What factors drive the Russian banks license withdrawal

Peresetsky, A. A.

National Research University Higher School of Economics, CEMI RAS

2011

What factors drive the Russian banks license withdrawal[1]

Anatoly Peresetsky

National Research University Higher School of Economics;
Central Economics and Mathematics Institute, Russian Academy of Science,
Nakhimovskii prospekt, 47, room 908. Moscow, 117418, Russia.

Abstract

The binary and multinomial logit models are applied for prediction of the Russian banks defaults (license withdrawals) using data from bank balance sheets and macroeconomic indicators. Significantly different models correspond to the two main grounds for license withdrawal: financial insolvency and money laundering. Analysis of data for the period 2005.2–2008.4 for accurate prediction of a bank's financial insolvency, which is the focus of interest for the Russian Deposit Insurance Agency, demonstrates that the multinomial model doesn't outperform the binary model.

Key words: Multinomial logit model, binary logit model, probability of default, Russian banks, money laundering, bank supervision.

JEL: G20, G21, G28, G33, C50, C54.

1. Introduction

A country's banking system plays an important role in that country's economic growth. Financial and banking crises decrease the economic growth and lead to economic stagnation. The main goal of the bank supervision authorities is to support the stable development of the banking system. This goal is especially important in the countries whose economies are in transition, where banks and bank supervisors have only short experience of working under conditions of the market economy.

Necessity for the stable development of the national banking system in Russian Federation was starkly revealed during the financial crisis of 1998, during the "credibility

[1] The author is grateful to the participants of the conferences in Metabief (France), January 2010; Vilnius (Lithuania), June 2010, Minsk (Belarus), September, 2010, EBES, Athens, October 2010 for helpful discussions.

crisis" in summer 2004, and again during the 2008 financial crisis. The number of banks in the Russian Federation which had been higher than 2000 before 1998, dropped from 1136 to 1108 during the year 2008. This number of banks is still too large for the regular on-site supervisory inspections by the Central Bank of the Russian Federation (CB RF), or the Deposit Insurance Agency of the Russian Federation (DIA). Hence there is urgent need for the off-site monitoring of the Russian banking system.

Regular off-site monitoring of banks' financial solvency using on-line analysis of their monthly, quarterly, or yearly balance sheets may allow the filtering out of an "at risk group" of banks whose financial solvency could be questionable in the near future. Of course, such off-site methods (Early Warning Systems, EWS) are not able to determine exactly the financial state of a bank. Nevertheless they can significantly reduce the expenses of banking supervision since a regulator may prioritize inspection of banks from the "at risk group" according to the off-site monitoring system. This would increase efficiency of the bank supervision system and hence, by preventing insolvency of the banks, increase stability of the banking system as a whole.

The subject of this paper concerns one aspect of the design of an efficient off-site system: the question of which are the best econometric tools to use for estimating the probability of the future failure of a bank, and if so, due to which criteria this failure will come about. In particular, two standard models are compared: the binary model and the multinomial model. Both models use only publicly available information on microeconomic factors (banks' balance sheet data) and macroeconomic indicators. The main questions are:

- Which factors drive license withdrawal on grounds of financial insolvency and which on grounds of money laundering?
- For the DIA activity, forecasting the probability of bank license withdrawal on the grounds of financial insolvency is especially important. A bank which loses its license as the penalty for money laundering often has enough money to fulfill its financial obligations, and then the DIA has no extra expenditures related to the bank liquidation. This is why the question of principal practical importance is if it is possible to increase accuracy of the forecast of bank license withdrawal on economic grounds (financial insolvency) using a multinomial model (with 3 possible outcomes) in comparison with a binary logit model.

2. Literature review

There are several approaches to the econometric modeling of a bank's solvency based on the use of publicly available information.

The first approach is to model the probability of a bank default by using historical data on bank defaults. A natural instrument for this is the binary choice model (logit-, probit-model). This approach was applied to bank defaults in the USA in a number of papers (e.g. Kolari, et al., 2002; Cole, et al., 1995a; Collier, et al, 2003), and for Russian banks in (Peresetsky et al., 2004a; 2007, 2011).

A second approach is to use econometric models of the ratings of financial stability assigned to banks by a rating agency. Such a model (ordered logit, probit) absorbs the information from the agency's rating which could be derived from public information. Using this model it is possible to calculate a forecasted "model rating" for each bank. Such model ratings reflect the opinion of a rating agency's experts. For non-financial firms in the USA this approach was realized for example in (Altman, Rijken, 2004), and for Russian banks in (van Soest, et al., 2003, Karminsky, Peresetsky, 2007; Peresetsky, Karminsky, 2008, 2011; Peresetsky, 2009).

A variant of this second approach is based on the use of information from a survey among independent financial experts. This approach was suggested in (Soest et al., 2003, Peresetsky et al., 2004b). The experts were asked to assign ratings to various real (named) banks and to other (unnamed) "virtual banks". They were provided with information consisting of selected indicators from bank balance sheets: real data for the named banks and artificial data for the unnamed banks (the values of the indicators comprising the virtual data were all in approximately the same ranges as those for the real banks). On the survey data one can design econometric models for "real" or "virtual" banks. A possible advantage of this approach is that the models reflect opinions of the experts from various financial structures, while the opinion of experts from a rating agency is in principle more narrowly defined. Moreover since the bank pays the rating agency for the rating, the situation may arise where a rating agency is not inclined to degrade the rating of a particular bank. This problem is widely discussed in the literature (e.g. Partnoy, 1999; Poon, 2003; Roy, 2006) especially after world financial crisis of 2008. A disadvantage is that independent experts do not have access to the internal information of a bank which is available to rating agency experts.

A third approach is based on the analysis of interest rates, for example a bank's interest rates on household deposits. In the presence of market discipline, which is one of the

Basel-II pillars, depositors require high deposit interest rates from banks with risky financial policies. That is, as long as market discipline exists, high interest rates for a bank's household deposits are a signal of excessive risk taking by that bank.

A fourth approach uses estimates of a bank's technical efficiency (or cost efficiency). There is a consensus that a bank's cost efficiency is correlated to that bank's solvency. It is why models for bank cost efficiency also provide information on bank solvency.

A fifth approach is based on the analysis of market information on prices of banks' securities quotations. This approach is very promising since market price accumulates all publicly available information. Unfortunately it still can not be applied to Russian banks since only a few of them issue securities quoted on the stock exchange.

The earliest models designed to forecast probability of a bank (firm, bond) default were based on analysis of financial ratios, calculated from balance sheet data and were offered in the 1960s (e.g. Beaver, 1966). Significant progress was achieved in the late 1960s, when the development of statistical and econometric models for forecasting defaults first started. The first such model appeared in the seminal paper by Altman (1968), where the discriminant analysis model was applied for the classification of firms in two classes: solvent firms and firms having a high probability of default on the basis of the firm's balance sheet data over some previous period of time. Altman proposed the "Z-score" (Altman's Z) — a linear combination of 5 financial indicators, which was enhanced later (Altman et al., 1977) to the ZETA model. Later, discriminant analysis was used for forecasting defaults in (Izan, 1984), (Scott, 1981).

Ten years later Martin (1977) was the first to apply a binary choice logit model to predict defaults of US banks in 1975–1976. That model has some advantages over the linear discriminant analysis model: 1) it doesn't assume a normal distribution for the financial indicators included in the model, and 2) the logit model does predict the probability of default, thus allows for more than only a binary outcome (default / no default). What is more important, it is possible to estimate significance of the indicators, included in the model. Binary choice models (logit, probit) are used to model probabilities of firm and bank defaults in a number of papers, e.g. (Wiginton, 1980), (Ohlson, 1980), (Bovenzi et al., 1983), (Cole, Gunther, 1995b, 1998), (Estrella et al., 2000), (Westgaard, Wijst, 2001), (Kolari et al., 2002), (Altman, Raijken, 2004), (Godlewski, 2007).

In the paper (Hirtle, Lopez, 1999) it was shown that expert opinion (CAMEL rating), in comparison with bank balance sheet data, ceased after about six to twelve quarters to provide any useful information, about the current condition of a bank.

There are few papers comparing the predictive power of discriminant analysis and binary choice models (logit, probit). Lennox (1999), Lin (2009) both come to the conclusion that the logit model outperforms the discriminant analysis model; Altman et al. (1994), Jagtiani et al. (2003) do not find any significant difference in the predictive power of the two models.

Some papers apply various non-statistical approaches to default forecasting: trait recognition model (Kolari et al., 2002), recursive partitioning (Espahbodi, Espahbodi, 2003), neural network analysis (Coats, Fant, 1993), (Jagtiani et al., 2003), (Lin, 2009). However, in papers where these methods were compared with others by applying them to real data (Altman et al., 1994), (Jagtiani et al., 2003), (Lin, 2009) it was demonstrated that the logit model outperforms non-statistical methods in predictive power.

In practice only bank supervising authorities in the two countries USA and Russia use any econometric probability of bank default models.

USA. Supervisory BOPEC ratings were assigned to bank holding companies (BHCs) during the years 1987 to 2004 as a summary of their overall performance and indication of the level of supervisory concern they provoked.[2] Similar ratings were assigned to the banks, by FDIC (Federal Deposit Insurance Corporation) which supervises state-chartered banks that are not members of the Federal Reserve System (Sahajwala, Bergh, 2000). Both supervisors accumulated significant amounts of (confidential) data — internal ratings — as well as results of on-site bank examinations. Researches of both agencies used this data to design econometric models for off-site analysis of banks' solvency and EWS (Early Warning System) (Collier et al., 2003), (Gilbert et al., 2002), (Jagtiani et al., 2003), (Krainer, Lopez, 2002, 2003, 2004, 2008, 2009), (Oshinsky, Olin, 2006), (Sahajwala, Bergh, 2000). The system SEER was designed at Federal Reserve (Gilbert et al., 2002), (Jagtiani et al., 2003), (Krainer, Lopez, 2002), (Sahajwala, Bergh, 2000), an early version of which was named FIMS (Cole et al., 1995a); and the SCOR system was designed in FDIC (Collier et al., 2003), (Oshinsky, Olin, 2006), (Sahajwala, Bergh, 2000). The systems SCOR and SEER are very similar; one essential difference is that SCOR did not take into account previous CAMEL ratings.

[2] Starting in 2005, the Federal Reserve's BHC supervisory rating system was changed from a method of historical analysis of BHC financial conditions to a RFI/C(D) rating system. Each inspected BHC is assigned a "C" composite rating, which is based on an evaluation of its managerial and financial condition as well as the future potential risk of its subsidiary depository institutions (Krainer, Lopez, 2009).

The SCOR system was developed in the late 1990s, as a complement to on-site inspections. The main purpose was to discriminate sound banks having CAMEL ratings of 1 or 2 from those with a rating of 3–5 which are assumed therefore to have some problems (Collier et al., 2003). The accuracy of the SCOR forecasts was measured by the probabilities of Type I and II errors. A Type I error is the failure to detect a downgrade before it occurs, while Type II error is a "false alarm", when the system forecasts a rating downgrade but the bank is found on subsequent examination to be sound. For the SCOR system, the accuracy check benchmark was CAEL, the off-site monitoring system developed at the FDIC during the mid-1980s. CAEL was an expert system that used basic ratios from the Call Reports which rated institutions on a scale of 0.5 to 5.5.

An initial choice of financial indicators for SCOR was made by experts, but the final selection of indicators and their weights was made by statistical analysis of the coefficients in econometric models used. The models were re-estimated quarterly. SCOR models for horizons of 16–18 months were designed. They used 12 financial bank variables as a percentage of assets, and they were based on the ordered choice econometric model. The models forecast probabilities p_i for each grade $i = 1,...,5$ of the rating. The rating forecasts were calculated as the weighted average $\sum_{i=1}^{5} i \cdot p_i$ (Collier et al., 2003).

In comparison with the expert model CAEL, the SCOR model outperformed CAEL at all forecast horizons and SCOR was adopted to replace CAEL. SCOR is not good at discriminating between banks with ratings 1 and 2, because the difference between these grades significantly depends on non-formalized factors (Collier et al., 2003).

The SEER system is similar in spirit to SCOR. It consists of two models which complement each other. First, the ordered choice model, which forecasts the probabilities of the CAMEL rating, second, the binary choice model, which forecasts "default" i.e. downgrading of the CAMEL rating from 1–2 to 3–5 (Gilbert et al., 2002).

Researchers from Federal Reserve and FDIC have been looking at some other directions for future improvements of these models:

Krainer, Lopez (2003, 2004, 2008) study whether market information can improve the predictive power of the models. Unfortunately that question is still open for Russian banks since only a few of them issue securities quoted on the stock exchange.

Oshinsky, Olin (2006) consider a multinomial (unordered multiple choice) model for forecasting the possible future state of a "problem" bank (with CAMEL rating 3–5): recover, merge, remain a problem, fail.

Russia. The Russian State Corporation "Deposit Insurance Agency" (DIA) uses econometrics models for the probability of bank default to estimate the adequacy of the Deposit Insurance Fund. These methods are based on the methodology developed in (Peresetsky et al., 2004a; Peresetsky, 2007, 2009).

Multinomial models. Several recent papers have used the multinomial model in order to predict the probability of one alternative which is the focus of interest. It turned out that the accuracy of the probability of prediction of that alternative is higher than that for the binary choice model. Examples are:

Baslevent et al. (2009) use a multinomial logit model to study which factors define an individual's choice in Turkey in favor of one of the political parties — the Justice and Development Party (Adalet ve Kalkınma Partisi; or AKP). Other alternatives are the Republican People's Party (CHP), the True Path Party (DYP), the Nationalist Action Party (MHP), the Democratic Peoples' Party (DEHAP).

Bussiere and Fratzscher (2006) argue that ignoring differences between the period immediately post-crisis and the stable period decreases the accuracy of the prediction of the probability of financial crisis (post-crisis bias). They suggest a multinomial model which discriminates between three states of the economy: stable, post-crisis, and pre-crisis (which is the focus of interest). Using the sample of 20 emerging markets (including Russia) for the period 1993–2001 they conclude that their model provides a substantial improvement in the ability to forecast financial crises in comparison with the binary choice model.

Correia et al. (2007) analyze the probability that a Portuguese tourist will choose Latin America as a vacation destination; the alternative destinations are Europe, the tropical Atlantic island of Sao Tome, and Guinea-Bissau in West Africa. They compare mixed logit and binary logit models.

Koetter et al. (2007) study the impact of the financial state of banks on the probability of bank mergers. To test whether distressed mergers are different from non-distressed mergers they use a multinomial model with 5 possible outcomes.

Wei et al. (2005) analyze the factors which are important for foreign direct investment (FDI) entry strategy. They focus on a binary choice between wholly owned enterprises (WOEs) and equity joint ventures (EJVs). They argue that classifying FDI into four entry modes (wholly owned enterprise (WOE), equity joint venture (EJV), joint stock company (JSC), and contractual joint venture (CJV)) increases precision of the analysis.

A binary logit model was used in the papers (Peresetsky et al., 2004; Peresetsky, 2007) to model the probability of default for Russian banks. The definition of default was withdrawal of the license from the bank by the Central Bank of Russia (CBR). Cases of mergers were analyzed individually and if a bank was in distress before the merger, the event was interpreted as being a default. This set of papers analyzed Russian banks over the 1996–2004. However during the later period 2005–2008 CBR orders on license withdrawal often gave the reason as "money laundering". This was related to increased control for the banks' financial reports which took place during the time when A.A. Kozlov occupied the position of First Deputy Chairman of the CBR.

3. License withdrawal. Binary choice models vs. multinomial models

3.1. Data

In this paper we use quarterly data for the period 2005.1 to 2008.4 for about 1200 Russian banks. During this period 124 banks had their banking licenses withdrawn. At the end of each quarter the state of a bank was fixed as either "still alive" (variable $live = 1$) or "default" ($live = 0$) if the bank license has been withdrawn in that quarter. If the bank license had been withdrawn the reason indicated in the CBR order was coded as $laundry = 1$ for money laundering; $law\_violation = 1$ for "violation of federal law and cheating in financial report"; $insolvency = 1$ for "financial insolvency and insufficient capital" and $voluntarily = 1$ if the bank ceased activity voluntarily. If several reasons were indicated, the value 1 was assigned to various appropriate dummy variables.

To avoid autocorrelation of observations and to get a balanced data set, the data were thinned out in line with an algorithm suggested in (Peresetsky, 2007). For the banks which lost their licenses at time t the data includes observations of their states at the moments $t,\ t-8,\ t-16,...$ that is backwards, with step-lengths of 8 quarters. For the banks which were sound at the end of 2008, an initial point was chosen at random from the 4 quarters of 2008, and, as for the procedure adopted for defaulted banks, observations at time moments $t,\ t-8,\ t-16,...$ were included into the data.

During the period 2005.1–2008.4 unlike during the earlier period 1996–2004 (Peresetsky, 2007) the CBR decision-making time became shorter. This was partly explained by the fact that a significant number of banking license withdrawals were for "money laundering" (Table 1). For this reason each observation of bank state at time t is attached to the data set together with its balance sheet data at the time $t-4$ (unlike $t-8$ adopted in (Peresetsky, 2007)). Thus, in this paper we study the question: to what extent could the probability of banking license withdrawal one year later on be estimated from current publicly available information?

Table 1. Distribution of grounds for bank license withdrawal during the period 2005.2–2008.4.

	laundry	voluntarily	insolvency	law_violation
laundry	76	0	3	1
voluntarily	0	5	0	0
insolvency	3	0	7	15
law_violation	1	0	15	17
Total	80	5	25	33

Source: CBR http://www.cbr.ru/credit/likvidbase/LikvidBase.aspx

For DIA purposes it is especially important is to be able to predict bank license withdrawal on economic grounds (poor financial state), whether or not "money laundering" is presented as additional grounds. Thus grounds of license withdrawals were aggregated as follows. Variable *reason* = 0, if license was not withdrawn; *reason* = 1, if in the CBR order the reason was indicated as "money laundering" (*laundry* = 1, and *law_violation* = 0, and *insolvency* = 0), but without economic reasons; and *reason* = 2 if any economic reasons were indicated. In this aggregation 5 voluntarily license withdrawals fell into the group *reason* = 2, which might be incorrect, since in some cases of voluntary license withdrawal the financial state of the bank could be solid (for example in the case of a merger between two solid banks).

Dummy variables *laundry1*, *economic*, are indicators of this aggregated reasons: *laundry1* = 1 if *reason* = 1; *economic* = 1 if *reason* = 2; and dummy variable *default* = 1 – *live* is an indicator of any type of license withdrawal.

Figure 1 presents the distribution of license withdrawals over the time period. Note that most of the CBR license withdrawal orders were issued within the period 2005–2006, when CBR orders were signed by the First Deputy Chairman of CBR A.A. Kozlov[3] (killed on September 13, 2006). Later most of these orders were signed by First Deputy Chairman of CBR G.G. Melikiyan.

[3] Since 2002 A.A. Kozlov was responsible for the supervision of banks, Also he supervised admission of banks into the deposit insurance system.

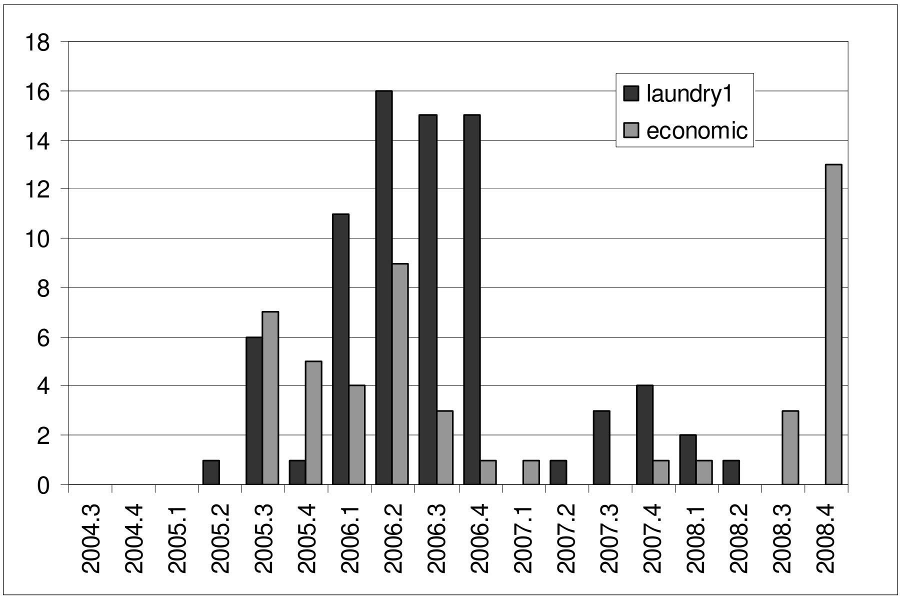

Figure 1. Distribution of Russian bank license withdrawals

Table 2 presents a list of macroeconomic indicators (quarterly data) which we use as a control for a varying macroeconomic environment. Table 3 presents the financial indicators reflecting the risk taken by a bank. All bank financial indicators are expressed in relative units, except for the measure of bank size, expressed as log of assets. A large bank is usually supposed to be more stable (too-big-to-fail) since it has more resources to smooth shocks and has more diversified risks. Five banks are excluded from the data: Sberbank, VTB, Gazprombank, Bank of Moscow, Russian Agricultural Bank, for which in our opinion the probabilities of defaults are negligible since they are likely to have government support in case of trouble.

The values of all indicators — microeconomic and macroeconomic — were taken at the time 4 quarters ahead of observation of the bank state. All data are deflated by the CPI price index (HSE). Table A1 in the Appendix presents the descriptive statistics of the data.

Table 2. Macroeconomic indicators

Notation	Macroeconomic indicator
d4_gdp	GDP growth rate during the last 4 quarters
d4_infl	CPI growth rate during the last 4 quarters
erate	Ruble/US Dollar exchange rate
unempl	Unemployment rate
trade	Export/Import ratio

Table 3. Bank financial indicators

Notation	Bank financial indicator
bpca	Profit / Assets
gdoca	Government securities / Assets
keca	Loans to non-financial firms / Assets
laca	Liquid assets / Assets
mbkca	Interbank loans / Assets
ncbca	Non-government securities / Assets
lnoksca	log (Turnover on correspondents accounts / Assets)
pnaca	Other non-working assets / Assets
reske	Reserves for possible losses on loans to non-financial firms / Loans to non-financial firms
skca	Equity / Assets
vdflca	Households' deposits / Assets
vdulca	Firms' deposits / Assets
lnca	log (Assets / CPI)
ke_fca	Loans to households / Assets

3.2. Binary choice models

A preliminary analysis is presented in Table 4. Each column shows binary logit model estimates for the variables *default* (license withdrawn); *laundry* ("money laundering" among the grounds for license withdrawal); *laundry1* ("money laundering" among the grounds for license withdrawal, but with no economic reasons); *economic* ("financial insolvency" among the reasons of license withdrawal). For each dependent variable 3 models are presented: the first includes both micro- and macroindicators, the second includes only macroindicators, and the third includes only microindicators.

Goodness-of-fit measure — pseudo-R^2.

- The full model, i.e. including all indicators, and the model with only microindicators have slightly better pseudo-R^2 values for the variable *laundry1* than for the variable *laundry*. Thus one could better forecast "money laundering" if it were not mixed in with license withdrawal on economic grounds. Thus we will consider below only models for *laundry1*.
- Prediction of a bank's financial distress is more precise than prediction of "money laundering" (the appropriate pseudo-R^2 values for full models are 0.340 and 0.284, respectively); the same is true for the two "short" models.
- Model fit for "money laundering" is determined mostly by microindicators (pseudo-R^2 = 0.203) and to a smaller extent by macroindicators (pseudo-R^2 = 0.0781). Contrary to what is seen for license withdrawal on economic grounds, the contribution of microindicators (pseudo-R^2 = 0.0875) is smaller than the contribution of macroindicators (pseudo-R^2 =

0.238). Thus license withdrawal on economic grounds depends on the macroeconomic environment to a greater extent than it does for "money laundering".

Values and significance of the *models' coefficients* differ according to the grounds for the default.

- Only 2 macroindicators are significant for the money laundering reason, while 4 out of 5 macroindicators are significant for the economic reason. The exchange rate (*erate*), inflation (*d4_infl*), and the GDP growth rate (*d4_gdp*) are significant for the economic reason and insignificant for the money laundering reason.
- Sets of the microindicators which are significant at the 10% level also differ for the two different grounds for default. In the model for license withdrawal on economic grounds 5 indicators are significant: *ncbca*, *mbkca*, *skca*, *bpca*, *reske*. All these indicators reflect risks inherent in the bank's financial state. Size of the bank, *lnca* is insignificant, may be due to multicollinearity. High values of non-government securities (*ncbca*) and reserves for possible losses (*resca*), low values of balance sheet profit (*bpca*) increase the probability of license withdrawal. Low involvement in the interbank market (*mbkca*) and high values of capitalization (*skca*) also increase the probability of license withdrawal. This less expected result probably reflects the structure of a bank's balance sheet in a pre-default state. Quite different factors are significant for license withdrawal due to money laundering. High values of correspondent accounts turnover (*lnoksca*) increase the probability of license withdrawal. Significant also are households' and firms' deposits: clients prefer not to make deposits in suspicious banks. Balance sheet profit is significant, but with opposite sign. Only the impact of the quality of loan portfolio on a bank's likelihood to default has the same direction for both models.

Other factors. It is quite plausible that there are other factors having significant impacts on the probability of bank license withdrawal which are not included in the models (Table 4). To reveal the existence of such factors and the direction of their influence on the license withdrawal let us consider the model (1).

$$P(default_{t+4}) = \Lambda(x_t'\beta + \gamma_\tau d_{t\tau}) \qquad (1)$$

Table 4. Binary logit models

Variable	***default***	***default***	***default***	***laundry***	***laundry***	***laundry***	***laundry1***	***laundry1***	***laundry1***	***economic***	***economic***	***economic***
erate	-0.778***	-0.616***		-0.126	-0.0319		-0.133	-0.0448		-1.104***	-1.061***	
trade	5.558***	4.683***		4.569***	3.779***		4.443***	3.605***		4.931***	4.702***	
unempl	-1.100***	-0.823***		-1.291***	-1.078***		-1.238***	-1.002***		-0.862	-0.510	
d4_gdp	92.29***	64.29***		-28.55	-39.67		-26.16	-37.93		136.1***	118.6***	
d4_infl	70.71***	61.15***		12.94	13.60		11.22	11.91		97.00***	91.45***	
lnca	0.507		0.529	1.232		1.464*	1.040		1.283	0.0936		0.113
lnca2	-0.0318		-0.0287	-0.0629*		-0.0710**	-0.0549*		-0.0635**	-0.0107		-0.00465
ncbca	4.252***		6.314***	3.029*		5.439***	3.134*		5.447***	5.713**		6.797***
laca	2.753*		5.647***	2.057		4.918***	2.210		4.948***	3.256		5.532***
mbkca	-4.109**		-1.678	-1.533		0.651	-1.423		0.751	-9.320**		-7.692**
lnoksca	0.380***		0.251**	0.374***		0.287**	0.396***		0.310**	0.324		0.123
pnaca	1.646*		0.962	1.490		1.013	1.744		1.330	0.521		0.0967
skca	1.802***		0.736	1.035		0.191	1.145		0.279	2.509**		0.903
vdflca	-2.766**		-1.810	-7.308***		-6.737***	-9.695***		-9.152***	1.134		1.775
vdulca	-3.639**		-3.451**	-3.628**		-3.468**	-3.899**		-3.726*	-2.117		-2.648
keca	2.493*		5.172***	1.930		4.525***	2.073		4.594***	3.225		5.311***
ke_fca	-2.449*		-2.029	-2.512		-2.315	-2.512		-2.379	-1.522		-1.424
gdoca	1.673		3.839**	2.102		3.751**	2.168		3.772**	0.883		3.310
bpca	1.678		1.627	5.426*		5.232**	5.171*		5.063*	-12.06**		-8.618**
reske	2.171***		2.059***	1.989***		1.954***	2.067***		2.024***	2.068*		1.694
Constant	-165.7***	-125.8***	-10.90***	9.437	25.24	-15.35***	9.789	25.34	-14.35***	-233.9***	-208.8***	-10.62*
Observatons	4429	4429	4429	4429	4429	4429	4429	4429	4429	4429	4429	4429
Pseudo-R2	**0.291**	0.132	0.141	**0.271**	0.0869	0.182	**0.284**	0.0781	0.203	**0.340**	0.238	0.0875
defaults (ones)	124			80			76			48		

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In equation (1) Λ is the c.d.f. of the logistic distribution, x_t is set of all factors (Table 4) at time t. The dummy variable $d_{t\tau}=\begin{cases}1, & |t-\tau|\le 1,\\ 0, & |t-\tau|>1\end{cases}$ is an indicator that the moment t is no more than one quarter away from the moment τ. Thus, this dummy variable aggregates the influence of all unaccounted factors in the models (Table 4) factors in the neighborhood of the moment τ. Accordingly, if the coefficient γ_τ is significantly different from 0 and positive it shows the existence at time τ of unaccounted factors which increase the probability of a bank's license withdrawal 4 quarters later, at time $\tau+4$.

Figure 2 presents plots of estimates of coefficients γ_τ against time period τ for 3 full regressions (all variables from Table 4 included) with dependent variables *default*, *laundry1*, *economic*. Circle marks indicate values, significantly different from 0 at 5% significance level; a missed point corresponds to a quarter with no defaults on specified grounds.

Note an interesting feature of the plot related to the license withdrawal on the grounds of money laundering. Unaccounted factors significantly increased the probability of banks' license withdrawal during the period 2004.4–2005.4, which corresponds to CBR orders issued during the period 2005.4–2006.4. The beginning of that period corresponds to the introducing of deposit insurance in Russia and the admission of banks to the deposit insurance system.[4] The end of the period coincides in time with the departure of First Deputy Chairman of the CBR, A.A. Kozlov (killed in September 2006). In 2003.4 and after 2006.1 unaccounted factors either decreased the probability of license withdrawal on grounds of money laundering, or were insignificant.

The impact of unaccounted factors on the probability of license withdrawal on economic grounds was significantly positive in 2003.3–2004.1 (CBR orders in 2004.3–2005.1), and was significantly negative or insignificant after 2004.4. The period of positive impact is related to the revision of the financial states of banks during their initial admission to DIS.

[4] Deposit Insurance Agency (DIA) was created in January 2004; in September 2004 the first banks were admitted to the Deposit Insurance System (DIS). By March 2005 most of all banks (around 800) had been admitted to DIS. The initial admission of banks to DIS was completed in September 2005.

Figure 2. Impact of unaccounted factors on the probability of bank license withdrawal

3.3. Multiple choice models

In this section we estimate the multinomial logit model to test if this model provides more accurate forecasting than the binary logit model for the probability of a bank's license being withdrawn on economic grounds. The possible preference of a multinomial model for the accurate prediction of one, focus of interest, alternative was discussed in Wei et al. (2005), Bussiere (2006), Correia et al. (2007), Koetter et al. (2007), Baslevent (2009).

The multinomial logit model has the form (2):

$$P(y_i = j) = \frac{\exp(x_i'\beta_j)}{\sum_{m=1}^{k}\exp(x_i'\beta_m)}, \quad i = 1,...,n; \quad j = 1,...,k . \tag{2}$$

Here i — observation number, j — number of the alternatives, x_i — vector of explanatory variables (factors) for the object i, β_j — coefficient vector for the alternative j, $P(y_i = j)$ — probability that object i choose alternative j. We use the usual normalization $\beta_1 = 0$.

In our case observations are bank–quarters, the number of possible alternatives k equals 3: (i) license is not withdrawn (*default* = 0, $j = 1$), (ii) license is withdrawn on the grounds of money laundering (*laundry1* = 1, $j = 2$), (iii) license is withdrawn on grounds of economic (financial insolvency) (*economic* = 1, $j = 3$).

The first two columns of table 5 present estimates of the two binary logit models from Table 4; columns 3 and 4 present estimates of the coefficient vectors β_2 and β_3 of the multinomial logit model (2) (remember that $\beta_1 = 0$ is the normalization).

Table 5. Binary and multinomial models

Model	logit	logit	multinomial logit	
factor	*laundry1*	*economic*	*laundry1*	*economic*
erate	–0.133	–1.104***	–0.188	–1.105***
trade	4.443***	4.931***	4.660***	5.191***
unempl	–1.238***	–0.862	–1.260***	–0.960
d4_gdp	–26.16	136.1***	–17.18	135.2***
d4_infl	11.22	97.00***	16.84	98.80***
lnca	1.040	0.0936	1.031	0.0847
lnca2	–0.0549*	–0.0107	–0.0550*	–0.0113
ncbca	3.134*	5.713**	3.509**	6.167**
laca	2.210	3.256	2.364	3.522
mbkca	–1.423	–9.320**	–1.676	–9.576**
lnoksca	0.396***	0.324	0.414***	0.373
pnaca	1.744	0.521	1.781	0.651
skca	1.145	2.509**	1.226	2.585**
vdflca	–9.695***	1.134	–9.697***	0.976
vdulca	–3.899**	–2.117	–3.966**	–2.321
keca	2.073	3.225	2.266	3.506
ke_fca	–2.512	–1.522	–2.583	–1.644
gdoca	2.168	0.883	2.309	1.164
bpca	5.171*	–12.06**	4.938	–12.19**
reske	2.067***	2.068*	2.153***	2.281*
Constant	9.789	–233.9***	–4.852	–234.7***
Observations	4429	4429	4429	4429
Pseudo-R^2	0.284	0.340	0.313	

*** p<0.01, ** p<0.05, * p<0.1

From Table 5 one can find that estimates of the multinomial model coefficients β_2 and β_3 are similar in their signs and significance to the coefficients of the corresponding binary logit models; also their values are not very different.

A comparison of predictions made with binary and multinomial models is presented in Figures 3–5. Predictions of the probability of license withdrawal by both economic (Figure 3) and money laundering (Figure 4) do not differ significantly between the two models. Figure 5 presents comparison of the predicted probabilities of bank survival. Predictions for the multinomial model were calculated from Table 5, and predictions for the binary model from Table 4 (column 1). Here predictions are a bit less similar than they were in the Figures 3 and 4.

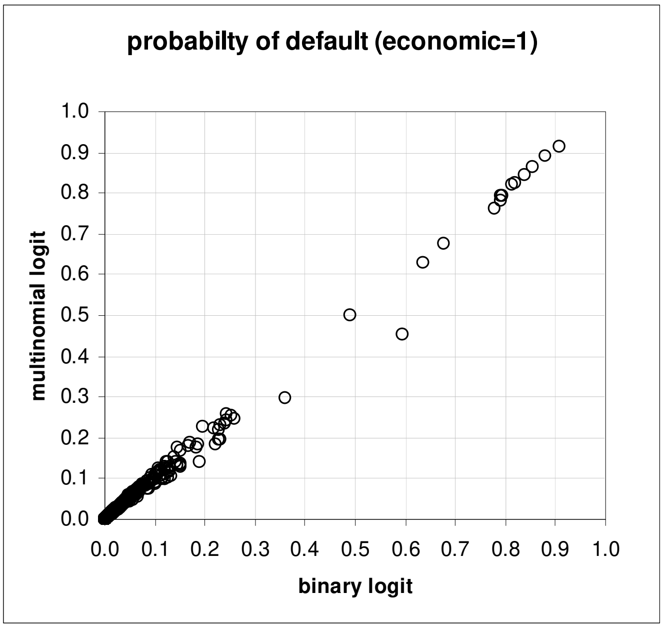

Figure 3. Predicted probabilities of license withdrawal on economic grounds

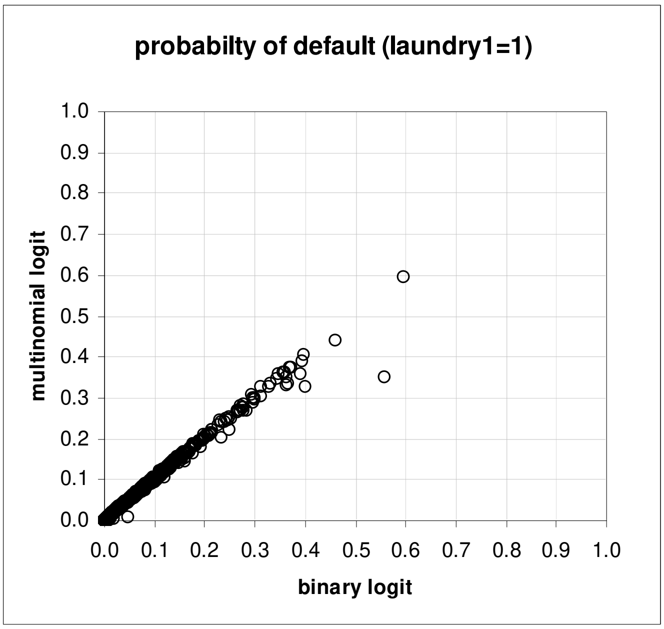

Figure 4. Predicted probabilities of license withdrawal for “money laundering”

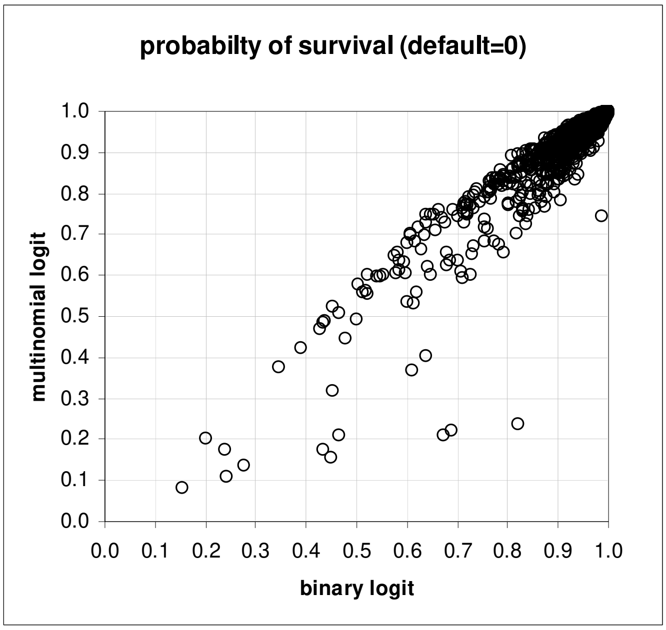

Figure 5. Predicted probabilities of the bank's survival

It is possible to compare the predictive power of the two models by calculating proportions of correct forecasts; more precisely — by scatter plots of the probabilities of Type I – Type II errors. For each model we can calculate, for each observation i, predictions of the probability of default $\hat{p}_i$. Also we can choose the threshold c ($0 < c < 1$) so that default is considered to be predicted for the observation i when $\hat{p}_i > c$. Comparing these predictions with real default data we get estimates $P_I(c)$ for the probability of Type I error (when a bank predicted as solid actually defaults) and $P_{II}(c)$ or the probability of Type II error (when a bank predicted to default actually survives). Changing the threshold c from 0 to 1, the points $(P_I(c),\ P_{II}(c))$ trace out some curve in the unit square in the $(P_I,\ P_{II})$ plane. If the prediction (default/ no default) is chosen at random, this curve is the diagonal line (1,0)–(0,1) of the square. The closer the curve is to the axes, the better is the predictive power of the model.

Figures 6 and 7 present plots of the probabilities of Type I – Type II errors for the forecasts of license withdrawal for arbitrary reason, and of license withdrawal on economic grounds (the focus of interest for DIA). Each figure presents results both for the binary and multinomial models. Contrary to the results in the papers mentioned above, in our case the multinomial model does not provide more accurate forecasts than the binary model.

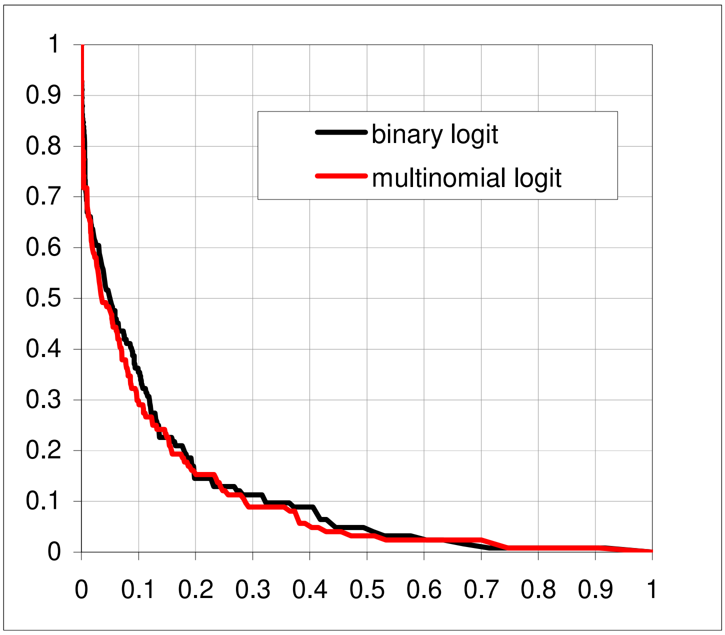

Figure 6. Graph of the probabilities of Type I–Type II errors for forecasts of license withdrawals

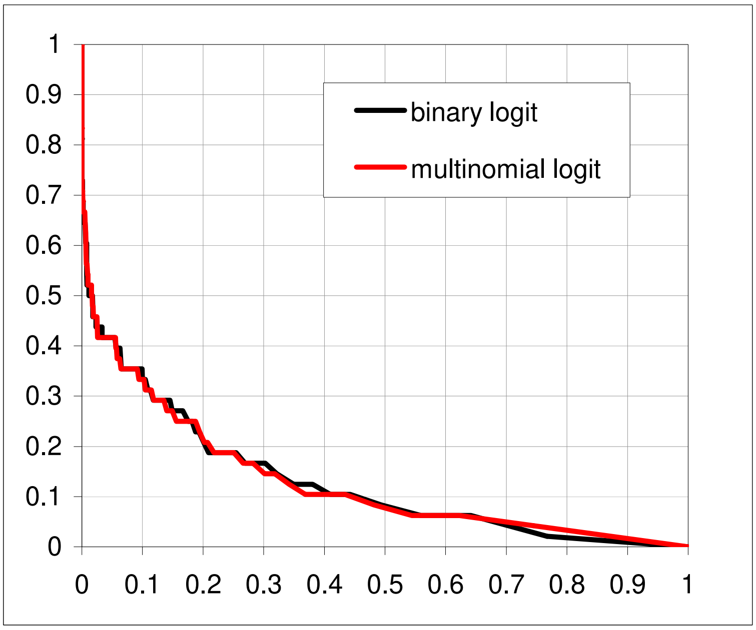

Figure 7. Graph of the probabilities of Type I–Type II errors for forecasts of license withdrawals on economic grounds

In contrast to the predictions of default probabilities, marginal effects of factors on the probability of default differ for the binary and multinomial models. Two scatter plots of the marginal effects $\dfrac{\partial P(laundry1_i = 1)}{\partial x_i}$ estimated by the two models are presented in the Figure 8 for the factor $x = skca$ (capitalization) and for the factor $x = ncbca$ (non-government securities to total assets ratio).

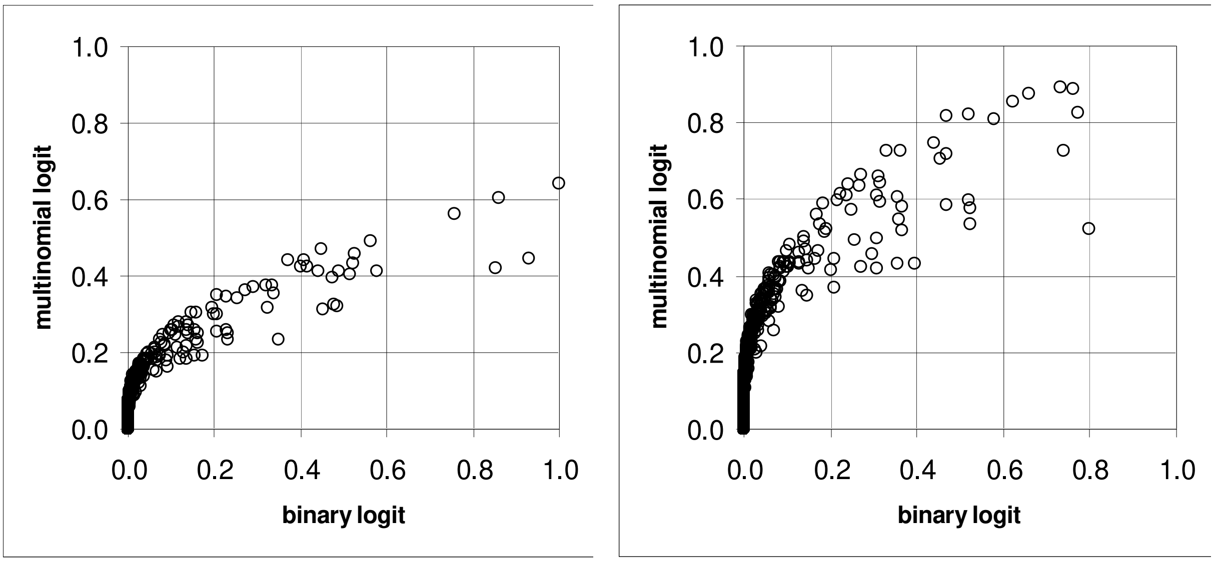

Figure 8. Comparison of the marginal effect of *skca* (left) and *ncbca* (right) on the probability of bank license withdrawal on economic grounds, estimated by binary and multinomial models

4. Conclusion

We used binary and multinomial logit models to model probability of a Russian bank default (bank's license withdrawal by CBR). The models use bank balance sheet financial indicators (microindicators) and indicators of macroeconomic environment (macroindicators) taken 4 quarters before observation of a bank's state (license is not withdrawn; license is withdrawn; license is withdrawn on grounds of "money laundering"; license is withdrawn on economic grounds, e.g. financial insolvency, fraud in bank reports, inability to fulfill financial obligations, etc.). All CBR orders for bank license withdrawals during the period 2005.2–2008.4 were included into the data.

We find that essentially different factors are significant in the models for bank license withdrawals by the CBR according to whether the grounds are "money laundering" or "economic". The "unaccounted factors" which significantly increased the probability of banks' license withdrawal during the period 2005.4–2006.4. could be related to the activity of First Deputy Chairman of the CBR, A.A. Kozlov.

For practical reasons it is especially important for the DIA to have accurate forecasts of bank license withdrawals when these are on "economic" grounds, since in that case the DIA is responsible for covering the losses of depositors of the defaulted bank. This is why we pay special attention of whether a multinomial model with 3 possible outcomes (the license is not withdrawn; the license is withdrawn for "money laundering"; the license is withdrawn for economic reasons) outperforms a binary logit model with two outcomes (the license is withdrawn for economics reasons; another outcome) in giving accurate predictions of bank defaults in which the DIA bears responsibility.

We found that in our case the predictive powers of multinomial and binary models are approximately equal. A multinomial logit model does not outperform a binary logit model.

References

Altman, E. I., Haldeman, R., & Narayanan, P. (1977). Zeta analysis: A new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance*, 1(1), 29–54.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, 23(4), 589–609.

Altman, E. I., Marco, G., & Varetto, F. (1994). Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience). *Journal of Banking and Finance*, 18(3), 505–529.

Altman, E. I., Rijken, H. A. (2004). How rating agencies achieve rating stability. *Journal of Banking and Finance*, 28, 2679–2714.

Baslevent, C., Kirmanoglu, H., & Senatalar, B. (2009). Party preferences and economic voting in Turkey (now that the crisis is over). *Party Politics*, 15(3), 377–391.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research, Empirical Research in Accounting: Selected Studies*. 4, 71–111**.**

Bovenzi, J. F., Marino, J.A., & McFadden F. E. (1983). Commercial bank failure prediction models. *Federal Reserve Bank of Atlanta*. *Economic Review*, 68, 14–26.

Bussiere, M., Fratzscher, M. (2006). Towards a new early warning system of financial crises. *Journal of International Money and Finance*, 25, 953–973.

Coats, P. K., Fant L. F. (1993). Recognizing financial distress patterns using a neural network tool. *Financial Management*, 22(3), 142–155.

Cole, R. A., Cornyn, B. G., & Gunther, J. W. (1995a). FIMS: A new monitoring system for banking institutions. *Federal Reserve Bulletin*, 81(1), 1–15.

Cole, R. A., Gunther, J. W. (1995b). Separating the likelihood and timing of bank failure. *Journal of Banking and Finance*, 19(6), 1073–1089.

Cole, R. A., Gunther, J. W. (1998). Predicting bank failures: A comparison of on- and off-site monitoring systems. *Journal of Financial Services Research*, 13(2), 103–117.

Collier, C., Forbush, S., Nuxoll, D. A., & O'Keefe, J. (2003). The SCOR system of off–site monitoring: its objectives, functioning, and performance. *FDIC Banking Review*, 15(3), 17–32.

Correia, A., Santos, C. M., & Barros, C. P. (2007). Tourism in Latin America. A choice analysis. *Annals of Tourism Research*, 34(3), 610–629.

Espahbodi, H., Espahbodi, P. (2003). Binary choice models and corporate takeover. *Journal of Banking and Finance*, 27(4), 549–574.

Estrella, A., Park, S., & Peristiani, S. (2000). Capital ratios as predictors of bank failure. *FRBNY Economic Policy Review*, 6(2), 33–52.

Gilbert, R. A., Meyer, A. P., & Vaughan, M. D. (2002). Could a CAMELS Downgrade Model Improve Off-Site Surveillance? *Federal Reserve Bank of St. Louis Review,* 2002, January, 47–63.

Godlewski, C. J. (2007). Are Ratings Consistent with Default Probabilities?: Empirical Evidence on Banks in Emerging Market Economies. *Emerging Markets Finance and Trade*, 43(4), 5–23.

Hirtle, B., Lopez, J. A. (1999). Supervisory information and the frequency of bank examination. *FRBNY Economic Policy Review*, 5(1),.1–19.

Izan, H. Y. (1984). Corporate distress in Australia. *Journal of Banking and Finance*, 8(2), 303–320.

Jagtiani, J., Kolari, J. W., Lemieux, C., & Shin, H. (2003). Early warning models for bank supervision: Simper could be better, *Federal Reserve Bank of Chicago. Economic Perspectives*, 27(3), 49–60.

Karminsky, A. M., Peresetsky, A. A. (2007). International agencies' ratings models. *Applied Econometrics,* 1, 3–19. (in Russian).

Koetter, M., Bos, J. W. B., Heid, F., Kolari, J. W., Kool, C. J. M., & Porath, D. (2007). Accounting for distress in bank mergers. *Journal of Banking and Finance,* 31, 3200–3217.

Kolari, J. W., Glennon, D., Shin, H., Caputo, M. (2002). Predicting large US commercial bank failures. *Journal of Economics and Business*, 54(4), 361–387.

Krainer, J., Lopez, J. A. (2002). Off-site monitoring of bank holding companies. *FRBSF Economic Letter*, 15.

Krainer, J., Lopez, J. A. (2003). How might financial market information be used for supervisory purposes? *FRBSF Economic Review*, 2003, 29–45.

Krainer, J., Lopez, J. A. (2004). Incorporating equity market information into supervisory monitoring models. *Journal of Money, Credit, and Banking*, 36(6), 1043–1067.

Krainer, J., Lopez, J. A. (2008). Using securities market information for bank supervisory monitoring. *International Journal of Central Banking*. 4, 125–164.

Krainer, J., Lopez, J. A. (2009). Do supervisory rating standards change over time? *FRBSF Economic Review*, 2009, 13–24.

Lennox, C. (1999). Identifying failing companies: a reevaluation of the logit, probit and DA approaches. *Journal of Economics and Business*, 51(4), 347–364.

Lin, T.-H. (2009). A cross model study of corporate financial distress prediction in Taiwan: Multiple discriminant analysis, logit, probit and neural network models. *Neurocomputing*, 72(16–18), 3507–3516.

Martin, D. (1977). Early warning of bank failure: A logit regression approach. *Journal of Banking and Finance*, 1(3), 249–276.

Ohlson, J.A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, 18(1), 109–131.

Oshinsky, R., Olin, V. (2006). Troubled banks: Why don't they all fail? *FDIC Banking Review Series*, 18(1), 23–44.

Partnoy, F. (1999). The siskel and ebert of financial markets?: Two thumbs down for the credit rating agencies. *Washington University Law Quarterly*,77(3), 619–722.

Peresetsky, A. A., Karminsky, A. M. (2008). Models for Moody's bank ratings. *Bank of Finland, BOFIT Discussion Papers*, No 17/2008.

Peresetsky, A. A., Karminsky, A. M. (2011). Models for Moody’s bank ratings. *Frontiers in Finance and Economics*, 8(1), 88–110.

Peresetsky, A. A. (2009). Measuring external support factor of Moody’s bank ratings. *Applied Econometrics,* 2, 3–23. (in Russian).

Peresetsky, A. A., Karminsky, A. M., & Golovan, S. V. (2004a). Probability of default models of Russian banks. *Bank of Finland, BOFIT Discussion Papers* No 21/2004.

Peresetsky, A. A., Karminsky, A. M., & Golovan, S. V. (2011). Probability of default models of Russian banks. *Economic Change and Restructuring*, 44(4), 297–334.

Peresetsky, A. A., Karminsky, A. M., van Soest, A. H. O. (2004b). Modeling Russian Banks Ratings. *Economics and Mathematical Methods*, 40(4), 10–25. (in Russian)

Peresetsky, A. A. (2007). Banks’ probability of default models. *Economics and Mathematical Methods*, 43(3), 37–62 (in Russian).

Poon, W. P. H. (2003). Are unsolicited credit ratings biased downward? *Journal of Banking and Finance*, 27, 593–614.

Roy, van P. (2006). Is there a difference between solicited and unsolicited bank ratings and, if so, why? *National Bank of Belgium working paper* 79/2006.

Sahajwala, R., Bergh van den, P. (2000). Supervisory risk assessment and early warning systems. *BIS Working Papers*, 4.

Scott, J. (1981). The probability of bankruptcy: A comparison of empirical predictions and theoretical models. *Journal of Banking and Finance*, 5, 317–344.

Soest van, A. H. O., Peresetsky, A. A., & Karminsky, A. M. (2003). An analysis of ratings of Russian banks. *Tilburg University CentER Discussion Paper Series,* 85/2003.

Wei, Y., Liu, B., & Liu, X. (2005). Entry modes of foreign direct investment in China: a multinomial logit approach. *Journal of Business Research*, 58, 1495–1505.

Westgaards, S., Wijst van der, N. (2001). Default probabilities in a corporate bank portfolio: A logistic model approach. *European Journal of Operational Research*, 135, 338–349.

Wiginton, J. C. (1980). A note on the comparison of logit and discriminant models of consumer credit behavior. *Journal of Financial and Quantitative Analysis*, 15(3), 757–770.

Appendix

Table A1. Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
d4_gdp	1.072	0.008	1.055	1.090
d4_infl	1.115	0.020	1.074	1.148
erate	28.577	1.603	24.650	31.640
unempl	7.767	0.905	5.700	9.300
trade	1.835	0.150	1.530	2.180
bpca	0.014	0.021	–0.295	0.439
gdoca	0.020	0.052	0.000	0.742
keca	0.473	0.206	0.000	0.965
laca	0.320	0.183	0.003	0.994
mbkca	0.046	0.074	0.000	0.676
ncbca	0.098	0.129	0.000	0.823
lnoksca	0.994	0.886	–4.993	5.177
pnaca	0.085	0.119	0.000	0.980
reske	0.080	0.103	0.000	1.000
skca	0.250	0.171	0.007	1.000
vdflca	0.145	0.146	0.000	0.785
vdulca	0.073	0.104	0.000	0.762
lnca	13.348	1.807	6.758	19.386
ke_fca	0.118	0.136	0.000	0.853