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# Ways to Improve the Mechanism for Preventing Bank Insolvency: an Economic Model for Assessing Insolvency Factors

***Abstract***

In the current conditions of economic instability, military challenges and global financial shocks, the issue of bank insolvency is becoming particularly relevant. The stability of the banking system is a fundamental prerequisite for the effective functioning of the national economy, and timely identification and prediction of signs of financial instability of banks allows not only to minimize risks for depositors, but also to maintain confidence in the financial sector as a whole. The paper analyzes existing approaches to assessing the solvency of banks, in particular based on the CAMELS system, and also justifies the need to improve the methods through the integration of econometric modeling and machine learning methods. It is concluded that CAMELS, although it remains a standard for supervision, has a number of shortcomings – in particular, limited coverage of non-financial risks, inefficiency and subjectivity of assessment. In this context, it is proposed to build a comprehensive economic model for assessing bank insolvency factors using logistic regression and machine learning algorithms, such as decision tree, random forest, XGBoost and neural networks. The model takes into account financial, macroeconomic and behavioral indicators, which allows identifying problem banks at an early stage. A comparative analysis of the methods was carried out, their advantages and limitations were identified. Based on the analysis of examples of banks that became insolvent in Ukraine, the effectiveness of the multidimensional approach was confirmed. Recommendations were made for integrating the model into the monitoring system of the National Bank of Ukraine. The proposed model can become an effective tool for state regulation of the financial sector and increasing the country's financial security.

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***Keywords***

bank insolvency, economic modeling, financial risks, machine learning, CAMELS system, bank supervision

**JEL:** G33, C51, G21, C55, G28, E58



## 1 Introduction

In the current conditions of economic instability and global financial turmoil, the issue of bank insolvency is becoming extremely relevant. The stability of the banking system is one of the key prerequisites for the effective functioning of the national economy. Preventing bank insolvency should be considered as a strategic task of state regulation of the financial sector.

Bank insolvency is the inability of a bank to fulfill its obligations to depositors and creditors within a certain period. Identifying factors that can lead to such a situation and modeling them allows you to form an effective risk prevention system. In this context, the economic model of insolvency assessment plays an extremely important role, as it provides a toolkit for making preventive decisions.

The purpose of the study is to develop recommendations for the formation of an economic model for assessing bank insolvency factors in the context of improving the insolvency prevention mechanism.

The subject of the study is economic models for assessing bank insolvency factors based on financial, macroeconomic and organizational-behavioral indicators, as well as methods for their application for early detection of crisis trends in the banking sector.

Objectives: justification of the need to improve insolvency prevention mechanisms, formation of

the main characteristics of an economic model for assessing bank insolvency factors.

The logic of the study includes: updating the problem, analysis of existing approaches to determining bank insolvency, justification of the need to improve the existing mechanism, determination of insolvency factors that affect the financial stability of banks; construction of an economic model, testing the model on the example of Ukrainian banks, formation of practical recommendations for integrating the model into the NBU monitoring system and improving supervision mechanisms.

## 2 The need to Improve Insolvency Prevention Mechanisms

Early detection of insolvency trends has always been a vital issue in bank management. The solution to this problem has led to the creation of many diagnostic models. Based on such models, the analysis of the current state shows results that are close to reality (Gontareva, 2020). But often this is not enough to state the insolvency of a particular bank, because:

- the best model may show results that are not entirely correct;
- to create reliable forecasts of the development of the situation, it is necessary to analyze the state of the bank for a certain period, the longer this period, the more reliable the forecast.

Differences between banks in terms of asset structure, fixed capital, professional sphere, funding bases, etc. make it difficult to create a single methodology for early diagnosis of bank insolvency. As for foreign diagnostic models, they are mostly built on the basis of the CAMELS system, which is an officially recognized bank rating system widely used by supervisory authorities in many countries of the world.

The CAMELS system is a point system and is based on a combination of accounting and expert approaches. Bank supervision, based on risk assessments under this rating system, consists of determining the overall condition of the bank based on uniform criteria that cover all areas of its activity.

The purpose of assessing banks under the CAMELS rating system is to determine their financial condition, quality of operations and management, identify deficiencies that could lead to the bankruptcy of the bank and require enhanced control by banking supervisors, as well as take appropriate measures to correct the deficiencies and stabilize the financial condition of the bank (Basel Committee on Banking Supervision, 2020).

However, the CAMELS system has certain shortcomings that do not allow for an adequate assessment. These include:

1. Limitations in the coverage of non-financial risks. CAMELS focuses mainly on the financial indicators of the bank. It does not cover reputational risks, cybersecurity risks or legal risks and ignores ESG factors (environmental, social, corporate governance), which are becoming increasingly important.

2. Obsolescence in a rapidly changing environment. This is because CAMELS may not keep up with the dynamics of digital banks, fintech companies and new types of risks. In particular, the speed of the spread of crises through social networks or the impact of AI algorithms on risk management are not taken into account.

3. The subjectivity of the assessment of some components involves the analysis of the quality of management (Management) or market sensitivity (Sensitivity), which is based on the assessments of inspectors, and therefore can lead to: bias, the influence of the human factor and different standards between inspectors.

4. Inefficiency is due to the fact that assessments are often carried out once a year, which makes them ineffective in the case of: rapid changes in the financial condition of the bank and economic crises that unfold rapidly.

5. Does not provide a complete picture for stakeholders, because CAMELS was created primarily for supervisory authorities, and information from this system is not always available to: investors, depositors, other stakeholders who require more transparent and frequent reporting.

In essence, the expert nature of this approach allows, by involving a large number of experts, to make a more or less correct verdict, however, a small set of banking indicators can cause errors in predicting the financial condition of some banks. At the same time, models for early detection of financial problems and prevention of bank insolvency have not only theoretical, but also significant practical value. They allow us to understand what factors lead a bank to bankruptcy, how to counteract banking problems, and what regulatory methods can be used before critical events occur and the bank's financial condition irreversibly deteriorates.

Many foreign researchers argue that structurally successful early warning systems should include (Demirgüç-Kunt, Pedraza, Ruiz-Ortega, 2020): indicators of the bank's main activity, indicators of investment investments, macroeconomic variables describing the state of the national banking system, and predictive analysis based on the CAMELS system (Beck, Radev, 2020).

The modern banking system of Ukraine faces numerous challenges – from military operations and political instability to exchange rate fluctuations and an imperfect legislative framework. Over the past decades, we have observed numerous cases of bank bankruptcies (National Bank of Ukraine, 2024).

According to the information presented on the official website of the Ministry of Finance as of

10.12.2024, 108 banks were recognized as insolvent in Ukraine. The presented list is promptly updated if a temporary administration has been introduced to the bank, the bank has been declared bankrupt and the liquidation of the bank is being prepared, and a curator has been introduced to the bank. For banks that are in the liquidation stage, agent banks are indicated that issue funds to clients of liquidated banks. Currently, 56 banks are in the liquidation process, in 7 of which debt payments have been completed, in another 7 the liquidation process has not been determined and the procedure has not been outlined, one of the banks – Kominvestbank, is managed by a temporary administration, the other 41 banks are making gradual payments on debts.

Regarding the banks that completed the liquidation process in 2024, it is advisable to estimate the duration of the liquidation process itself, Figure 1.

It can be noted here that the terms of liquidation directly depend on the adequacy of the bank's assets.

The use of multidimensional analysis models, which are also applicable to banks, is recognized as one of the most effective methods for identifying the insolvency of an organization. Multidimensional analysis models provide an approximate understanding of their current state.

If many calculations are made over a certain period of time (monitoring), the dynamics of these data can show what distribution law the state of the object under study obeys, and calculate the value of the system's reliability. The use of several models allows for higher reliability of forecasts, since the opinion of several experts allows for a more truthful picture of the changes taking place than the assessment of one expert.

Thus, in the future, it is advisable to rely on the integrated application of several multidimensional analysis models that will take into account both the organizational structure and the planning and management structure. Minor shortcomings in the activities of banks and low productivity lead to a critical state of the entire bank structure, or manifestations of insolvency and, as a result, the development of internal problems, and therefore a decrease in resistance to environmental influences. Emerging crises must be recognized in a timely manner. Translating this to the sphere of the bank's life cycle, we note that in order to prevent possible complications, it is necessary to conduct constant diagnostics of the state of the system and predict the development of changes. Multidimensional analysis models provide an approximate understanding of the current state of the bank. If many calculations are made over a certain period of time (monitoring), the dynamics of such indicators can show which distribution law corresponds to the state of the studied object of subordination and affects the reliability of the entire system.

The system can be improved by creating an economic model for assessing insolvency, which is based on a quantitative analysis of financial and non-financial indicators of the bank's activities. The main problems of the existing mechanism are:

– lack of an early warning system;
– low level of transparency of bank activities;
– imperfection of stress testing tools;
– delayed reaction of regulators;
– insufficient control over related parties and risky assets.

The purpose of the economic model for assessing insolvency factors is to identify banks with an increased risk of insolvency at the early stages by assessing the set of financial ratios, macroeconomic conditions and behavioral characteristics of managers.

The main tasks of this model are:

– building a system of risk indicators;
– formalizing the impact of factors on solvency;
– classifying banks by risk level;
– modeling development scenarios.

It is advisable to build the model using logistic regression or machine learning (for example, random forest, XGBoost), which allows you to work with a

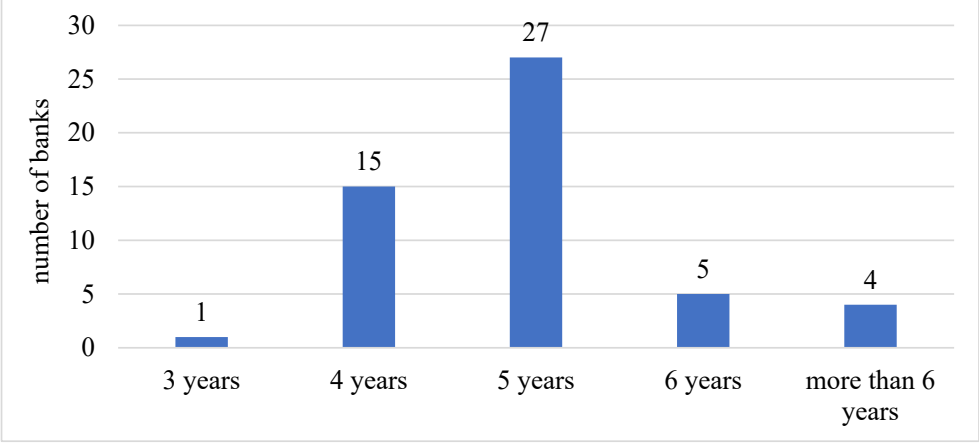


FIGURE 1 Distribution of insolvent banks by terms of the liquidation process (National Bank of Ukraine, 2024)

large number of factors and form conclusions taking into account interrelationships. Based on the fact that the goal is to build a model that would predict the probability of default or bankruptcy of a bank based on a number of financial and non-financial indicators, the following approaches can be considered: logistic regression (Logit model) and machine learning (ML) methods, in particular decision tree, random forest, XGBoost, neural networks, etc. Logistic regression is a classic econometric approach, where the target variable can be represented in the form of:

$$Y = \begin{cases} 1, if\ the\ bank\ is\ insolvent \\ 0, if\ the\ bank\ is\ solvent \end{cases}$$

The model itself will look like:

$$P(Y=1) = \frac{1}{1+e^{-(\beta_0+\beta_1 X1+\beta_2 X2+\cdots+\beta_n Xn)}}$$

So, typical independent variables (risk factors) here can be:

– capital – Capital Adequacy Ratio (CAR);
– profitability – Return on Assets (ROA), Return on Equity (ROE);
– asset quality – Share of problem loans (NPL ratio);
– liquidity – LCR (Liquidity Coverage Ratio);
– external factors, such as GDP, inflation, discount rate.

Machine learning is a more flexible alternative, because machine learning methods use the same variables, but can: better take into account nonlinearities; automatically detect relationships between variables; provide higher forecast accuracy. A comparison of popular algorithms is presented in Table 1.

At the same time, ML models often use cross-validation to check the accuracy and evaluation metrics: ROC AUC, Precision / Recall, F1-score. Machine learning offers various models for predicting bank bankruptcy, each of which has its own strengths and weaknesses. For example, Decision Tree is easy to interpret, but it is prone to overtraining, while XGBoost provides high accuracy, but requires complex tuning.

Thus, if the indicators of Khreschatyk Bank have the values presented in Table 2, then by logistic regression or XGBoost the probability of bankruptcy is estimated according to the principle: $P(Y=1) = 0.82 \Rightarrow$ high risk.

A comparison of logistic regression and machine learning is given in Table 3.

Thus, it is necessary to consider and justify the main characteristics of the economic model for assessing insolvency factors.

## 3 Main Characteristics of the Economic Model for Assessing Bank Insolvency Factors

Thus, it is possible to distinguish the main groups of factors that should be taken into account in the multidimensional model for assessing bank insolvency.

The first group is financial indicators, which include:

– capital adequacy ratio (CAR);
– ratio of problem loans to the total portfolio;
– liquidity ratio;
– return on assets (ROA) and equity (ROE);
– share of insider loans.

TABLE 1 Comparison of popular machine learning algorithms for assessing bank insolvency

| Method | Advantages | Disadvantages |
|---|---|---|
| Decision Tree | Interpretable, simple | Can be retrained |
| Random Forest | High accuracy, stability | Less interpretable |
| XGBoost | Powerful, Kaggle leader | Requires parameter tuning |
| Neural Network | Detects complex patterns | “Black box”, requires data |

TABLE 2 Main indicators of liquidated insolvent banks in Ukraine

| Indicator | Khreshchatyk Bank(4 years) | Eurogasbank (5 years) | Bank Kyiv (more than 6 years) |
|---|---|---|---|
| ROA | 0,3% | 0,5% | 0,2% |
| NPL ratio | 22% | 34% | 27% |
| CAR | 7% | 3% | 4% |
| LCR | 95% | 92% | 89% |
| GDP Growth | -3% | -5% | -8% |
| Result (Y) | 0,82 | 0,77 | 0,91 |

TABLE 3 Comparison of logistic regression and machine learning for assessing bank insolvency

| Logistic regression | Machine learning |
|---|---|
| Simple interpretation (econometrics)<br>Standards of financial regulators (in particular the NBU) | Higher accuracy<br>Adaptability to large data sets |

The second group is macroeconomic indicators:
– GDP growth;
– inflation;
exchange rate;
political stability.

The third group is behavioral and organizational factors, which take into account:
– frequency of management changes;
– ownership structure;
– presence of litigation;
– customer trust (for example, by volume of deposits).

When building an economic model for assessing bank insolvency factors, it is advisable to implement the stages presented in Figure 2.

In addition, it is necessary to highlight the main advantages and limitations of implementing this model.

The advantages include:
– early detection of problems;
– the possibility of scenario analysis;
– transparent assessment of management effectiveness;
– a tool for NBU supervision and audit.

The main limitations are:
– dependence on the reliability of input data;
– the need for regular model updates;
– the probability of false positive/negative signals;
– the influence of informal or "shadow" factors.

However, in combination with the NBU supervisory functions and automatic monitoring through IT solutions, such a model can become a reliable support for regulating the banking sector.

Thus, the main practical aspects of the recommendations for improving the mechanism are:

1. Integration of the model into the NBU monitoring system – through monthly assessment of key risks and automated generation of reports.

2. Increasing the transparency of bank reporting – mandatory publication of a detailed structure of assets and liabilities.

3. Strengthening requirements for corporate governance – control over the activities of shareholders, supervisory boards, restrictions on insider lending.

4. Development of analytical infrastructure – creation of a centralized hub of banking risks based on the NBU.

5. Training of analysts – training programs for economists with an emphasis on risk modeling.

Therefore, preventing bank insolvency requires a systemic approach, where an economic model of risk assessment plays an important role. Its use will allow for early identification of problem banks, regulatory intervention and ensuring the stability of the financial system. Given the challenges facing Ukraine in the context of war and economic pressure, such models should become the basis of the state's financial security policy.

## 4 Conclusions

The study found that the issue of bank insolvency is critically important for ensuring the financial stability of the state, especially in conditions of economic turbulence, military threats and transformation

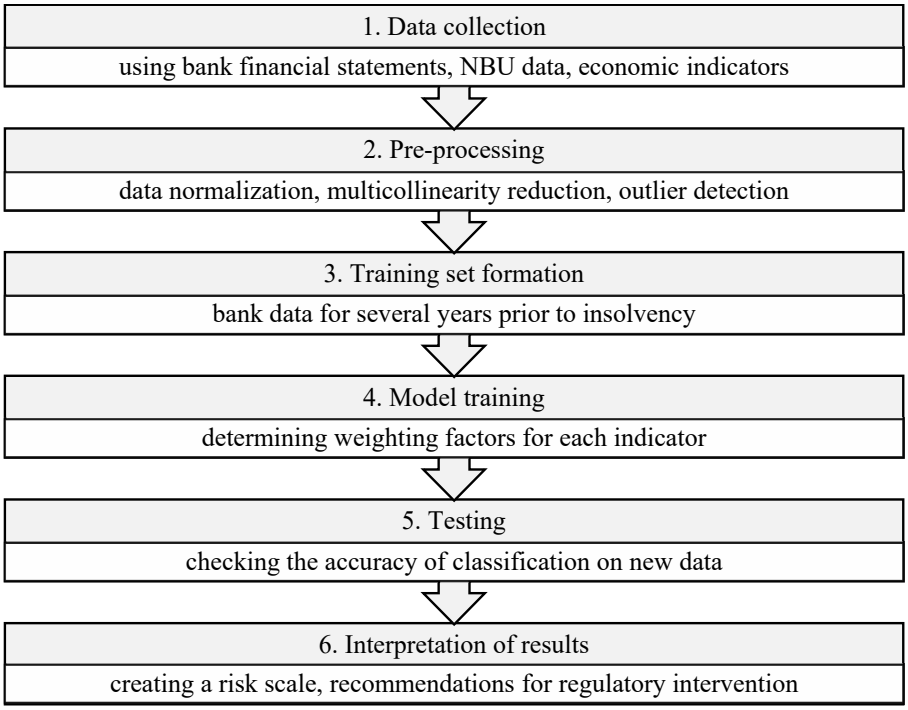


FIGURE 2 The main stages of building an economic model for assessing bank insolvency factors

of the global financial environment. The modern banking system of Ukraine requires not only constant monitoring, but also deep analytical tools capable of identifying problems at an early stage.

The analysis showed that the traditional CAMELS system, which is widely used in banking supervision, has a number of limitations. It does not cover non-financial risks, is not sufficiently operational in crisis conditions and is often based on subjective expert assessments. Therefore, to improve the effectiveness of monitoring, it is advisable to introduce more flexible tools, in particular methods of multivariate analysis and machine learning.

The work substantiates the feasibility of using logistic regression, Random Forest algorithms, XGBoost and neural networks as modern methods of predicting bank insolvency based on financial, macroeconomic and behavioral indicators. An assessment of examples of Ukrainian banks that were declared insolvent was carried out, which confirmed the possibility of more accurate forecasting when using the compiled models.

The results of the study indicate the need to develop a comprehensive economic model that allows for early risk diagnosis, scenario analysis, and transparency in regulation. The proposed system can be integrated into the monitoring structure of the National Bank of Ukraine and used as a basis for improving the effectiveness of banking supervision. This will strengthen the country's financial security and ensure confidence in the banking system even in times of crisis.

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