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Probability of default models of Russian banks

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Contents

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Abstract

This paper presents results from an econometric analysis of Russian bank defaults during the period 1997–2003, focusing on the extent to which publicly available information from quarterly bank balance sheets is useful in predicting future defaults. Binary choice models are estimated to construct the probability of default model. We find that preliminary expert clustering or automatic clustering improves the predictive power of the models and incorporation of macrovariables into the models is useful. Heuristic criteria are suggested to help compare model performance from the perspectives of investors or banks supervision authorities. Russian banking system trends after the crisis 1998 are analyzed with rolling regressions.

Keywords: banks, Russia, probability of default model, early warning systems
JEL classification:

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Anatoly A. Peresetsky, Alexandr A. Karminsky and Sergei V. Golovan

Probability of default models of Russian banks

Tiivistelmä

Tutkimus käsittelee ekonometrisin menetelmin venäläisten pankkien konkursseja vuosina 1997-2003. Haluamme selvittää, onko pankkien neljännesvuosittain julkaisemista tasetiedoista apua konkurssien ennustamisessa. Käytämme logit-menetelmää konkurssimallin rakentamiseen. Havaintoaineiston ryhmittely joko asiantuntijoiden arvioiden tai automaattisen algoritmin avulla parantaa mallin ennustuskykyä. Myös makrotaloudellisten muuttujien lisääminen malliin auttaa ennustamaan konkursseja. Arvioimme mallien ennustuskykyä sijoittajille ja pankkivalvojille tärkeiden kriteerien avulla. Venäjän pankkijärjestelmän kehitystä vuoden 1998 kriisin jälkeen analysoidaan liukuvan regression avulla.

Asiasanat: Venäjä, konkurssimallit, kaukovaroitusmallit

1 Introduction and brief literature survey

This paper investigates the usefulness of econometric probability of default models based on publicly available information drawn from banks' balance sheets in predicting the future solvency of Russian banks.

Many experts on financial structures, however, including those at the Economic Education and Research Consortium (EERC),[1] hold out little hope for constructing such models for the Russian case. They note that factors besides the financial condition of banks and the macroeconomic environment are also important in determining long-term solvency. These include many less-formalized factors such as politics, bank affiliations with industrial or financial groups, bank activities profile, practices and quality of management.

Moreover, Russian bank balance sheet data, which are still based on Russian accounting practices, are of questionable quality and lack the transparency of books prepared in accordance with internationally accepted standards.

The importance of the quality of the accounting data for statistical models of bank risk is demonstrated on US banks data in Gunther and Moore (2003). In their study of failures of high-yield bond prediction, Marchesini et al. (2004) observe "balance sheets … can be and have been severely manipulated."

The rapid development of Russia's banking system (since Russia began the transition to a market economy) has brought with it a rich body of numerical material for econometric analysis. Russia still has many commercial banks, although the number has dropped from about 2500 in 1995–1996 to around 1300 at present. This situation offers a wealth of material for econometric study. In contrast, the 1989 sample of 1030 of largest US banks used by Kolari et al. (2002) only included 18 defaults. The sample of 5598 observations of US banks between 1970 and 1976 used by Martin (1977) includes just 23 failures.

Our sample of Russian banks is not especially skewed. Skewed samples in a logistic regression (two substantially unequal-sized response groups) are known to produce biased test statistics and potentially faulty conclusions (e.g. Aldrich and Nelson, 1985; Stone and Rasp, 1991).

The New Basel Capital Accord (Basel 2004) proposes that banks could use the Internal Ratings Based Approach (IRB) in evaluating potential bank partners and bank su-

[1] EERC, July 2003, M. Shaffer et al.

pervision authorities could use Early Warning Systems (EWS) in monitoring of the banking system. These measures are expected to enhance the stability of banking and financial systems. Statistical models of bank credibility based on publicly available information could logically be included as part of an IRB or EWS.

Investors, banks and firms need to be able to evaluate the credibility of potential banking partners, while expediency dictates that banking supervision authorities need to be able to screen banks off-site to identify troubled banks and concentrate their efforts on on-site examinations of such banks.

International credit rating agencies such as Standard and Poor's, Moody's and Fitch rate the creditworthiness and quality of many banks. These ratings could be used in the IRB or EWS. However, such ratings are fundamentally lacking in Russia's case. First, the top international rating agencies only rate a couple dozen Russian banks. The ratings they do provide are consistently low; S&P rated 22 Russian banks in September 2004 with only three rating categories: CCC, B or BB (state-owned Vneshtorgbank was the sole BB rating). Second, these ratings tend to be conservative and rarely get changed (Löffler, 2004, and Altman and Rijken, 2004, detail the reasons for rating stability and related loss of information). Russia itself has only a few credit rating agencies, and they hardly compare with the international agencies in the eyes of Russian financial experts or the world (Soest et al., 2003).

Actually, there are only a limited number of approaches to statistical modeling of bank credibility based on publicly available information.

First, one could use existing bank ratings issued by a rating agency and construct a statistical model for such ratings. The model would reflect that part of the rating information derived from public information. The natural choice of econometric model here is likely the ordered response model (ordered logit/probit). Once the model is designed, the rating criteria could be extended to an entire set of banks. That model would reflect the opinion of the rating agency experts. This approach has been suggested for Russian banks in Soest et al. (2003) and for non-financial US firms in Altman and Rijken (2004).

A second approach is based on surveying experts. The experts are asked to rate a number of real banks and "virtual" banks, consisting solely of numerical information of parameters from balance sheets. Thereafter, it is possible to fit an ordered probit model that reflects the opinion of the set of experts. A possible advantage of this method is that the model incorporates the opinion of experts representing various financial structures. Of course, when banks pay the rating agency for their rating, this may potentially lead to a situation where the rating agency is reluctant to give a downgrade. On the other hand, rating agency experts are likely to have extensive information on the rated bank. That approach was realized in Soest et al. (2003).

The third is to derive a statistical model of bank risk, stability and credibility (which we generally refer to here as "reliability") based on historical data of bank defaults. The natural choice for an econometric model here would be the binary choice model (logit/probit). This approach is applied to Russian banks in Golovan et al. (2003, 2004).

Efforts at designing a model for predicting the probability of bank defaults has a long history. To the best of our knowledge, Altman (1968) was the first to apply a statistical model to predicting bankruptcy of non-financial firms. He uses discriminant analysis to construct a model to predict firm bankruptcy. The model uses input values from five financial ratios for the firms, one or two years before the firm enters (or avoids) bankruptcy. Martin (1977) pioneered application of a binary choice model (logit) to prediction of bank failure. He employs a two-year horizon between the statement year for the financial ratio data and the observation year of the bank's situation (failed/operating).

Numerous papers discuss the use of the logit/probit approach in modeling probability of default. Wiginton (1980) finds the logit model results superior to discriminant analysis for consumer credit scoring. Ohlson (1980) applies a logit model to data from 1970–1976 to discern statistically significant factors for predicting the probability that a firm will fail in the coming year. Lawrence et al. (1992) use logit analysis of default risk in mobile home credits in the US in 1974–1980. Westgaard and Wijst (2001) employ a logit model for analysis of default factors affecting Norwegian limited liability companies during 1995–1999, finding that a two-year period between the firm status and firm accounting data is optimal. They use the log of firm's total assets as a measure of firm size and find that removing observations with extreme values from the dataset and truncating the parameters improves the statistical quality of the model. Kolari et al. (2002) takes a logit approach to modeling probability of default for US banks in 1989–1990. Lenox (1999) uses a sample of 949 UK firms (6416 observations) to study logit, probit and discriminant analysis models performance for the prediction of the firm failure. He finds logit/probit models with specification of heteroscedasticity are superior to logit/probit models without heteroscedasticity or discriminant analysis. The paper is unclear, however, as whether the improvement in model performance is due to correct heteroscedasticity specification or simply to a model with more parameters.

Some papers use non-statistical methods to set up a model for default prediction. For example, Kolari et al. (2002) use a trait recognition model, or TRA (a kind of the image recognition algorithm), while H. and P. Espahbodi (2003) use recursive partitioning. Other non-statistical methods include neural networks, Markov models, CAMELS and financial ratios. There is no evidence that these methods perform better than the statistical approach. On the contrary, Altman et al (1994) conclude that discriminant analysis and logit model outperform neural networks in prediction of corporate distress. Jagtiani, Kolary et al. (2003) conclude that a “simple linear (logit) model performs better than more complex EWS models such as TRA.”

The paper is innovative for at least four reasons. First, we focus on constructing probability of default models for Russian banks. Second, we discuss the need for preliminary clustering of banks and the possible need for separate logit models for each cluster. Of course, it would be better to have a cluster procedure oriented to the best fit of logit model in clusters. For this purpose, we introduce a model that combines a clustering procedure with logit model fitting. Third, we examine the extent to which macroeconomic variables are helpful in predicting bank defaults. Fourth, we introduce a new approach to model comparison, because comparison of model performance is a bit problematic. One can compare statistical significance of the models or rates of correct prediction, but such information is not particularly important to an investor. Thus, we apply heuristic criteria that reflect the expected extra profit for an investor using the model.

The paper is organized as follows: In section 2, we examine how helpful clustering of the banks is for determining model performance. We use expert and automatic clustering procedures. The probability of a bank to survive during the financial and banking crisis of the August 1998 is modeled. In section 3, we construct probability of defaults models for Russian banks during 1996–2003. During this period, Russia’s macroeconomic environment changed considerably, so it makes sense to use macrovariables to improve model performance. The heuristic criteria for model comparison are introduced. In section 4, the study of the models estimated on one- and two-years rolling windows are used to analyze changes in the Russian banking system after the 1998 financial crisis. Section 5 concludes.

2 Does clustering help?

Historical bank accounts data are rarely used in constructing probit/logit models for determining probability of bank default. We find US bank data are used in the papers of Martin (1977), Bovenzi et al. (1983), Cole and Gunther (1995, 1998), Estrella (2000), Kolari et al. (2002), and Russian bank data are employed in Golovan et al. (2003, 2004). Godlewski (2004) takes data for banks in emerging market economies (excluding Russia). To the best of our knowledge, the US Federal Reserve is the only supervisory authority to use such a model (SEER) as a part of its EWS (Sahajawala, Berg, 2000).

In this section, we examine factors that predict bank survival after Russia's financial and banking crisis of August 1998. Prior to 1998, banks had little involvement in financial intermediation in the real sector. Instead, they preferred to speculate in financial markets, a problem all too familiar to the government and the Central Bank of Russia (CBR) at the time. This is why we place special emphasis on the role of the ratio of credits to real economy to bank's total assets in this study.

Russian banks vary considerably in terms of size, activities, involvement in the government bond market (GKOs), volumes of credits extended to the real sector of economy, volumes of private deposits, etc. Many small banks and more than half of the twelve largest banks did not survive the 1998 crisis. This suggests that a single logit model may be insufficient for modeling the probability of default for such a diverse set of banks, and models for several bank clusters are preferable.

To the best of our knowledge, only Korobow and Stuhr (1983) use clustering of banks for an early warning system. They suggest clustering (peer groups) by bank size or by the existence of at least one foreign office.

But how helpful is clustering of Russian banks for model performance? To find out, we first cluster banks using a financial ratio. Thereafter, we design and test an automatic procedure.

The CBR uses de facto clustering in bank regulation. For example, it has separate capital adequacy requirements for small and large banks (see Table 1).

Table 1

	Equity over €5 million	Equity less than €5 million
01.02.1999 – 01.01.2000	8%	9%
01.01.2000 – present	10%	11%

2.1 Data

Our sample comprises 1569 Russian and their accounting data for April 1, 1998.[2] We examine our sample to determine which banks were failed as of April 1, 2000. The two-year period was chosen for two reasons: it covers the average time between license withdrawal and bank liquidation, and the two-year period appears to have the highest predictive power.

For our purposes, a bank is marked “failed” and the binary variable LIVE set to 0 if the bank meets one of three conditions:

- The license was withdrawn before April 1, 2000,
- The bank is under the administration of ARCO (Agency for Restructuring Credit Organizations), or
- The bank is merged with another bank and was in poor financial shape at the time of the merger (each case is separately analyzed).

For all other banks, the variable is set equal 1. We have 263 defaults and 1306 operating banks in our sample. Notably, we remove the three state-owned banks – Sberbank, Vnesheconombank and Vneshtorgbank from the sample. We also removed from the sample several banks with incomplete or erroneous accounting information. Otherwise, our sample includes all the Russian banks operating as of April 1, 1998.

We test about 30 bank parameters for significance in the default models. Table 2 includes descriptions of those included in at least one of the model in sections 2, 3 or 4.

Our models do not use bank parameters themselves, but rather select ratios to total assets (i.e. RES/TA, LNI/TA, GB/TA, Eq/TA, LA/TA, DPC/TA, CANW/TA, NGS/TA) that characterize the proportion of certain bank activities to total assets. The best results for measuring bank size seem to be achieved with the log of total assets (LNTA). The same ratios are used in the models of Golovan et al. (2003, 2004). Similar financial ratios are also found in Martin (1977), Kolari (2002) and Estrella (2000). Altman (2004) and several others use the log of assets to characterize firm size.

[2] Data are kindly provided by the Mobile Information Agency.

Table 2

Parameter	Description
TA	Total assets* (*valuta balansa*)
RES	Bank reserves for possible losses.
LNI	Loans to non-financial institutions
GB	Government bonds
Eq	Equity
LA	Liquid assets**
DPC	Private customers' deposits and accounts
CANW	Capital assets and other non-working assets
NGS	Non-government securities
As	Assets (excluding loans and debts to own branches)
PBT	Profit before tax
CFB	Amounts owed to credit institutions (credits from other banks)
NWA	Non-working assets
OVL	Overdue loans (over 5 days)

* Under Russian accounting, credits and debts to own branches are included.
** Calculated per methodology of the Russian journal "Banks and Finance" (Banki i finansi).

Descriptive statistics of the parameters for the complete set of banks as of April 1, 1998 are presented in Table 3.

Table 3

	LNTA	Eq/TA	LNI/TA	GB/TA	LA/TA	NGS/TA	CANW/TA	DPC/TA	RES/TA
Mean	10.72	0.28	0.29	0.07	0.14	0.12	0.20	0.06	0.03
Maximum	17.88	0.99	0.97	0.89	1.00	0.98	1.00	0.48	0.41
Minimum	3.22	-0.79	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Std.dev.	1.90	0.23	0.19	0.12	0.16	0.16	0.16	0.08	0.04

Preliminary analysis reveals differences between banks that survived or failed during the crisis. Table 4 separates the descriptive statistics of banks that failed (LIVE=0) and those that are still operating (LIVE=1) as of April 2000.

Table 4

	Num.	LNTA	Eq/TA	LNI/TA	GB/TA	LA/TA	NGS/TA	CANW/TA	DPC/TA	RES/TA
ALL	1569	10.719	0.281	0.290	0.073	0.136	0.117	0.202	0.063	0.034
LIVE=0	263	10.533	0.174	0.267	0.024	0.073	0.139	0.285	0.049	0.056
LIVE=1	1306	10.757	0.303	0.295	0.083	0.149	0.113	0.185	0.065	0.029

To visualize Table 4, each parameter is normalized to its average value with respect to all banks. These relative mean values of the parameters are presented in Figure 1.

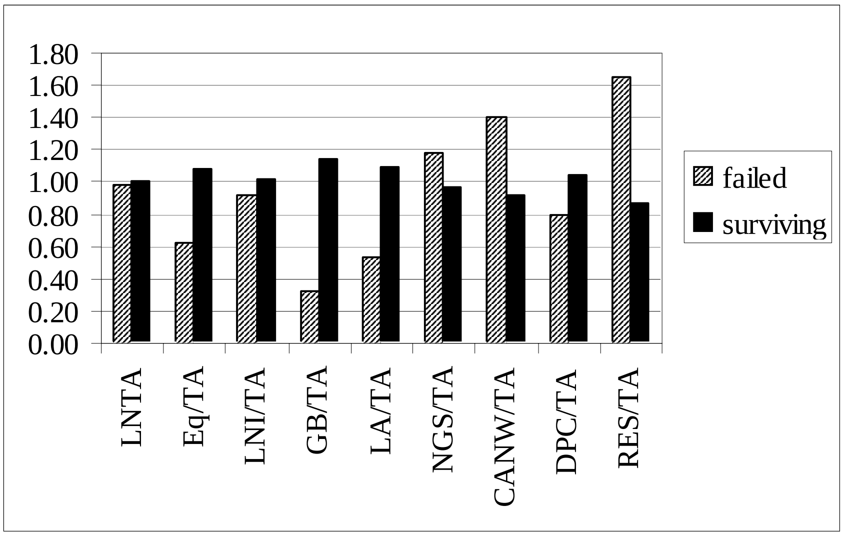

Figure. 1. Relative mean values for failed/surviving bank parameters

The largest differences between mean values of the two pools of banks are found for the parameters Eq/TA, GB/TA, and LA/TA, which are significantly higher for the surviving banks, and CANW/TA and RES/TA, which are significantly higher for the failed banks.

Most of these findings are unsurprising. The Eq/TA ratio is similar to the CBR's capital adequacy parameter H1. High share of liquid assets LA/TA and a low share of non-working assets CANW/TA characterize a bank's ability to mobilize resources quickly. A high share of reserves RES/TA may suggest the bank pursues an aggressive lending policy.

During the crisis, the Russian government defaulted on GKOs. Unexpectedly, the share of government bonds GB/TA is considerably higher for the surviving banks. We offer two explanations for this. First, in a stable developed economy, it is prudent for banks to hold government bonds. Thus, non-zero investment into government bonds in 1998 may suggest good bank financial management skills. Second, after the crisis, the government provided support to certain banks highly invested in the GKO market, thus assuring their survival.

Note that the diagram does not account for differences in bank size (LNTA mean values for failed and surviving banks).

The correlations for bank financial ratios are presented in Appendix A. The size of a bank is negatively correlated with the parameters RES/TA, Eq/TA, LA/TA. Large bank have better partners and no need to create big reserves for loans. Such a bank (potentially, at least) is more stable and could allow lower values of the capital adequacy and liquid assets. Having many partners, the large bank has good access to the interbank credit market and other resources.

The total banking system equity in the first quarter of 1998 was small compared to GDP and there were too many small banks. At the time, bank strategies mostly involved strong affiliations with industry or speculation in the highly profitable GKO market.

2.2 Models and clusters

We use the binary choice model (1) for modeling probability of bank default

$$P(LIVE_i = 1) = F(x'_i \beta), \tag{1}$$

where x is the vector of the bank i parameters. We found that the logit specification $F(z) = (1 + e^{-z})^{-1}$ is marginally better than the probit specification. The equation (1) could be estimated using the complete set of banks. If we suppose, however, that for different clusters of the banks impact of some of parameters may have different signs, we can conclude such parameters insignificant. This argues for a clusterization algorithm.

Standard cluster analysis procedures, such as the most commonly used *k*-means clustering procedure, that might give interesting results (Bobyshev, 2001) are not suited for our purposes as they tend to put points with similar parameter values into one cluster. This minimizes the sum of distances between points and cluster centers. However, we want clusters that best fit the logit model.

Wescott (1984) uses the *k*-means clustering procedure for prediction of US municipal bond ratings in 1977. He concludes that modeling the ratings in each cluster do not improve the model's ability to explain the rating (and thus bolstering our argument above).

An alternative approach is to classify banks by their profile of the activity (e.g. pocket banks, banks affiliated with some industrial group, banks oriented to serving export-import operations). Unfortunately, we lack this information for most banks in the sample.

Below we use "expert approach" that asks bank experts to classify banks into three clusters by giving values to a bank parameter. The expert defines two thresholds, so we have three clusters with "small", "medium" and "large" values of the chosen parameter (say, bank size). The logit model is fitted separately for each of cluster. The advantage here is ease of cluster interpretation. The disadvantage lies in the subjective choice of thresholds.

The automatic cluster procedure we use searches for the optimal choice of clusters, taking into account the quality of model fit in each cluster. Algorithms that combine model-fitting with clustering are well demonstrated (for a very different problem) in Borodovsky and Peresetsky (1994) and Mathe et al. (1999).

2.3 Expert approach

Four bank parameters are used for our expert classification. The two thresholds are chosen for each of the parameters, respectively, and the banks are classified into three clusters with small, medium and large parameter values.

- **Total assets, TA.** Cluster of small banks, TA=1% contains the smallest banks with total assets equal to 1% of banking system assets. The large bank cluster, TA=90%, contains all banks with total assets equal to 90% of banking system assets.
- **Government bonds ratio (GB/TA).** The cluster of banks not participating in the GKO market, GB/TA<0.01%, and the cluster of banks heavily invested in GKOs, GB/TA>10%.
- **Credits-to-non-financial-firms ratio (LNI/TA).** The cluster of “passive” banks, LNI/TA<15%, and the cluster of the “active” banks, LNI/TA>40%.
- **Equity ratio, Eq/TA.** The cluster of banks with low equity ratios, Eq/TA<11%, and the cluster of the banks with high equity ratios, Eq/TA>30%.

The distribution of the banks over the clusters and the intersections of the clusters is presented in Table 5.

Table 5

	TA =1%	TA =90%	GB/TA <0.01%	GB/TA >10%	LNI/TA <15%	LNI/TA >40%	Eq/TA <11%	Eq/TA >30%
TA=1%	624	0	403	100	197	179	94	359
TA=90%	0	261	22	93	50	54	78	34
GB/TA<0.01%	403	22	624	0	187	203	126	301
GB/TA >10%	100	93	0	378	110	51	40	149
LNI/TA <15%	197	50	187	110	392	0	89	187
LNI/TA >40%	179	54	203	51	0	425	50	194
Eq/TA<11%	94	78	126	40	89	50	268	0
Eq/TA>30%	359	34	301	149	187	194	0	615

The means of bank ratios over the clusters are presented in Appendix C. The proportion of defaults is higher for low values of equity, government bonds, and credits-to-non-financial institutions ratios. The proportion of defaults is lower for mid-sized banks than small or large banks.

For more detailed study, we divided the entire range of variation of the log of total assets LNTA into intervals and plotted the proportion of failed and surviving banks at each interval (Figure 2). The plot shows the number of failed banks at each interval. The U-shaped plot indicates that medium-size banks were more likely to weather the crisis.

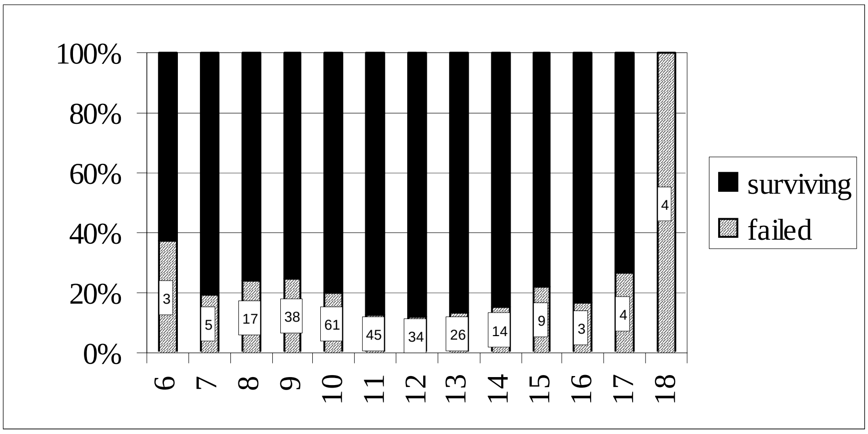

Figure 2. Distribution of bank defaults over LNTA

A similar, but rather monotonous, plot for the default distribution over reserves ratio is presented in Figure 3.

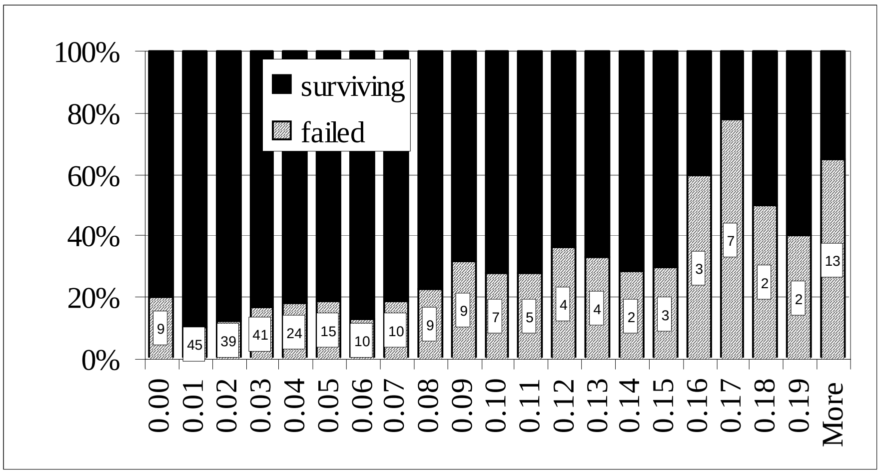

Figure 3. Distribution of bank defaults over RES/TA

The U-shaped distribution of defaults over the private deposits ratio DPC/TA is similar to Figure 2. Likewise, the default distribution over ratios for capital assets and other non-liquid assets and non-government securities has a distribution similar to Figure 3. These plots support the preliminary hypothesis that high values of reserves, non-government securities and non-liquid assets ratios increase the probability of default in a crisis. Banks with average values for their private customer-deposits-and-accounts ratio have higher probabilities of survival. This may appear strange at first glance, but remember that during the 1998 crisis many banks simply froze the accounts of their private customers and used the money to fulfill other obligations. This is at least part of the reason increases in this ratio increase probability of bank survival.

For each of the clusters the logit model is selected. Model selection is based on the values of LR and McFadden R2 statistics and the z-statistics of the coefficients. A few results are presented below.[3]

Small and large bank clusters, TA=1% and TA=90%. The small bank cluster, TA=1%, has a high mean equity ratio (34%, compared to 28% for all banks and 18% for large banks) and a 17% liquid assets ratio (14% for all). All other ratio means do not differ significantly from those of all banks. In the small bank cluster, 21% of banks failed (compared to 17% of all banks and 18% of large banks).

The best models for the two clusters are presented in Table 6. Value $s_x \beta_x$ measures the economic significance of the variable, characterizing the degree of influence of the variable on the probability (β_x is the estimated coefficient, and s_x is the standard deviation of the variable in the cluster).

The coefficients have the expected signs. High equity and liquid assets ratios (Eq/TA, LA/TA) increase the probability of survival, while high ratios of reserves, non-liquid assets and non-government securities increase the probability of default. Bank size (LNTA) has a different effect depending on the cluster. Large total assets increase the probability of survival for a small bank, but not a large bank. In fact, the four largest commercial banks (SBS-Agro, Incombank, Menatep and Rossiisky Credit) all failed during the crisis. Eleven of Russia's 28 largest banks failed.

[3] Models for other clusters are found in Golovan (2003), and are also available by email request.

Table 6[†]

Cluster TA=1%		
Variable	Coefficient	$s_x\beta_x$
C	-2.05*	
Eq/TA	1.65***	0.43
LNTA	0.26**	0.27
NGS/TA	-1.67**	-0.31
CANW/TA	-1.82**	-0.32
LNI/TA	4.50***	**0.95**
$(LNI/TA)^2$	-5.64***	**-0.87**
GB/TA	8.41***	**1.02**
LA/TA	3.35***	0.65
RES/TA	-5.09**	-0.27
DPC/TA	3.93**	0.29
McFadden R-squared		0.22
Obs with Dep=0		132
Obs with Dep=1		492
Total observations		624

Cluster TA=90%		
Variable	Coefficient	$s_x\beta_x$
C	7.24***	
Eq/TA	5.71***	**0.81**
LNTA	-0.39***	-0.46
NGS/TA	-5.94***	-0.59
CANW/TA	-2.66**	-0.41
McFadden R-squared		0.17
Obs with Dep=0		47
Obs with Dep=1		214
Total observations		261

The model for the small banks cluster includes a larger number of significant parameters that can be readily interpreted. The signs of the coefficients at LNI/TA and $(LNI/TA)^2$ suggest the optimal value of the credits-to-non-financial-institutions ratio is about 40%, which is close to the current level of real-economy investments of the banking sector. The average value for this cluster is 28%, which may suggest non-optimal behavior by the banks.

The private deposits ratio increases the probability of survival. Only 50 failed banks and more than 320 surviving banks had non-zero volumes of private deposits.

The most influential ratios for the small banks are GB/TA and LNI/TA. This is partially explained by the significant amount of pocket banks in that cluster. For large banks the equity ratio (i.e. the parameter similar to the H1 capital adequacy coefficient used by the CBR) is most important.

Clusters of banks with low and high investments in government bonds, GB/TA<0.01% and GB/TA>10%. Mean size (LNTA) of a bank from the cluster with low investments in government bonds is 9.62, while the average size of the bank from the second cluster is 11.36 (see Appendix C), which is significantly different from the overall average of 10.72. The mean values of other ratios are close to the overall averages.

[†] In all tables *, ** and *** indicates significance at the 10%, 5% and 1% levels.

The proportions of failed banks are significantly different in the two clusters: 26% and 4%, respectively, and differ from the overall proportion of 17%.

As mentioned earlier, this may suggest that participation at the GKO market is a sign of sophistication in bank financial management or that the bank, with its high exposure in the GKO market, was a recipient of state support after the crisis.

The models for the two clusters are presented in Table 7. Credits to the real economy are significant for banks that have low investments in government bonds. As before, we find the optimal value of the LNI/TA ratio is 58%, which much higher that the cluster average of 30%. This could mean that banks should have invested more in the real economy. The liquid assets and credit-to-non-financial-institutions ratios are most important for the banks from that cluster.

We do not find LNI/TA ratio to be significant for banks in the second cluster. The non-liquid assets and non-government securities ratios are significant, however, and hurt the credibility of banks that are heavily invested in government bonds. The most important factor here is the equity ratio Eq/TA. Bank size has a negative impact, which is explained by the fact that most large banks belong to this cluster.

Table 7

Cluster GB/TA<0.01%			
Variable	Coefficient		$s_x\beta_x$
C	-2.81	***	
Eq/TA	1.38	***	0.38
RES/TA	-3.37	*	-0.19
LNTA	0.24	***	0.37
LA/TA	4.69	***	**0.95**
LNI/TA	4.28	***	**0.92**
$(LNI/TA)^2$	-3.70	*	-0.59
McFadden R-squared			0.135
Obs with Dep=0			161
Obs with Dep=1			463
Total observations			624

Cluster GB/TA>10%			
Variable	Coefficient		$s_x\beta_x$
C	8.69	***	
Eq/TA	6.45	***	**1.18**
RES/TA	-15.48	**	-0.45
LNTA	-0.39	**	-0.70
CANW/TA	-7.93	***	-0.72
NGS/TA	-5.74	**	
McFadden R-squared			0.22
Obs with Dep=0			16
Obs with Dep=1			362
Total observations			378

Models for other clusters are found in Golovan et al. (2003). The Table in Appendix C shows the estimation results of a model specification that includes all ratios found significant in at least one cluster. The ratios Eq/TA, LA/TA and GB/TA are significant in most models.

The overdue-loans-to-total-assets ratio, which was found to be important for bank failure prediction in Bovenzi et al. (1983), is not significant in any of our models. A possible explanation may be that Russian banks masked the actual number of overdue loans at the time of observation. Standards of Russian accounting allow banks to reregister and prolong credits easily, thus decreasing the reported value of the indicator OVL/TA.

McFadden R^2 shows that the model fit is better for some clusters than for the entire sample. Is this improvement in the statistical measure of the model fit important for the predictive power of the model?

In-sample forecast

Given the estimated model, one can calculate the estimates of probability of survival $\hat{p}_i$ for the each bank *i* in the sample. To make a forecast, it is necessary to choose a threshold for the decision. The bank is expected to fail if $\hat{p}_i < c$, and survive if $\hat{p}_i \geq c$. A Type I error occurs when we predict a bank will survive, and, in fact, it fails. Conversely, a Type II error occurs when a bank that was expected to fail survives. The Type I error is obviously more costly. The choice of threshold would depend on balancing the cost (aversion) to the investor of Type I and Type II errors (see discussion of the Type I-II errors trade-off in Bovenzi et al., 1983). For each choice of the threshold, given the sample, we have the pair $(p_{i1}(c),\ p_{i2}(c))$ of the probabilities of Type I and Type II errors. For all *c*, we plot the probabilities of Type I–II errors. One model is considered uniformly superior to another if the corresponding plot lies below the plot for the other model.

In Figure 4, the plots of probabilities of Type I–II errors are presented for the models without clustering and with clustering with respect to GB/TA, TA and Eq/TA. In the most interesting area of small probabilities of Type I error, we note improvement with GB/TA. Of course, we should also remember that the model with GB/TA clustering contains three times more coefficients. The charts for separate clusters look more impressive (e.g. see Figure 5 for the cluster GKO>10% and more examples in Golovan et al., 2003). For the probability of Type I error less than 20%, the probability of a Type II error decreases by 15–35%.

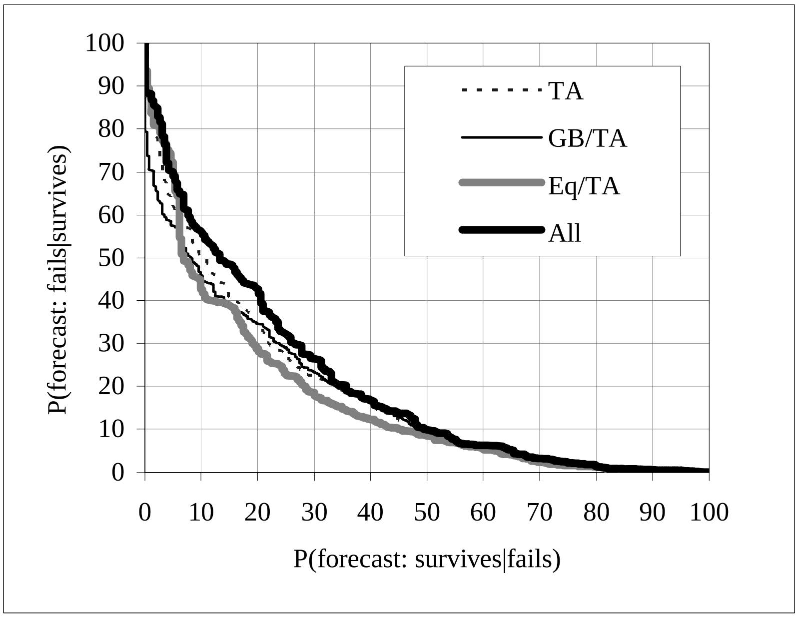

Figure 4. Probabilities of Type I–II errors

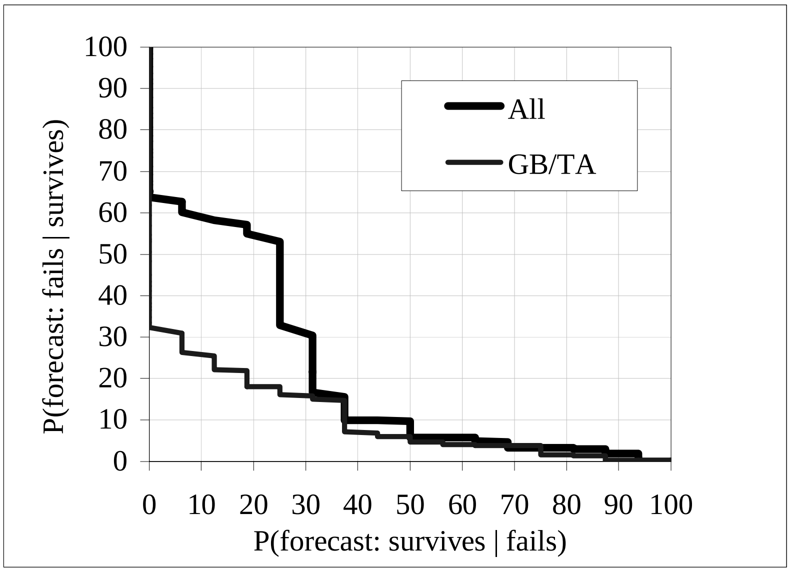

Figure 5. Probabilities of Type I–II errors for banks from the cluster GB/TA>10%.
The GB/TA model is only estimated for banks from the cluster GB/TA>10%

Out-of-sample forecast

An out-of-sample forecast is obviously the preferred method of model comparison. We use a random number generator here to divide the sample into the two parts: a main group (1465 banks) and a control group (100 banks). Models are estimated using the main group, and then error probabilities are estimated for the control part of the sample. The averaged results of 1000 trials are presented in Figure 6. The plots are quite similar to the in-sample forecast plots in Figure 4.

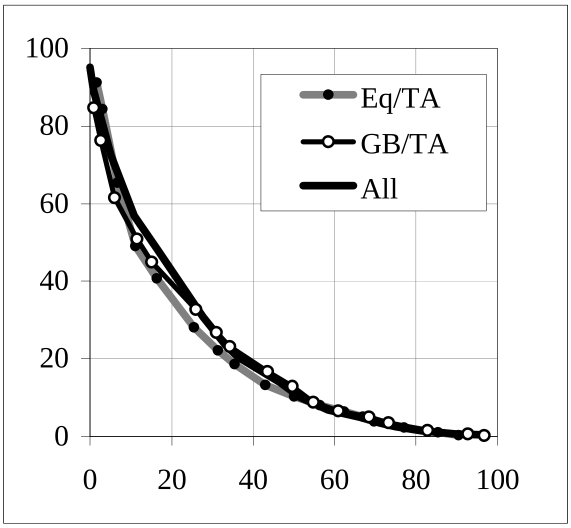

Figure 6

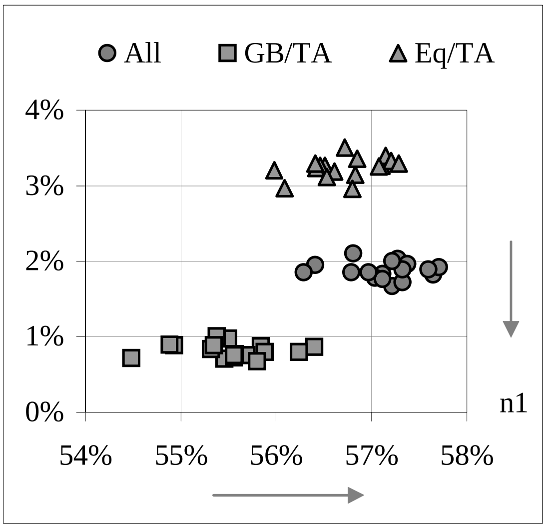

Figure 7

To reveal the model's ability to forecast reliable and unreliable banks, we calculate the proportions n1 and n2 of banks that actually failed of the "worst" and "best' ten banks in each control part of the sample. In an ideal forecast, n1=100% and n2=0%. Our results for 1000 trials are averaged and 17 attempts are presented in Figure 7.

In forecasting reliable banks, the best results are obtained with clustering by the government bonds ratio GB/TA, which gives less than 1% error for the 10% of the best banks in the control sample of 100. For the revealing of the problem banks better works the model without clusters and the model with clustering by the equity ratio Eq/TA. They give about 57–55% of correctly forecasted defaults for the worst 10% banks in the control sample.

2.4 Automatic classification

The model that allows two different probability of default logit models in each of the two clusters may be described as follows:

Consider a logit model that separates banks into two clusters. The probability that a bank with the vector of parameters z belongs to the first cluster is $F(z'\gamma)$, where γ is the vector of the coefficients and F is the cumulative distribution function of the logit distribution. The probability that the bank belongs to the second cluster is then $1 - F(z'\gamma)$.

For each of the two clusters, we have a logit model of bank survival. Let $F(x'\beta_1)$ and $F(x'\beta_2)$ be the probabilities of the bank with the vector of parameters x to survive, conditionally it belongs to the first or second cluster. Different sets of bank parameters may be used for bank classification and probability of survival.

The contribution of bank j to the likelihood function is

$$L_j = F(z'\gamma)\left(F(x'\beta_1)^{y_j}(1 - F(x'\beta_1))^{1-y_j}\right) + (1 - F(z'\gamma))\left(F(x'\beta_2)^{y_j}(1 - F(x'\beta_2))^{1-y_j}\right), \quad (2)$$

where $y_j = 1$ if the bank survives and 0 if it fails. The estimates of the parameters of the model, β_1, β_2 and γ are obtained by maximizing the log-likelihood function

$$\ln L(\gamma, \beta_1, \beta_2) = \sum_j \ln L_j \to \max_{\gamma, \beta_1, \beta_2}. \quad (3)$$

Since there is no guarantee the function (3) has a global maximum, there is an apparent problem in parameter estimation. For example, if the set $(\gamma, \beta_1, \beta_2)$ is the solution of the problem, then the set $(-\gamma, \beta_2, \beta_1)$ is the solution as well.

We find the best solution to the problem (2)–(3) contains parameters z = {Eq/As, LNTA} for cluster discrimination and x = {Eq/TA, RES/TA, LNI/TA, GGO/TA, LA/TA} for the probability of survival/default in each cluster. The results of the model clustering estimates are presented in Table 8. Note that the clustering suggested by the model is similar to the CBR's division (Table 1), i.e. the CBR allows a lower capital adequacy for large banks. Indeed, the results of automatic clustering could be used as is by the CBR to give greater flexibility to capital adequacy requirements.

Table 8

Variable	Coefficient γ
C	–3.14
Eq/As	13.29***
LnTA	–0.0129***

We choose the threshold 0.5 for clustering, i.e. we assign a bank to the first cluster when $F(z'\gamma) < 0.5$; otherwise, it gets assigned to the second cluster. In both clusters, the logit model can be estimated separately. The plot of the probabilities of Type I–II errors for the logit model with the set of the parameters *x* without clustering and for the forecast based on the clustering (2)–(3) and separate logit models[4] in each cluster is presented in Figure 8. The plots show the improvement of the model's predictive power with automatic clustering.

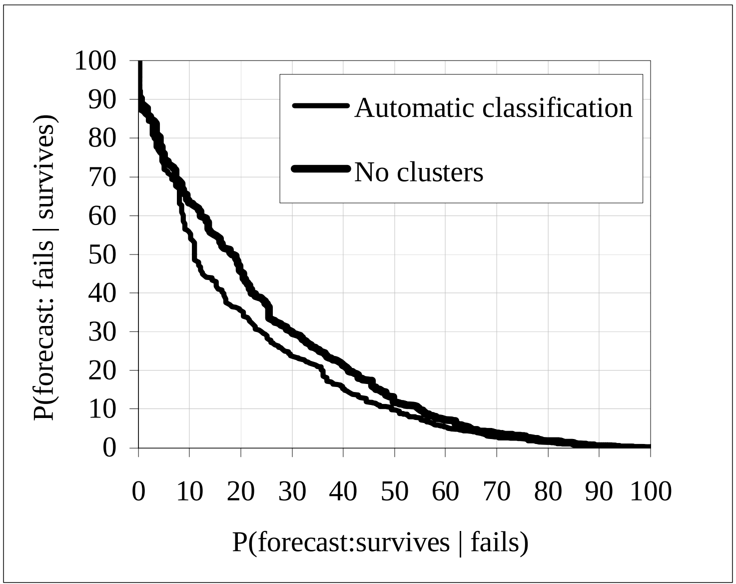

Figure. 8. Automatic classification

Models (2)–(3) may be slightly modified to get an automatic classification algorithm for several clusters.

The comparison of in-sample forecast performance of the various models with clustering is presented in Tables 9 and 10. As seen, out-of-sample and in-sample forecasts are roughly similar in terms of performance.

Table 9 compares the models from an investor's point of view. For each model (100, 200, etc.) the "best" banks are chosen and the number of actually failed bank among those chosen is calculated.

For example, column 3 (with the heading 200) contains information on the 200 "best" banks. Row "average" shows the expected number (34) of the failed banks, if the sample of 200 is chosen randomly; row "basic" presents results for the model m0 from the table in Appendix D, where only 5 banks failed. The rows marked GB/TA, TA, Eq/TA and

[4] Coefficients of the separate logit models are presented at the Appendix E.

LNI/TA present the results for the model with the same set of parameters, but estimated separately in the clusters (“expert” cluster procedure). The last row presents the results of automatic classification described in this section. It is clear that using the model significantly reduces the likelihood of choosing a bank that will default. Clustering in respect to the government bonds ratio decreases the number of failed banks to 0. In comparing the results of the automatic procedure with the expert approach, one should consider that the automatic clustering model has 15 parameters, less than the expert cluster models (36 parameters). The “basic” model has 12 parameters.

Table 9. Number of failed banks in the *** best rankings

***	*100*	*200*	*300*	*400*	*500*	*600*	*700*	*800*
Average	17	34	50	67	84	101	117	134
Basic	**0**	**5**	**9**	**12**	**18**	**26**	**37**	**53**
GB/TA	0	0	1	4	8	16	24	33
TA	1	2	6	8	13	22	29	39
Eq/TA	1	3	8	13	16	16	21	28
LNI/TA	0	6	9	15	18	25	33	43
Automatic clust.	1	3	6	11	18	23	28	34

Table 10 compares the models from the point of view of the bank supervisory authority. For each model (100, 200, etc.), the “worst” banks are chosen and calculated against the number of actually failed bank among them. For example, selecting from the 250 “worst” banks (16% of all banks), we detect as many as 136 banks that will eventually fail (52% of all failed banks). This ability to narrow the field of potentially troubled banks can likely save supervisory authorities considerable time and money in in-site inspections.

Table 10. Number of failed banks in the *** worst ranking (total 263)

***	*50*	*100*	*150*	*200*	*250*	*300*	*350*
Average	8	17	25	34	42	50	59
Basic	**39**	**67**	**91**	**115**	**128**	**138**	**152**
GB/TA	41	71	92	116	129	142	152
LNI/TA	42	73	94	114	129	144	158
Eq/TA	41	74	96	116	136	153	166
TA	42	68	92	114	128	144	155
Automatic clust.	39	75	101	119	130	146	156

3 Macroeconomic variables

Papers that model bank defaults (e.g. Martin, 1977; Estrella et al., 2000; Kolari et al., 2002) do not use macrovariables in their models. All these papers consider the US banking system, which traditionally has enjoyed relatively stable economic conditions. The economic situation in Russia during 1996–2003 was far from stable, and it seems to be plausible that including macroeconomic indicators into our models might improve model performance.

Several papers use macrovariables in studies of probability of default for firms, loans and bonds. Engelmann and Porath (2003) show that the growth of real GDP and growth of money (M3) improve results of the logit models of German company defaults in 1989–2000. Lawrence and Smith (1992) use the unemployment rate in a study of US home credit defaults. Golovan et al. (2004) use macroindicators in their probability of default models for Russian banks.

A number of Basel committee publications stress the role of the macroenvironment in estimating the risk of default, e.g. Amato and Furfine (2003), Borio (2003), Segoviano and Lowe (2002).

Godlewski (2004) in his paper on banks in emerging market economies (does not include Russia) pointed out that the use of macrovariables may improve bank scoring models.

Among papers studying the macroeconomic indicators that drive banking and financial crises, Demirguc-Kunt and Detragiache (1998) apply a pooled logit model in their study of banking crises in developed and developing countries in 1980–1994. They find that GDP growth, the real interest rate, inflation and terms of trade are highly significant in all model specifications. They do not detect an independent effect from the exchange rate, noting that inflation and terms of trade already capture that effect.

Komulainen and Lukkarila (2003) use a panel probit model in their study of the financial crises in 31 emerging market countries in 1980–2001. They found many macroindicators are important for financial crises prediction, including the unemployment rate, industrial production and others not identified by Demirguc-Kunt and Detragiache (1998). Since financial and banking crises are often related, these macroindicators preliminarily can also be important for identifying bank defaults.

3.1 Data

Bank data. The quarterly balance sheet data of the Russian banks for the period 1996–2002 are used in this section.[5] The variable LIVE was constructed according to the definition of bank default described in section 2.1.

To avoid estimation problems with the correlated observations and to increase the ratio of failed banks in the sample, we reduce the sample. Remember, we want to retain all information on defaults and do not have for the bank observations for our banks closer than two years in time.

For each failed bank, we take the time of failure *t* (measured in quarters) and let LIVE=0. We connect to this observation the appropriate bank parameter values (Table 1) and macroindicators (Table 11) at the time $t-8$.[6] We then take the same bank at time $t-8$ and let LIVE=1. We connect to this observation bank parameter values and macroindicators at time $t-16$. We continue at that manner while we still have the data for that bank in the complete sample.

For a surviving bank, the procedure is a bit different. We randomly choose a quarter *t* from the eight quarters in the period 2001–2002, let LIVE=1 and connect to this observation bank parameter values and macroindicators at time $t-8$. We continue to track this bank back in time in the same way as described for a failed bank.

The sample reducing procedure described above leads to biased estimators (Scott and Wild, 1986). However, the estimates of slope coefficients are unbiased, hence our economic interpretations of regression results would not be affected. Nor does the bias in the intercept affect our results as we consider all possible thresholds *c* for model comparison.

[5] Again, data kindly provided by the Mobile Information Agency.
[6] Again as in section 2.1, using a two-year lag between bank data and observed status provides the best results.

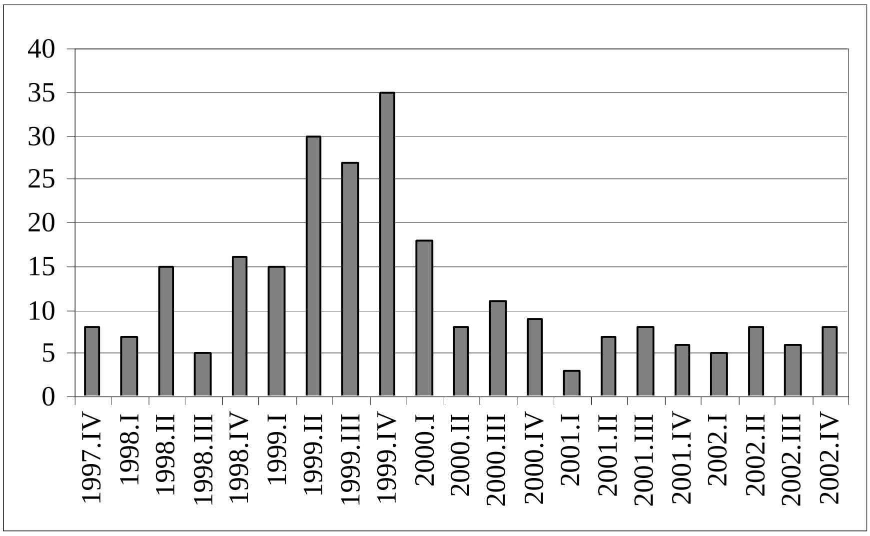

Figure 9. Distribution of bank defaults in our sample, section 3

After the described above selection procedure we have got the sample with 3158 observations, with 255 defaults among them (8.07%). The distribution of the bank defaults in that sample is presented in Figure 9. The distribution does not coincide with the overall distribution of the defaults, because in our sample only those defaults are included for which we have balance sheet data from two years before the default. The overall distribution of Russian banks defaults is presented in Appendix B.

Macroeconomic indicators. The list of macroindicators considered for the models is presented in Table 11. Our choice of a set of possible macrovariables was driven by expert opinion and macrovariables identified elsewhere as significant.[7] For some indicators, their rate of change is also considered.

Table 11. List of macroindicators

Macroindicators		
Real GDP index (seasonally adjusted)*	VVP	%
Consumer price index	CPI	%
Deflator **	Defl	
Unemployment	UNEMPLN	million
Unemployment rate	UNEMPLP	%
Index of investments in capital (seasonally adjusted)***	INV	%
Exchange rate RUR/USD	ERATE	ruble/dollar
Export/Import ratio	EXP/IMP	
Increase of industry production	PRPROD	%
Change in real income	REALINC	%
Increase in exchange rate (year)	DERATE	ruble/dollar
Increase in exchange rate (quarter)	DERATE1	ruble/dollar
Change in GDP rate (year)	DVVP	%
Change in GDP rate (quarter)	DVVP1	%

* 1994.01 = 100; ** based on CPI; *** 1993.I=100

Table 12 presents the descriptive statistics of some bank financial ratios in our sample. All bank parameters in the dataset are measured in thousands of rubles. The mean value of the total assets in the sample, measured in US dollars by historical exchange rate, is about \$100 million. This is a tiny value compared to the total assets of major international banks and even Russia's largest banks. This in itself is reason enough to take the log of this parameter to reduce its variability. Data are distributed over time here, so it seems reasonable to take the deflated value of the total assets as a measure for bank size, i.e. log(TA/defl).

Table 12

	LNI/TA	NGS/TA	NWA/TA	CFB/TA	Log(TA/defl)	Log(TA/defl)^2	Eq/TA	PBT/TA
Mean	0.300	0.087	0.105	0.030	10.37	111.3	0.301	0.016
Max	0.988	0.978	0.943	0.933	16.98	288.2	0.997	0.783
Mean	0.000	0.000	0.000	0.000	3.98	15.9	–0.729	–0.716
Std.dev.	0.205	0.143	0.121	0.084	1.95	41.7	0.221	0.057

To decide whether to include macrovariables in our models, we first consider the correlations of these macrovariables (Table 13). Most macrovariables are highly correlated, which means that including two or more of them into the model may cause a multicollinearity problem. Selected below in Table 13 are the pairs of macrovariables that are least correlated and potentially could be included into the model.

[7] For bank and financial crises, we take from Demirguc-Kunt and Detragiache (1998) and Komulainen and Lukkarila (2003). For the firm defaults, we use Engelmann and Porath (2003). For the Russian banks, we follow Golovan et al. (2004).

Table 13

	CPI	ERATE	EXP/IMP	REALINC	PRPROD	UNEMPLN	UNEMPLP	VVP
CPI	1	-0.040	-0.010	-0.521	-0.586	0.287	0.301	-0.441
ERATE	-0.040	1	0.933	0.043	0.609	0.037	0.081	0.680
EXP/IMP	-0.010	0.933	1	0.156	0.534	-0.069	-0.028	0.669
REALINC	-0.521	0.043	0.156	1	0.401	-0.816	-0.822	0.711
PRPROD	-0.586	0.609	0.534	0.401	1	-0.178	-0.153	0.723
UNEMPLN	0.287	0.037	-0.070	-0.816	-0.178	1	0.996	-0.618
UNEMPLP	0.301	0.081	-0.028	-0.822	-0.153	0.996	1	-0.584
VVP	-0.441	0.680	0.669	0.711	0.723	-0.618	-0.584	1

3.2 Models with macroindicators

In the following section, we consider whether including macrovariables improves the performance of our probability of default model. We now select the model without macrovariables (base model). As in section 2, our model selection is based on statistical criteria: *z*-statistics of coefficients, McFadden R^2, Akaike criterion and economic interpretation. The base model is presented in the first column of Table 14. Intuitively, it appears the signs of the coefficients fit our preliminary expectations.

We use a pooled probit model because it shows marginally better results than the pooled logit model. The panel data model (quite appropriate here) and the probit panel model with random effects give exactly the same results. The ρ parameter is insignificant in all model specifications.

The profit-before-tax ratio (PBT/TA), which can be used as a measure of management quality, has a positive impact. The credits-to-non-financial-institutions ratio (LNI/TA) produces a negative effect. This differs from the conclusion in section 2, but note that, in contrast to section 2, which examines the crisis, this model uses data for a five-year period and the level of credits significantly vary with macroenvironment. The non-government securities and non-working assets ratios (NGS/TA and NWA/TA) show a negative effect, indicating poor asset management. This model allows for optimal value of bank size, i.e. ln(TA/defl) = 10.44, which is slightly higher than the mean value of that parameter in the sample. Surprisingly, the equity ratio Eq/TA is insignificant when included in the model. This may be explained by multicollinearity with the set of already included ratios (obviously, all possible ratios add up to 1).

Now we add our macroindicators (Table 11) to the base model. The best two models in terms of statistics values appear in columns 2 and 3 of Table 14. Macromodel 1 includes the export-import ratio, while macromodel 2 includes the ruble/dollar exchange rate. All statistical criteria of the two macromodels (log likelihood, Akaike, McFadden R^2) are better than those for the base model. Some improvement could be achieved by including two macrovariables. It remains unclear whether these improvements are economically significant. The next two sections, 3.3 and 3.4, consider this issue.

Table 14 shows that the signs of the coefficients agree with the economic intuition. The profit-before-tax ratio (PBT/TA), which measures management quality, enhances bank reliability. The non-government securities and non-working assets ratios (NGS/TA and NWA/TA) have a negative effect and indicate poor asset management. The credit-to-non-financial-institutions ratio (LNI/TA) also has a negative impact.

Including macrovariables increases the value of the PBT/TA coefficient and decreases the values of the NGS/TA and NWA/TA coefficients. The marginal effect of the PBT/TA declines after the crisis. The marginal effects of LNI/TA, NGS/TA and NWA/TA are also less negative after the crisis. The marginal effect of bank size, ln(TA/DEFL), does not change after the crisis.

Table 14

Variable	Coefficient		
	Base model	Macromodel 1	Macromodel 2
C	0.150	–0.847	–0.331
PBT/TA	1.226**	1.541**	1.663***
LNI/TA	–1.188***	–0.976***	–0.930***
NGS/TA	–1.008***	–1.247***	–1.394***
NWA/TA	–1.346***	–1.223***	–1.204***
CFB/TA	–0.546	–0.277	–0.113
Ln(TA/DEFL)	0.376***	0.367***	0.368***
$Ln(TA/DEFL)^2$	–0.0181***	–0.0181***	–0.0184***
EXP/IMP		0.621***	
ERATE			0.0346***
Log likelihood	–845.11	–807.73	–799.74
LR statistics (8, 9 df)	81.99	156.76	172.72
Akaike criterion	0.5403	0.517	0.512
McFadden R2	0.0463	0.088	0.097

A positive EXP/IVP coefficient may imply that a higher export-import ratio characterizes a healthier economy, and hence macroeconomic stability. In such circumstances, the stability of the banking system should also be expected to increase.

Less obvious is the interpretation of the positive sign of the ERATE coefficient. In Russia, a rising exchange rate (ruble depreciation) is always associated with economic destabilization. On the other hand, a high exchange rate boosts the export-import ratio. In fact, the two variables are highly correlated (Table 13).

3.3 Model comparison: Type I – II errors

In-sample forecast. The probabilities of Type I and II errors in the sample are calculated for each threshold *c*. The plots, corresponding to the three models (Table 14) are presented in Figure 10. Improvements from including macrovariables are observed, but none of the two macromodels is uniformly better than another; the corresponding plots often intersect.

To test the in-sample predictive power of the models, we choose samples of 100 and 500 of the most reliable and most distressed banks according to the rankings generated by each of the three models. The proportions of actually failed banks captured by the samples are presented in Table 15.

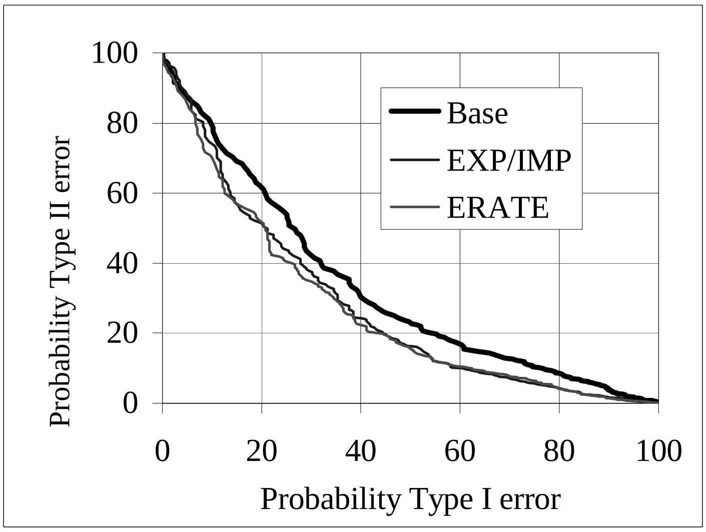

Figure 10. Probabilities of Type I–II errors

We recall here that a random assigning of banks into sets of 100 would capture 100/3158, or 3.2% of all 255 defaults, while a random sample of 500 would capture 15.8% of all defaults. From the supervisory point of view, an examination of 500 banks identified as most distressed by the base model (15.8% of the total) would identify as much as 34.5% of all banks that will enter into default within two years. Adding macrovariables, the model increases this proportion to 46.3%. For the investor, selection of the 100 most reliable banks using our model decreases the expected number of failed banks in the sample from 255*3.2% = 8 to 3 (base model) and to 1 (macromodel 2). The results are compatible with those from section 2.

Table 15

Banks	Sample size	Model		
		Base model	Macromodel 1 (EXP/IMP)	Macromodel 2 (ERATE)
“distressed”	100	8.2%	12.2%	14.1%
	500	34.5%	45.5%	46.3%
“reliable”	100	1.2%	1.2%	0.4%
	500	7.5%	6.3%	6.3%

Out-of-sample forecast. Our procedure involves selecting 300 observations randomly and excluding them from the whole sample. For the rest of the sample, all three models are evaluated and the selected 300 observations are ranked according to each of the three models. The proportion of the total number of all defaults in the sets of 10 and 50 most reliable and most problematic banks of these 300 from the point of view of the each of the three models are calculated. The results are presented in Table 16. Again, as in section 2, we do not find a significant difference in our in-sample and out-of-sample model performance evaluations.

Table 16

Banks	Sample size	Model		
		Base model	Macromodel 1 (EXP/IMP)	Macromodel 2 (ERATE)
“distressed”	10	7.3%	11.9%	12.5%
	50	34.5%	46.6%	47.0%
“reliable”	10	1.3%	1.5%	0.6%
	50	8.1%	6.9%	6.3%

3.4 Model comparison: Heuristic criteria

As noted, the cost of a Type I error (classifying a failed bank as a reliable) to an investor would be distinctly higher than the cost of a Type II error. If the ratio between the two costs for the investor were available, then it would be possible to identify an optimal value of threshold *c* that minimizes a linear loss function over the curve in a plot of Type I–II error probabilities. Below two heuristic criteria are suggested, based on two rough models of investor behavior.

Let the investor use a model and threshold c for bank classification. X_c^- is the set of the banks classified as "distressed" ($\hat{p} < c$), while X_c^+ is the set of banks classified as "reliable" ($\hat{p} \geq c$). Notations for the number of banks for all four possible outcomes appear in Table 17.

Table 17

Banks	Bankruptcies	Still solvent
Classified as "distressed", X_c^-	I. m_c	II. $n_c - m_c$
Classified as "reliable" X_c^+	III. $M - m_c$	IV. $N - M - (n_c - m_c)$

Consider a naive investor, without a model, who invest S amount of money in banks. This investor can use a "uniform" investment strategy, i.e. equal parts of S/N are invested in all banks, or a "proportional" strategy in which the size of each investment is proportional to the size of the bank, i.e. an investment in bank k would equal $S_k = S \cdot (VB_k / \Sigma_{all})$, where $\Sigma_{all} = \sum_{j=1}^{N} VB_j$. The first strategy models the behavior of an investor eager to diversify investments, while the second strategy closely models the behavior of the entire set of investors.

Let r is the bank deposit interest rate, constant over time (we will take later r = 15% or 20%, i.e. average figures in Russia for the considered time period). We now assume that the investments in the failed banks are completely lost. Under this assumption, the net income of under the "uniform" strategy and the "proportional" strategy will equal (4) and (5), respectively.

$$\frac{S}{N}(N-M)r - \frac{S}{N}M = S\frac{r(N-M)-M}{N}, \tag{4}$$

$$\frac{S}{\Sigma_{all}}\left(r\Sigma_{\mathrm{II+IV}}(c) - \Sigma_{\mathrm{I+III}}(c)\right). \tag{5}$$

(Summations are evaluated over the groups of banks. See notation in Table 17, e.g. $\Sigma_{\mathrm{I+III}}(c) = \sum_{\mathrm{I+III}} VB_j$.)

Now consider the behavior of a savvy model-wielding investor. After choosing a threshold c, this investor classifies banks as "distressed" or "reliable." On the basis of this classification, the savvy investor only invests in "reliable" banks and holds any money that would otherwise have been invested in a "distressed" bank under the strategies of the naive investor.[8] We then consider this excessive net income of the savvy investor as a utility function to be optimized. The utility functions have the form (6) for the uniform investment strategy and (7) for the proportional strategy.

$$PR_U(c) = \frac{m_c}{N} - r\frac{n_c - m_c}{N}, \tag{6}$$

$$PR_P(c) = \frac{\Sigma_{\mathrm{I}}(c)}{\Sigma_{all}} - r\frac{\Sigma_{\mathrm{II}}(c)}{\Sigma_{all}}. \tag{7}$$

Of course, the savvy investor can determine the optimal threshold c. Finally, the two utility measures, heuristic criteria for the model comparison are

$$PR_U = \max_{0<c<1} PR_U(c), \qquad PR_P = \max_{0<c<1} PR_P(c). \tag{8}$$

Table 18 presents the statistical and heuristic criteria for the model comparison for the base model (number 0, first row) and for the 24 models that differ from the base model in terms of added regressors. One additional macrovariable is included in models 1–14; models 15–22 contain two additional macrovariables. For comparison purposes, we include model 23, which contains time dummies for all quarters and thus shows the limit of the model improvements after including additional macrovariables. Model 24 contains a dummy for Russia's August 1998 financial crisis.

[8] In the case where the investor has incentive to invest all his/her money in "reliable" banks, the optimal behavior is simply to invest all money S into one, the most "reliable" bank.

Table 18. Model efficiencies

Num	Model	Statistics			Heuristic criteria			
		McFadden R2	LogL	Akaike	PR_U (r=0,15)	PR_P (r=0,2)	PR_U (r=0,15)	PR_P (r=0,2)
0	Base	0.046	-845.1	0.540	1.04	0.34	10.00	7.97
1	EXP/IMP	0.088	-807.7	0.517	2.01	1.50	13.32	12.14
2	ERATE	0.097	-799.7	0.512	2.02	1.46	12.79	11.28
3	CPI	0.055	-837.2	0.536	1.34	0.60	10.50	8.93
4	VVP	0.060	-833.0	0.533	1.10	0.39	10.44	8.61
5	INV	0.049	-842.7	0.539	1.14	0.28	10.14	8.34
6	DERATE	0.062	-830.8	0.532	1.35	0.64	10.21	7.91
7	DVVP	0.055	-837.7	0.536	1.01	0.46	10.08	8.08
8	DERATE1	0.051	-841.0	0.538	1.17	0.45	10.34	8.69
9	DVVP1	0.064	-829.4	0.531	0.99	0.57	9.75	7.81
10	DERATE/ERATE	0.056	-836.5	0.535	1.23	0.52	10.21	8.21
11	DERATE1/ERATE	0.049	-842.6	0.539	1.14	0.33	10.21	8.23
12	REAL_INC	0.048	-843.3	0.540	0.97	0.27	10.10	8.17
13	UNEMPLP	0.046	-845.0	0.541	0.94	0.22	9.99	7.96
14	UNEMPLN	0.046	-845.1	0.541	1.00	0.31	10.01	7.98
15	ERATE, CPI	0.106	-792.2	0.508	2.12	1.51	12.36	11.17
16	ERATE, VVP	0.100	-797.7	0.512	2.15	1.51	12.23	10.88
17	EXP/IMP, CPI	0.095	-801.6	0.514	2.04	1.56	13.54	12.40
18	EXP/IMP, VVP	0.089	-807.3	0.518	2.01	1.48	13.30	12.09
19	ERATE*(LNI/TA), ERATE	0.100	-797.1	0.511	1.96	1.32	12.72	11.20
20	ERATE*(NWA/TA), ERATE	0.098	-799.0	0.512	2.04	1.43	12.70	11.60
21	EXP/IMP*(LNI/TA), EXP/IMP	0.092	-805.0	0.516	1.87	1.37	13.26	12.23
22	EXP/IMP*(NWA/TA), EXP/IMP	0.089	-806.8	0.517	1.96	1.49	13.33	12.11
23	DUMMIES	0.129	-772.1	0.507	2.16	1.65	13.51	12.47
24	CRISIS	0.105	-793.1	0.508	2.14	1.50	12.62	11.12

Table 18 shows that the inclusion of the macrovariables improves the statistical criteria of the models and almost all models improve the heuristic criteria. The best performance of models 1–14 is found in models 1 and 2, which include exchange rate, ERATE and the export-import ratio EXP/IMP. For these models, the heuristic criterion PR_U increases (in comparison with the base model) from 1% to 2%, while the heuristic criterion PR_P increases (compared to the base model) from 10% to 13%.

In some cases, e.g. if the rate of the GDP grows, DVVP1, is added to the model 9, the values of the heuristic criteria fall. It should not be misleading. The model are estimated by the maximum likelihood, maximizing the likelihood function, which automatically mean maximizing McFadden R-square, but the heuristic criteria.

Including two macrovariables (models 15–18) or the cross-terms (models 19–22) insignificantly improve the statistical and heuristic criteria.

The statistical and heuristic criteria of the model 23 are so close to the criteria values for the models 1 or 2, which it is possible to conclude, that including one of the two macrovariables already captures almost all effect of the varying macroenvironment.

The model 24 includes the dummy variable CRISIS, which is equal 1 after the crisis of August 1998. Figure 11 presents the time plots of the variables ERATE and CRISIS, which look very similar. It is no surprise then that the models' criteria are similar as well. Thus, there still is the open question if it is the influence of the macrovariable to the bank default which is found or the structural break in the Russian banking system after the crisis. That question is partially addressed in the section 4, which studies the Russian banking system after the crisis.

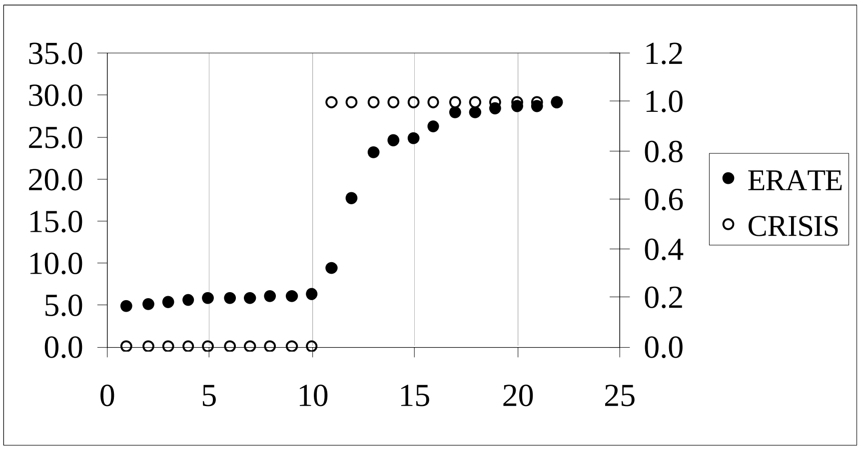

Figure 11. Exchange rate dynamics

In Table 19, the optimal threshold c^* for the three models in Table 14 are calculated for the heuristic criteria for interest rate r = 15%.

Table 19

Criterion	Base model	Macromodel 1	Macromodel 2
PR_U (r=0.15)	0.884	0.853	0.848
PR_P (r=0.15)	0.869	0.848	0.834

The table shows that the optimal threshold varies in the interval 0.834 – 0.884, and its variation for the models with a macrovariable is even smaller (0.834 – 0.853). These figures are lower than the generally recommended threshold for binary models equal to the ratio of 1 in the sample (0.92 in our case).

We now detail model 21 (see Table 18). The relevant coefficient estimates are presented in Table 20.

Table 20

Variable	Coefficient
C	-0.507
PBT/TA	1.474 **
LNI/TA	-2.295 ***
NGS/TA	-1.218 ***
NWA/TA	-1.232 ***
CFB/TA	-0.277
LOG(TA/DEFL)	0.381 ***
LOG(TA/DEFL)^2	-0.0187 ***
EXP/IMP	0.363 ***
EXP/IMP*(LNI/TA)	0.865 **

The sign of the LNI/TA coefficient is the sign of the expression

$$2.295 + 0.865 \cdot \text{EXP/IMP} ,$$

which says that the impact of credit to the real economy may be positive when $\text{EXP/IMP} > 2.655$. However, during the period under the consideration (January 1996 – April 2001) this variable was less than 2.5.

4 After the crisis

We now attempt to identify changes in the Russian banking system over time. We use a rolling window with the window sizes of four, six and eight quarters, estimating the probit probability of default model in the window. Since our sample (rolling window) is now much smaller than the one we use in section 3, we consider two alternative ways for constructing the data set. First, using all available observations, we again establish that the pooled probit model gives the same result as the random-effect panel probit model. Second, we apply a sample selection procedure similar to that described in section 3.1. The sole difference is that we use a one-year interval between observations of same bank rather than a two-year interval as in section 3.1.

All possible combinations for window size and data type give similar results in terms of economic interpretation. For our purposes, we only need to discuss one result. In Table 21, we present the pooled probit estimation with an eight-quarter rolling window. The row “Time” corresponds to the beginning of the rolling window.

From the table, we observe the structural change in the banking system after the 1998 crisis (third quarter, 1998.3). Variables PBT/TA, LNI/TA and OVL/TA, which were insignificant before the crisis, became significant after the crisis. That could mean that banks became more involved in financing the real economy after the crisis, and that the quality of balance sheet data, particularly overdue loans (OVL) and profit (PBT), improved from 2000 onwards. In the late 1990s, banks were using several accounting tricks such as “tax optimization” and not declaring overdue loans on their balance sheets (Soest van et al., 2003).

For the periods following 1999.2, both variables LNI/TA and $(LNI/TA)^2$ are significant. This permits estimating the implied “optimal” value of an investment in the real sector of the economy. The plot of this estimated optimal value is presented at Figure 12. We see that the value steadily increases from 0.35 to 0.41 during the last three years. This evidence suggests gradual improvements in the Russian banking system (i.e. financing of the real sector of economy should be the main function of a banking system). Note that the ratio of Russian banks’ total investments in the real economy to their total assets also grew during the period, i.e. 1999 (28.6%), 2000 (29.5%) and 2001 (35.1%).

Table 21. Rolling window probit regression[9]

Time	1996.2	1996.3	1996.4	1997.1	1997.2	1997.3	1997.4	1998.1	1998.2	1998.3	1998.4	1999.1	1999.2	1999.3	1999.4	2000.1	2000.2	2000.3	2000.4
PBT/TA	-0.03	-1.03	-1.79	-0.16	-0.36	-0.32	-0.08	0.91	1.26	1.54	***2.11***	1.89	2.16	2.02	1.77	**5.83**	**4.84**	**4.86**	**5.93**
LNI/TA	-1.54	-2.09	-1.21	-0.92	-1.26	-1.10	-1.02	-1.49	-0.72	0.01	0.30	1.30	**2.04**	**2.48**	**3.51**	**3.52**	**4.42**	**4.23**	**4.39**
$(LNI/TA)^2$	0.93	1.73	1.08	0.95	1.34	1.21	1.16	1.85	1.07	-0.06	-0.83	-1.95	**-2.91**	**-3.51**	**-4.63**	**-4.44**	**-5.62**	**-5.23**	**-5.36**
NGS/TA	**-2.02**	**-2.41**	**-1.70**	**-1.50**	**-1.44**	**-1.40**	**-1.30**	**-1.31**	**-1.03**	***-0.71***	**-1.10**	**-1.03**	**-1.03**	**-1.16**	**-1.05**	***-0.76***	***-0.76***	-0.65	-0.60
NWA/TA	**-1.80**	**-1.79**	**-1.39**	**-1.08**	**-1.00**	**-1.02**	**-0.83**	-0.55	-0.26	-0.22	-0.39	-0.33	-0.40	-0.35	-0.42	0.06	0.08	0.42	0.69
ln(TA/DEFL)	0.33	0.41	0.33	0.33	0.32	0.25	0.16	0.07	0.05	-0.09	-0.01	-0.19	-0.20	-0.25	-0.34	-0.32	-0.50	-0.29	-0.75
$\ln(TA/DEFL)^2\times10$	-0.17	***-0.20***	-0.16	***-0.16***	***-0.16***	-0.14	-0.10	-0.06	-0.04	0.02	-0.02	0.06	0.07	0.10	0.14	0.13	0.19	0.10	0.27
OVL/TA	2.84	1.64	1.62	0.82	0.67	-0.63	-0.38	-1.29	-0.73	-0.55	-0.59	-1.78	-1.87	-0.77	-0.96	-1.91	***-3.64***	**-4.57**	**-6.53**
RES/TA	-1.21	-0.35	-0.53	0.25	0.34	1.36	0.81	2.04	0.40	0.40	0.87	1.26	1.15	0.30	-0.03	1.50	1.40	1.81	2.32
ERATE	**2.86**	**0.19**	**0.05**	**0.03**	**0.03**	**0.03**	**0.02**	***0.01***	0.00	0.00	0.00	-0.02	0.03	***0.11***	-0.04	-0.01	0.031	0.02	-0.03
Constant	***-16.2***	-0.27	0.763	0.763	0.863	1.293	1.86	**2.63**	**2.78**	**3.40**	**2.88**	**4.33**	3.08	0.87	***5.41***	***4.29***	***4.33***	3.39	**7.69**
Observations	1590	2447	3327	4184	5063	5937	6807	6929	6908	6880	6821	6771	6706	6641	6582	6527	6488	6485	5666
McFadden R^2	0.077	0.103	0.073	0.061	0.066	0.07	0.058	0.044	0.025	0.019	0.029	0.033	0.045	0.057	0.064	0.076	0.092	0.087	0.109

[9] Bold means significance at 5% level; bold italic means significance at 10% level.

The exchange rate variable became insignificant after the crisis, suggesting that after the crisis this parameter has much less impact on bank reliability than earlier. Financial market volatility also decreases and operations become more transparent. The volume of high-risk financial operations decreases.

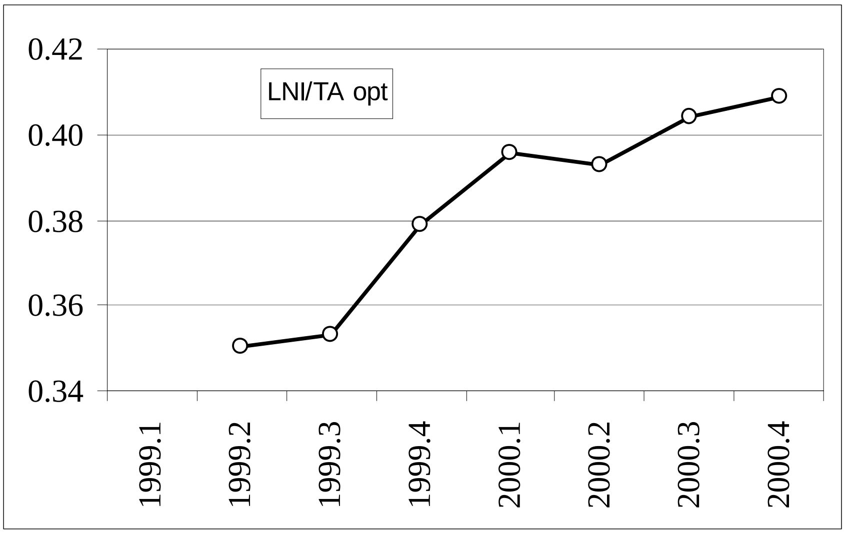

Fig. 12. Implied “optimal” values of LNI/TA

Figure 13 shows the evolution of the measure of the model fit, McFadden R^2, over time. The lowest point in the plot corresponds to the crisis. The measure rises steadily after the crisis, indicating both stabilization of the Russian banking system after the crisis and increasing adequacy of bank balance sheets.

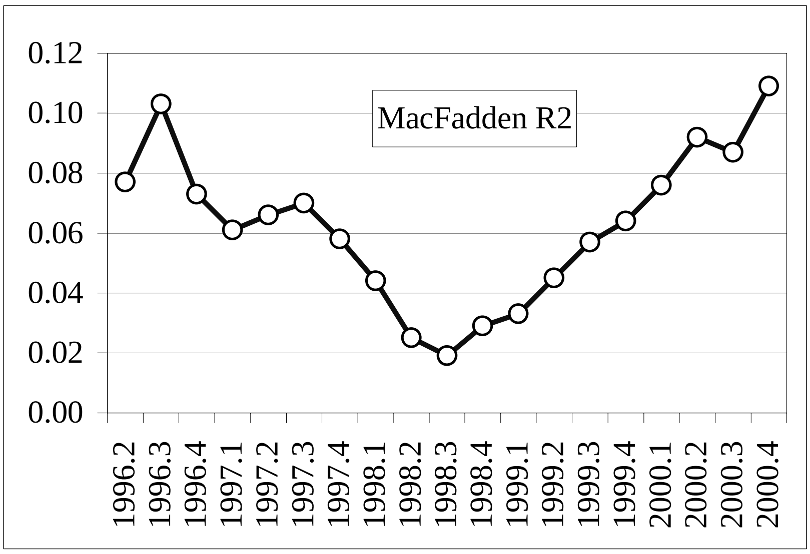

Figure 13. Plot of McFadden R^2 statistic over time

5 Conclusions

Our results found the following:

- Despite the poor quality of the Russian balance sheet data, the bank probability of default models can be used for an EWS.
- Model modifications that took into account the structural non-homogeneity of the set of banks proved helpful.
- Including macroindicators improves the model performance.
- Russian banking supervision authorities could use the results of automatic clustering in designing more flexible capital adequacy requirements.
- The models are not stable and need regular reestimation in a varying macroeconomic environment if they are to be used in an EWS.

Heuristic criteria that reflect the point of view of an investor were suggested for model comparison.

The rolling window estimation of the models indicated several features of development of the Russian banking system after the 1998 crisis. Increasing goodness-of-fit measure revealed stabilization of the banking system. This may be explained by development and stabilization of the Russian banking system and a more predictable macroeconomic environment. Emerging significance in the models of bank parameters such as profit-before-tax and overdue loans ratios hinted at improving quality of bank accounting reports. Reasonable increases in the implied “optimum” value of the credits-to-non-financial-institutions ratio was seen as evidence of increasing opportunities for bank investment in the real sector of the economy. The data on overall bank investments in the real economy showed that tendency is realized with a lag of 1-1.5 years.

Models similar to those proposed in this paper could be used by Russian bank supervision authorities as an element of an EWS and for establishing more flexible capital adequacy requirements. The models also could be used by commercial banks in an IRB framework for estimating risk in line with the Basel II Accord.

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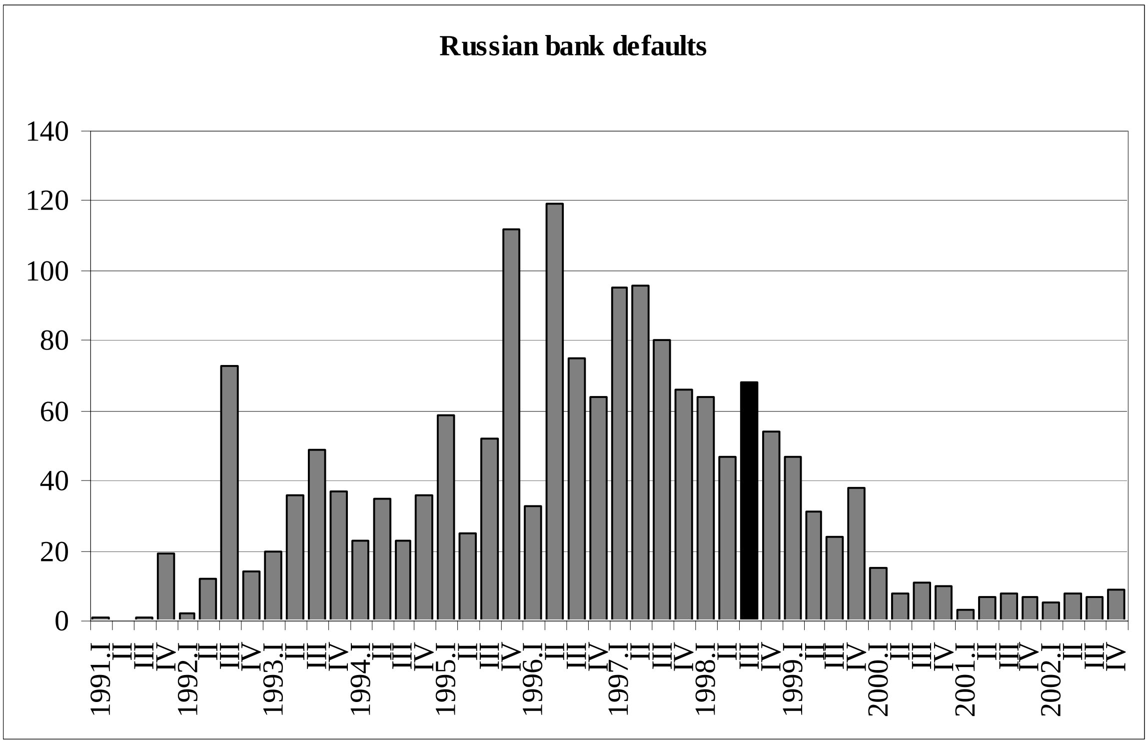
Appendix

A. Correlation of bank ratios, April 1998

	LNTA	RES/TA	LNI/TA	GB/TA	Eq/TA	LA/TA	DPC/TA	CANW/TA	NGS/TA
LNTA	1	-0.12	0.02	0.18	-0.29	-0.25	0.13	-0.04	0.00
RES/TA	-0.12	1	0.12	-0.16	-0.25	-0.22	-0.03	0.23	-0.07
LNI/TA	0.02	0.12	1	-0.22	0.03	-0.25	0.29	-0.15	-0.34
GB/TA	0.18	-0.16	-0.22	1	0.06	-0.09	-0.04	-0.25	-0.09
Eq/TA	-0.29	-0.25	0.03	0.06	1	0.11	-0.09	-0.23	0.24
LA/TA	-0.25	-0.22	-0.25	-0.09	0.11	1	-0.14	-0.28	-0.16
DPC/TA	0.13	-0.03	0.29	-0.04	-0.09	-0.14	1	0.05	-0.12
CANW/TA	-0.04	0.23	-0.15	-0.25	-0.23	-0.28	0.05	1	-0.24
NGS/TA	0.00	-0.07	-0.34	-0.09	0.24	-0.16	-0.12	-0.24	1

B. Distribution of Russian bank defaults, 1991–2002



(The August 1998 crisis is indicated with a black bar.)

C. Mean values of ratios over clusters, 1998

	obs.	%defaults	RES/TA	DPC/TA	CANW/TA	NGS/TA	LA/TA	GB/TA	LNI/TA	Eq/TA	LNTA
All	1569	17%	0.034	0.063	0.202	0.117	0.136	0.073	0.29	0.281	10.72
live=0	263		0.056	0.049	0.285	0.139	0.073	0.024	0.267	0.174	10.53
live=1	1306		0.029	0.065	0.185	0.113	0.149	0.083	0.295	0.303	10.76
TA=1%	624	21%	0.039	0.048	0.216	0.11	0.174	0.051	0.282	0.343	8.96
TA_other	684	12%	0.032	0.073	0.194	0.135	0.123	0.08	0.297	0.265	11.2
TA=90%	261	18%	0.024	0.071	0.189	0.09	0.082	0.11	0.29	0.175	13.67
LNI/TA<15%	392	22%	0.021	0.027	0.213	0.199	0.202	0.103	0.062	0.312	10.3
15%<LNI/TA<40%	752	16%	0.037	0.068	0.219	0.114	0.121	0.078	0.275	0.25	11.05
LNI/TA>40%	425	13%	0.038	0.087	0.161	0.048	0.103	0.037	0.526	0.307	10.52
GB/TA<0.01%	624	26%	0.043	0.048	0.233	0.127	0.158	0	0.301	0.3	9.6
0.01%<GB/TA<10%	567	15%	0.03	0.079	0.213	0.12	0.122	0.037	0.315	0.246	11.52
GB/TA>10%	378	4%	0.024	0.062	0.135	0.099	0.122	0.248	0.234	0.303	11.36
Eq/TA<11%	268	40%	0.054	0.045	0.273	0.072	0.112	0.051	0.246	-0.012	11.28
11%<Eq/TA<30%	686	13%	0.031	0.076	0.196	0.108	0.134	0.081	0.302	0.205	11.21
Eq/TA>30%	615	10%	0.028	0.056	0.178	0.148	0.15	0.074	0.296	0.494	9.92

D. Model fitted for various clusters, 1998

model	m0	m1	m2	m3	m4	m5	m6	m7	m8
Variable	All	TA=1%	TA=90%	GB/TA <0.01%	GB/TA >10%	LNI/TA <15%	LNI/TA >40%	Eq/TA <11%	Eq/TA >30%
C	-7.30***	-0.27	-5.40	-1.80	-9.06	-6.23***	-7.18	-6.35*	-2.47
Eq/TA	2.24***	1.65***	6.05***	1.54***	7.11***	1.64***	1.76**	1.85*	-1.34
RES/TA	-5.19***	-5.06***	-8.30	-2.58	-10.84	-7.40*	-1.27	-12.30***	1.03
LNTA	1.42***	-0.19	1.51	0.15	2.42	1.21***	1.73***	1.32***	0.60
$LNTA^2$	-0.06***	0.03	-0.07	0.005	-0.11*	-0.05**	-0.07***	-0.057***	-0.016
LNI/TA	3.27***	4.56***	-4.74	2.80*	-10.59	2.42	-10.22	0.785	2.72
$(LNI/TA)^2$	-4.18***	-5.64***	7.67	-3.19	21.77	-24.09	8.81	0.218	-3.18
GB/TA	6.07***	8.40***	1.25	12459.2	-0.03	5.86***	10.93**	5.53*	12.7***
LA/TA	3.80***	3.37***	0.13	3.92***	9.38	3.83***	8.82***	3.21**	3.85**
NGS/TA	-1.76***	-1.62*	-5.70***	-0.95	-6.62**	-1.57*	1.23	-1.74	0.16
CANW/TA	-1.68***	-1.77**	-2.19	-1.12	-6.55*	-2.12***	0.97	-1.44	-1.80
DPC/TA	1.59	3.94**	-1.99	3.96**	-3.54	1.47	0.98	-0.94	4.22*
McFadden R^2	0.2	0.22	0.19	0.15	0.28	0.29	0.14	0.26	0.2
Obs with Dep=0	263	132	47	161	16	86	57	107	64
Obs with Dep=1	1306	492	214	464	362	306	368	161	551
Total observations	1569	624	261	625	378	392	425	268	615

E. Separate models in clusters

The table below presents results of the separate logit models in each of the clusters obtained through automatic classification and model (2)–(3) estimates for β_1, β_2.

	Cluster 1 (646 banks)		Cluster 2 (923 banks)	
Variable	Logit	Model	Logit	Model
C	–0.24	–0.45	1.56	2.08
Eq/TA	2.08**	0.97	–1.38**	–2.51***
RES/TA	–10.05***	–10.59***	–1.35	1.84
LNI/TA	2.21***	2.45***	1.35**	1.02*
GB/TA	5.94***	5.80***	12.12***	286.89***
LA/TA	6.06***	5.69***	3.10***	3.01***
McFadden R^2	0.24		0.10	

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