Šegrt, S., Ranđelović, A., & Đurić, D. (2024). Application of specific methods in assessment and develop-ment of rating systems of financial institutions, *SCIENCE International journal, 3*(3), 33-39.
doi: 10.35120/sciencej0303033s UDK: 336.71/.73]:005.52:005.334}:303.724

APPLICATION OF SPECIFIC METHODS IN ASSESSMENT AND DEVELOPMENT OF RATING SYSTEMS OF FINANCIAL INSTITUTIONS

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Abstract: The rating system is an important factor in risk management and financial performance assessment. Until the beginning of the eighties of the last century, credit risk assessments of clients were carried out in a traditional way, which was mainly reduced to intuition and subjective assessment of internal rating by the management of financial institutions, while counting on their ability to make quality decisions based on knowledge and expertise. After that period, the global standardization of the rating system was carried out, which enabled an easier assessment and comparison of financial institutions. Activities related to evaluations and development of rating systems in financial institutions today must necessarily be an integral part of their ongoing operations and risk management culture, and it is also important that financial institutions are able to respond to the specific minimum requirements of the internal rating system, risk management process and capabilities assessments of their necessary components. For some risk exposure classes, the Basel Committee proposes a basic methodology by which financial institutions take their own risk assessment as an input, while assessments of additional risk factors are carried out through the application of standardized rules. At the same time as the basic methodology, advanced methodologies have been established that allow the use of one's own internal assessments of risk components. Wide use of such assessments is an important part of the dynamic and risk-sensitive IRB approach (Internal Rating Based) in such a way as to recognize and differentiate those financial institutions that are able to conduct a sufficiently valid and quantified risk assessment. Along with the standardization of these activities and the development of information systems, quantitative models are largely included in this type of analysis in order to improve the objectivity of predicting the probability of default (PD - Probability of Default) and expected losses. These models include financial indicators, macroeconomic conditions and historical data on loans and borrowers. Regression analysis, discriminant analysis, panel models, hazard models and neural networks are the most common and sophisticated techniques that can be used to assess the probability of debtor default. It can be concluded that, through the results obtained through the mentioned methods, the management of financial institutions can look more complexly and objectively at the real pictures of potential debtors, which in the end enables a better assessment of their default, and therefore the mentioned results of the analysis have a favorable effect on the development of the rating of financial institutions. It is recommended that when approaching this type of analysis, several techniques and methods mentioned above are simultaneously used and that the causes of the differences in the results are thoroughly analyzed, which in any case reduces the probability of the risk of non-payment.

Keywords: default probability, debtor, models, internal rating, regression analysis.
Field: Economy

1. INTRODUCTION

The financial system in general represents one of the most complex systems in society, which is accompanied by turbulence and the general dynamics of changes in market conditions. Optimum management of these systems is a big challenge nowadays. A huge number of internal and external factors affect their operations, so it is imperative for the management of financial institutions to identify them in time and to define the optimal strategy in the development of their rating system in accordance with them (Alastair L. 2022).

On external factors (market conditions and macroeconomic factors, general economic conditions, growth rates, unemployment rates, financial market conditions, interest rates, inflation, competition in the banking sector, availability of advanced technologies for modeling and data analysis, etc.), financial institutions do not have influences, they can only constantly adapt to them and improve their rating systems in order to survive, remain competitive and also comply with regulatory and market expectations.

Internal factors include factors within the financial institutions themselves that influence the development and effectiveness of their rating system. Management can and must influence these factors in order to minimize the negative effects on the level of business and profitability. Some of the key internal factors are: clearly defined roles and responsibilities in the process of determining the rating, effective procedures for validation and monitoring of ratings, skills and expertise of employees, competence of

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credit analysts and personnel involved in the rating system, continuous education and improvement of skills, automation of processes and flows information, effective management and control, etc.

The goal of the management of financial institutions is to create conditions for the construction of the best possible rating system, which will be able to adapt to all challenges in their business, through adequate measures of internal control of business processes. Optimal management of a consistent and adequate policy in maintaining the rating system of financial institutions is also a prerequisite for their dominant positioning in this area of economic activity.

Due to the increasing complexity and complexity of numerous factors that can positively or negatively affect the rating system of financial institutions, it is imperative for financial management to use the most modern methods and techniques such as regression analysis, discriminant analysis, panel models, hazard models for the purpose of analyzing the aforementioned factors. , neural networks, etc., for better credit risk modeling and more precise determination of their rating, and less and less to rely on the subjective and experiential assessments of financial experts.

What represents the condition of all conditions in this area of analysis is the fact that, before approaching the complex assessment of the rating system of financial institutions through the mentioned techniques, it is necessary to assess the quality of the data and their sources, as well as the representativeness of the sample, bearing in mind that it is impossible to carry out the analysis in question on basis of data from the entire statistical set.

At the most developed financial institutions today, specific and advanced techniques in this type of analysis have become the standard in risk assessment, while at the same time further improvement of rating methodologies is continuously carried out (Matz L. 2017).

The development and improvement of the rating system enabled banks to better assess risks, comply with regulatory requirements and manage the credit portfolio more effectively.

The focus of the work will be on understanding the techniques that provide financial institutions with the opportunity to build adequate models of complex relationships between participants in the financial market in the most adequate way and more accurately predict possible risks in their operations.

2. MATERIALS AND METHODS

In this section, we will prioritize some specific quantitative techniques and methods that are most often used when evaluating and developing the rating system of financial institutions. (regression analysis, discriminant analysis, panel models, hazard models and neural networks)

Regression analysis: In statistical modeling, regression analysis is a tool used to determine the relationships between dependent or criterion variables and independent variables. In practice, for example, we may be interested in the dependence between employees' earnings and their education, as well as the connection between the level of national income per capita and their individual indebtedness. Observing the intensity and nature of those connections and dependencies is solved through the aforementioned regression model (Dowling E.T. 2017).

Regression analysis is one of the key techniques and methods used in determining the rating of financial institutions.

The basis of this type of analysis depends primarily on the objective identification of relevant indicators. In addition to the above, it is necessary to analyze historical data on changes in that data. In the end, it is important to choose those variables that have the most influence on non-fulfillment of obligations or the occurrence of default.

Using regression or other techniques, a model is formed that links the independent and dependent variables. This procedure evaluates the influence and importance of each independent variable individually on the dependent variables.

Statistical indicators of the accuracy of the model are analyzed, such as the coefficient of determination of the parameters and the standard error of their estimation. After that, the model is validated on independent samples, in order to evaluate its strength and objectivity.

A regression model is used to estimate the occurrence of default for each client based on its characteristics. The rating assignment is based on the ranking of clients according to the estimated default.

Model performance is regularly monitored through analysis of forecast accuracy, rating migration and default rates. The model is also periodically updated and adjusted to remain accurate and adequate.

Regression analysis provides an objective and statistically based approach to determining the rating, with the possibility of continuous improvement and adaptation to changes in credit risk. It is a key component of advanced rating systems of financial institutions (Engeimann & Rauhmeier, 2018).

A key advantage of regression models in financial institutions is their ability to analyze complex relationships between variables and provide quantitative estimates that support informed business decision making.

Input characteristics, which are not relevant to the model, can seriously impair the quality and stability of the model when used to predict the credit risk associated with this data. It is preferable that the variables, which do not have a great influence on the results of the model, are simply ignored and thereby simplify the model, which in any case makes the work easier for persons performing regression analysis. However, the exclusion of some variables, regardless of their marginal importance for the research results, in any case contributes to a slight increase in the prediction error.

In financial institutions, regression analysis is most often used in the following cases: to assess the credit risk of clients, predict the level of deposits and loans, which helps them manage their balance sheet and liquidity-related risks, identify the most profitable customer segments and determine the most effective marketing channels and campaigns, discover suspicious transactions and patterns of behavior that may indicate fraud, determination of optimal interest rates and fees based on market conditions and risk profile of clients and to assess the credit, market and operational risk to which the financial institution is exposed (Greuning H. 2018).

Discriminant analysis is a sophisticated technique used in managing the rating system of financial institutions. It is used to classify clients and assign them to strata that depends on the calculated probability of default. The place where the client will be assigned depends on his individual characteristics regarding the mentioned probability of default of the debtor.

Discriminant analysis predicts the probability that the client will default. This probability is then used as the basis for assigning a credit rating. On the other hand, the accuracy of the classification of clients into rating groups, as well as the prediction of the probability of default are used to evaluate the quality of the discriminant analysis model. This evaluation is crucial for the validation and continuous improvement of the rating system.

Monitoring of rating changes helps financial institutions to respond in a timely manner to changes in the credit profile of clients. The combination of regression analysis and discriminant analysis forms a solid foundation and is the best way to accurately assess and monitor the risk of default.

The discriminant analysis is performed in a similar way as in the case of the regression model. In fact, the proportions between the coefficients of the regression model are equal to the corresponding proportions of the discriminant analysis. The difference between these two methods is theoretical: while in the regression model the characteristics have a deterministic nature, and the state of default is a random variable, in discriminant analysis it is quite the opposite, i.e. characteristics represent a random variable while the default state is deterministic. These differences are virtually unimportant in practice.

Panel models represent an advanced statistical technique used in modeling the credit rating of financial institutions. This technique has several key advantages over other methods.

Panel models use a combination of cross-sectional (different clients) and time series (data on clients over time). This makes it possible to look at more complex relationships and effects compared to models that use only cross-sections or only time series.

Panel models can remove or control for the influence of unobserved and time-invariant factors specific to each client. This improves the precision of the estimation of the effect of the observed variables on the probability of default.

Panel models can include dynamic elements, such as the dependence of ratings on previous ratings.

This enables better modeling of rating changes over time and provides financial institutions with the ability to develop sophisticated and accurate rating models based on the complex relationships and effects occurring in their portfolios of credit exposures (Brealey R. 2021).

The methods described so far are cross-sectional methods because all variables refer to the same time period. Financial institutions typically spread sets of variables over more than one period with each borrower. In this case, it is possible to extend cross-sectional data inputs to panel data sets.

In this way, we increase the number of available observations and also increase the stability and precision of the rating model. Panel models can also integrate macroeconomic variables.

Macroeconomic variables can improve the model for several reasons. Many sources of macroeconomic data are more up-to-date and more accessible than meso- and micro-level data, as data on macroeconomic variables are published by official national statistics. For example, financial ratios calculated on the basis of balance sheet information are usually updated annually and are no older than two years when we use them for risk assessment (Gitman L. 2019).

Oil prices, for example, are available to us according to the daily frequency of data, as well as prices of precious metals, stock prices on the stock exchanges, and the like change several times during the day, and we can get that information.

Since macroeconomic variables primarily affect the absolute values of default probabilities, it is reasonable to incorporate macroeconomic imputations into these classes of models when estimating default probabilities.

Hazard models represent another advanced and sophisticated approach used in modeling credit ratings of financial institutions. These models focus on analyzing the time until the occurrence of a certain event, in this case default.

The hazard model analyzes the time until the client defaults. This allows banks to better understand the dynamics of credit risk changes over time. The model assesses the influence of various factors (financial indicators, macroeconomic factors, etc.) on the probability and speed of default. This helps banks identify the most significant drivers of credit risk.

Hazard models provide dynamic risk assessment, allowing the estimate of the probability of default to be updated over time. This is particularly useful for monitoring and managing a portfolio of credit exposures.

Hazard models generate survival and default rate curves, which show the probability that a client will not default by a certain time. These curves provide banks with important information for credit risk management.

Hazard models can include heterogeneity at the client level, such as industry specificity, location, etc. This enables a more individual and precise assessment of credit risk (Bessis J. 2019).

The models provide advanced capabilities for dynamic credit risk modeling and help financial institutions make better rating decisions.

All the models listed so far have tried to assess the riskiness of the borrower by estimating a certain type or score that would indicate whether or not the borrower is prone to default within a specific forecast horizon.

However, no exact prediction of default in time has been made. In addition, such approaches do not allow the evaluation of the debtor's risk in the future, which would not enter into default during a reference period of time.

These shortcomings can be overcome by using a hazard model, which explicitly handles the survival function and consequently the time at which we consider debt default.

Hazard models allow estimation of the survival function for all borrowers. The time period of historical data on default is the basis for assessing the debtor's survival and the probability of default in the following time period. These models indirectly estimate realistic assumptions about default in the future time period.

Neural networks represent sophisticated machine learning techniques that are increasingly used in modeling credit ratings of financial institutions.

Neural networks are used to estimate the probability of customer default. They can model complex and non-linear relationships between input parameters (financial data, macroeconomic factors, etc.) and output variables (customer default probabilities) (Bessis J. 2019).

Neural networks are applied to classify customers into different rating categories, such as low, medium or high probability of default. They learn to recognize patterns that determine belonging to rating categories.

Neural networks have the ability to continuously learn and adapt to changes in the credit portfolio and market conditions. This allows financial institutions to maintain the accuracy and relevance of the rating model.

Neural networks can detect non-linear and interactive patterns in data, which can be relevant to credit risk assessment. This overcomes the limitations of traditional statistical models.

Examples of neural networks used in bank rating systems include multilayer perceptrons, recurrent neural networks, and convolutional neural networks.

This advanced technology represents the future in credit risk modeling, providing powerful tools for accurate assessment and efficient portfolio management.

Neural networks are a type of computer system inspired by the structure and functions of biological neural networks in the brain.

The main components of neural networks are its network architecture, learning and non-linearity ie. have the ability to model complex, non-linear relationships between inputs and outputs.

Neural networks are a powerful machine learning tool that can recognize and model complex relationships among data. They are intensively researched and widely used in modern IT and technology.

The application of neural networks in the financial sector is of great importance. Neural networks can analyze large amounts of transaction data to identify patterns of fraudulent activity, such as unusual spending behavior or suspicious transactions. This helps financial institutions detect and prevent fraud more effectively. They can analyze credit history, income and other financial data to assess the creditworthiness of loan applicants. This helps financial institutions to make more accurate credit decisions based on the obtained data and to adapt their products and services to the needs of clients.

Neural networks can be used to analyze customer data, such as transaction histories and browsing patterns, to better understand customer behavior and preferences.

They can be used to automate and streamline the loan underwriting process by analyzing information about applicants and making more accurate loan approval decisions, and can also be trained on historical stock data to try to predict future stock price movements, which can be useful for investment and trading strategies.

Financial institutions are already making extensive use of neural network-based chatbots and virtual assistants to provide personalized customer service and support, answer questions, and assist with tasks.

Key benefits of using neural networks in banking include improved accuracy, speed and scalability in areas such as risk assessment, fraud detection and customer insight. This helps creditors make better decisions and provide better service to their clients.

In previous years, neural networks have been intensively discussed as alternatives to statistical models.

The characteristics of a neural network easily model highly complex, non-linear relationships between inputs and outputs. These models can be quickly adapted to new information inputs (depending on the training or training algorithm). There are no formal procedures that would determine the optimum and type of network for connecting the layers and nodes connecting the input and output variables. Neural networks are black boxes because they are very difficult to interpret. Using this method, calculating the probability of default is only possible up to certain limits with considerable additional effort. They are partially suitable when there are no expectations (based on experience or on theoretical arguments) (Samuels J. 2016).

3. RESULTS

The application of advanced techniques in the modeling of banks' rating systems has brought a number of significant results that improve the efficiency and precision of credit risk management.

Regression-based analyses, both linear and logistic, have proven to be a powerful tool for identifying key determinants of the probability of default (PD) of financial institution clients. These models enabled banks to quantify the impact of various financial indicators, macroeconomic and other factors on credit risk assessment. The results of regression analyzes provide banks with a deeper understanding of the drivers of credit risk in their portfolios.

The application of discriminant analysis in bank rating systems has demonstrated its ability to effectively classify clients into different rating categories. This technique generated discriminant functions that maximize the differences between groups of clients with different credit profiles. The identification of key parameters that best describe groups of clients allowed banks to focus credit risk assessment on the most relevant areas.

The introduction of panel models in the rating systems of banks brought a significant improvement compared to standard regression approaches. These models used a combination of cross-sectional and time-series data, allowing banks to control for the influence of unobserved and constant factors specific to each customer.

The results of the panel models provided financial institutions with information for a deeper understanding of the dynamic effects that influence changes in credit ratings over time.

The implementation of the hazard model in rating systems focused on the analysis of the time until default. These models generated survival and default rate curves, providing financial institutions with key information about the probability that a customer will default at different time intervals. This has improved the ability of financial institutions to dynamically monitor and manage the credit risk of their portfolios.

The adoption of neural networks in financial institution rating systems has brought advances in automation, adaptability, and detection of complex nonlinear patterns in credit risk data. Neural networks enable the automation of the process of credit risk assessment and rating assignment.

Neural networks have demonstrated the ability to accurately predict default probabilities and reliably classify clients into rating categories. This advanced machine learning technique has enabled banks to improve their rating processes and maintain model relevance in a dynamic environment.

The simultaneous application of these methods ensures a continuous and efficient rating system in financial institutions. In this way, they have the possibility to make more realistic assessments and approximation of the risk of default and take adequate measures in order to optimize the use of capital as well as its allocation to the most profitable jobs.

4. DISCUSSIONS

The application of advanced statistical techniques represents a key step in improving the rating system of financial institutions and their efficiency in credit risk assessment and management. Compared to traditional approaches based on the subjective assessment of credit officers, statistical methods provide a more objective and dynamic basis for assigning credit ratings.

Regression analysis, either linear or logistic, allows banks to identify the most significant determinants of default probability and quantify their impact. This gives banks a better understanding of the key factors driving their customers' credit risk.

On the other hand, discriminant analysis provides an advanced technique for classifying clients into different rating categories. The mentioned method generates discriminant functions that maximize the differences between groups of clients with different credit profiles. This enables financial institutions to identify the most relevant factors for differentiating the risk profiles of clients.

Panel models represent a sophisticated extension of the regression technique, taking into account panel data that contain cross-sections and time series. This provides the ability to control for the influence of unobserved, time-invariant factors specific to each client, as well as to model the dynamic effects of rating changes over time.

Hazard models, on the other hand, focus on analyzing the time to default. They provide financial experts with important information about the dynamics of credit risk, including survival rates and default probabilities over different time intervals. This enables more precise portfolio management and making better business decisions.

The latest trends in the financial market also recognize the potential of applying neural networks in rating systems. This advanced machine learning technique enables the discovery of complex and non-linear patterns in data, which overcomes the limitations of traditional statistical methods. Neural networks can automate credit risk assessment and rating processes, with the ability to continuously adapt to changes.

The common feature of these methods and techniques is that they enable financial institutions to assess, monitor and manage credit risk in an objective and quantitatively based way. This results in accurate rating systems that comply with the regulatory framework and provide bankers with a competitive edge in the market.

However, the application of these advanced methods requires appropriate knowledge, high quality data and continuous monitoring of their performance. Financial institutions must therefore invest in the development of expertise, the construction of complex and reliable information systems, as well as a quality management structure in order to fully utilize the potential of the approach in question in determining the credit rating.

5. CONCLUSION

The application of advanced and specific methods in determining the rating system of financial institutions is a key factor for improving the quality, precision and efficiency of their operations. Due to the increasing complexity and complexity of relations between participants in the financial market, the traditional approach based on the subjective assessment of the rating system is increasingly giving way to sophisticated techniques such as regression analysis, discriminant analysis, panel models, hazard models and neural networks.

These methods allow banks to better understand and model the complex relationships between different determinants of credit risk. They provide a more objective and dynamic assessment of the probability of default, which is key information for assigning adequate credit ratings.

Additionally, these approaches provide the ability to continuously monitor and update the rating model, as well as assess the quality and consistency of the entire rating system. This achieves compliance with regulatory requirements and improves credit portfolio management.

By moving to advanced and sophisticated techniques, financial institutions can improve their ability to assess and predict credit risk, make better lending decisions and allocate capital more efficiently. This represents a key competitive advantage in a dynamic financial environment.

Therefore, the continuous improvement of the rating system using the methods mentioned in the paper is a strategic priority area for financial institutions that want to improve their credit risk management performance and maintain a competitive advantage in the market.

Financial institutions are required to have a sophisticated system of assessing the accuracy and consistency of the rating system, process, and internal monitoring of risk factors. Historical time frames for the data used in assessing the degree of data correlation should be as long as possible and ideally cover the entire business cycle.

The relevant analyzes must also identify future changes in economic conditions and possible events that could adversely affect default assessments and therefore the overall level of capital adequacy.

ACKNOWLEDGMENTS

During the preparation of this work, Dr. Radenko Subotić, an expert in the field of information technology, as well as Master of Economics Sanja Šegrt, who performed the translation and proofreading of the text, provided great help and support. In addition to those named, special thanks should be given to Aleksandra Penješević, representative of SCIENCE IJ Journal in the Republic of Serbia, who greatly facilitated and accelerated communication with the responsible persons in the Republic of North Macedonia.

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