maximum Likelihood R2:         0.043     Cragg & Uhler's R2:             0.043
McKelvey and Zavoina's R2:     0.107     Efron's R2:                     0.046
Variance of y*:                3.684     Variance of error:              3.290
Count R2:                      0.868     Adj Count R2:                  -0.005
AIC:                           0.734     AIC*n:                      12930.659
BIC:                     -159214.285     BIC':                        -727.889
```

Model 3:

```
. logit br  lagROA lagINFL lagRUBUSD lagRDIR dstate ddis

Iteration 0:   log likelihood =   -1899.25
Iteration 1:   log likelihood = -1798.9013
Iteration 2:   log likelihood = -1793.5472
Iteration 3:   log likelihood = -1793.4912
Iteration 4:   log likelihood = -1793.4912

Logistic regression                             Number of obs     =       3971
                                                LR chi2(6)        =     211.52
                                                Prob > chi2       =     0.0000
Log likelihood = -1793.4912                     Pseudo R2         =     0.0557

------------------------------------------------------------------------------
          br |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lagROA |    .220233   .1010189     2.18   0.029     .0222396    .4182264
    lagINFL  |  -.0539626   .0219382    -2.46   0.014    -.0969607   -.0109644
  lagRUBUSD  |   .1593527    .038461     4.14   0.000     .0839706    .2347348
    lagRDIR  |   .7516239   .1118953     6.72   0.000     .5323131    .9709347
     dstate  |  -1.165962   .4623499    -2.52   0.012    -2.072151   -.2597727
       ddis  |  -1.054611    .086693   -12.16   0.000    -1.224527   -.8846962
      _cons  |  -7.768546   1.262964    -6.15   0.000    -10.24391   -5.293182
------------------------------------------------------------------------------

. fitstat

Measures of Fit for logit of br

Log-Lik Intercept Only:    -1899.250     Log-Lik Full Model:         -1793.491
D(3964):                    3586.982     LR(6):                        211.518
                                         Prob > LR:                      0.000
McFadden's R2:                 0.056     McFadden's Adj R2:              0.052
Maximum Likelihood R2:         0.052     Cragg & Uhler's R2:             0.052
McKelvey and Zavoina's R2:     0.098     Efron's R2:                     0.051
Variance of y*:                3.647     Variance of error:              3.290
Count R2:                      0.814     Adj Count R2:                  -0.007
AIC:                           0.907     AIC*n:                       3600.982
BIC:                     -29261.787      BIC':                        -161.797
```

Model 4:

```
. logit br logASSETS lagGDP lagRUBEUR dstate ddis

Iteration 0:   log likelihood = -6871.2143
Iteration 1:   log likelihood = -6434.1466
Iteration 2:   log likelihood = -6391.8267
Iteration 3:   log likelihood = -6391.3811
Iteration 4:   log likelihood = -6391.3791
Iteration 5:   log likelihood = -6391.3791

Logistic regression                             Number of obs     =      17686
                                                LR chi2(5)        =     959.67
                                                Prob > chi2       =     0.0000
Log likelihood = -6391.3791                     Pseudo R2         =     0.0698

------------------------------------------------------------------------------
          br |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   logASSETS |  -.2418534   .0144649   -16.72   0.000    -.2702039   -.2135028
      lagGDP |   .3737524    .050635     7.38   0.000     .2745097    .4729952
   lagRUBEUR |   .0347223   .0090468     3.84   0.000      .016991    .0524537
      dstate |  -.9362899   .2657858    -3.52   0.000    -1.457221   -.4153593
        ddis |  -.9206846   .0473475   -19.45   0.000    -1.013484   -.8278851
       _cons |   -1.91614   .6724058    -2.85   0.004    -3.234031   -.5982484
------------------------------------------------------------------------------

. fitstat

Measures of Fit for logit of br

Log-Lik Intercept Only:     -6871.214     Log-Lik Full Model:          -6391.379
D(17680):                   12782.758     LR(5):                         959.671
                                          Prob > LR:                       0.000
McFadden's R2:                  0.070     McFadden's Adj R2:               0.069
Maximum Likelihood R2:          0.053     Cragg & Uhler's R2:              0.053
McKelvey and Zavoina's R2:      0.138     Efron's R2:                      0.058
Variance of y*:                 3.819     Variance of error:               3.290
Count R2:                       0.869     Adj Count R2:                   -0.003
AIC:                            0.723     AIC*n:                       12794.758
BIC:                      -160136.988     BIC':                         -910.768
```

Significance summary statistics:

```
. estout m1 m2 m3 m4
```

	m1 b	m2 b	m3 b	m4 b
br				
lagDEBTR	1.010516			
dforeign	.3650439			
ddis	-.2055855	-1.003544	-1.054611	-.9206846
lagINFL	.082239		-.0539626	
lagCA		.0528269		
lagGDP		.4462577		.3737524
lagRUBEUR		.0202338		.0347223
dstate		-1.355569	-1.165962	-.9362899
lagROA			.220233	
lagRUBUSD			.1593527	
lagRDIR			.7516239	
logASSETS				-.2418534
_cons	-2.143009	-5.796943	-7.768546	-1.91614

```
. roccomp br xb1 xb2 xb3 xb4, graph summary
```

	Obs	ROC Area	Std. Err.	Asymptotic Normal [95% Conf.	Interval]
xb1	3137	0.6890	0.0130	0.66349	0.71459
xb2	3137	0.6834	0.0129	0.65803	0.70874
xb3	3137	0.6834	0.0129	0.65803	0.70874
xb4	3137	0.6890	0.0130	0.66349	0.71459

```
Ho: area(xb1) = area(xb2) = area(xb3) = area(xb4)
    chi2(1) =     0.27       Prob>chi2 =    0.6042
```

Classification table –model 1:

br	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lagDEBTR	1.010516	.561892	1.80	0.072	-.0907716	2.111804
dforeign	.3650439	.219967	1.66	0.097	-.0660836	.7961713
ddis	-.2055855	.1109651	-1.85	0.064	-.423073	.011902
lagINFL	.082239	.0219677	3.74	0.000	.0391831	.1252949
_cons	-2.143009	.5985215	-3.58	0.000	-3.31609	-.9699285

. estat class

Logistic model for br

Classified	True D	True ~D	Total
+	70	60	130
-	521	801	1322
Total	591	861	1452

Classified + if predicted Pr(D) >= .5
True D defined as br != 0

Sensitivity	Pr(+| D)	11.84%
Specificity	Pr(-|~D)	93.03%
Positive predictive value	Pr(D| +)	53.85%
Negative predictive value	Pr(~D| -)	60.59%
False + rate for true ~D	Pr(+|~D)	6.97%
False - rate for true D	Pr(-| D)	88.16%
False + rate for classified +	Pr(~D| +)	46.15%
False - rate for classified -	Pr(D| -)	39.41%
Correctly classified		59.99%

Classification table –model 2:

br	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lagCA	.0528269	.0047331	11.16	0.000	.0435502	.0621037
lagGDP	.4462577	.0507221	8.80	0.000	.3468442	.5456712
lagRUBEUR	.0202338	.009031	2.24	0.025	.0025334	.0379342
dstate	-1.355569	.2641778	-5.13	0.000	-1.873348	-.8377904
ddis	-1.003544	.0468649	-21.41	0.000	-1.095397	-.9116903
_cons	-5.796943	.6486998	-8.94	0.000	-7.068371	-4.525514

. estat class

Logistic model for br

Classified	True D	True ~D	Total
+	0	11	11
-	2312	15290	17602
Total	2312	15301	17613

Classified + if predicted Pr(D) >= .5
True D defined as br != 0

Sensitivity	Pr(+| D)	0.00%
Specificity	Pr(-|~D)	99.93%
Positive predictive value	Pr(D| +)	0.00%
Negative predictive value	Pr(~D| -)	86.87%
False + rate for true ~D	Pr(+|~D)	0.07%
False - rate for true D	Pr(-| D)	100.00%
False + rate for classified +	Pr(~D| +)	100.00%
False - rate for classified -	Pr(D| -)	13.13%
Correctly classified		86.81%

Classification table –model 3:

br	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lagROA	.220233	.1010189	2.18	0.029	.0222396	.4182264
lagINFL	-.0539626	.0219382	-2.46	0.014	-.0969607	-.0109644
lagRUBUSD	.1593527	.038461	4.14	0.000	.0839706	.2347348
lagRDIR	.7516239	.1118953	6.72	0.000	.5323131	.9709347
dstate	-1.165962	.4623499	-2.52	0.012	-2.072151	-.2597727
ddis	-1.054611	.086693	-12.16	0.000	-1.224527	-.8846962
_cons	-7.768546	1.262964	-6.15	0.000	-10.24391	-5.293182

```
. estat class

Logistic model for br
```

Classified	True D	True ~D	Total
+	1	6	7
-	732	3232	3964
Total	733	3238	3971

```
Classified + if predicted Pr(D) >= .5
True D defined as br != 0
```

Sensitivity	Pr(+| D)	0.14%
Specificity	Pr(-|~D)	99.81%
Positive predictive value	Pr(D| +)	14.29%
Negative predictive value	Pr(~D| -)	81.53%
False + rate for true ~D	Pr(+|~D)	0.19%
False - rate for true D	Pr(-| D)	99.86%
False + rate for classified +	Pr(~D| +)	85.71%
False - rate for classified -	Pr(D| -)	18.47%
Correctly classified		81.42%

Classification table –model 4:

br	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
logASSETS	-.2418534	.0144649	-16.72	0.000	-.2702039	-.2135028
lagGDP	.3737524	.050635	7.38	0.000	.2745097	.4729952
lagRUBEUR	.0347223	.0090468	3.84	0.000	.016991	.0524537
dstate	-.9362899	.2657858	-3.52	0.000	-1.457221	-.4153593
ddis	-.9206846	.0473475	-19.45	0.000	-1.013484	-.8278851
_cons	-1.91614	.6724058	-2.85	0.004	-3.234031	-.5982484

```
. estat class

Logistic model for br
```

Classified	True D	True ~D	Total
+	8	14	22
-	2311	15353	17664
Total	2319	15367	17686

```
Classified + if predicted Pr(D) >= .5
True D defined as br != 0
```

Sensitivity	Pr(+| D)	0.34%
Specificity	Pr(-|~D)	99.91%
Positive predictive value	Pr(D| +)	36.36%
Negative predictive value	Pr(~D| -)	86.92%
False + rate for true ~D	Pr(+|~D)	0.09%
False - rate for true D	Pr(-| D)	99.66%
False + rate for classified +	Pr(~D| +)	63.64%
False - rate for classified -	Pr(D| -)	13.08%
Correctly classified		86.85%

Figure 12: Sensitivity calculation for Model 1, 2, 3, and 4

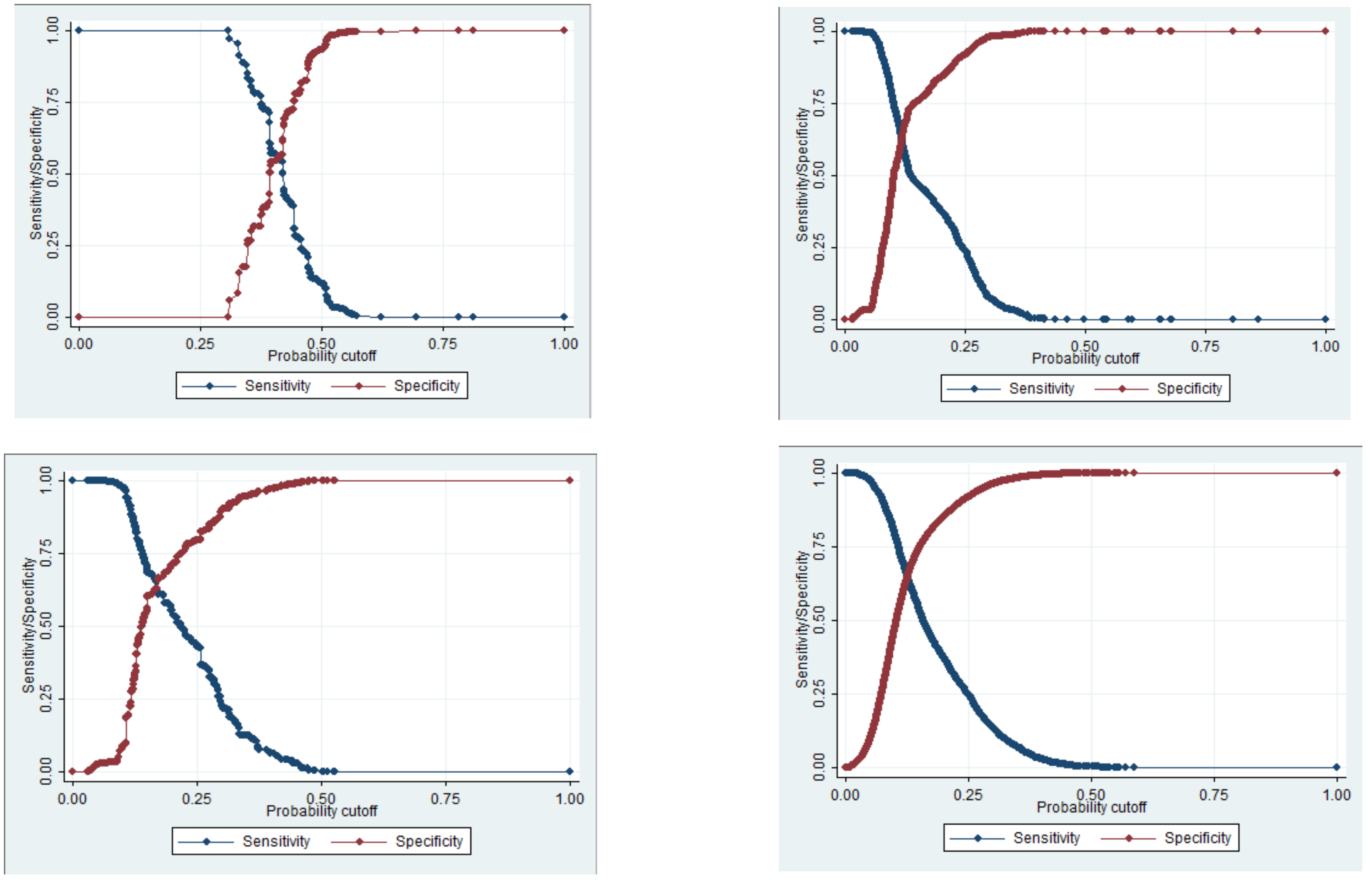


Figure 13: Specificity calculation for Model 1, 2, 3, and 4