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Modeling bank's probability of default in IRB framework

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Looks familiar?

Lucky if not!

БАНК ПУШКИНО

- Bank Pushkino faced bankruptcy on 30 September 2013.
- Over 60 thousand clients with 20 bn. RUR on accounts in Pushkino know this picture.
- My model warned about extremely high default probability of The Bank in June 2013 (3 months before the default event).
- About 10% of the Russian Deposit Insurance Fund was spent to repay deposits.

Structure

- Research background
  - Review of the Russian banking system
  - Brief literature review on the PD model development
  - Default definition
- Data and model
- Empirical model estimation
  - Types of explanatory variables in the model
  - Estimation results
  - Key findings
- Further steps

Research background (1/6)

Review of the Russian banking system

Commercial banking revived in Russia in late1980's. More than 3500 charters of incorporation have been issued by the Central Bank of Russia to date.

Russia ranks third in the number of banks, after the United States and Germany.

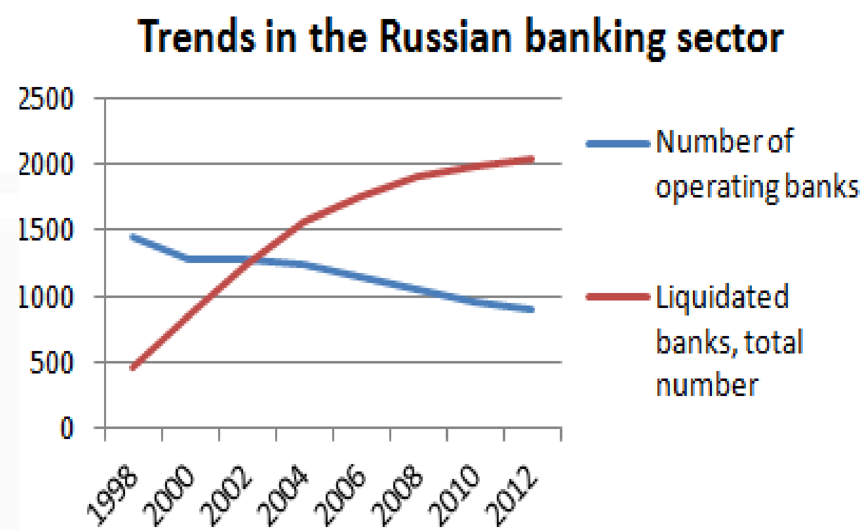
The Russian banking sector has passed through two stages of development with crises bounding them:

<u>Formation: 1989 – 1999</u>

More than 2500 banks were launched by 1995. This stage was characterized by unsystematic development, an excessive number of banks and many regulatory loopholes. Ends with crisis in 1998 – 1999 with massive license revocations.

<u>Quick development: 2000 – 2008</u>

Most of the systematic problems in the Russian banking system were resolved. Rapid growth of quantitative measures of the banking sector led to an upturn of bad debts.



Review of the Russian banking system (2/2)

Sustainable growth: since 2010

Throughout the period a great emphasis has been put on the proportional development of the Russian banking system.

Russia still has 978 credit institutions. Consequently, it is impossible for the Bank of Russia to conduct field inspections regularly. So the Central bank as well as other banking market participants needs remote systems to monitor the performance of commercial banks.

The probability of default model can be applied:

- to predict defaults of banks in advance.
- to identify the group of the most vulnerable banks in the banking sector for proper supervision.
- to improve capital regulations, being sensitive to risk.
- by a commercial bank for assessment of its counterparties and exposures (see IRB approach, Basel agreements).

Research background (3/6)

Brief literature review

The probability of default (PD) is the likelihood of a bank failure over a fixed assessment horizon.

Numerous papers dedicated to the PD model creation studied circumstances associated with recessions in developed countries, not in transition ones. So we considered paper about financial stability and efficiency of banks in developing countries with specific economic environment.

Generally speaking, balance sheet structure of banks provides the most meaningful information to predict their defaults (Peresetsky et al., 2011).

Non-linear relationship between PD and financial characteristics of banks, such as capitalization is possible.

The inclusion of macroeconomic factors improves the PD model performance (Karminsky et. all., 2005), (Mannasoo & Mayes, 2009).

The similar pattern is evident for institutional factor, such as ownership type (Fungacova & Solanko, 2009), competition (Fungacova & Weill, 2009) and others.

Research background (4/6)

Brief literature review

“Too big to fail hypothesis”: larger banks are more stable because they will be saved by the public authorities in case of a crisis. Also big banks have better diversified assets and liabilities. On the other side, they could demonstrate excessive love to risk.

In emerging markets bank size matters (Chernykh & Theodossiou, 2011), (Claeys & Schoors, 2007).

Bank size is a significant predictor of bank performance in Russia (Fungacova & Weill, 2009).

“Bank PD depends on the state of the economic cycle”. Upturn is characterized by high GDP growth rates, strong currency and low inflation.

Macroeconomic environment does not influence PD of any particular bank. (Cole, 2009).

In upturn there are less defaults in the banking sector (Cebula, 2011).

Research background (5/6)

Brief literature review

“Ownership type matters for bank performance”.

In line with Clarke et al., 2005 state-run banks have higher default probability:

- an agency problem is inevitable in the case of governmental bank management.

- politicians often interfere with internal procedures of such banks to influence the economy in a desirable way, particularly before elections.

- state banks are artificially protected from pure competition.

Micco et al. (2007) claims that state banks hire excess employees, carry vast administrative expenses, and are less profitable than the others.

At the save time state-run banks often enjoy unlimited support from the government and access to the interbank market.

(Bhaumik & Piesse, 2007): foreign banks work with credit clients of higher quality than local banks.

Research background (6/6)

Default definition

There is no common opinion in literature what default is. In our research, the sygnals to register default are

- a bank's capital sufficiency level falls below 2%.
- the value of bank's internal resources drops lower than the minimum established at the date of registration.
- a bank fails to reconcile the size of the charter capital and the amount of internal resources.
- a bank is unable to satisfy creditors' claims and make compulsory payments.
- a bank is subject to sanitation by the Deposit Insurance Agency or another bank.

So, the aim of this research is to propose an adequate forward-looking model, which rests on the relationship between banks’ default rates and public information.

Data and model (1/4)

Sources of bank-specific financial statistics: balance sheet, profit and loss statements:

- «Banks and Finance», Mobile information agency.
  - High coverage of the Russian banking sector since 1990s.
  - Monthly data.
  - Highly unbalanced, a lot of musings.

- BankScope, Bureau van Dijk information agency.
  - High coverage of the Russian banking sector since 2000s.
  - Annual data.

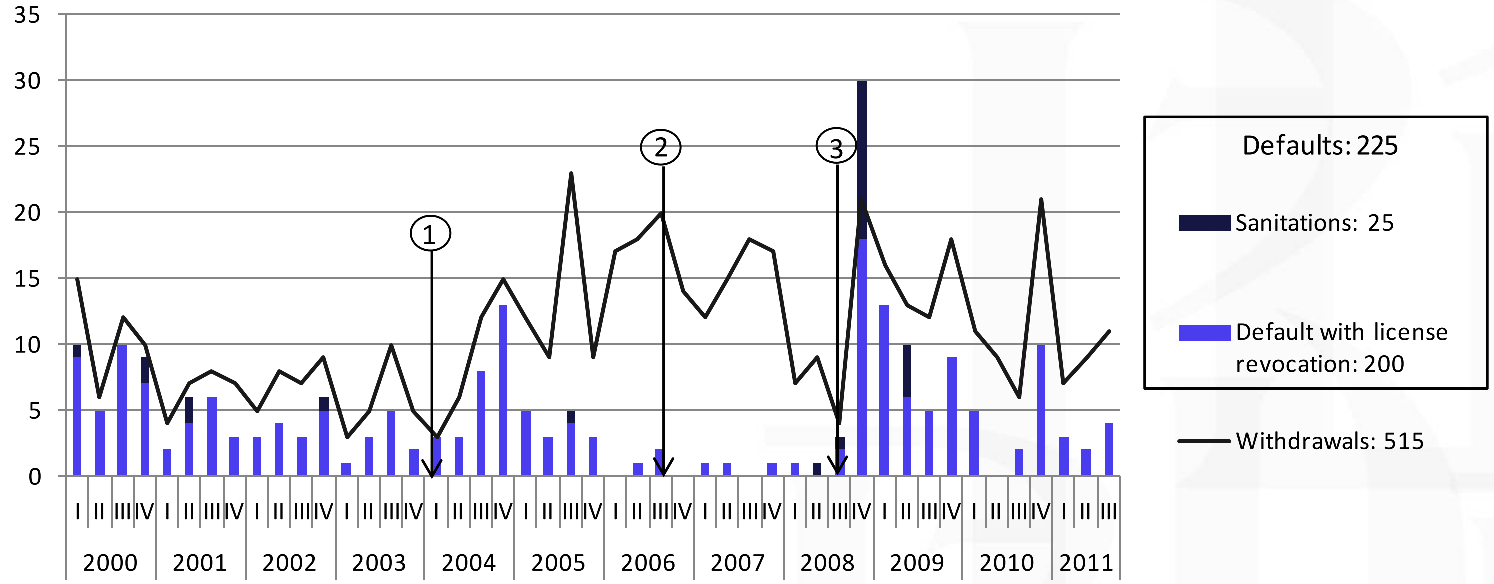
- Spark, Interfax information agency
  - Medium coverage of the Russian banking sector since 2000s.
  - Monthly data.

Sources of data on default frequency:

- The Bank of Russia website. Reports on license withdrawals (since June 2005)
- Banki.ru agency, «Recollection book».

Data and model (2/4)

Withdrawals of license and Bank defaults in Russian banking sector: Jan 2000 - Sep 2011



1: Jan 2004, Deposit insurance system was launched in Russia.
2: Sep 2006, Andrey Kozlov, chairman of The Bank of Russia, was murdered.
3: Sep-Oct 2008, World Economic Crisis of 2008 – 2009 began.

Data and model (3/4)

We constructed the quarterly bank-specific financial database on the basis of Mobile's information from 1998 to 2011: data in accordance with Russian Financial Reporting Standards, taken from bank Balance sheets and Profit & Loss statements.

A typical observation from the database

Bank's license number_period	Bank performance	A set of explanatory variables with lag				
				Variable names		
507_1/4/2005	default (1) or alive (0)			values		

Problems with data revealed and solved:

1. The database is highly unbalanced.
2. Raw bank-specific statistics in Mobile's base contains missing values, outliers and measurement errors.
3. No information about structure of Russian banks' ownership.

Over the considered 14-year period there were 467 defaults in compliance with our definition as well as 37 bank sanitations.

Data and model (4/4)

Types of default probability models:

1. Traditional approaches
- Expert systems
- Ratings
- Scoring models (including logit and probit models).

E.g. for logit model: $P(default = 1) = \Lambda\,(x * \beta)$, $\Lambda(x * \beta) = \dfrac{\exp\,(x * \beta)}{1 + \exp\,(x * \beta)}$

$x*\beta$ – linear combination of factors, that influence default probability.

2. Modern approaches
- Rating-based models (take into account bank rating changes).
- Approaches based on corporate bond market data (implied PD).
- Asset-based models: compare market value of assets and equity to estimate default probability.
- Advanced mathematical models (work like black box with bank characteristics as inputs and PD as an output).

Empirical model estimation (1/6)

Types of explanatory variables in the model

Financial ratios

Firstly, we constructed financial ratios which seem to be significant to determine bank's PD as provided by the literature review and a common sense.

Secondly, we tested the separating power of that ratios between classes of bankrupt and healthy banks.

Thirdly, prominent variables were divided into blocks according to CAMELS methodology.

Block	Ratio / Variable	Reason to include
Capital	Capital to Total assets ratio	Financial troubles immediately result in a sharp decline in bank's capital
Assets	Non-performing loans to Total loans to the economy Logarithm of Total assets	Asset quality is a dominant factor of future profits and losses
Management	Turnover on correspondent accounts to Total assets ratio	This variable reflects the level of economic activity in a bank
Earnings	Balance profit to Total assets ratio	Profitability creates the economic value of a bank
Liquidity Sensitivity	Non-government securities to Total assets ratio	This variable reflects vulnerability of business to market risks

Empirical model estimation (2/6)

Types of explanatory variables in the model

Financial ratios

We have also employed nonlinearities in our model and found the optimal lag on financial ratios

Macroeconomic environment

Basically, we went through the same steps as for financial ratios, but the macroeconomic variables are highly correlated. That is why only two variables were used in order to account for the effect of macroeconomic environment on bank performance: quarterly GDP growth rates and Consumer price index.

Institutional environment

We controlled for the impact of:

- monopoly power of a bank on the market (with Lerner index);
- its participation in a Deposit insurance system (with dummy variable);
- and territorial location of bank's operational activity (Moscow or regional)

on bank's default probabilities.

Empirical model estimation (3/6)

Estimation results

$$P(default = 1) =$$
$$\Lambda\,(sk\_ca_{lag2}\,;\,(sk\_ca_{lag2})^2; \ln\_ca_{lag2}\,;\,(\ln\_ca_{lag2})^2\,; pzs\_ke_{lag2};\ \ln\_oks\_ca_{lag2};$$
$$bp\_ca_{lag2}; (bp\_ca_{lag2})^2;\ ncb\_ca_{lag2};\ d_{2009};\ d_{q1}; gdp\_gr_{lag2}; cpi_{lag2}; l_{index}; region).$$

sk_ca – Capital to Total assets ratio;
ln_ca – Logarithm of Total assets;
pzs_ke – Non-performing loans to Total loans ratio;
bp_ca – Balance profit to Total assets ratio;
ncb_ca – Non-government securities to Total assets ratio;

cpi – Consumer price index
gdp_qr – quarterly GDP growth rates
d_{q1} – dummy variable on first quarter
d_{2009} – Lerner index2009;
l_{index} – Lerner index
region – dummy variable on Moscow location

Our general findings are:

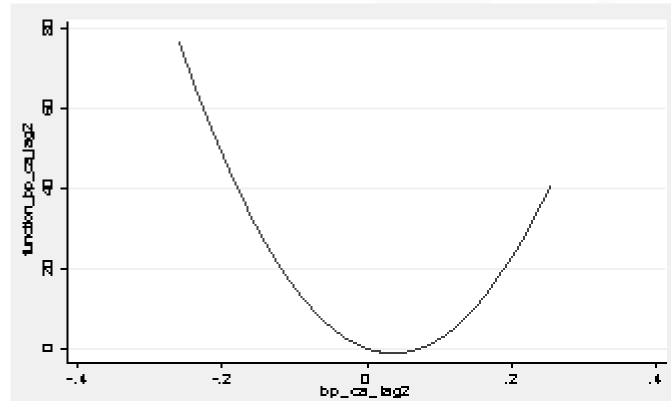
- 2 quarters is an optimal lag size for financial and macroeconomic variables.
- Including squared capital – to – assets and profit – to – asset ratios improved the model quality.
- Bank size is an insignificant factor to determine default probability without nonlinearity.

Empirical model estimation (4/6)

Our key findings

Banks with extremely high and **low profitability** have higher default rates.

Impact of profit – to – assets ratio on default probability:



Reasoning:

- poor banks lack funds to pay the bills.
- banks with really high earnings take excessive risk: at the efficient markets it is impossible to claim to an outstanding profitability without bearing appropriate financial risks.

Banks with a higher **proportion of corporate securities** in assets carry higher risk of a price slump at the market.

Lower Turnover on correspondent accounts in comparison with Total assets increases the probability of default: the ratio indicates a bank's inability to proceed payments and incentives of managers to curtail business.

Empirical model estimation (5/6)

Our key findings

Bank with considerable **amount of bad debts** are less stable.

A **growing consumer price index** increases bank's default probability:

- inflation reduces the real returns on loans.
- depositors are able to withdraw money and put it into the bank again at a higher interest rate or spend it.

Banks with higher **monopoly power** are financially stable.

The **Moscow-based** banks have higher PDs on the average:

- banking market competition is sharper in Moscow.
- the Bank of Russia is reluctant to withdraw licenses out of Moscow region.

We found no evidence that bank **participation in the Deposit insurance system** influence its PD. The explanation is that the set of System participants is too diversified.

Empirical model estimation (6/6)

Our key findings

The out-of-sample prediction performance of the model (for 2010 – 2011) is prominent: over 60% of bank failures were correctly classified with a moderate size of a risk group.

Condition: a bank with PD over x is a candidate to fail	Quarterly average size of a risk group	Number of correctly predicted defaults, of 19. (Proportion)
$x = 10\%$	54	16 (84%)
$x = 20\%$	34	12 (63%)
$x = 30\%$	30	12 (63%)
$x = 40\%$	28	10 (52%)

At the same time, the developed model underestimates default probabilities for the year 2009. This result reveals some unrecorded channels that significantly increased risks in the period of the recent financial crisis

Further Steps

Bank ratings can be mapped into default probabilities.

However, default probabilities offered by rating agencies and our model are significantly different.

Possible reasons:

- Rating agencies have access to confidential information. Non – numeric information is also considered.
- Moral hazard of rating agencies.

The latter issue is very interesting to address in the future.

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Thank you! Questions?

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