NATIONAL RESEARCH UNIVERSITY
HIGHER SCHOOL OF ECONOMICS

Maria Bondarenko, Maria Semenova

DO HIGH DEPOSIT INTEREST RATES SIGNAL BANK DEFAULT? EVIDENCE FROM THE RUSSIAN RETAIL DEPOSIT MARKET

BASIC RESEARCH PROGRAM
WORKING PAPERS

SERIES: FINANCIAL ECONOMICS
WP BRP 65/FE/2018

Maria Bondarenko[1] , *Maria Semenova*[2]

DO HIGH DEPOSIT INTEREST RATES SIGNAL BANK DEFAULT? EVIDENCE FROM THE RUSSIAN RETAIL DEPOSIT MARKET[3]

In recent years the Russian banking system has witnessed numerous bank license withdrawals. Many of the failed banks had significant volumes of retail deposits in their liabilities, thus, transmitting the default burden to the Deposit Insurance Agency and ultimately to the taxpayers. In their attempt to stay in the market banks may try to attract the depositor funds even more intensively when the failure is not far away. The main assumption of this paper is that banks raise additional funds through inflated deposit interest rates – the overstatement strategy – before leaving the market. We use unique data on Russian bank deposit interest rates for deposits of different maturities in 2015–2016 combined with data about bank fundamentals coming from their financial statements. The results suggest that if a bank offers too generous interest rates for deposits for 180-365 days this can be a signal of a significantly higher probability of license withdrawal in 3 quarters. In their attempt to urgently attract funds when moving closer to default banks assign the highest rates for the longest-term deposits, with the maturity over one year. The interest rates higher than the market average dramatically increase the probability of a bank failure in 2 quarters.

JEL: G21, G01, P2

Keywords: Bank failure, Deposit interest rates, Market discipline, Personal deposits, Russia

[1]mashabondarenko@yandex.ru, Bachelor student, National Research University Higher School of Economics, Moscow, Russia

[2]Corresponding author: msemenova@hse.ru, Senior Research Fellow, Associate Professor, Center for Institutional Studies and Department of Finance, National Research University Higher School of Economics, Moscow, Russia

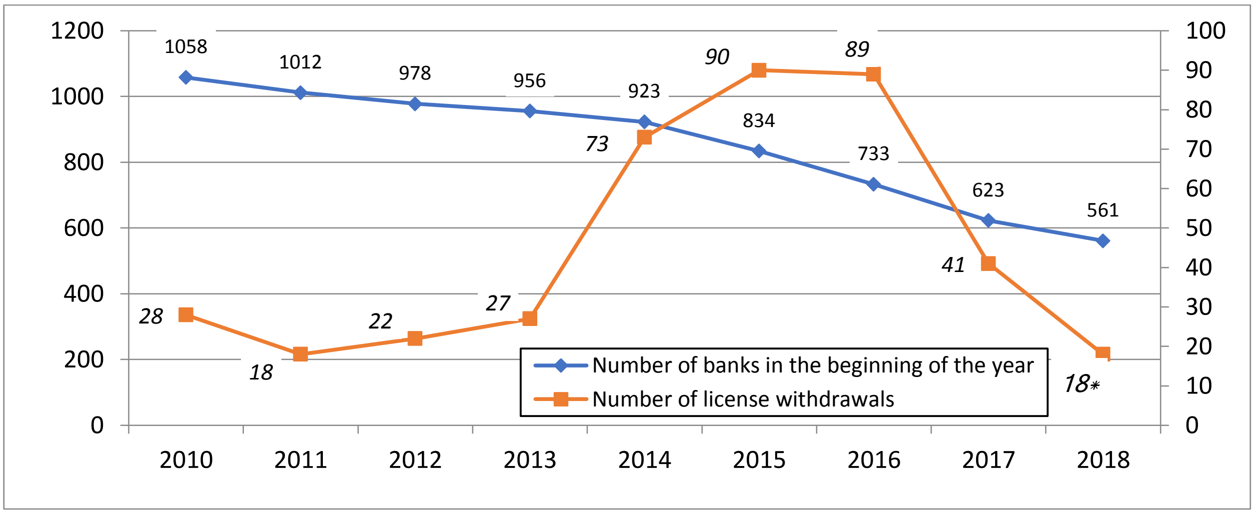
[3] The paper was prepared within the framework of the Basic Research Program at the National Research University Higher School of Economics (HSE) and supported within the framework of a subsidy granted to the HSE by the Government of the Russian Federation for the implementation of the Global Competitiveness Program. The financial support from the Government of the Russian Federation within the framework of the implementation of the 5-100 Program Roadmap of the National Research University Higher School of Economics is acknowledged.

I. Introduction

The most important risk depositors face is the risk of their bank's insolvency and, therefore, the possibility of its failure to meet its obligations to return invested funds. Depositors – especially retail ones – are usually too unsophisticated to correctly predict the probability of bank default. This means that besides the complicated early warning systems, the main essence of which is to identify problem banks before the license is revoked, the market needs simple signals for depositors. Such signals can prevent investing into the deposits in banks which are close to default, however, they should provide the opportunity to easily distinguish between risky and stable banks and keep depositors who lack trust to the banking sector, in the market. The latter is particularly important for banking systems facing frequent license withdrawals. In this case, depositor confidence in the banking system may be undermined, which in turn will lead to a reduction in private savings and, therefore, investment opportunities for banks, and as a consequence, these processes will have a negative impact on the real sector and the economy as a whole. A good example of a banking sector where the banks are losing licenses quite frequently nowadays is the Russian banking sector. The last decade has witnessed a severe reduction of the number of banks, with numerous license withdrawals (see

Figure **1**).

Figure 1. Number of banks in Russia, 2010-2018



Source of data: CBR
** - as for April 25, 2018*

The failures of banks which heavily relied on depositor funds are the most painful for the economy, as the funds of the deposit insurance system (DIS) are involved. The problem is aggravated by the fact that in their attempt to stay in the market the banks may try to attract depositors' funds even more intensively when the failure is not far away, as they face difficulties getting funds from other sources. To gain additional clients they offer high interest rates on their deposits. There is an implicit ceiling for the deposit interest rates established by the central Bank of Russian Federation (CBR), which is regularly calculated as the average highest rate the top-10 Russian banks[4] assign for their deposits, plus 1.5 percentage points. If the restriction is violated, CBR conducts supervisory work with the bank to check the level of real risk taken. The interest rates offered by such banks can signal a high probability of bank default in the near future. This paper investigates whether banks offering abnormally high deposit interest rates are more likely to face license withdrawal in the following quarters. The main assumption of the study is that banks raise additional funds through inflated interest rates before leaving the market.

We use the unique data on Russian bank deposit interest rates for deposits of different maturities – up to 90 days, from 90 to 180 days, from 181 to 365 days and more than 365 days – for the period 2015–2016 combined with data on bank fundamentals from their financial statements. Unlike previous studies using an implicit deposit interest rate (the interest payments divided by the average deposit amount) we use data on actual interest rates offered by the banks and, therefore, observed by retail depositors. We show that there exists a statistically significant and positive relationship between abnormally high deposit interest rates on long-term deposits and the probability of bank failure in the next 2–3 quarters.

We contribute to two streams of the literature. First of all we contribute, to the vast literature on the determinants and predictors of bank default probability. The literature usually identifies the key determinants of bank defaults in terms of profitability, liquidity, capitalization, credit risk, etc. Nevertheless, the range of bankruptcy indicators is not limited solely to financial fundamentals. We add another factor which is associated with a higher probability of bank default – the bank's strategy of high deposit interest rates. We also add to the literature on market discipline in the deposit market. The price mechanism of market discipline implies that more risky banks have to offer higher interest rates. We develop this idea further showing that particularly high deposit interest rates may signal not only higher risks, but significantly a higher probability that a bank will lose its license.

The rest of the paper is organized as follows. Section II reviews the relevant literature on bank default determinants and market discipline in deposit markets. Section III describes our methodology and data sources. Section IV presents the main estimation results followed by robustness checks. Section V concludes.

[4] Top-10 by the volumes of retail deposits in the liabilities

II. Literature

Determinants of bank failures

To estimate the probability of bank failure different methods are used, including rating predictions, expert surveys and econometric – usually binary choice – models of the default probability based on default data (Peresetsky 2007). The latter is used most frequently, and the growing literature introduces new factors which can add to the predictive power of those models. Both probit and logit approaches appear in this literature. In (Martin 1977), one of the earliest papers in this line, the possibility of using the logit model as an approach to the early warning system of bank defaults is justified. In a recent paper by (Wang, Jiang, and Zhen-Jia-Liu 2016) using logistic regressions, the authors analyze possible factors that affect the probability of a bank default. In (Klieštik, Kočišová, and Mišanková 2015) both models of binary choice are considered, as, in the authors' opinion, they are similar and can be equally used to model the probability of bankruptcy.

In one of the earliest papers on bank default determinants – (Meyer and Pifer 1970) – four key groups of factors that explain the causes of bank failures are introduced: national and local economic conditions (exogenous factors), quality of management and conscientiousness of employees (endogenous factors). Based on US bank defaults that occurred between 1948 and 1965, the authors aim to explain them and predict new ones. Among the possible financial determinants of bank defaults, the authors show that a lack of current liquidity and low profitability negatively affect the probability of default, while difference in interest rates on term deposits and the share of fixed assets in total assets have a statistically significant positive effect. The authors conclude that, first, financial indicators can be determinants of default only if the lags do not exceed two years, and, second, it is necessary to include financial determinants not only in their pure form, but also in the form of trends, errors, variations etc., because this improves the predictive power of the model.

In (Hwang, Lee, and Liaw 1997), using the logit model to estimate the probability of bank default and a wide range of bank fundamentals, the authors try to predict the bankruptcy of US credit institutions and determine the size of an actuarially fair insurance premium on deposits. They found that only 18 of the 48 financial indicators considered are statistically significant, and equally affect the probability of bank default over time. For example, the ratio of net interest income to assets, equity to assets ratio, the share of liquid assets, sensitive deposits to the total amount of deposits, net income to assets, and others negatively affect the probability of bank default. Other variables, such as the share of non-performing loans, the share of loans for agricultural needs in total loans, the loans to deposits ratio, on the contrary, have a positive impact on the probability of bank default. As for the remaining financial indicators (loans for industrial, commercial and other purposes, real estate owned by the company, etc.), their influence on the bank's chance of default changes over time.

(Kolari et al. 2002) compare the logit model and the Trait Recognition model in terms of their predictive power (based on a sample of 50 large bankrupt banks and 50 operating lending institutions) and use approximately 28 independent variables to characterize the financial position of banks. Among the main determinants of bankruptcy, the authors identify indicators of profitability, capitalization, credit risk (measured by the ratio of reserves for possible loan losses, or loan loss provisions, to total assets), and the ratio of securities to assets. In a cross-country study (Zhen 2015) in which the countries included in the G-20, G-8, EU, NAFTA were analyzed, in addition to the macro-factors (the growth of GNP, CPI, etc.) the following bank characteristics were considered as the main determinants of bank failures: the ratio of Tier I capital to assets, fixed assets to long-term liabilities, loans to assets, LLP to loans, net income to capital, share of non-performing loans and interest (non-interest) incomes to interest (non-interest) expenses. As a result, the authors concluded that the indicators of overdue and issued loans, and fixed assets, positively affect the probability of a bank default, while the other determinants (LLP, capital adequacy ratio, return on equity, etc.) have a negative impact. Similar factors were considered in (Shen and Hsieh 2011), where the main goal was an attempt to combine micro- and macro-factors to predict bank defaults. In their paper, the ratio of equity to assets, non-interest expenses and net income to assets were used as significant microeconomic indicators of bank default risk, whose impact on the probability of a credit institution's bankruptcy was negative, while the macro-factors the authors considered were the relationship of total loans to GNP, short-term foreign debt to foreign reserves, exchange rate, GDP growth, etc. Thus, it was found that the slow growth of the economy and a fall in the value of the national currency increases the probability of a bank failure. A recent study (Lin and Yang 2016), analyzing countries of East Asia, found that the financial determinants of a bank's default play a more critical role in estimating the probability of bankruptcy than macro variables. Among the key micro-factors of default, the authors identify capital adequacy, profitability, liquidity, and an increase in the deposit interest rate.

There are several papers dealing with the determinants of bank default in Russia using the same methodology. Analyzing the Russian banking sector, Lanine and Vennet (2006) show that a more profitable bank with a high level of capital adequacy and liquidity has a lower probability of default and the size of the bank does not play a key role. Similar results were obtained in other studies on the bankruptcy probability of Russian banks (Emelianov and Bryukhova 2013, 2015): higher values of capital adequacy, liquidity and profitability lead to a lower probability of the bank default. In (Golovan et al. 2004; Drobyshevsky and Zubarev 2011; Ivanov and Fedorova 2015) both financial and macroeconomic factors are singled out as factors affecting the stability of Russian banks. Among the bank fundamentals that characterize the bank's default probability (in addition to indicators of profitability, liquidity and capital adequacy), the authors highlight the ratio of LLP to total loans, the share of government securities in total assets, the ratio of non-government debt obligations to assets, and as macro-indicators they use the ratio of exports to imports, the exchange rate, CPI, etc. The influence of these variables was similar to that obtained in many previous papers. Papers focusing on Russian bank default predictions (Karminsky, Kostrov and Murzenkov 2012; Peresetsky 2013) confirm that the key predictors of bank failure are capital adequacy, profitability, loan portfolio quality (measured by the LLP ratio), the share of non-government securities in assets, turnover on correspondent accounts and the share of personal deposits in total liabilities.

The literature discussed above focuses on bank fundamentals and their combinations, which can explain bank defaults and predict them accurately. However bank fundamentals usually come from banks' financial statements, which the bank stakeholders – especially unsophisticated ones such as retail depositors – rarely monitor. What is publicly observed and monitored are the banks' interest rates for deposits. This is not just a menu of interest rates, this is the tool the banks use to influence the supply of the deposited funds. In this study, controlling for the banks' financial conditions, we focus on the deposit interest rate strategy as a signal of bank stability.

Market discipline

This paper is in the strand of the literature exploring market discipline in the deposit market. In accordance with Basel II, market discipline is the third component, complementing the minimum capital requirements and supervisory processes, in the system of recommendations to enhance the stability of the financial system. Market discipline is usually defined as "a set of market incentives that depositors discipline banks, "punishing" them for excess risk in their financial policies" (Peresetsky 2008, p. 3). There are two basic ways depositors may demonstrate their sensitivity to increased risk-taking. Disciplining by quantity means that depositors withdraw funds from riskier banks and the latter suffer from decreased deposit growth. Disciplining by price means that depositors require higher interest rates – or risk premia – for riskier deposits. Thus, "the hypothesis of [price-based] market discipline is that high interest rates on deposits correspond to high risk of the bank's assets structure" (Peresetsky 2008, p. 3).

This attention to disciplining mechanisms appeared in 1990s and many papers were focused only on disciplining by price, using the evidence from US banks (see, for example, (Ellis and Flannery 1992)*;* (Hannan and Hanweck 1988), (Landskroner and Paroush 2008)). One of the first papers examining market discipline mechanisms is (Cook and Spellman 1994). They show that higher financial leverage and lower bank profitability result in higher CD spreads in the US market. They also demonstrate that, as any institution that guarantees covering deposits in case of bank's default (even the state) is risky, and their services are costly, market requires establishing premiums on such deposits as well. In other words price-based market discipline exists even in insured deposit markets. (Park and Peristiani 1998) also prove the existence of market discipline in the US deposit market by considering the relationship between the bank's risk level and the price and volume of uninsured deposits. They demonstrate that riskier banking institutions set higher interest rates for uninsured deposits, but attract fewer of them. The combination of price (high interest rates) and quantitative (low growth in the volume of uninsured deposits) mechanisms justify the need for introducing risk compensation. (Martinez et al. 2001) analyze the impact of deposit insurance and banking crises on market discipline and confirm the existence of the latter using the experience of Argentina, Chile and Mexico. The study shows that banks with high liquidity and capitalization ratios, and a smaller share of overdue loans, set lower interest rates on deposits. The introduction of a deposit insurance system does not reduce market discipline (as not all insurance schemes are credible), and its relative importance increases after a banking crisis (the authors argue that during this period the vigilance of depositors increases). Moreover, as mentioned, the policy of deposit interest rate regulation (in addition to the regulation of minimum capital requirements) can be used as a tool to reduce the moral hazard risk the banks demonstrate, because if banking institutions set interest rates on deposits freely, it creates additional incentives for investing in more risky assets, while reducing the franchise value of the bank[5]. By controlling deposit rates, the regulator increases the stability of the banking system (Hellmann, Murdock, and Stiglitz 2000). An example of a cross-country study of market discipline is (Nier and Baumann 2006), where, based on data from 32 different countries, it was found that the existence of implicit government support leads to lower bank capital, which increases the risk of bank default and depositors require higher interest rates on deposits for increased risk. Higher proportion of uninsured deposits in the bank liability structure disciplines banks, encouraging them to create additional capital buffers, reducing the risk of bankruptcy.

As for the Russian banking sector, (Karas et al. 2009) show that the Russian banking sector is characterized by the presence of quantitative market discipline, while evidence of the

[5]The franchise value of a bank means a discounted stream of future earnings of the bank, which is possible only if the bank operates (Hellmann, Murdock, and Stiglitz 2000).

price discipline is weak. They emphasize the positive relationship between liquidity, capitalization and inflows of deposits, while the growth of overdue loans in the bank's loan portfolio adversely affects the volume of deposits. This result persisted even after the crisis, and it confirms the conclusion made earlier in (Martinez et al. 2001) on the increasing vigilance of the population in the post-crisis period. For price discipline, there is no evidence that banks with smaller capitalization set higher rates as compensation for risk, which is in line with Ungan et al. (2008), who also provide evidence for disciplining by quantity rather than by price in the Russian personal deposit market. Nevertheless, they underline that this result does not deny the existence of market discipline as such, it just indicates that in this case there may be a more complex form of market discipline in which interest rates on deposits reflect a more complex mechanism than simply compensation to depositors for the observed risk and the result of bank competition for resources. To test their assumption, the authors assessed deposit supply functions to determine whether the deposit interest rate is a proxy for bank risk levels. The first type of functions consider only the non-linear relationship between the interest rate and the volume of deposits, and in second type, the joint effect of the price (interest rate) and risk measures (bank capitalization) is added. Analyzing the models, the authors find that the suspicions of depositors that the interest rate reflects other unobservable sources of risk are sensitive to an observed risk measure – the level of bank capitalization. This means that if depositors are confident banks will fulfill their obligations (this confidence stems from the observed capitalization of the institution), an increase in the interest rate signals an increased return on the invested funds, which contributes to an increase in the inflow of deposits. Conversely, a bank with a low capitalization does not inspire confidence among depositors, and raising its interest rate on deposits signals additional risk, which leads to a reduction in the inflow of deposits. The deposit rate is considered as a proxy for unobserved bank risk. Our paper continues this discussion focusing on the deposit interest rates as a predictor of bank default.

Analyzing market discipline in Russia, (Karas, Pyle, and Schoors 2013) study the combined effect of the DIS, introduced in 2004, and the banking crises on market discipline by comparing the behavior of insured and uninsured depositors. Analyzing the period from the end of 1995 to 2007, the authors conclude that after the introduction of DIS, the sensitivity of insured depositors to decreases in bank risk, even in the context of the financial crisis, while uninsured depositors react to the crisis by strengthening market discipline. The introduction of DIS had a negative impact on market discipline, therefore, during the period of financial instability, the regulator should be cautious in pursuing a policy of expanding deposit insurance, as in this situation additional incentives for moral hazard are created for weak and unstable banks.

(Semenova 2007) analyzes how market discipline changes after the introduction of DIS and depending on the type of bank ownership (foreign, national public and private institutions are considered) in the period from July 2004 to June 2006. The results suggest that for foreign banks none of the disciplining mechanisms (price or quantitative) exist. State credit institutions are characterized by the presence of quantitative discipline (however, only in terms of the bank size, i.e. the depositors are sensitive to changes in the size of banks' total assets), while private banks are marked by the presence of both types of disciplinary mechanisms. In addition, the author shows that the introduction of DIS did not change the nature of market discipline and for private banks, the price mechanism became more pronounced after the introduction of DIS.

Focusing solely on price-based market discipline in the Russian personal deposit market, (Peresetsky 2007b) adds evidence that riskier banks offer higher deposit interest rates. This effect was undermined by the introduction of DIS, which resulted in higher interest rates and, therefore could stimulate the competition accompanied by additional risk-taking by banks.

In this paper we combine the ideas of interest rates signaling higher bank risks developed in (Karas et al. 2009) with the approach of (Peresetsky 2007b) using data on actual deposit interest rates collected from the market instead of implicit interest rates, which are usually used in the absence of other data. With this set-up we contribute to the literature on bank default probability determinants, discussing the pricing policies – namely the excessively high deposit interest rates – signaling that the bank has a higher risk of imminent bankruptcy.

III. Methodology and Data

Models

To determine whether the price policy pursued by Russian banks in the deposit market, expressed in raising the deposit interest rates too high, signals the possibility of their rapid bankruptcy, we use probit model techniques and perform two consecutive estimation steps.

Before describing the regressions, we define the interest rate overstatement. We measure this in two ways. Over-the-market overstatement ($OMIR_{i,t,m}$) refers to the positive difference between the interest rate on deposits of maturity m at bank i in quarter t ($IR_{i,t,m}$) and the average interest rate of all other banks ($\overline{IR}_{t,m}$) for the same type of deposits in the same quarter.

We also consider an even more articulated interest rate overstatement, introducing an over-over-the-market overstatement ($OOMIR_{i,t,m}$). It measures the degree to which the overstatement of bank i exceeds that of the other overstating banks in the market. In other words, it is the positive difference between the interest rate overstatement of the first type on deposit of the maturity *m* of the bank *i* in the quarter *t* ($OMIR_{i,t,m}$) and the average overstatement of other overstating banks ($\overline{OMIR}_{t,m}$) in the same quarter.

We calculate the overstatements for four types of deposits according to their maturity: short-term deposits (up to 90 days), medium-term deposits (90 to 180 days), long-term-deposits (from six months to one year), and the longest-term deposits (over one year).

At the first step we study whether banks which pursue such a pricing policy are more prone to bankruptcy. For this, for each type of overstatement a binary variable (DO_n, where n=1,2, with 1 standing for an over-the-market overstatement and 2 for an over-over-the-market one) was introduced, which equals to 1 if there is an overestimation, and 0 otherwise. For each overstatement type and each maturity we estimate the following probit regression:

$$\Pr\left(Bankruptcy_{i,t} = 1\right) = \Phi\left(b_0 + b_1 DO_{n,i,t-k} + b_2 H1_{i,t-1} + b_3 {}^{PZS}/_{KE_{i,t-1}} + b_4 {}^{KE}/_{CA_{i,t-1}} + b_5 Ln(CA)_{i,t-1} + b_6 Ln({}^{OKS}/_{CA})_{i,t-1} + b_7 {}^{CP}/_{CA_{i,t-1}} + b_8 H3_{i,t-1} + b_9 {}^{NCB}/_{CA_{i,t-1}} + b_{10} Time\right) \quad (1)$$

Where Φ (·) is a function of the standard normal distribution, specific for the probit model, and the condition *Bankruptcy = 1* means license revocation. These features are typical for all models of this study.

At the second step we estimate how the degree of the bank's overstatement of the deposit interest rate affects the probability of its default, that is, if the first model considers the entire Russian banking sector, then in the second model only those banks that show an overstatement, are analyzed. We estimate the following model with the new independent variables on the limited samples:

$$\Pr\left(Bankruptcy_{i,t} = 1\right) = \Phi\left(b_0 + b_1 OMIR_{i,t-k} \left(or\ OOMIR_{i,t-k}\right) + b_2 H1_{i,t-1} + b_3 {}^{PZS}/_{KE_{i,t-1}} + b_4 {}^{KE}/_{CA_{i,t-1}} + b_5 Ln(CA)_{i,t-1} + b_6 Ln\left({}^{OKS}/_{CA}\right)_{i,t-1} + b_7 {}^{CP}/_{CA_{i,t-1}} + b_8 H3_{i,t-1} + b_9 {}^{NCB}/_{CA_{i,t-1}} + b_{10} Time\right) \quad (2)$$

As the deposit collection at an extremely high price usually appears not long before the license withdrawal, we consider 2 and 3 quarter lags for the overstatement variables (k=2,3). This means that for each type of deposit eight basic models are estimated.

The choice of control group for the explanatory variables was made based on the previous experience on this topic. The entire control group can be divided according to economic meaning in accordance with the *CAMELS* classification:

$H1_{i,t-1}$ is the ratio of the bank's capital to risk-weighted assets, measuring capital adequacy. It is calculated according to the methodology used by CBR, according to CBR requirements, the minimum level for *H1* is 10%. A higher ratio signals a more stable bank. For robustness checks we replace this ratio with a simpler one – the ratio of equity to net assets ($SK/CA_{i,t-1}$). It is assumed that highly capitalized banks are less likely to go bankrupt.

$PZS/KE_{i,t-1}$ reflects the quality of assets. It is expressed as the ratio of overdue loans to total bank loans. A higher ratio is expected to increase the probability of bank default, i.e. the more overdue loans a bank has in its portfolio, the more likely bankruptcy is. For robustness checks after main estimations we replace it with the ratio of loan loss provisions to the total loans ($LLP/KE_{i,t-1}$).

$KE/CA_{i,t-1}$ is the ratio of total bank loans to the value of the bank's net assets. A higher ratio is expected to increase the probability of bankruptcy, as the larger the size of the bank's loan portfolio, the greater the risk of non-return.

$Ln(CA)_{i,t-1}$ is the natural logarithm of bank net assets, being a proxy for bank size. It is assumed to reduce the probability of bank default according to the hypothesis of "too big to fail", which is that the bankruptcy of large, significant financial institutions could have catastrophic consequences for the national economy, and therefore the state will not allow such a development of events.

$CP/CA_{i,t-1}$ is ROA, measuring earnings. It is expressed as the ratio of a bank's net income to its net assets. It is expected that this index will adversely affect the probability of bank default, i.e. banks with low profitability are more likely to go bankrupt.

$H3_{i,t-1}$ represents the current liquidity ratio. This indicator along with other similar standards was developed by CBR as one of the ways to manage the risk of liquidity shortage. According to CBR, *H3* is calculated as follows[6]:

$\mathrm{H3} = \frac{Lat}{(Ovt - Ovt^{*})} * 100\%$, where

Lat are highly liquid bank assets (can be received and sold in up to 30 days);

[6] Instruction of the Bank of Russia of 03.12.2012 № 139-I "On mandatory standards of banks"

Ovt are liabilities for on-demand accounts, for which the depositor and (or) the creditor may demand immediate repayment or for which the time for fulfillment of obligations is up to 30 calendar days;

Ovt^* is the minimum aggregate balance of individuals' and legal entities' on-demand accounts, the maturity of obligations under which is up to 30 days.

The minimum size of the *H3* standard is 50%. It is assumed that banks that have sufficient liquidity are less likely to cease operations. In robustness checks we replace it with a simpler ratio of liquid assets over total assets ($^{LA}/_{CA_{i,t-1}}$).

$^{NCB}/_{CA_{i,t-1}}$ reflects both the bank's liquidity level and its sensitivity to risk. It is defined as the ratio of non-government securities to net assets. The assumptions about the expected effect of this indicator are ambiguous. Investing in non-government securities is one of the ways to manage liquidity, and therefore, banking institutions that have sufficient liquidity are less likely to default. However, such securities are riskier, and the bank can invest large resources in them.

The control variables are included in the model with a 1 quarter lag, as the market cannot react instantly to changes in banks' financial statement indicators. In conditions of frequent revocation of licenses, and the possible overstatement of deposit interest rates for the emergency attraction of funds, it is considered rational to establish a maximum lag of one quarter.

Data

We use the quarterly data from April 2015 to December 2016. The data on bank fundamentals for the entire Russian banking sector, represented by 729 banks at the beginning of the study, was taken from the IAS "Banks and Finance" (Mobile) database. Mobile includes about 80 financial indicators of Russian banks, calculated based on financial statements reported by CBR. The deposit interest rates come from a unique database Bankovedenie.ru. The data there comes from regular monitoring of bank deposit rates and the average rates per bank and per deposit type. The project existed for the mentioned quarters only, limiting the period of study. The data on license withdrawals come from the Kommersant system[7]. Kommersant accumulates the list of all Russian bank license withdrawals and classifies them by the reason(s) given by CBR. The period under consideration witnessed 83 banks which run bankrupt.

The top 5 banks were excluded from the sample. The data set for 724 Russian banks was cleaned of any misreporting or mistakes. The following restrictions were introduced to remove the extreme values of various indicators:

[7] URL: http://www.kommersant.ru/doc/2645323

1) ${SK}/{CA_{i,t-1}} > 0$, since capital to assets ratio cannot be negative;

2) ${PZS}/{KE_{t-1}} \leq 1$, since overdue loans cannot be more than all loans issued by the bank;

3) ${LA}/{CA_{i,t-1}} \leq 1$, since liquid assets are a part of total assets.

Table. 1 shows the descriptive statistics of the variables used in the study. The temptation to assign a higher interest rate compared to all the rest increases with the deposit maturity. For short-term deposits only 36% of banks are above the average and 17% are above the average surplus; for the longest-term deposits the proportions are 61% and 27% respectively. On average the overstatement of deposit interest rates is up to 1–2 p.p., while for the second type banks set interest rates 0.7–0.9 p.p. above the average overstatement. Nevertheless, we observe a significant rise in interest rates for the extreme cases and the longest-term deposits: up to 7.7 p.p. for the first type of overstatement, and 6 p.p. for the second type.

Table. 1 Descriptive statistics

Variable	N	Mean	Standard deviation	Min	Max
Overstatement variables					
DO_1_90	3276	0.3657	0.4817	0	1
DO_2_90	3276	0.1700	0.3757	0	1
DO_1_91_180	2992	0.5137	0.4999	0	1
DO_2_91_180	2992	0.2306	0.4213	0	1
DO_1_181_365	2826	0.5902	0.4919	0	1
DO_2_181_365	2826	0.2689	0.4435	0	1
DO_1_366	2798	0.6104	0.4877	0	1
DO_2_366	2798	0.2716	0.4449	0	1
Size of overstatement variables					
OMIR_90	1198	1.6314	1.0147	0.0008	6.2172
OOMIR_90	557	0.8280	0.6279	0.0015	4.0091
OMIR_91_180	1537	1.2321	0.8473	0.0016	5.5513
OOMIR_91_180	690	0.6993	0.5542	0.0021	3.7823
OMIR_181_365	1668	1.1429	0.8191	0.0012	5.0818
OOMIR_181_365	760	0.6595	0.5334	0.0010	3.2864
OMIR_366	1708	1.0613	0.7895	0.0014	7.7474
OOMIR_366	760	0.6515	0.5602	0.0014	6.0594
Control variables					
H1	3252	28.4655	39.9064	1	1233
H3	3213	506.5768	6517.775	3	272792.7
PZS/KE	3783	0.0737	0.1034	0.0000	0.9117
KE/CA	3783	0.4984	0.1932	0.0000	0.9734
Ln(CA)	3783	15.7973	1.7228	12.7696	21.8605
CP/CA	3783	0.0005	0.0261	-0.4729	0.2360
NCB/CA	3358	0.0651	0.0897	0.0000	0.7060
Robustness check variables					
SK/CA	3783	0.2285	0.1482	0.0005	0.9642
LA/CA	3783	0.3366	0.1800	0.0060	0.9589
LLP/KE	3276	1.6885	43.5171	0	1796.386

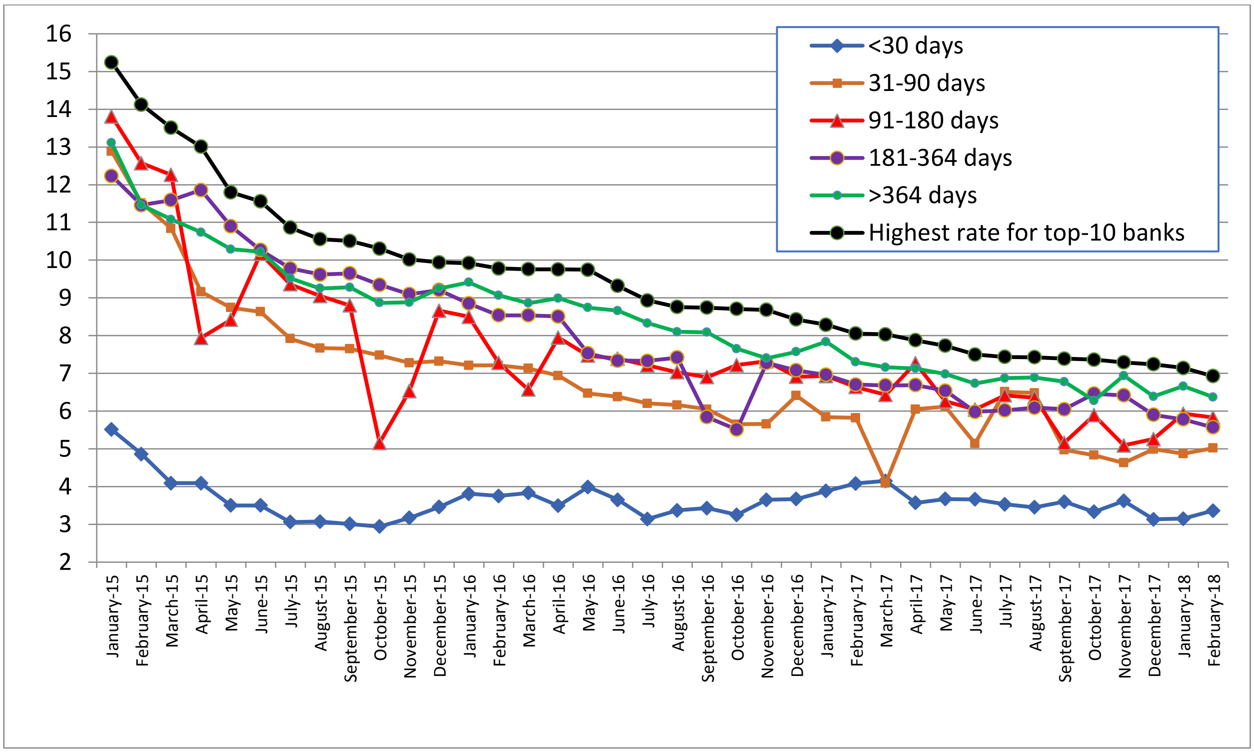
Table. 2 Correlation matrix

	H1	H3	PZS/KE	KE/CA	Ln(CA)	CP/CA	NCB/CA
H1	1.0000						
H3	0.0825	1.0000					
PZS/KE	0.0731	-0.0196	1.0000				
KE/CA	-0.2109	-0.0267	-0.2321	1.0000			
Ln(CA)	-0.3333	-0.0238	-0.0331	0.0899	1.0000		
CP/CA	0.0244	0.0470	-0.1270	-0.1024	0.0165	1.0000	
NCB/CA	-0.0785	0.0533	0.0163	-0.3420	0.1630	-0.0090	1.0000

The average share of overdue loans in the sample was around 7% of all loans issued. This indicates that banks are cautiously select potential borrowers, carrying out a qualitative analysis of their solvency. However several banks demonstrated weak positions, as they do not comply with the CBR's minimum capital and current liquidity requirements.

Table. 2 shows the correlation matrix of the control variables used in the models. All values of the pairwise correlation are low enough to allow them to be used in the regressions.

Figure 2. Personal deposit interest rates, 2015-2018

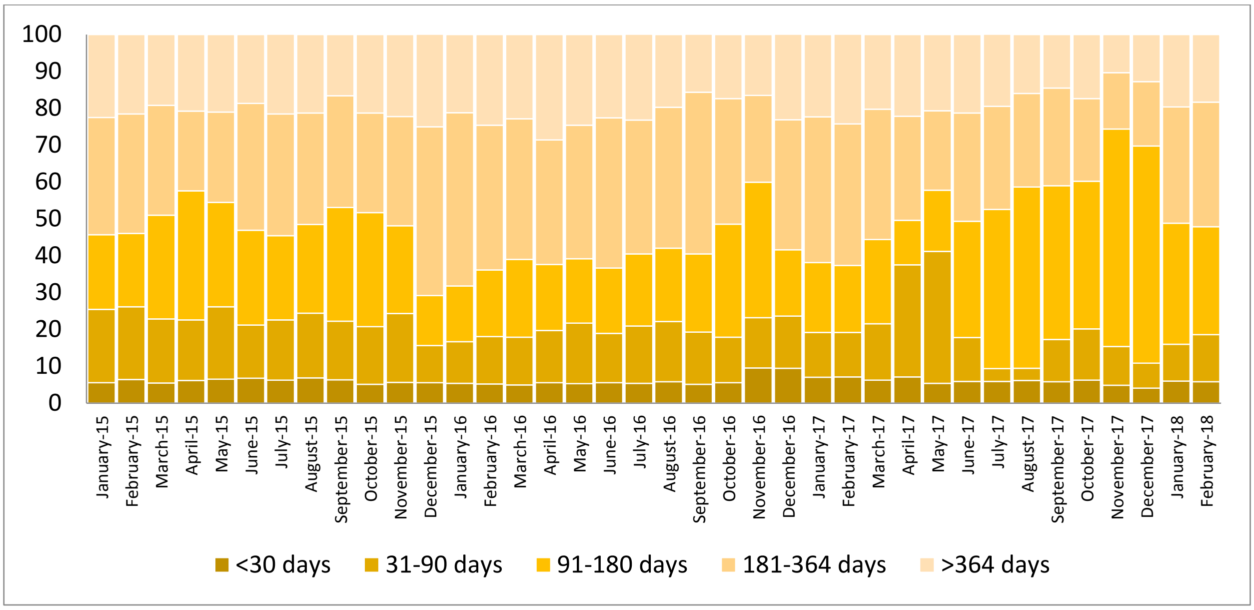


Source of data: CBR

During the quarters under consideration the retail deposit market observed an overall decrease of deposit interest rates (see Figure 2). At the beginning of the period the interest rates were 13-14%. However with the less-than-30-day deposits – the category that we do not consider separately in this study – being almost unchanged in price, other deposits gain not more than several percentage points profitable by 2018. In this market even a 0.5 p.p. increase in the rate may attract additional funds.

Over the same period the preferences for short-term and the longest-term deposits did not change dramatically (see Figure 3). However the last months of 2017 witness the gradual contraction of the share of deposits with a maturity of 181-364 days in favor of those with a maturity of less than half a year. This could signal that depositors are becoming more cautious about long-term investments observing frequent bank license withdrawals and an unstable overall economic situation.

Figure 3. Personal deposit maturity structure, 2015-2018



Source of data: CBR

IV. Results

The results for the first step of estimations suggest that there is no relationship between deposit interest rate overstatement and the probability of bank default, if short-term or medium-term deposits are considered (see Table A. 1 First step results, first and second deposit types (AME)in the Appendix). The overstatement strategy gains benefits when the attracted funds allow some time for a bank to recover, so quite naturally the banks prefer to collect longer-term deposits. Table. 3 shows the average marginal effects for the probit regressions with data on deposits over 6 months, separating them from those with a maturity less than one year, and the those for a year and more. We provide evidence that assigning too high interest rates – putting the interest rate above the market average – significantly increases the probability of license withdrawal after three quarters. For those banks the probability of default is 46 p.p. higher than for those who did not pursue this strategy. Half a year before bank default the interest rates become higher for the deposits over one year. As the extended maturity is an additional benefit for the depositors, banks which are even closer to bankruptcy, combine longer maturities with higher interest rates to attract deposits even more intensively. For deposits over 1 year, both types of overstatement signal license withdrawal: the probability is 77 p.p. higher for banks offering interest rates higher than the average market rate, and 43 p.p. higher for those offering the highest rates.

Table. 4 shows the relationship between bank default probability and the size of deposit interest rate overstatement for deposits over half a year (Table A. 2 in Appendix confirms that there is no statistically significant influence for other deposits). Both specifications II and IV for deposits for 181-365 days suggest that moving further from the average interest rate signals a higher probability of license withdrawal in three months. A 1 p.p. increase over the average interest rate results in a 26 p.p. higher probability of default, but if a bank goes beyond the average overstatement over the average rate, an additional 1 p.p. increase signals an additional 62 p.p. of default probability. Both results are economically significant as both overstatement levels are quite low – 1.14 and 0.66 p.p. respectively.

As for the most long-term deposits, specification I shows that the size of deposit rate overstatement half a year prior to bankruptcy has a significantly large effect as well: if a bank offers a rate 1 p.p. higher than the average deposit interest rates, this signals a 34 p.p. higher probability of license withdrawal. This effect does not change for particularly high interest rates.

The control variables are also significant and are in line with the literature; the effects are quite stable across the specifications. The probability of bank license withdrawal is higher for banks with low capital adequacy ratio (H1): a 1 p.p. increase results in a 1.6–2.4 p.p. lower probability. The same is true for bank size: larger banks in terms of assets are more stable. This also may reflect the hypothesis of "too big to fail": the bankruptcy of large banks is unlikely due to implicit government support. Higher profitability – as predicted – increases bank stability as well: a 1p.p. higher ROA results in a 12–35 p.p. lower probability of default, which is economically important as is an average ROA lower than 1 percent. The effects which do not appear in both steps include those related to investment in non-government securities and loan portfolio size. Nevertheless our results suggest that a lower expansion into the credit market (the first step) and a lower share of non-government securities in the bank assets (the second step) increase bank stability, protecting it from bankruptcy in the following quarter. The effect for liquidity is surprisingly negative for bank stability, but it is unstable and its size is negligible.

Table. 3 First step results, long-term deposits (AME)

Variables	181-365 days				More than 365 days			
	(I)	*(II)*	*(III)*	*(IV)*	*(I)*	*(II)*	*(III)*	*(IV)*
$DO_{1,t-2}$	0.1015				0.7737**			
	(0.2361)				(0.3528)			
$DO_{1,t-3}$		0.4079				0.3010		
		(0.2642)				(0.2846)		
$DO_{2,t-2}$			0.0260				0.4313*	
			(0.2330)				(0.2275)	
$DO_{2,t-3}$				0.4599**				0.3228
				(0.2264)				(0.2376)
$H1_{t-1}$	-0.0163*	-0.0162	-0.0169*	-0.0174*	-0.0193	-0.0172	-0.0239**	-0.0184*
	(0.0093)	(0.0102)	(0.0092)	(0.0101)	(0.0125)	(0.0111)	(0.0122)	(0.0107)
PZS/KE_{t-1}	-1.8214	-1.6973	-1.8442	-1.5737	1.0541	0.1219	0.7626	0.0874
	(1.9537)	(1.9882)	(1.9392)	(1.9761)	(1.2770)	(1.4726)	(1.2665)	(1.4555)
KE/CA_{t-1}	1.0471	1.2513*	1.0161	1.1373	1.6837**	1.0678	1.3397*	0.9954
	(0.6589)	(0.7262)	(0.6502)	(0.6997)	(0.8396)	(0.7684)	(0.7760)	(0.7575)
$Ln(CA)_{t-1}$	-0.3035***	-0.3216***	-0.2946***	-0.3161***	-0.2677**	-0.2873***	-0.2473**	-0.2878**
	(0.1131)	(0.1150)	(0.1104)	(0.1157)	(0.1042)	(0.1096)	(0.1030)	(0.1119)
CP/CA_{t-1}	-11.9238***	-13.7291***	-11.8822***	-13.0867***	-15.2358***	-14.0201***	-14.1643***	-14.1887***
	(3.7950)	(3.8366)	(3.7807)	(3.8168)	(4.1182)	(4.0561)	(3.9548)	(4.0163)
$H3_{t-1}$	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
NCB/CA_{t-1}	0.9400	1.1526	0.9488	1.1906	1.2359	1.6932	0.9881	1.5760
	(1.2512)	(1.2812)	(1.2486)	(1.2916)	(1.4402)	(1.3410)	(1.4099)	(1.3602)
Time fixed effects	+	+	+	+	+	+	+	+
Constant	3.9050	4.0205	5.9007	6.4303*	2.3813	2.5911	2.3284	2.6655
	(2.8030)	(2.4983)	(6.8225)	(3.8184)	(1.8800)	(1.9114)	(1.8625)	(1.9315)
Observations	857	828	857	828	1,132	814	1,132	814
$\chi 2$	29.44	37.94	29.27	39.55	44.97	31.32	42.56	31.99
p-value	0.00194	0.0000802	0.00206	0.0000428	0.0000104	0.000981	0.0000268	0.000765

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Table. 4 Second step results, long-term deposits (AME)

Variables	181-365 days				More than 365 days			
	(I)	*(II)*	*(III)*	*(IV)*	*(I)*	*(II)*	*(III)*	*(IV)*
$OMIR_{t-2}$	-0.0431				0.3439**			
	(0.2102)				(0.1748)			
$OMIR_{t-3}$		0.2643*				0.2034		
		(0.1410)				(0.1880)		
$OOMIR_{t-2}$			-1.1921				0.3814	
			(0.8327)				(0.3077)	
$OOMIR_{t-3}$				0.6181**				0.0484
				(0.2974)				(0.4244)
$H1_{t-1}$	-0.0207	-0.0257	-0.0081	-0.0314	-0.0142	-0.0733**	0.0058	-0.0381
	(0.0159)	(0.0167)	(0.0284)	(0.0217)	(0.0146)	(0.0314)	(0.0167)	(0.0383)
PZS/KE_{t-1}	-1.4763	-0.4908	-0.8626	3.2295	1.1776	1.3578	0.4619	0.1551
	(2.7076)	(2.2908)	(3.3416)	(2.7874)	(1.4493)	(1.9999)	(2.2652)	(2.6616)
KE/CA_{t-1}	0.3322	-0.3252	-0.1248	0.5413	1.1011	0.6450	1.4276	3.0759*
	(0.9310)	(0.9550)	(2.6240)	(1.3832)	(0.9521)	(1.1547)	(1.2564)	(1.7090)
$Ln(CA)_{t-1}$	-0.3928**	-0.3637**	-0.5968	-0.6013**	-0.2697**	-0.4309***	-0.1843	-0.3273
	(0.1645)	(0.1454)	(0.4144)	(0.2433)	(0.1212)	(0.1597)	(0.1509)	(0.2022)
CP/CA_{t-1}	-14.5145**	-15.6077***	-28.7154***	-18.8266***	-24.1566***	-25.9670***	-35.9035***	-32.9991***
	(6.1095)	(5.6287)	(10.9593)	(6.7597)	(6.1822)	(6.5165)	(8.8261)	(9.6925)
$H3_{t-1}$	0.0012*	0.0015*	0.0097***	0.0046**	0.0000	0.0001	0.0021	-0.0006
	(0.0007)	(0.0008)	(0.0031)	(0.0018)	(0.0002)	(0.0015)	(0.0014)	(0.0025)
NCB/CA_{t-1}	-0.8278	-0.6663	-1.8897	0.7984	0.7633	2.3332	0.4269	6.2008**
	(1.8972)	(1.8867)	(5.0974)	(2.7044)	(1.5303)	(1.8745)	(1.9394)	(2.6866)
Time fixed effects	+	+	+	+	+	+	+	+
Constant	3.9050	4.0205	5.9007	6.4303*	0.4453	4.9322*	-1.1282	1.6093
	(2.8030)	(2.4983)	(6.8225)	(3.8184)	(2.1204)	(2.7777)	(2.5919)	(3.5671)
Observations	516	491	197	230	669	485	348	244
χ2	22.86	31.21	27.71	28.52	41.87	41.20	36.86	30.88
p-value	0.0185	0.00102	0.00201	0.00270	0.000035	0.0000222	0.000236	0.00115

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

As mentioned above for the robustness check we changed a number of the control variables in our estimations for simpler ones. Instead of capital over risk-weighted assets we use the capital over total assets. The share of non-performing loans is replaced by the loan loss provisions over the loan portfolio. The share of liquid assets in total assets appears in the place of the liquidity ratio designed by CBR. The results for both steps of estimations are presented in Table A. 3 and Table A. 4 respectively[8]. The only result which is not stable is the signal provided by extremely high interest rates for the deposits with the longest maturity 2 quarters before the license withdrawal. All the other effects remain unchanged: higher than average and extremely high deposit interest rates for deposits for 180-365 days signal financial problems 3 quarters in advance, higher than average interest rates for the deposits over a year are a sign of bankruptcy half a year before the event. The size of all the effects is still both statistically and economically significant.

V. Conclusion

The market discipline hypothesis implies that if disciplining by price is in force, riskier banks have to offer higher deposit interest rates. On the other hand, the deposit interest rate can itself be the signal of excessive risk-taking by the bank. As suggested in (Karas et al. 2009) depositors may treat higher interest rates as an attribute of a too risky bank. This becomes even more pronounced when a bank is close to bankruptcy. In attempt to attract additional funds even at a high price – to ensure survival in the absence of other funding sources – it can offer very high deposit interest rates especially for long-term deposits, to gain depositors interested in long-term profitability but – as most retail depositors are – not very sophisticated to estimate correctly the probability of bank license withdrawal. In this paper we provide evidence for this overstatement strategy as a clear signal of bank default in less than a year.

Using unique data on Russian bank deposit interest rates for deposits of different maturities for the period of 2015–2016, we show that overstatement of deposit interest rates has a statistically significant positive effect on the probability of bank failure, but only for deposits over half a year. The results suggest that if a bank offers too generous interest rates for deposits for 180-365 days this can be a signal of a significantly higher probability of license withdrawal in 3 quarters. The highest is the effect for those banks which not only go beyond the market average rate, but also exceed the average overstatement. In their attempt to urgently attract funds when moving closer to default the banks offer the highest rates for the longest-term deposits,

[8] The results for short-term and middle-term deposits are available upon request. In main model estimation, they do not provide any significant effects

with maturities over one year. The interest rates higher than the market average dramatically increase the probability of a bank failure in 2 quarters.

These results provide a simple rationale for both depositors and regulators. For the former they clearly suggest taking into account the overall financial position of a bank before rushing into an extremely lucrative deposit offers in attempt to invest savings safely, profitably and for a long period of time. The regulators tracing the pricing policy of banks in the retail deposit market should go beyond the interest rate ceilings based on the rates of top-10 banks. Assigning the rates above average could be a signal for special attention and even special treatment from the regulators as those banks may accumulate high volumes of deposits before default, resulting in the need to compensate using the deposit insurance agency which relies ultimately on the taxpayer.

References

Головань, С.А., А.М. Евдокимов, А.М. Карминский, А.А. Пересецкий. 2004. “Модели вероятности дефолта российских банков II. Влияние макроэкономических факторов на устойчивость банков.” WP#2004/043. Препринты РЭШ. Москва.

Дробышевский, С.М., А.В. Зубарев. 2011. “Факторы устойчивости российских банков в 2007-2009 годах.” Научные труды Института экономической политики имени Е.Т. Гайдара. №155Р

Емельянов, А.М., О.О. Брюхова. 2013. “Оценка вероятности банкротства банка.” *Финансы и кредит* 27 (555): 47–59.

———. 2015. “Исследование причин отзыва лицензий у российских коммерческих банков в посткризисный период (2010-2011).” *Экономика и математические методы* 51 (3): 41–53.

Иванов, В.В., Ю.И. Федорова. 2015. “Результаты моделирования вероятности наступления дефолта банка на примере российской банковской системы.” *Экономика и современный менеджмент: теория и практика* 50: 6–20.

Карминский, А.М., А.В. Костров, Т.Н. Мурзенков. 2012. “Вероятность дефолта банка и ее моделирование.” *Финансовая аналитика: проблемы и решения* 41 (131): 2–13.

Пересецкий, А.А. 2013. “Модели причин отзыва лицензий российских банков. Влияние неучтенных факторов.” *Прикладная эконометрика* 30 (2): 49–54.

Пересецкий, А.А. 2007a. “Методы оценки вероятности дефолта банка.” *Экономика и математические методы* 3: 37–62.

———. 2007b. “Процентные ставки российских банков. Рыночная дисциплина и страхование депозитов.” *Экономика и математические методы* 43 (1): 3–15.

Пересецкий, А. А. 2008. “Рыночная дисциплина и страхование депозитов.” *Прикладная* *эконометрика* 3 (11): 3–14.

Cook, Douglas O., and Lewis J Spellman. 1994. “Repudiation Risk and Restitution Costs: Toward Understanding Premiums on Insured Deposits.” *Journal of Money, Credit and Banking* 26 (3): 439. doi:10.2307/2078011.

Ellis, David M., and Mark J. Flannery. 1992. “Does the Debt Market Assess Large Banks, Risk?. Time Series Evidence from Money Center CDs.” *Journal of Monetary Economics* 30 (3): 481–502. doi:10.1016/0304-3932(92)90008-P.

Hannan, Timothy H, and Gerald A Hanweck. 1988. “Bank Insolvency Risk and the Market for Large Certificates of Deposit.” *Source Journal of Money, Credit and Banking* 20 (2): 203–11.

Hellmann, Thomas F., Kevin C. Murdock, and Joseph E. Stiglitz. 2000. “Liberalization, Moral Hazard in Banking, and Prudential Regulation: Are Capital Requirements Enough?” *American Economic Review* 90 (1): 147–65. doi:10.2139/ssrn.92288.

Hwang, Dar Yeh, Chengfew F. Lee, and K. Thomas Liaw. 1997. “Forecasting Bank Failures and Deposit Insurance Premium.” *International Review of Economics and Finance* 6 (3): 317–34. doi:10.1016/S1059-0560(97)90041-1.

Karas, Alexei, William Pyle, and Koen Schoors. 2013. “Deposit Insurance, Banking Crises, and Market Discipline: Evidence from a Natural Experiment on Deposit Flows and Rates.” *Journal of Money, Credit and Banking* 45 (1): 179–200. doi:10.1111/j.1538-4616.2012.00566.x.

Karas, Alexei, William Pyle, Koen Schoors, William Pyley, and Koen Schoorsz. 2009. “How Do Russian Depositors Discipline Their Banks? Evidence of a Backward Bending Deposit Supply Function.” *Oxford Economic Papers* 62 (1): 36–61. doi:10.1093/oep/gpp006.

Klieštik, Tomáš, Katarína Kočišová, and Mária Mišanková. 2015. “Logit and Probit Model Used for Prediction of Financial Health of Company.” *Procedia Economics and Finance* 23: 850–55. doi:10.1016/S2212-5671(15)00485-2.

Kolari, James, Dennis Glennon, Hwan Shin, and Michele Caputo. 2002. “Predicting Large US Commercial Bank Failures.” *Journal of Economics and Business* 54 (4): 361–87. doi:10.1016/S0148-6195(02)00089-9.

Landskroner, Yoram, and Jacob Paroush. 2008. “Bank Management and Market Discipline.” *Journal of Economics and Business* 60 (5): 395–414. doi:10.1016/j.jeconbus.2007.06.001.

Lanine, Gleb, and Rudi Vander Vennet. 2006. “Failure Prediction in the Russian Bank Sector with Logit and Trait Recognition Models.” *Expert Systems with Applications*. doi:10.1016/j.eswa.2005.10.014.

Lin, Ching Chung, and Shou Lin Yang. 2016. “Bank Fundamentals, Economic Conditions, and Bank Failures in East Asian Countries.” *Economic Modelling* 52: 960–66. doi:10.1016/j.econmod.2015.10.035.

Martin, Daniel. 1977. “Early Warning of Bank Failure. A Logit Regression Approach.” *Journal* *of Banking and Finance* 1 (3): 249–76. doi:10.1016/0378-4266(77)90022-X.

Martinez, Maria Soledad, Sergio L. Schmukler, Maria Soledad Martinez Peria, Sergio L. Schmukler, Maria Soledad Martinez, Sergio L. Schmukler, Maria Soledad Martinez Peria, and Sergio L. Schmukler. 2001. "Do Depositors Punish Banks for Bad Behavior? Market Discipline, Deposit Insurance, and Banking Crises." *Journal of Finance* 56 (3): 1029–51. doi:10.1111/0022-1082.00354.

Meyer, Paul A., and Howard W. Pifer. 1970. "Prediction of Bank Failures." *The Journal of Finance* 25 (4): 853–68. doi:10.1111/j.1540-6261.1970.tb00558.x.

Nier, Erlend, and Ursel Baumann. 2006. "Market Discipline, Disclosure and Moral Hazard in Banking." *Journal of Financial Intermediation* 1295 (3): 332–61.

Park, Sangkyun, and Stavros Peristiani. 1998. "Market Discipline by Thrift Depositors." *Journal of Money, Credit and Banking* 30 (3): 347–64. doi:10.2307/2601105.

Semenova, Maria. 2007. "How Depositors Discipline Banks: The Case of Russia." *EERC Working Paper*, EERC Working Papers, 07/02.

Shen, Chung-Hua, and Meng-Fen Hsieh. 2011. "Prediction of Bank Failures Using Combined Micro and Macro Data." *International Review of Accounting, Banking & Finance* 3 (2): 1–40.

Ungan, Ece, Selçuk Caner, S Özyıldırım, Süheyla ÖzyIldIrIm, S Özyıldırım, and Süheyla ÖzyIldIrIm. 2008. "Depositors' Assessment of Bank Riskiness in the Russian Federation." *Journal of Financial Services Research* 33 (2): 77–100. doi:10.1007/s10693-007-0025-0.

Wang, Yi-Shu, Xue Jiang, and Zhen-Jia-Liu. 2016. "Bank Failure Prediction Models for the Developing and Developed Countries: Identifying the Economic Value Added for Predicting Failure." *Asian Economic and Financial Review* 6 (9): 522–33. doi:10.18488/journal.aefr/2016.6.9/102.9.522.533.

Zhen, J.-L. 2015. "Cross-Country Study on the Determinants of Bank Financial Distress." *RAE Revista de Administracao de Empresas* 55 (5): 593–603. doi:10.1590/S0034-759020150510.

Corresponding author
Maria Semenova **-** msemenova@hse.ru, Senior Research Fellow, Associate Professor, Center for Institutional Studies and Department of Finance, National Research University Higher School of Economics, Moscow, Russia

APPENDIX

Table A. 1 First step results, first and second deposit types (AME)

Variables	Less than 90 days				91-180 days			
	(I)	*(II)*	*(III)*	*(IV)*	*(I)*	*(II)*	*(III)*	*(IV)*
$DO_{1,t-2}$	0.1112				-0.0106			
	(0.2160)				(0.2015)			
$DO_{1,t-3}$		-0.0898				0.2297		
		(0.2356)				(0.2219)		
$DO_{2,t-2}$			0.0056				0.0402	
			(0.2446)				(0.2044)	
$DO_{2,t-3}$				-0.1447				0.3011
				(0.2698)				(0.2129)
$H1_{t-1}$	-0.0326**	-0.0369**	-0.0333***	-0.0372**	-0.0352***	-0.0366***	-0.0346***	-0.0366***
	(0.0128)	(0.0144)	(0.0128)	(0.0145)	(0.0122)	(0.0129)	(0.0121)	(0.0128)
PZS/KE_{t-1}	0.8958	0.3306	0.8299	0.3726	0.1506	1.0949	0.1655	1.1373
	(1.1305)	(1.4574)	(1.1252)	(1.4571)	(1.3715)	(1.3588)	(1.3713)	(1.3442)
KE/CA_{t-1}	1.7067**	2.1399***	1.6698**	2.1528***	1.9107***	2.3064***	1.9314***	2.2952***
	(0.7230)	(0.8146)	(0.7140)	(0.8104)	(0.7208)	(0.7809)	(0.7239)	(0.7761)
$Ln(CA)_{t-1}$	-0.2185**	-0.2165**	-0.2050**	-0.2228**	-0.2564***	-0.3652***	-0.2575***	-0.3515***
	(0.0883)	(0.0962)	(0.0846)	(0.0930)	(0.0864)	(0.1047)	(0.0852)	(0.1021)
CP/CA_{t-1}	4.7555	3.8689	4.6002	3.9847	-4.9625	-1.0381	-4.9326	-0.9356
	(3.7094)	(4.1135)	(3.6921)	(4.1257)	(3.7920)	(3.4683)	(3.7735)	(3.4628)
$H3_{t-1}$	-0.0010	-0.0009	-0.0010	-0.0009	-0.0004	-0.0000	-0.0004	-0.0000
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0007)	(0.0002)	(0.0007)	(0.0002)
NCB/CA_{t-1}	2.2179**	2.6719**	2.2243**	2.6749**	2.7240**	2.7345**	2.7424**	2.7279**
	(1.0991)	(1.2237)	(1.0989)	(1.2248)	(1.1477)	(1.2665)	(1.1511)	(1.2647)
Time fixed effects	+	+	+	+	+	+	+	+
Constant	0.4016	0.9861	0.2867	1.0737	0.9646	3.0735*	0.9313	2.8972*
	(1.4936)	(1.6109)	(1.4705)	(1.5997)	(1.4865)	(1.7571)	(1.4982)	(1.7457)
Observations	1,524	1,104	1,524	1,104	1,305	930	1,305	930
$\chi 2$	32.69	29.78	32.42	29.93	41.62	37.80	41.66	38.67
p-value	0.00108	0.00171	0.00119	0.00162	0.0000386	0.0000845	0.0000381	0.0000602

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Table A. 2 Second step results, first and second deposit types (AME)

Variables	Less than 90 days				91-180 days			
	(I)	*(II)*	*(III)*	*(IV)*	*(I)*	*(II)*	*(III)*	*(IV)*
$OMIR_{t-2}$	-0.1151				0.1853			
	(0.1501)				(0.1560)			
$OMIR_{t-3}$		-0.1280				0.0039		
		(0.1789)				(0.1430)		
$OOMIR_{t-2}$			0.4635				0.3708	
			(0.4016)				(0.2848)	
$OOMIR_{t-3}$				-0.1212				0.3835
				(0.4735)				(0.3355)
$H1_{t-1}$	-0.1494**	-0.0959	-0.1869	-0.1282	-0.1146***	-0.0923***	-0.2068***	-0.1099**
	(0.0762)	(0.0607)	(0.1320)	(0.1182)	(0.0408)	(0.0337)	(0.0801)	(0.0456)
PZS/KE_{t-1}	0.5168	1.4801	-1.7390	-0.3473	-0.2673	2.6985*	-2.7383	3.2310
	(2.7151)	(2.4349)	(3.9515)	(3.0857)	(2.4556)	(1.6404)	(4.2043)	(2.2877)
KE/CA_{t-1}	1.2738	1.1746	2.6831	0.3273	3.4933**	1.6600	2.8350	3.0741
	(1.5085)	(1.7016)	(2.5644)	(2.2227)	(1.4361)	(1.2430)	(1.9491)	(2.0060)
$Ln(CA)_{t-1}$	-0.1828	-0.1925	-0.2491	-0.3793	-0.3357***	-0.4826***	-0.5762**	-0.7187***
	(0.1268)	(0.1418)	(0.2346)	(0.3058)	(0.1280)	(0.1557)	(0.2726)	(0.2730)
CP/CA_{t-1}	-5.6271	-13.1756	-6.3761	-0.7215	-12.9143**	-11.5197*	-26.0432	-22.2393**
	(14.0359)	(13.6843)	(18.5679)	(21.2954)	(5.7808)	(6.3080)	(16.0759)	(11.0152)
$H3_{t-1}$	-0.0017	-0.0019	0.0032	0.0029	0.0000	0.0003	0.0026	-0.0001
	(0.0022)	(0.0025)	(0.0036)	(0.0041)	(0.0012)	(0.0011)	(0.0034)	(0.0019)
NCB/CA_{t-1}	-0.6035	-0.0266	-0.8524	-2.5433	3.8439*	1.4555	0.5524	6.1888*
	(2.6742)	(2.8690)	(4.9308)	(4.8716)	(2.0185)	(2.0064)	(3.2036)	(3.3243)
Time fixed effects	+	+	+	+	+	+	+	+
Constant	2.5737	2.2258	1.4365	5.5744	1.8809	6.2507**	7.4850	8.3225*
	(2.6223)	(2.8170)	(4.7315)	(5.6845)	(2.4483)	(2.8987)	(4.7854)	(4.7537)
Observations	561	420	186	114	680	500	282	242
$\chi2$	15.77	11.16	9.035	4.773	37.42	33.44	22.39	29.89
p-value	0.202	0.430	0.529	0.854	0.000191	0.000447	0.0215	0.00165

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Table A. 3 First step results, long-term deposits, robustness check (AME)

Variables	180-365 days				More than 365 days			
	(I)	*(II)*	*(III)*	*(IV)*	*(I)*	*(II)*	*(III)*	*(IV)*
$DO_{1,t-2}$	-0.0116				0.6523*			
	(0.2420)				(0.3776)			
$DO_{1,t-3}$		0.3099				0.0698		
		(0.2731)				(0.3000)		
$DO_{2,t-2}$			0.0032				0.3685	
			(0.2338)				(0.2384)	
$DO_{2,t-3}$				0.4183*				0.1987
				(0.2260)				(0.2428)
SK/CA_{t-1}	-2.7163**	-3.0375**	-2.7036**	-3.1294**	-2.6361*	-2.6870**	-3.0317**	-2.5839**
	(1.1835)	(1.3405)	(1.1579)	(1.3375)	(1.5054)	(1.2723)	(1.4799)	(1.2323)
LLP/KE_{t-1}	-0.8667	-0.9536	-0.8614	-0.9751	-0.0893	-0.7041	-0.3295	-0.6624
	(0.8295)	(0.9017)	(0.8246)	(0.9082)	(0.9141)	(0.8782)	(0.8885)	(0.8443)
KE/CA_{t-1}	1.4866	2.1321*	1.4906	2.0917*	0.8431	0.2545	0.5792	0.2651
	(0.9987)	(1.0947)	(1.0008)	(1.0935)	(1.0179)	(0.9660)	(0.9733)	(0.9590)
$Ln(CA)_{t-1}$	-0.3531***	-0.3694***	-0.3540***	-0.3663***	-0.3016***	-0.3456***	-0.2948***	-0.3467***
	(0.1151)	(0.1160)	(0.1147)	(0.1170)	(0.1047)	(0.1143)	(0.1054)	(0.1158)
CP/CA_{t-1}	-10.6834***	-12.9266***	-10.6801***	-12.5941***	-13.2517***	-13.3508***	-12.5586***	-13.2684***
	(4.0487)	(4.0918)	(4.0510)	(4.1213)	(4.5241)	(4.5594)	(4.5012)	(4.5223)
LA/CA_{t-1}	-0.0657	0.6114	-0.0629	0.6258	-1.7058	-1.7346*	-1.8383*	-1.6789*
	(1.0243)	(1.0685)	(1.0280)	(1.0831)	(1.0500)	(1.0221)	(1.0392)	(0.9985)
NCB/CA_{t-1}	1.8563	2.2976*	1.8523	2.3804*	0.8116	1.3444	0.6557	1.2823
	(1.2901)	(1.3108)	(1.2871)	(1.3395)	(1.4881)	(1.4048)	(1.4765)	(1.4235)
Time fixed effects	+	+	+	+	+	+	+	+
Constant	3.2269	2.9446	3.2276	2.9591	1.8575	3.9340*	2.3959	3.8838*
	(2.1009)	(2.1296)	(2.1039)	(2.1532)	(2.0591)	(2.0952)	(2.0085)	(2.0727)
Observations	882	852	882	852	1,164	838	1,164	838
$\chi 2$	32.27	41.62	32.27	43.71	48.05	35.96	46.86	36.58
p-value	0.000690	0.0000189	0.000690	0.0000818	0.0000307	0.000172	0.00000492	0.000135

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Table A. 4 Second step results, long-term deposits, robustness check (AME)

Variables	180-365 days				More than 365 days			
	(I)	*(II)*	*(III)*	*(IV)*	*(I)*	*(II)*	*(III)*	*(IV)*
$OMIR_{t-2}$	-0.0648				0.3438*			
	(0.2189)				(0.1812)			
$OMIR_{t-3}$		0.2671*				0.2726		
		(0.1481)				(0.2080)		
$OOMIR_{t-2}$			-0.8208				0.3254	
			(0.5866)				(0.3056)	
$OOMIR_{t-3}$				0.5675**				0.2075
				(0.2845)				(0.4348)
SK/CA_{t-1}	-7.2011**	-7.1594**	-2.8152	-7.1323*	-2.7736	-6.3320**	-1.6697	-2.6688
	(3.0212)	(2.8551)	(4.3138)	(3.9483)	(2.0364)	(2.9774)	(3.0497)	(3.8835)
LLP/KE_{t-1}	0.6534	0.2881	0.7456	1.5883	0.2967	0.0050	-1.2046	1.7451
	(1.4016)	(1.1013)	(2.0661)	(1.7620)	(1.2206)	(1.3249)	(2.1974)	(2.1567)
KE/CA_{t-1}	0.5895	-0.2422	-1.3089	-0.5774	-0.4191	-1.6294	0.3051	0.1120
	(1.4652)	(1.5221)	(2.5384)	(1.9541)	(1.1705)	(1.3777)	(1.5989)	(1.8258)
$Ln(CA)_{t-1}$	-0.5784***	-0.4895***	-0.3819	-0.5897**	-0.3637***	-0.5074***	-0.2214	-0.3955**
	(0.2159)	(0.1705)	(0.2760)	(0.2565)	(0.1298)	(0.1600)	(0.1564)	(0.2001)
CP/CA_{t-1}	-12.9976**	-15.3601***	-18.7378**	-17.1526**	-23.2724***	-26.1316***	-36.6746***	-37.0536***
	(6.4283)	(5.7146)	(9.0589)	(7.4325)	(6.7150)	(7.4553)	(9.6695)	(11.5711)
LA/CA_{t-1}	0.1340	0.0743	0.2769	-0.2919	-2.5560**	-5.4230***	-0.2457	-6.2254**
	(1.4795)	(1.4263)	(2.4741)	(1.9025)	(1.2345)	(1.7418)	(1.6342)	(2.5038)
NCB/CA_{t-1}	-0.2609	-0.2581	-1.5793	0.0720	-0.3397	0.9145	-0.2257	4.0508
	(1.9721)	(1.9375)	(3.5783)	(2.6660)	(1.6705)	(1.8784)	(2.2949)	(2.6497)
Time fixed effects	+	+	+	+	+	+	+	+
Constant	7.4507*	6.7390**	5.3879	8.4336*	3.7024	8.3953***	1.1526	4.9418
	(3.8803)	(3.2629)	(5.4437)	(4.7320)	(2.5432)	(3.0733)	(3.1368)	(3.9420)
Observations	524	499	199	235	675	490	351	246
$\chi2$	27.03	35.76	14.71	27.41	47.51	50.77	35.51	38.10
p-value	0.00454	0.000186	0.143	0.00398	0.00000381	0.000000455	0.000389	0.0000752

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*