The Early Prediction of Bank Defaults by Central Banks

Alexander Larionov
School of World Economy, Faculty of World Economy and International Affairs, HSE University, Russia alarionov@hse.ru

Received: 31 January 2020; Accepted: 8 September 2024

Summary

This article elucidates the approach used by central banks to monitor bank stability at an early stage. Existing default prediction models use CAMELS to estimate bank stability. This research, using Russian regional data, suggests that the internal bank data available to central banks are crucial for default prediction and are complementary to CAMELS. The combined use of central bank payment system data and Basel norms improves the quality of default prediction, benefiting from the absence of information asymmetry. The empirical results support the need to use three categories of indicators to predict banks' financial stability: CAMELS, the indicators available to central banks, and the indicators of the external economic environment. Central banks can use internal payment system data to analyse banks' financial conditions in real time. The use of external indicators is especially significant in Russia, given the wide disparities in the economic development across Russia's regions.

Keywords

Central Bank, Default, Lender of last resort, Payment system, Cash flow·, Volatility.

JEL: H12

Introduction

This research suggests an approach to the monitoring of bank stability at an early stage. Maintaining bank stability ensures the sustainability of national socio-economic development, as banks play a key role in lending. The risks affecting the functioning of banks are increasing owing to new financial technologies and the emergence of new forms of interaction, such as digital financial platforms and the increasing digitalization of the economy (Woźniak-Jęchorek, B. and Kuźmar, S., 2023). The increasing pace of interaction in financial markets leads to increased competition among financial institutions, which determines the need to develop new approaches to ensuring financial stability. Threats to the financial stability of banks increased during major challenges such as the COVID-19 pandemic (Kristóf, T., and Virág, M., 2022).

An incorrect assessment of bank solvency leads to significant losses (Phillip Swagel, 2015). These losses are associated with the emergence of financial contagion and further systemic risk. To prevent the negative effects of financial contagion, government agencies and financial institutions need to improve the early prediction of distress (Savas Papadopoulos, Pantelis Stavroulias & Thomas Sager, 2019). Given the widespread use of digital technologies, it is necessary to use high-frequency data available in real time for monitoring. The sources of such data include central bank payment services. The importance of central bank payment services is increasing with the development of digital currencies by central banks to monitor cash flows, including government cash flows (Bank of Russia, 2021). The goal of this study is to assess the applicability of the data available to Russia's central bank for predicting bank defaults. It is necessary to assess the available information resources of central banks for developing timely monitoring to prevent defaults at an early stage. The results can improve new forms of supervision, in particular behavioural oversight.

The novelty of the study lies in demonstrating the possibility of using payment system data to predict financial distress. Central banks ensure the functioning of payment systems by acting as operators, for example TARGET2 in the EU (European Central Bank (ECB), 2019). In Russia, the central bank operates the Bank of Russia Payment System. Information from payment systems, i.e. the direction of cash flows and the turnover of funds can serve as an indicator of financial stability. Monitoring cash flows in payment systems allows central banks to mitigate the negative consequences associated with the increased volatility of cash flows. The data generated by payment systems are available in real time to most central banks.

The Bank of Russia, like other central banks, collects data related to banking oversight. Banking oversight is based on Basel I, II, and III. The oversight data could help to estimate the financial stability of banks more accurately. The novelty of the research is also related to the possibility of using the Basel norms to improve the monitoring of the financial stability of banks by combining them with CAMELS.

This paper consists of six sections: Section 2 provides a literature review on the probability of default. Section 3 describes the empirical strategy and data. Section 4 provides the results using data from Russia. It evaluates the factors influencing the probability of bank default. Section 5 discusses the practical application of the results. Section 6 concludes.

2. Literature review

Predicting the stability of banks is paramount for the sustainable development of financial markets. Following the global financial crisis in 2008, central banks began to implement new approaches to banking supervision. In particular, the Bank for International Settlements developed Basel III. Basel III includes standards that consider the 2008 global financial crisis. However, central banks also continue to use pre-crisis monitoring practices, such as CAMELS for banks and CARAMELS for insurance companies, even though these methods have proven to be somewhat unreliable in predicting the default of financial institutions. These shortcomings highlight the need to find additional indicators to complement the existing methods for assessing financial stability. The experience of the global financial crisis in 2008 demonstrated the interdependence of financial institutions, as the bankruptcy of one systemically important financial institution had a negative impact on others. This domino effect led to a special focus on the stability of systemically significant financial institutions, whose default could threaten global and national socio-economic sustainability. It is necessary to develop new practices based on digital technologies for the regular monitoring of bank stability, considering new approaches to determining the occurrence of default and the factors that predict it.

Determining the occurrence of default

Default is a situation of *failing to perform financial obligations* (Moody's, 2014). As a result, borrowers and lenders lose deposits and loans. The issue of default has become more crucial in the wake of the 2008 global financial crisis. The default of one bank could cause huge losses for the entire banking system (Stephan Paul and Gregor N. F. Weiß, 2012). Strategic market game theory has examined this issue (Dmitriy Levando, 2012). Unfortunately, these theoretical implications did not fully translate into practice. After the global financial crisis in 2008, the Bank for International Settlements developed a coherent set of policies aimed at preventing defaults (Bank for International Settlements (BIS, 2012). The main goal of the BIS recommendations is to support the smooth functioning of the banking system. Considering these recommendations, central banks should have a system of rules to avoid defaults. The main challenge is to statistically define what constitutes *a default.*

One purpose of central banks is to prevent the occurrence of bank defaults by providing liquidity in emergency situations as a lender of last resort (Jasova et al., 2021). Some researchers consider the situation of providing financial assistance to a bank as a default (Frank Betz et al., 2014), when the number of real default cases is small. Betz et al. classify a subsidised bank as financially unstable and on the verge of default. Violation of the capital requirements could serve as an indirect source of default symptoms (ECB, 2016). Several studies classify a default as a bank run, bailout, or failure (Chen, T. H. et al, 2022).

However, such examples do not always reflect actual default cases. In Russia, there are officially recorded cases of bank defaults that are stipulated in the 'Order to revoke the licence', published on the Bank of Russia website (Bank of Russia, 2017). In some cases, the revocation of the licence means a default (Zuzana Fungáčová and Laurent Weill, 2013). However, there are several reasons why a bank in Russia can lose its licence: actual default (the inability to meet its obligations), imminent default (a high probability of insolvency), false information about banking activities provided to the Bank of Russia, illegal financing, or violation of the Bank of Russia's requirements. Therefore, the total number of revoked licences does not represent the total number of defaults in Russia. Providing incorrect information is a likely symptom of poor financial stability or financial mismanagement. Default may not occur if a bank is still able to meet its obligations. Most revoked licences in Russia are due to a failure to comply with the requirements of the Bank of Russia, or problems with the implementation of banking regulations (Table 1).

Table 1. Distribution of reasons for the licence revocation in the Russian banking system from 2010 to 2017

	Number of causes	**Share, %**
Failure to perform the requirements of the Bank of Russia	214	29
Failure to comply with banking regulations	135	19
Financing of illegal operations	95	13
Actual default (inability to meet obligations)	91	12
Voluntary liquidation	85	12
Real threat to creditors and depositors (expected default)	61	8
Misreporting	50	7
Total	731	100

Source: compiled by the author based on (Bank of Russia, 2017)

In international practice, the number of officially recorded defaults is limited, while the Bank of Russia registered more than 140 defaults in the period 2010–2017. The Russian case is interesting for international distress forecasting because of its rich real default background. The necessary financial indicators for default prediction analysis are available in Russia monthly.

Financial indicators such as CAMELS help to define default cases within a given period. Central Banks need time to plan because every financial intervention is unique. It is therefore crucial to estimate the time to default correctly (Jorge A Chan-Lau and Amadou N R Sy, 2007). When the probability of default is high, the central bank assesses its significance and decides whether to save the bank or revoke its licence. The early prediction model should include parameters describing internal bank operations and the macroeconomic environment. In addition, several studies include approaches to the use of expert assessments, such as the number of forecasts that predict the occurrence of default (Hafeez, Bilal et al., 2021). Financial digitalization allows us to significantly expand the practice of using standard financial indicators.

Factors predicting the onset of default

Each default case has different origins relating to operational or financial challenges (Anna Zabai, 2014). International research on the prediction of distress suggests using balance sheet indicators to estimate the probability of default. Most researchers use the CAMELS rating system (see Table 1). The use of CAMELS proved to be effective for the Russian banking sector in predicting banking distress (Alexander Karminsky, Alexander Kostrov, and Taras Murzenkov, 2012). However, not all central banks monitor CAMELS. Most central banks use Basel I, II, and III (Rachdi, H., 2010). CAMELS does not use Basel ratios as indicators for estimating the probability of default. The Bank of Russia often uses the Basel norms to monitor the stability of banks (Bank of Russia, 2016) and is actively implementing the requirements of Basel III (Bank of Russia, 2020). As CAMELS proved its effectiveness in monitoring banking stability in Russia, they could be used in conjunction with the Basel norms. The combination of these financial tools could improve the quality of ongoing financial monitoring in Russia.

Hypothesis 1: Basel III ratios are significant for monitoring the probability of bank default in Russia.

The Bank of Russia payment system is crucial for the Russian national banking system as it conducts transactions between banks (Bank of Russia, 2015). Central Bank payment systems are used worldwide, for example TARGET2 in the EU, Fedwire Funds Service in the US, and CIPS in China. Central Bank payment systems generally provide payment services to national banks and budget systems. Such payment systems collect a large amount of data on financial flows, including the volume and volatility of transfers. A change in turnover within a central bank’s payment system can indicate a bank's declining activity and its increasing probability of default. To make full use of payment system data, it is necessary to develop payment classifiers on an ongoing basis as the types and volumes of transactions increase. A central bank, as an operator and settlement centre, has complete information on transactions, as banks cannot manipulate this data.

The Bank of Russia has full information on each bank’s turnover in the payment system, the timing of operations, and overdraft requests. The data on the Russian banking system are available in real time and, therefore, they are particularly relevant for predicting bank defaults. This means that the Bank of Russia could use the data from the payment system to forecast bank instability.

Hypothesis 2: Central bank payment system indicators are significant for monitoring the probability of bank default in Russia.

International research focuses on the role of the macro environment in predicting default. For example, a downturn in oil prices leads to a decrease in liquidity flows, which increases the probability of debt default (BIS, 2016). Macroeconomic conditions affect banking systems, especially in emerging economies (Reinout De Bock and Alexander Demyanets, 2012). Banking profitability depends on the success of the real economy, which affects the solvency of potential borrowers and lenders.

Researchers have included countries' macro variables in the estimation of bank stability, thereby increasing the predictive power of the distress model. For example, (Frank Betz, Silviu Oprică, Tuomas A. Peltonen, Peter Sarlin, 2014) use the variables for countries included in integrated unions or for groups of countries located in the same region. However, it is possible to expect the same effect at the regional level within a given country. The use of regional macro indicators is most relevant for large countries such as Russia. In the case of Russia, the use of regional macro indicators is significant because the possible insolvency of borrowers is a source of bank failures that varies from region to region. Historically, there have been problems with debt repayment discipline (Kathryn Hendley, Peter Murrell, and Randi Ryterman, 1999). This situation varies dramatically across regions and affects their financial behaviour differently (Benjamin Hammer, Heiko Hinrichs, and Bernhard Schwetzler, 2018). Therefore, if regional indicators are significant, then regional macro indicators are also significant for predicting distress.

Hypothesis 3: Regional banking and macro indicators are significant for monitoring the probability of bank default in Russia.

Confirmation of the hypotheses will allow us to improve early-warning models. The research predicting the probability of default in the banking sector is summarised in Table 2.

Table 2. Research predicting bank default

Author & Article	Main idea	Significant result for research
(James Kolari, Dennis Glennon, Hwan Shin, and Michele Caputo, 2002)	The paper predicts bank failure in the US.	The period determines the quality of the predictive power. Logit and trait recognition models demonstrate good results.
(Ioannidou, 2005)	Monetary policy affects banking regulation.	The Bank of Russia's policy determines the criteria for getting financial aid.
(Lanine & Vennet, 2006)	The work provides a model to predict bank default.	The research examines bank failures in Russia in late 1998. Logit and trait recognition models are constructed. A bank size variable could be implemented.
(Zuzana Fungáčová and Laurent Weill, 2013)	The paper claims that an increase in banking competition leads to more bank failures.	Financial indicators are implemented (for example ROA, Lerner index). To estimate the default probability an estimated time to default without recovery is necessary.

		The research uses Russian banking sector data from 2001 to 2007
(Frank Betz, Silviu Oprică, Tuomas A. Peltonen, Peter Sarlin, 2014)	The paper suggests an early-warning model to predict default. The article supports including macroeconomic variables to improve the predictive power	A binary probit approach demonstrates a good result in predicting banking defaults. The following groups of variables could be used to predict default: Financial variables (ROA, ROE etc.), macroeconomic indicators (total asset to GDP etc.), and macrobanking indicators (Real GDP, inflation).
(Adonis Antoniades, 2015)	Low quality assets determine bank failures.	It is necessary to take into account the specialization of a bank and to assess the influence exposure to a particular sector.
(Alexey Ponomarenko and Andrey Sinyakov, 2017)	Active banking regulation improves the banking sector and makes it more stable.	The Bank of Russia aims at implementing new banking methods, offering new policy tools for regulation.
(Laura Chiaramonte and Barbara Casu, 2017)	The research uses structural liquidity and capital ratios to estimate a bank's probability of failure.	The Basel III indicators can be used to assess the probability of a bank default.
(Petropoulos et al., 2020)	The study uses the CAMELS indicators, the significance of which varies dramatically.	It is possible to assume the significance metrics related to earnings and capital.
(Alberto Citterio, 2024)	The study systematizes the results of empirical studies that predict the probability of bank default.	Traditional approaches to forecasting non-standard defaults can be improved by applying new data. Several researchers use information about the bank's news background to predict default. However, not all indicators are applicable to predict the default. For example, the relationship between ESG and a bank's financial distress is not confirmed.

Source: compiled by the author

In terms of the hypotheses formulated and the research reviewed in Table 2, the model in this research includes three groups of factors:

Indicators of the external economic environment (macro-banking indicators). This group of factors examines the tendencies of the banking system in each region. It determines the level of competitiveness between banks and represents the regional financial conditions for lenders and borrowers (Hendley, 1999). As indicators of the external environment, it is also possible to consider factors related to government regulation (Fritsche et al., 2021). It is possible to take these aspects into account by analysing when the bank's financial assessment took place. In the case of Russia, for example, the peak in the number of revoked licenses was reached in 2016. This was due to the specifics of banking supervision and the tightening of requirements following the expansion of the Bank of Russia's functions as a mega-regulator in 2013.

The Bank of Russia policy parameters. The Bank of Russia sets banking rules and is the lender of last resort. It could maintain the banking system's stability by changing the targets of the Basel norms, as demonstrated in the EU (Chiaramonte and Casu, 2017). The Bank of Russia collects data on bank transfers within the Bank of Russia payment system in real time. To monitor the financial stability of banks, the Bank of Russia can use all the available data, including data obtained from bank supervision. The policy parameters should consist of two groups: Basel norms and payment system indicators.

The bank's financial indicators. Financial indicators, such as CAMELS, describe the internal functioning of the bank. Previous research has proven that these parameters are the most important for early distress models (Carmona et al., 2019). Our research uses CAMELS which makes the result relevant for international research.

If the proposed hypotheses are not rejected, CAMELS can be equipped with additional parameters, such as Basel norms and central bank payment system data. This study was conducted using a sample from the Russian banking system. The Russian case provides a wide range of monthly data from the central bank payment system, Basel norms, and information on bank licence revocations. The Russian experience may be relevant for other central banks. To test the hypotheses, it is necessary to consider the datasets available to the Bank of Russia and to clarify the approach to their evaluation.

3. Empirical strategy and data description

Bank defaults in Russia are split into two categories: actual defaults and imminent defaults. An actual default is a situation when a bank loses its licence by failing to meet its obligations. Imminent default is when a bank is expected to default. The fact of default is a binary variable, i.e. 1 for actual and expected defaults and 0 otherwise. The three groups of factors were chosen as explanatory variables. Given the statistical indicators, a logit regression was chosen. A logit regression of the following type was chosen:

$$Y_i = \beta F_i + \gamma M_i + \delta B_i + \alpha,$$

where the dependent variable Y_i reflects the fact of default for bank i, F_i is the set of financial indicators for bank i, M_i is the set of macro-banking indicators for bank i, B_i is the set of policy parameters, and α is the error term. The parameters β, γ, and

δ determine the effect of the variables on the probability of default. The financial indicators are based on CAMELS. For a comprehensive assessment of the external environment, the model also includes dummy variables reflecting the year of the assessment. The third group of variables are policy indicators of the Bank of Russia. They include policy regulations, mandatory reserves, and Basel III norms. The third group also includes the variables related to the bank's activities in the payment system, which are the focus of our research (Table 3).

Table 3. The description of econometric modelling variables

Variable name	Definition and description	Source
	1. Financial indicators	
(C) Impaired assets	Nonperforming Assets/Total Assets	Information agency Mobile and Bank of Russia
(A) Reserves to impaired assets	Reserves for Loan losses/ Non-Performing Assets	Information agency Mobile and Bank of Russia
(M) ROE	Profit/Average Equity during the last 2 months	Information agency Mobile and Bank of Russia
(E) Interest expenses to liabilities	Interest expenses/Total liabilities	Information agency Mobile and Bank of Russia
(L) Liquid asset ratio	Liquid assets/Total assets	Information agency Mobile and Bank of Russia
(S) Market liquidity indicator	Liquid assets/short-term liabilities	Information agency Mobile and Bank of Russia
	2. Macro-banking indicators	
LNDebt obligations	Logarithm of debt obligations (in the region)	Bank of Russia
KOL_KO	Number of credit organizations (in the region)	Bank of Russia
Udel_KO_ubit	Share of credit organizations that sustain losses	Bank of Russia
Dummy_year2013	Takes the value 1 if the data were collected in 2013 and 0 otherwise	Author's calculations
Dummy_year2014	Takes the value 1 if the data were collected in 2014 and 0 otherwise	Author's calculations
Dummy_year2015	Takes the value 1 if the data were collected in 2015 and 0 otherwise	Author's calculations
Dummy_year2016	Takes the value 1 if the data were collected in 2016 and 0 otherwise	Author's calculations

Dummy_year2017	Takes the value 1 if the data were collected in 2017 and 0 otherwise	Author's calculations
3.	**Bank of Russia policy parameters**	
LNKSCB	Logarithm of money in the correspondent account of the Bank of Russia (payment system variable)	Information agency Mobile and Bank of Russia
OKS_KSCB	Total turnover in the correspondent account or money in the correspondent account (payment system variable)	Information agency Mobile and Bank of Russia
LNORCB	Logarithm of mandatory reserves in the Bank of Russia (monetary policy variable)	Information agency Mobile and Bank of Russia
NORM_N1	Norm N1 (min 8%) – Basel norm	Information agency Mobile and Bank of Russia
NORM_N2	Norm N2 (min 15%) – Basel norm	Information agency Mobile and Bank of Russia
NORM_N3	Norm N3 (min 50 %) – Basel norm	Information agency Mobile and Bank of Russia
NORM_N4	Norm N4 (Max 120 %) – Basel norm	Information agency Mobile and Bank of Russia

There are four main Basel III norms available to the Bank of Russia (N1, N2, N3, and N4). Other Basel norms are not included in the Bank of Russia's database. In practice, these norms can be used to forecast the financial stability of the bank. The N1 ratio determines the bank's ability to reduce the negative impact of financial losses using its own financial assets. The minimum value of N1 is 8 %. The N2 liquidity ratio is the ratio of assets that can be sold within one day to the liabilities that the bank must meet within 24 hours. The minimum value of the N2 liquidity ratio is 15 %. The N3 liquidity ratio measures the financial solvency of banks within 30 days. The minimum value of N3 is 50 %. The N4 long-term liquidity ratio measures the ability to meet obligations in the long term (up to one year). The maximum value of N4 is 120 %. The Bank of Russia determines the method of calculation of the Basel norms.

Some researchers claim that financial indicators, such as CAMELS, play the most significant role in default modelling (Alexander Karminsky, Alexander Kostrov, and Taras Murzenkov, 2012). It can be expected that these indicators will be significant for Russia. If macro regional banking indicators are important, it will provide new opportunities for testing the probability of bank default, especially for those countries with different levels of regional development. Given a bank's possible regional specialisation, the local macroeconomic environment has a significant impact on bank stability.

The Bank of Russia monitors the liquidity flows in the Bank of Russia payment system and as banks cannot manipulate these data, they are not subject to moral hazard and information asymmetry. Banks do not incur additional costs in providing data to the Bank of Russia on their turnover in the Bank of Russia's payment system. The Bank of Russia could also take into consideration monetary policy parameters, including mandatory reserve requirements. If the Bank of Russia's policy parameters are significant to predict the probability of default among banks, then the Bank of Russia could combine available internal data with CAMELS.

4. Results

The model was estimated using a binary logit estimation (Table 4). We observe a low level of Prob (LR statistic). Most of the factors are significant at the 10 % level. The model includes monthly data from 01.01.2011 to 01.08.2017 and 140 default cases. Cases of licence revocation due to violations of reporting rules, etc. have been excluded from the sample. A limitation for the application of the suggested approach is the share of defaults in the total volume of the observations. As the rarity of events is related to the rarity in the general statistical population, the magnitude of the bias is uncritical. The number of positive outcomes is sufficient to a conventional logit model. When constructing prediction models, it is also possible to apply other approaches related to adjusting the model for rare events.

Some CAMELS indicators are not significant. This is mainly since CAMELS is not widely used in Russia as Russian banks use national accounting standards. To improve the early prediction of distress, CAMELS could be combined with the national accounting indicators (Alexander Karminsky, Alexander Kostrov, and Taras Murzenkov, 2012). We exclude the factors that are insignificant.

The reduced econometric model is still robust and supports the use of the Basel norms to predict financial distress (Table 4). By using the Basel norms, the Bank of Russia will not incur additional transaction costs. Some of the regional macroeconomic variables are significant. These variables were collected from the regions where the banks are located.

Table 4. Estimated results for the model

Variable	Dependent variable: fact of default (1,0)				
	Full model	**Full model with CAMELS (Model 1)**	**Full model with central bank variables (Model 2)**	**Reduced model used with significant variables (Model 3)**	**Average marginal effects**
(C) Impaired assets	2.53892**	0.6181643		2.692833***	0.0065244***
(A) Reserves to impaired assets	0.0070391	-0.0030324			
(M) ROE	0.0008328	0.0000388			
(E) Interest expenses to liabilities	3.058333**	3.8441***		3.765061***	0.0091222***
(L) Liquid asset ratio	-12.6025***	-17.79087***		-12.4335***	-0.0301247***
(S) Market liquidity indicator	-0.0085882	-0.0099295			
LNDebt obligations	0.0333847	0.0196392	0.0510965		
KOL_KO	-0.0006675	0.0002323	-0.0002717		
Udel_KO_ubit	0.0096145	0.0138499*	0.0145962	0.0123161*	0.0000298*
Dummy_year2013	0.3633688	-0.3515623	0.1842881		
Dummy_year2014	0.6535308	0.558477	0.8845731		
Dummy_year2015	0.0692475	-0.6534196	0.2500235		
Dummy_year2016	1.546075*	0.7991214	1.873258**	1.120739***	0.0027154***
Dummy_year2017	0.7320329	-0.2983636	1.150069		
LNKSCB	-0.8727701***		-1.073832***	-0.8038204***	-0.0019476***
OKS_KSCB	-0.0001176		-0.0004117***		
LNORCB	0.3948144**		0.5864099***	0.309626***	0.0007502***
NORM_N1	-0.0469722***		-0.0652684***	-0.0565779***	-0.0001371***

NORM_N2	0.0004222		0.0003676		
NORM_N3	-0.0007072		-0.0016966		
NORM_N4	-0.0161843***		-0.0154963***	-0.0142933***	-0.0000346***
C	0.968334	-5.011433***	-0.182427	1.903104	
Observations	21942	26241	22059	23867	23867
Prob>chi2	0.0000	0.0000	0.000	0.0000	-
Pseudo R2	0.3324	0.1926	0.2522	0.3284	-
AUC	0.9034	0.8762	0.8728	0.8961	-
Overall rate of correct classification	99.75	99.71	99.74	99.74	-

Notes: *** p<0.01, **p<0.05, *p<0.1

The Basel norms and regional variables are available to all central banks. First, any central bank can use the Basel norms to predict bank distress. Prior to our research, researchers mostly used CAMELS or other financial indicators. Central Banks apply the Basel norms to monitor financial stability. These seem to be more practical in predicting a bank's default because central banks do not require additional data Second, the importance of macroeconomic parameters has been demonstrated at the national level. This paper shows that the following approach is applicable *to macro regional data* when it is necessary to estimate the probability of default within a country. The prediction models could include both national and regional data. Third, payment system data could be used to monitor financial solvency. As the operator of the payment system, the Bank of Russia collects a large amount of daily data in real time. The prediction distress models should also rely on payment system data to monitor bank solvency.

A model using two sets of variables simultaneously has better quality than models using a single class of variables. To analyse the predictive power of the reduced model with significant variables (Model 3), it is possible to construct an ROC-curve. The AUC for Model 3 is 0.8961 (Table 5). The total correct classification rate shows that the model could predict the cases of default in the Russian banking system with 99.74% accuracy. The positive predictive value is equal to 75 %, and the negative predictive value is 99.75 %. The Pseudo R2 is equal to 0.3284. A model that includes all categories of significant variables gives the best results. Model 3 can be used for further analysis and the interpretation of the results to assess the factors of financial stability.

Table 5. The description of econometric modelling variables

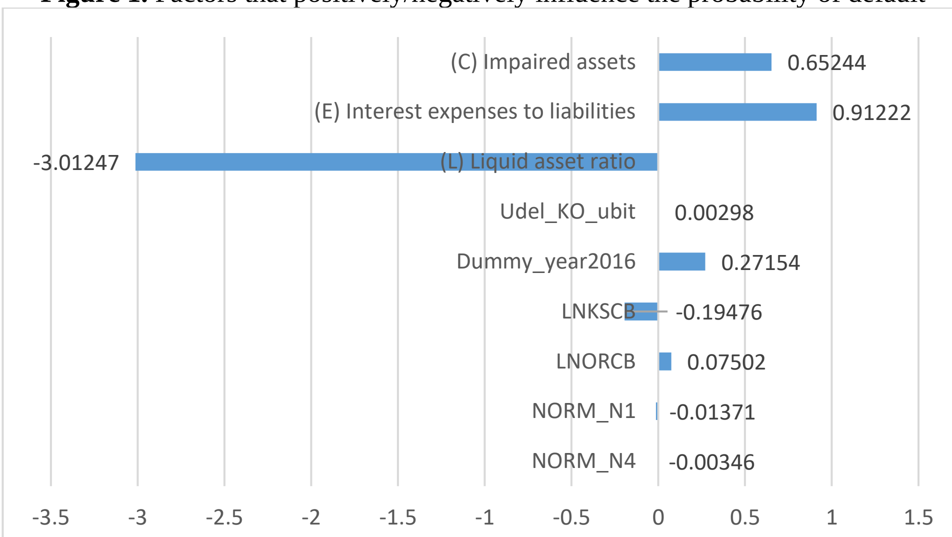
Name of model	**Pseudo R2**	**AUC**	**Overall rate of correct classification**
Full model with CAMELS (Model 1)	0.1926	0.8762	99.71
Full model with central bank variables (Model 2)	0.2522	0.8728	**99.74**
Reduced model used with significant variables (Model 3)	**0.3284**	**0.8961**	**99.74**

Source: compiled by the author

The inclusion of central bank variables could improve the predictions of bank distress. The difference between some indicators is not significant, therefore, it would be impractical to focus on only one indicator. The estimation of quality is based on all three indicators: R2, AUC, and total correct classification rate. Comparing Model 2 and Model 1, the R2 for Model 2 is higher than for Model 1. The difference between the models is small, so it makes no sense to use a model with more variables as they do not increase the quality. Accordingly, Model 3 is the most appropriate for further interpretation. Groups of central bank indicators and macrobanking indicators demonstrate better predictive results. The combination of these variables with CAMELS improves the prediction of bank default.

To analyse the impact on banking default probability, it is necessary to estimate the average marginal effects. These effects demonstrate how much the probability of default increases with a one-fold increase in the dependent variables. The average marginal effects show the true extent of the impact of our variables on banking default probability (Figure 1).

Figure 1. Factors that positively/negatively influence the probability of default



Source: compiled by the author

The results demonstrate that an increase in interest expenses on liabilities and impaired assets have the greatest impact on the probability of bank failure. For Russia, the metrics related to capital and earnings contribute to the prediction of bank default. The same results are supported in (Petropoulos et al., 2020). CAMELS indicators predict bank default, which is consistent with the research in Frank Betz et al., (2014). The increase in mandatory reserves also increases the probability of default. The increase in N1, N4, and funds in the corresponding accounts positively affects the banking stability. Thus, the hypotheses presented in this paper are empirically proved.

Although the impact of the central bank and the external environment indicators is relatively small compared to CAMELS, which make the value of the suggested approach relatively modest, these indicators are statistically significant. The importance of central bank parameters for forecasting bank default can be increased by detailing the data on settlements in the Bank of Russia Payment System for urgent and non-urgent transfer services. The indicators can include turnover data and information on the volatility of cash flows by the time of payment. The importance of monetary policy parameters can be increased by analysing the debt accrued on Bank of Russia loans for various refinancing instruments, including loans secured by market and non-market assets. Such indicators can complement the methodology of the central bank for early forecasting of bank instability. The latter is especially important in times of crisis.

5. Discussion

According to experts, we could expect a new global financial crisis soon (Neil Irwin, 2019), (Portanskiy et al., 2020). The global economic crisis may be the result of imbalances accumulated during the COVID-19 pandemic. Given the high probability of a new global financial crisis, central banks are faced with the important task of developing new approaches to monitoring the financial stability of banks. After the global financial crisis of 2008, central banks improved the quality of bank regulation and internal risk management approaches (Claudia Buch, 2018). However, central banks need to continuously develop and improve their systems for monitoring and supporting the financial stability of banks. Central banks can expand their practice of using different analytical methods, including machine learning (Kristóf, T., and Virág, M., 2022). Central banks also require more data, increasing the frequency of data collection, but this policy imposes additional costs on banks. Central Banks also incur additional costs due to the increased volume of data analysis. To avoid this, central banks should try to make full use of all available data related to banking oversight. Banks use CAMELS to predict the level of financial stability with a high degree of accuracy, but this tool could also be improved. To improve the early-prediction model, it is necessary to expand the set of predictive indicators. This study expands the set of CAMELS by including additional indicators available to central banks, such as Basel III and central bank payment system data.

A promising direction for the development of this study is to extend the analysis to the period of the COVID-19 pandemic. During the pandemic, there were major changes in cash flows and mechanisms for collecting statistical information. As the study has confirmed the possibility of using these payment system data, the relevance of the study will only increase. The use of central bank payment system data to monitor bank stability on a daily/weekly basis also has significant prospects. The development of such high-frequency indicators is especially relevant in the context of increasing “deep” uncertainty when it is necessary to shorten the time between the emergence of a crisis and government intervention. The construction of such high-frequency indicators is one direction for further research.

The analysis of central bank payment system data allows central banks to identify the dynamics of economic activity of institutions in different sectors, the target groups of economic institutions, etc. The data obtained through the analysis of cash flows in the payment system can be used to generate indicators for a more accurate prediction of the onset of financial crises. The importance of cash flow analysis is increasing due to the digitalization of finance and the development of non-cash payments. All non-cash payments are carried out within the country's national payment system. The use of cash flow indicators makes it possible to identify changes in the dynamics of interaction between organizations in real time. As the volatility of cash flows in the payment system increases, central banks can provide information to the relevant authorities and request government intervention. The analytical capabilities of central banks to predict crisis phenomena in the economy will increase with the introduction of new payment methods, for example, digital currencies. Central banks are also responsible for issuing currency. Improvements in technologies for recording cash flows may make it possible to use data on cash in the early detection of crisis phenomena in the economy. The information on cash can complement the data obtained by monitoring non-cash flows in payment systems.

Expanding the list of financial indicators for predicting financial stability is relevant in the context of the large-scale development of financial ecosystems (Hendrikse, R. et al, 2020). For example, in Russia, the digital ecosystem of Sber simultaneously performs the roles of various financial institutions, including a bank, an insurance company, and a payment system. Using only financial indicators that are relevant to the bank will not identify a crisis for other components of the financial ecosystem. Thus, the expansion of the set of financial indicators is important from the perspective of the current stage of development of the financial market.

6. Conclusion

The research identified several methodological improvements to the CAMELS models. First, the study demonstrated the possibility of applying the Basel norms and payment system data to the analysis of bank stability. The importance of monitoring the stability of a single bank in the payment system was discussed (Rochet and Tirole, 1996). Second, the Bank of Russia should rely more on regional macro banking variables to improve the accuracy of estimating the probability of default. According to the results, the use of these groups of indicators, in combination with CAMELS, improves the predictive power of bank defaults. The significance of the results can be increased by expanding the set of central bank indicators. This study is based on indicators that are publicly available for analysis. The information systems of central banks contain additional information that can become the basis for developing additional central banks' indicators for accurate forecasting of a bank's financial distress. Improving the quality of the monitoring increases the level of trust between the central bank and commercial banks.

The turnover and the number of transactions through the payment system are process indicators that record the activity of economic actors. Changes in the indicators during a crisis do not affect the quality of the statistical information received within the payment system of central banks. Thus, payment system data have a significant monitoring potential, as these indicators remain relevant even during a crisis. A combination of Basel norms, CAMELS, and other financial indicators improves not only monitoring, but also the quality of banking oversight and regulation. The statistical significance of the Basel norms provides the Bank of Russia with an opportunity to choose optimal target values of the Basel indicators to minimise the probability of bank defaults.

The results obtained for the Russian banking system will be useful for other central banks to improve oversight and monitoring. Further research in this area could focus on the links between banking stability and central banks' monetary policy parameters. The results of this study will help central banks to contribute to the maintenance of banking stability, and thus to ensure the sustainability of national socio-economic development.

References:

Alberto Citterio. 2024. “Bank failure prediction models: Review and outlook”. *Socio-Economic Planning Sciences,* 92: 1-26. https://doi.org/10.1016/j.seps.2024.101818.

Antoniades, Adonis. 2015. “Commercial Bank Failures During The Great Recession: The Real (Estate) Story”. *BIS Working Papers,* 530: 1-45.

Bank for International Settlements, G20. 2009. Guidance to assess the systemic importance of financial institutions, markets and instruments: initial considerations. Bern: BIS.

Bank for International Settlements. 2012. Principles for financial market infrastructures. Bern: BIS.

Bank for International Settlements. 2016. BIS Quarterly review. International banking and financial market developments. Bern: BIS.

Bank of Russia. 16.09.2016. About interest rates on specialized credit instruments: http://cbr.ru/press/PR/?file=16092016_134449dkp2016-09-16T13_34_00.htm

Bank of Russia. 16.12.2017. Specialized credit instruments. Retrieved from About percentage rate on specialized credit instruments: http://cbr.ru/DKP/standart_system/int_rates_spec/

Bank of Russia. 20.11.2017. The liquidation of credit organizations: http://cbr.ru/credit/likvidbase/LikvidBase.aspx

Bank of Russia. 2016. Annual report 2016. Moscow: Bank of Russia.

Bank of Russia. 2016. Banking supervision report. Moscow: Bank of Russia.

Bank of Russia. 2016. The report on the banking sector and regulation development in 2015. Moscow: Bank of Russia.

Bank of Russia. 2017. Bank liquidation: http://cbr.ru/credit/likvidbase/LikvidBase.aspx

Bank of Russia. 2017. The banking sector overview. Moscow: Bank of Russia.

Bank of Russia. 2017. The liquidation of credit organizations: http://cbr.ru/credit/likvidbase/LikvidBase.aspx

Bank of Russia. 2021. The concept of digital currencies. Moscow: Bank of Russia.

Bank of Russia. 22.11.2018. BaikalBank. Information on credit institutions: http://www.cbr.ru/credit/coinfo.asp?id=810000006

Bank of Russia. 22.11.2018. Emergency liquidity support mechanism. Percentage rates on emergency liquidity support mechanism: http://cbr.ru/hd_base/eci/

Bank of Russia. 22.11.2018. The Bank of Russia Payment System (BRPS): https://www.cbr.ru/eng/psystem/br_pay/

Bank of Russia. 23.01.2020. About time on Basel III implementation. Retrieved from Bank of Russia: http://www.cbr.ru/press/pr/?file=06022018_120000ik2018-02-06t11_55_45.htm

Bank of Russia. 25.11.2017. Data on the national payment system. http://cbr.ru/statistics/?PrtId=psrf

Bank of Russia. 28.06.2017. Retrieved from Information on assets and equity in Russian banking sector: http://cbr.ru/statistics/print.aspx?file=bank_system/assets-capital_17.htm&pid=pdko_sub&sid=ITM_26599

Betz Frank, Silviu Oprică, Tuomas A. Peltonen, Peter Sarlin. 2014. Predicting distress in European banks. *Journal of Banking&Finance*, 45 (C): 225-241. http://dx.doi.org/10.2139/ssrn.2338998.

Buch Claudia, Gerard Dages. 2018. Structural changes in banking after the crisis. Bank For International Settlements, 1-125.

Carmona Pedro, Climent Francisco, Momparler Alexandre. 2019. Predicting failure in the U.S. banking sector: An extreme gradient boosting approach. *International Review of Economics and Finance*, 61: 304-323. https://doi.org/10.1016/j.iref.2018.03.008.

Chan-Lau Jorge A., Amadou N. R. Sy. 2007. Distance-to-Default in Banking: A Bridge too far? *Journal of Banking Regulation*, 9: 14-25. https://doi.org/10.1057/palgrave.jbr.2350056.

Chen Ting-Hsuan, Lee Chien-Chiang, Shen Chung-Hua. 2022. Liquidity indicators, early warning signals in banks, and financial crises. *The North American Journal of Economics and Finance*, 62, 101732. https://doi.org/10.1016/j.najef.2022.101732.

Chiaramonte Laura, Casu Barbara. 2017. Capital and liquidity ratios and financial distress. Evidence from the European banking industry. *The British Accounting Review*, 61: 304-323. https://doi.org/10.1016/j.bar.2016.04.001.

De Bock Reinout, Demyanets Alexander. 2012. Bank Asset Quality in Emerging Markets: Determinants and Spillovers. Washington: International Monetary Fund. https://doi.org/10.5089/9781475502237.001.

European Central Bank. 2016. Financial stability review. Brussel: ECB.

European Central Bank. 2019. What is TARGET2?: https://www.ecb.europa.eu/paym/target/target2/html/index.en.html.

Fritsche Jan Philipp, Klein Mathias, Rieth Malte. 2021. Government spending multipliers in (un)certain times. *Journal of Public Economics*, 203, 104513:1-18. https://doi.org/10.1016/j.jpubeco.2021.104513.

Fungacova Zuzana, and Laurent Weill. 2013. Does competition influence bank failures? Evidence from Russia. *Economics of Transition*, 10: 301-322. https://doi.org/10.1111/ecot.12013.

Hafeez Bilal, Xiping Li, Kabir M. Humayun, Tripe David. 2022. Measuring bank risk: Forward-looking z-score. *International Review of Financial Analysis*, 80, 102039. https://doi.org/10.1016/j.irfa.2022.102039.

Hammer Benjamin, Heiko Hinrichs, and Bernhard Schwetzler. 2018. Does culture affect the performance of private equity buyouts? *Journal of Business Economics*, 88: 393-469. https://doi.org/10.1007/s11573-017-0886-0.

Hendley Kathryn, Peter Murrell, and Randi Ryterman. 1999. How Russian Enterprises Cope With Payments Problems. *Post-Soviet Affairs*, 15(3): 201-234.

Hendrikse Reijer, Michiel van Meeteren, Bassens David. 2020. Strategic coupling between finance, technology and the state: Cultivating a Fintech ecosystem for incumbent finance. *Environment and Planning A: Economy and Space*, 52(8), 1516-1538. https://doi.org/10.1177/0308518X19887967.

Ioannidou Vasso P. 2005. Does monetary policy affect the central bank's role in bank supervision? *Journal of Financial Intermediation*, 14 (1): 58-85. https://doi.org/10.1016/j.jfi.2004.04.002.

Irwin Neil. 2019. How the Recession of 2020 Could Happen. *The New York Times*: https://www.nytimes.com/2019/08/17/upshot/how-the-recession-of-2020-could-happen.html (accessed February 11, 2020).

Karminsky Alexander, Kostrov Alexander, and Murzenkov Taras. 2012. *Approaches to Evaluating the Default Probabilities of Russian Banks with Econometric Methods*. Moscow: National Research University "Higher School of Economics". https://www.hse.ru/data/2012/10/22/1245987109/WP7_2012_04_ff.pdf. http://dx.doi.org/10.2139/ssrn.2152384.

Kolari James, Glennon Dennis, Shin Hwan, and Caputo Michele. 2002. Predicting large US commercial bank failures. *Journal of Economics and Business*, 54(4): 361-387. https://doi.org/10.1016/S0148-6195(02)00089-9.

Kristóf Tamás, Miklos Virag. 2022. EU-27 bank failure prediction with C5. 0 decision trees and deep learning neural networks. *Research in International Business and Finance*, 61:101644. https://doi.org/10.1016/j.ribaf.2022.101644.

Lanine Gleb, Vennet Rudi Vander. 2006. Failure prediction in the Russian bank sector with logit and trait recognition models. *Expert Systems with Applications*, 30(3): 463-478. https://doi.org/10.1016/j.eswa.2005.10.014.

Levando Dmitriy. 2012. A survey on strategic market games. *Economic Annals*, 57(194):63-106. https://doi.org/10.2298/EKA1294063L.

Martina Jasova, Caterina Mendicino, Dominik Supera. 2021. Policy uncertainty, lender of last resort and the real economy. *Working Paper Series ECB*, 2521: 1-67. https://doi.org/10.2139/ssrn.3797141.

Moody's. 2014. *Proposed Bank Rating Methodology*. New York: Moody.

Papadopoulos Savas, Stavroulias Pantelis, and Sager Thomas. 2019. Systemic early warning systems for EU14 based on the 2008 crisis: proposed estimation and model assessment for classification forecasting. *Journal of Banking Regulation*, 20:226-244. https://doi.org/10.1057/s41261-018-0085-0.

Paul Stephan, and Gregor N. F. Weiß. 2012. Detecting and explaining systemic risks of mortgage banks–evidence from the subprime crisis. *Zeitschrift für Betriebswirtschaft*, 82:109-132. https://doi.org/10.1007/978-3-8349-3864-0_5.

Petropoulos Anastasios, Siakoulis Vasilis, Stavroulakis Evangelos, Vlachogiannakis Nikolaos E. 2020. "Predicting bank insolvencies using machine learning techniques". *International Journal of Forecasting*, 36:1092-1113. https://doi.org/10.1016/j.ijforecast.2019.11.005.

Ponomarenko Alexey, Andrey Sinyakov. 2017. *The impact of strengthening of banking supervision on the structure of the banking system: conclusions on the basis of agent-based simulation.* Moscow: Bank of Russia. 19:1-30.

https://cbr.ru/content/document/file/87559/wp_19_e.pdf. https://doi.org/10.31477/rjmf.201801.26.

Portanskiy Alexey, Sudakova Yulia, Larionov Alexander. Assumptions of the Global Economic Crisis and Its Inception in the Spring of 2020 Due to the COVID-19 Pandemic. *International Organizations Research Journal*, 15:191-212. https://doi.org/10.17323/1996-7845-2020-02-09.

Rachdi Houssem. 2010. The Link between International Supervision and Banking Crises. *Panoeconomicus*, 57(3), 321-332. https://doi.org/10.2298/PAN1003321R.

Rochet Jean-Charles, Tirole Jean. 1996. Controlling risk in Payment Systems. *Journal of Money, Credit, and Banking*. 28: 832-862.

Swagel Phillip. 2015. Legal, Political and Institutional Constraints on the Financial crisis Policy Response. *Journal of Economic Perspectives*, 29(2): 107-122. https://doi.org/10.1257/jep.29.2.107.

Woźniak-Jęchorek Beata, Kuźmar Sławomir. 2023. Income Inequalities in the Accelerating Digital Era: Evidence from EU Countries and COVID-Time. *Panoeconomicus*, 70(4):551-572. https://doi.org/10.2298/PAN2304551W.

Zabai Anna. 2014. *BIS Working Papers No 467 Managing Default Risk*. Bank of International Settelments. 1-48.