DOI: 10.55643/ser.4.58.2025.639

FINANCIAL STABILITY OF COMPANIES: INTEGRATING FORECASTING INSIGHTS INTO RISK MANAGEMENT PROCESSES

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ABSTRACT

In conditions of increasing economic uncertainty, higher financial volatility, and more frequent external shocks, the issue of corporate financial stability has become especially relevant. Traditional approaches to financial risk management, which are mainly based on retrospective analysis of financial indicators, do not always allow potential threats to be identified in a timely manner or adequately addressed. In this context, financial forecasting acts as an important tool for developing a proactive approach to managing corporate financial stability.

The purpose of this article is to justify the role of financial forecasting in ensuring corporate financial stability and to develop a conceptual approach to integrating forecasting insights into financial risk management processes. The study is based on the issue of general scientific and specialized methods, including system and process approaches, structural and logical modeling, as well as an analysis of modern forecasting methods and risk management tools.

The article demonstrates that financial forecasting performs preventive, adaptive, and stabilizing functions by enabling early identification of financial risks and improving the quality of managerial decision-making. It is shown that the application of scenario analysis, risk metrics, early warning systems, and machine learning methods makes it possible to detect potential financial imbalances in a timely manner and reduce the likelihood of crisis scenarios. It is argued that the greatest effect is achieved when forecasting models are systematically integrated into financial risk management processes.

The main scientific result of the study is the development of an original conceptual model for integrating financial forecasting into financial risk management processes, which forms a closed management cycle and contributes to strengthening corporate financial stability. The obtained results have both theoretical and practical significance and can be applied in corporate financial management systems.

Keywords: financial stability, financial forecasting, financial risk management, forecasting insights, proactive risk management, scenario analysis, early warning systems, machine learning in finance, corporate finance, financial resilience

JEL Classification: C53, G17, G31, G32, M21

Received: 09/09/2025
Accepted: 23/12/2025
Published: 31/12/2025

INTRODUCTION

In conditions of growing economic instability and a highly dynamic external environment, the issue of ensuring corporate financial stability becomes particularly relevant. Global financial fluctuations, macroeconomic imbalances, geopolitical factors, and a higher level of uncertainty significantly affect companies' financial performance, making planning processes and managerial decision-making more complex. Under these circumstances, financial stability should be viewed not only as a reflection of a company's current financial position but also as a strategic prerequisite for sustainable development and long-term viability.

The increasing impact of risks has led to a growing role of financial risk management in modern corporate governance. An effective risk management system is intended to ensure the timely identification, assessment, and mitigation of financial threats that arise in the course of business activity. At the same time, both academic research and management practice increasingly point to the limitations of traditional risk management approaches, which are largely focused on historical data analysis and do not always take future changes in the financial environment into account.

In this context, financial forecasting gains special importance as a tool for forward-looking analysis and support of corporate financial stability. The use of forecasting methods makes it possible not only to estimate future financial indicators but also to generate forecasting insights into potential risks, alternative development scenarios, and possible deviations from planned results. As a result, financial forecasting provides an informational basis for shifting from reactive to proactive financial risk management.

However, despite the extensive body of research in the fields of financial forecasting and risk management, forecasting results are often used fragmentarily in corporate practice and are not systematically integrated into the financial risk management process. This reduced the potential of forecasting as a tool for ensuring financial stability and limited companies' ability to respond in a timely manner to growing threats. Identifying and addressing this methodological and practical gap highlights the need for further research in this area.

The purpose of this article is to substantiate the role of financial forecasting in ensuring corporate financial stability and to develop a conceptual approach to integrating forecasting insights into the financial risk management process. The scientific novelty of the study lies in the development of a conceptual model for integrating financial forecasting insights in the processes of identifying and assessing financial risk, and in the author's interpretation of the relationships between forecasting, risk management, and corporate financial stability.

The research follows a logical structure that includes a review of academic approaches to financial stability, financial risk management, and financial forecasting; identification of existing research gaps; justification of the proposed conceptual approach to integrating forecasting insights into risk management; and analysis of the practical significance of the proposed solutions for strengthening corporate financial stability.

LITERATURE REVIEW

In contemporary economic literature, corporate financial stability is widely regarded as one of the key prerequisites for long-term viability and competitiveness under conditions of growing uncertainty. Recent studies interpret financial stability not only as a state of balance of financial indicators, but as a dynamic ability of companies to maintain solvency, financial flexibility, and adaptability in the presence of internal and external shocks. Modern approaches emphasize the need to combine static financial indicators with dynamic characteristics that reflect the sustainability of cash flows, the quality of capital structure, and firms' capacity to respond to adverse development scenarios (Ross et al., 2022; Gatzert & Martin, 2015).

A substantial body of research focuses on identifying the determinants and indicators of corporate financial stability. Traditionally, these include liquidity, solvency, financial leverage, and profitability ratios, which remain fundamental tools of financial analysis. At the same time, recent literature increasingly highlights the importance of financial flexibility, volatility of operating cash flows, diversification of funding sources, and firms' ability to access capital during periods of stress. These factors are considered critical for maintaining financial stability in an unstable macroeconomic environment characterized by elevated risk levels (OECD, 2020; Tressel & Ding, 2021).

Alongside the development of financial stability theory, financial risk management has become a central topic in academic research as a means of reducing the negative impact of uncertainty on corporate performance. Contemporary risk management concepts are largely based on an integrated approach known as enterprise risk management (ERM), which involves the systematic incorporation of risks into strategic and operational decision-making. According to the COSO ERM framework, risk management is defined as "a process, effected by an entity's board of directors, management, and other personnel, applied in strategy setting and designed to manage risk in order to create, preserve, and realize value" (COSO, 2017). This approach underlines the close relationship between risk management practices and the information base used for managerial decision-making.

Within this framework, financial forecasting is viewed as an essential component of corporate financial management, as it supports the formation of expectations regarding future financial outcomes and potential risk scenarios. Recent studies emphasize the transformation of forecasting practices driven by advances in data analytics, machine learning, and scenario modeling. In addition to traditional time-series analysis and econometric models, artificial intelligence tools are increasingly applied to forecast financial indicators, assess credit and market risks, and analyze corporate sensitivity to macroeconomic changes (Hyndman & Athanasopoulos, 2021; Vancsura et al., 2025). At the same time, researchers stress the importance of ensuring the interpretability of forecasting models and managing model risk.

Research on the application of forecasting methods in financial risk management systems is mainly focused on scenario analysis and stress testing. These approaches gained particular relevance after the global financial crisis, which stimulated the development of methodologies for assessing companies' resilience to adverse shocks. Analytical reports by the IMF and BIS indicate that forecasting scenarios should be used not only to estimate potential losses but also as a basis for defining managerial triggers and preventive risk management measures (Tressel & Ding, 2021; Baudino et al., 2024). However, most of these studies are applied or sector-specific in nature and do not offer universal conceptual solutions for the corporate sector as a whole.

A synthesis of the existing literature reveals several research gaps in the analysis of the relationship between financial forecasting, financial risk management, and corporate financial stability. In particular, insufficient attention has been paid to approaches for the systematic integration of forecasting insights into risk management processes, as well as to mechanisms for transforming forecasting results into concrete managerial decisions aimed at strengthening financial stability. This highlights the need to develop a conceptual model that combines financial forecasting and risk management into a unified logical framework, which defines the scientific direction of the present study.

AIMS AND OBJECTIVES

The aim of this article is to substantiate the role of financial forecasting in ensuring corporate financial stability and to develop a conceptual approach to integrating forecasting insights into financial risk management processes. Achieving this aim is intended to deepen the theoretical and methodological foundations of forecast-oriented financial risk management and to form a comprehensive view of the relationships between financial forecasting, risk management, and corporate financial stability under conditions of increasing economic uncertainty.

Within the framework of the study, financial forecasting is considered not only as a tool for estimating future financial indicators but also as an important element of the information support for managerial decision-making, which enhances the effectiveness and preventive nature of financial risk management. This perspective provides a basis for developing a conceptual model for integrating forecasting insights into corporate risk management systems and expands traditional views on the mechanisms for ensuring financial stability.

To achieve the stated aim, the article addresses the following objectives:

1. To analyze theoretical approaches to the interpretation of corporate financial stability and to identify its key determining factors.
2. To examine the essence, functions, and tools of financial forecasting within the system of corporate financial management.
3. To determine the role of forecasting methods in corporate financial risk management processes.
4. To develop a conceptual approach to integrating financial forecasting into risk management practices.
5. To assess the practical significance of using forecasting insights to enhance corporate financial stability.
6. To formulate general conclusions and outline directions for further research in the fields of financial stability and financial risk management.

METHODS

To achieve the research aim and accomplish the stated objectives, the study employs a combination of general scientific, theoretical, economic, and financial methods, which ensures a systematic approach to examining the integration of financial forecasting into corporate risk management processes. Among the general scientific methods, analysis, synthesis, and generalization were used to structure existing academic approaches to defining corporate financial stability and risk management mechanisms. The system approach made it possible to examine the interconnections between financial forecasting, risk management, and corporate stability in a comprehensive manner.

The main theoretical methods applied in the study include comparative analysis and structural and logical modeling. Comparative analysis was used to compare different academic concepts of financial stability and risk management, identify

DOI: 10.55643/ser.4.58.2025.639

their strengths and limitations, and reveal existing gaps that justify the development of a conceptual model for integrating forecasting insights into corporate management practices. Structural and logical modeling served as the basis for developing the author's conceptual model, which combines financial forecasting and risk management into a single, coherent system.

Economic and financial methods included financial statement analysis, ratio analysis of key indicators of financial stability, and financial risk assessment. The application of these methods made it possible to identify critical aspects of solvency, liquidity, financial flexibility, and capital management efficiency, which represent core factors supporting corporate stability in modern conditions. In addition, these methods provided a basis for the quantitative assessment of the impact of various risks on companies' financial performance.

Special attention was given to financial forecasting methods used to develop scenarios for financial indicators and to assess potential risk situations. The study applied both classical forecasting techniques, such as time series analysis and econometric modeling, and modern data analytics and machine learning tools, which enabled more accurate prediction of financial fluctuations and early identification of potential threats. To test corporate resilience to adverse scenarios, scenario analysis and elements of stress testing were employed, allowing the modeling of the effects of external and internal shocks on financial stability.

The information base of the study includes corporate financial statements, statistical and analytical materials from international organizations (IMF, OECD, BIS), as well as recent academic publications on financial forecasting, risk management, and corporate stability. The integrated application of these methods ensured the combination of theoretical and practical perspectives and supported well-grounded conclusions regarding the role of forecasting insights in corporate financial risk management systems.

RESULTS

In modern conditions characterized by rising financial market volatility, increased pressure on supply chains, and rapid technological transformation, ensuring corporate financial stability becomes critically important. Financial stability should be understood not only as the absence of crisis situations, but also as a company's ability to withstand shocks, maintain solvency, and ensure operational continuity in the medium and long term. In this context, financial forecasting acts as a fundamental tool that transforms informational uncertainty into well-grounded managerial decisions. The article systematizes and generalizes theoretical approaches to defining the role of financial forecasting in shaping corporate financial stability, taking into account current academic and practical perspectives.

1. Financial forecasting represents a systematic process of estimating future cash flows, profitability, capital needs, and other financial indicators based on historical data, macroeconomic variables, and scenario-based assumptions. From a theoretical perspective, forecasting performs four interrelated functions that directly influence corporate financial resilience:
2. Preventive function (early risk identification). Forecasting signals make it possible to identify trends that may lead to liquidity shortages or declining profitability, allowing timely adjustments to corporate policies. This corresponds to the modern forward-looking principle widely applied in supervisory frameworks and stress-testing practices (Jobst & Ong, 2020).
3. Adaptive function (supporting operational flexibility). Scenario-based and stochastic models enable the development of alternative development paths and the preparation of response measures such as hedging strategies, cost control, or refinancing options (BIS, 2018).
4. Stabilizing function (reducing volatility). Regular forecasting of cash flows and capital requirements helps limit the occurrence of cash gaps and temporary liquidity deficits, thereby reducing the amplitude of financial fluctuations (Hyndman & Athanasopoulos, 2021).
5. Communication function (building trust). Transparent forecasting processes strengthen the confidence of investors and creditors, reducing the cost of capital through lower information asymmetry. Institutions that regularly disclose scenario-based assessments tend to obtain more favorable financing conditions (Tressel & Ding, 2021).

The synthesis of theoretical approaches makes it possible to identify the key functions of financial forecasting, the implementation of which forms the institutional foundation of corporate financial stability. Their systematization and the main channels of influence on financial resilience are summarized in Table 1.

Table 1. The main forecasting functions and their impact on stability. *(Source: developed by the authors based on (Jobst & Ong, 2020; BIS, 2018; Hyndman & Athanasopoulos, 2021; Tressel & Ding, 2021))*

Forecasting functions	Tools	Direct impact on stability
Preventive function	Short- and medium-term, cash flow forecasting, rolling forecasts	Reduction of cash flow gap risk
Adaptive function	Scenario modeling, stress-testing	Increased flexibility of managerial responses
Stabilizing function	Stochastic modeling, VAR, RCF	Reduced volatility of financial indicators
Communication function	Reporting and forecast presentations for stake-holders	Improved conditions for raising capital

As shown in Table 1, financial forecasting has a multifunctional nature and provides a comprehensive impact on corporate financial stability through the combination of preventive, adaptive, stabilizing, and communication mechanisms. The joint implementation of these functions strengthens companies' resilience to financial risks and uncertainty.

The theoretical foundation of financial forecasting combines classical time-series and regression-based methods with modern machine learning (ML) approaches. Traditional techniques such as ARIMA models, exponential smoothing, and linear regression offer a high level of interpretability and forecast stability in relatively predictable environments. However, in conditions characterized by frequent regime shifts and nonlinear relationships, ML-based approaches, including Random Forest, XGBoost, and LSTM neural networks, demonstrate clear advantages due to their ability to capture complex patterns and improve forecasting accuracy (Wasserbacher & Spindler, 2021).

In international practice, stress testing is defined as a forward-looking tool for assessing resilience to macroeconomic and firm-specific shocks. For example, the IMF Global Corporate Stress Test (2021) used scenario-based projections of profitability and liquidity stress to identify sectoral vulnerabilities following the COVID-19 crisis and to inform targeted support policies. This case illustrates the practical value of an integrated forecasting cycle consisting of scenario design, projection development, and the implementation of managerial policies (Tressel & Ding, 2021).

The review of academic literature also points to differences in the application of forecasting methods. ML-based models tend to perform better in short-term forecasting when large and high-quality datasets are available, while classical statistical models ensure greater stability and stronger economic interpretability under conditions of limited information. This finding supports the relevance of hybrid approaches that combine traditional statistical techniques with machine learning methods in corporate forecasting practice (Wasserbacher & Spindler, 2021).

Empirical evidence confirms the practical effectiveness of such combined solutions. Studies conducted during 2020-2024 indicate that the introduction of ML tools in FP&A departments increased the accuracy of short-term cash flow forecasts by an average of 10-25% compared to classical methods. The results vary across industries and depend on data quality, which highlights the importance of a comprehensive forecasting approach and the integration of multiple methods to ensure corporate financial stability (Gao et al., 2024).

Overall, the available theoretical and empirical evidence confirms that integrating forecasting insights into risk management enables companies not only to identify potential financial risks at an early stage but also to adjust managerial decisions more effectively, thereby strengthening overall financial resilience.

The theoretical generalization of the role of financial forecasting in ensuring corporate financial stability logically leads to the need to move to a more applied level of analysis – namely, to justify the importance of forecasting methods in the processes of identifying and quantitatively assessing financial risks. Under conditions of heightened macroeconomic uncertainty, financial shocks, and increasing complexity of financial systems, risks increasingly emerge in a latent and cumulative form. In such circumstances, retrospective analysis of financial statements loses its ability to provide timely warning signals, whereas forecasting methods enable early detection of risk trends and create an analytical basis for preventive risk management.

Forecasting methods play a key role in transforming financial risk management from a reactive to a proactive model, as they allow the integration of historical data, current financial indicators, and expectations regarding future changes in the external environment. This integration makes it possible to identify risks before they materialize in the form of liquidity shortages, declining solvency, or disruptions in financial balance.

Research in the field of financial risk management confirms that the use of forecasting models significantly improves early warning capabilities and reduces the likelihood of severe crisis scenarios across different economic sectors. For instance, according to an IBM study, companies that implemented predictive analytics reduced operational risks by 10-20% and

DOI: 10.55643/ser.4.58.2025.639

were able to identify potential risks up to two years earlier compared to firms relying on reactive approaches. In contrast, companies that do not use forecasting methods face up to 25 % higher risk exposure due to delayed threat identification, resulting in missed opportunities and substantial financial losses. Statistical evidence also shows that the application of machine learning in financial forecasting increased forecast accuracy from approximately 80 % to around 90 %, supporting more precise cash flow planning and strategic risk management decisions (Takyon, 2024).

In financial analysis practice, forecasting methods are applied to identify various types of risks, including liquidity, credit, market, and financial distress risks. A synthesis of recent academic studies makes it possible to systematize the main forecasting tools used for the identification and assessment of financial risks, as summarized in Table 2.

Table 2. Forecasting methods for the identification and assessment of financial risks in contemporary research. *(Source: summarized by the authors based on (Altman et al., 2016; Chang et al., 2024; Jorion, 2006))*

Method group	Primary purpose	Types of risks	Sources
Time series models (ARIMA, GARCH)	Forecasting the dynamics and volatility of financial indicators	Market risk, liquidity risk	Jorion (2006)
Indicator-based models (Altman Z-score and its modification)	Early detection of financial distress and bankruptcy	Insolvency risk	Altman et al. (2016)
Risk metrics (VaR, CVaR)	Quantitative assessment of potential financial losses	Market risk, portfolio risk	Jorion (2006)
Stress-testing and scenario analysis	Assessment of resilience to extreme shocks	Systemic and combined risks	Basel-oriented studies
Machine learning methods (RF, XGBoost, NN)	Forecasting defaults and financial distress	Credit risk, financial stability risk	Chang et al. (2024)

It is important to emphasize that forecasting methods are not limited to risk identification alone, but also provide opportunities for quantitative risk measurement, which is critical for informed managerial decision-making. In particular, the application of Value at Risk (VaR) makes it possible to estimate the maximum expected portfolio loss at a given confidence level, while Conditional Value at Risk (CVaR) complements this measure by focusing on tail risks. Empirical studies indicate that the use of VaR in combination with stress testing improves the accuracy of risk assessment during periods of financial turbulence, including the crisis shocks of 2008-2009 and the 2020s.

Special attention in recent academic research has been devoted to the application of machine learning methods for forecasting financial risks. According to the study by Chang et al. (2024), the use of XGBoost and Random Forest algorithms in credit risk prediction tasks led to an average increase in the AUC indicator of 8-15 % compared to classical logistic regression, indicating a higher capacity of these models for early detection of potential defaults. Similar findings are reported in survey studies on deep learning in financial forecasting, which document the consistent superiority of nonlinear models in complex, multi-factor environments.

The logic of applying forecasting methods within financial risk management systems can be presented in the form of a generalized conceptual framework (Figure 1), which illustrates their integration into the managerial decision-making process.

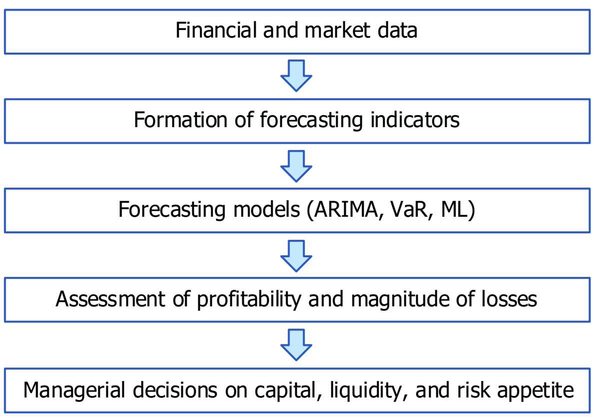

Figure 1. Conceptual framework for the application of forecasting methods in financial risk management. *(Source: developed by the authors based on (Jorion, 2006; Altman et al., 2016; Chang et al., 2024))*

DOI: 10.55643/ser.4.58.2025.639

Thus, forecasting methods should be viewed not as isolated analytical tools, but as a core element of an integrated financial risk management system. They enable a shift from the mere recording of financial outcomes to the generation of forecasting insights that extend management time horizons, enhance companies' adaptability to changes in the external environment, and contribute to strengthening financial resilience in the long term. The combination of traditional financial models with modern analytical approaches creates a methodological basis for more accurate risk assessment and reduces the probability of systemic financial disruptions.

In this context, there is a clear need for a holistic understanding of the role of forecasting in its interaction with risk management processes and corporate financial stability, which justifies the development of an original conceptual approach.

Corporate financial stability is defined as the ability to maintain key financial functions – ensuring liquidity, meeting debt obligations, and preserving investment capacity – under conditions of internal and external shocks. Within this framework, forecasting performs the role of a central informational element by generating signals about potential changes in financial parameters. These signals are transformed into risk management decisions, including adjustments to capital structure, the level of liquid reserves, or credit policy. The implementation of such managerial actions affects the company's financial structure and stability, forming a cyclical interaction mechanism: "forecasting – managerial decisions – changes in financial indicators – an updated basis for subsequent forecasts".

The integration of forecasting and risk management can therefore be understood as a sequential process of financial information transformation. The forecasting system converts primary data – transactions, cash flows, and market indicators – into key risk metrics, including probability of default (PD), loss given default (LGD), Value at Risk (VaR), and stress-scenario outcomes. These indicators are incorporated into managerial processes through threshold systems and scenario matrices aligned with the company's risk appetite and capital objectives. Reaching critical levels of such indicators triggers predefined corrective actions, which accelerate management response and reduce the amplitude of fluctuations in cash flows and net profit.

The practical effectiveness of this approach is supported by empirical evidence. For example, Chang et al. (2024), in their analysis of credit card default prediction models, found that the application of the XGBoost algorithm led to a substantial improvement in classification accuracy compared to logistic regression. The values of AUC and other key metrics increased by several percentage points depending on the dataset and data preprocessing methods, which in managerial terms translates into earlier identification of high-risk segments and a reduction in expected portfolio losses when timely actions are taken.

In practice, the integration of forecasting into risk management processes is implemented through the use of various types of predictive models that generate signals about potential financial threats and initiate appropriate managerial responses. Depending on the nature of input data, forecasting horizon, and management objectives, predictive models can be grouped into three main categories.

First, market-based indicators, including stock price dynamics and volatility measures, serve as tools for early detection of overheating or instability in financial markets. Signals derived from these indicators are used in risk management for portfolio rebalancing and hedging exposures, which helps reduce capital volatility and strengthen margin stability (Chen & Svirydzenka, 2021).

Second, statistical and econometric models, such as Value at Risk (VaR) and Conditional Value at Risk (CVaR), are designed to assess potential tail losses of portfolios. Their application provides a quantitative basis for determining capital buffers and setting limits on risk exposures, thereby minimizing the likelihood of critical financial losses under stress conditions (Jorion, 2006).

Third, machine learning methods and classification algorithms, including XGBoost and Random Forest, are used to forecast default probabilities and other risk events based on multidimensional financial and behavioral data. Compared with traditional approaches, these models offer higher predictive accuracy and earlier risk detection; however, their effective use in financial management requires additional tools for result interpretation and robust validation procedures (Chang et al., 2024; Shi et al., 2022).

Summarizing the practical mechanisms of interaction between forecasting and risk management, predictive tools can be systematically classified according to the type of signals generated, corresponding managerial responses, and their expected impact on corporate financial stability. This approach makes it possible to clearly demonstrate how forecasting indicators are transformed into specific managerial actions and to assess their contribution to strengthening financial resilience. The corresponding systematization is presented in Table 3, which shows how different groups of forecasting

DOI: 10.55643/ser.4.58.2025.639

tools are integrated into the risk management system and generate practical effects for ensuring corporate financial stability.

Table 3. Integration of forecasting tools into risk management and financial stability. *(Source: summarized by the authors based on (Chen & Svirydzenka, 2021; Jorion, 2006; European Central Bank, 2021; Chang et al., 2024; Shi et al., 2022))*

Forecasting tool	Signal	Reaction of risk management	Expected impact on financial stability	Sources
Market indicators (equity price, volatility)	Signal of overheating or instability	Portfolio rebalancing, exposure hedging	Reduced capital volatility, increased margins	Chen & Svirydzenka, 2021
VaR / CVaR analysis	Assessment of tail losses	Setting capital buffers, position limits	Lower likelihood of critical portfolio losses	Jorion, 2006
Early Warning Systems (багатоіндикаторні)	"Upper-tail risk" signal	Activation of liquidity plans, debt restructuring	Improved survivability under stress scenarios	European Central Bank, 2021
ML-класифікатори (XGBoost, Random Forest)	PD / default scoring	Targeted reviews, adjustment of credit policy	Reduced expected portfolio losses	Chang et al., 2024; Shi et al., 2022

Despite their high potential, forecasting models have certain limitations. Historical data may fail to capture structural changes or unexpected shocks, while threshold-based signals can generate false alarms, which makes it necessary to combine statistical forecasts with expert judgment. In addition, complex machine learning algorithms require transparent interpretation mechanisms and rigorous validation procedures in order to be reliably used in financial decision-making.

Thus, the integration of forecasting, risk management, and financial stability forms a practical framework for enhancing corporate resilience in a volatile economic environment by enabling timely risk identification and effective responses to emerging threats.

The author's interpretation of the relationship between financial forecasting, risk management, and financial stability substantiates their consideration as interrelated components of a unified management mechanism, which highlights the need for further structuring and practical systematization. In response, based on theoretical generalization and analytical observations, an original conceptual model for integrating financial forecasting into the financial risk management system is proposed (Figure 2). This model envisages the transformation of forecasting insights from a supporting analytical tool into an active element of the managerial framework for ensuring corporate financial stability.

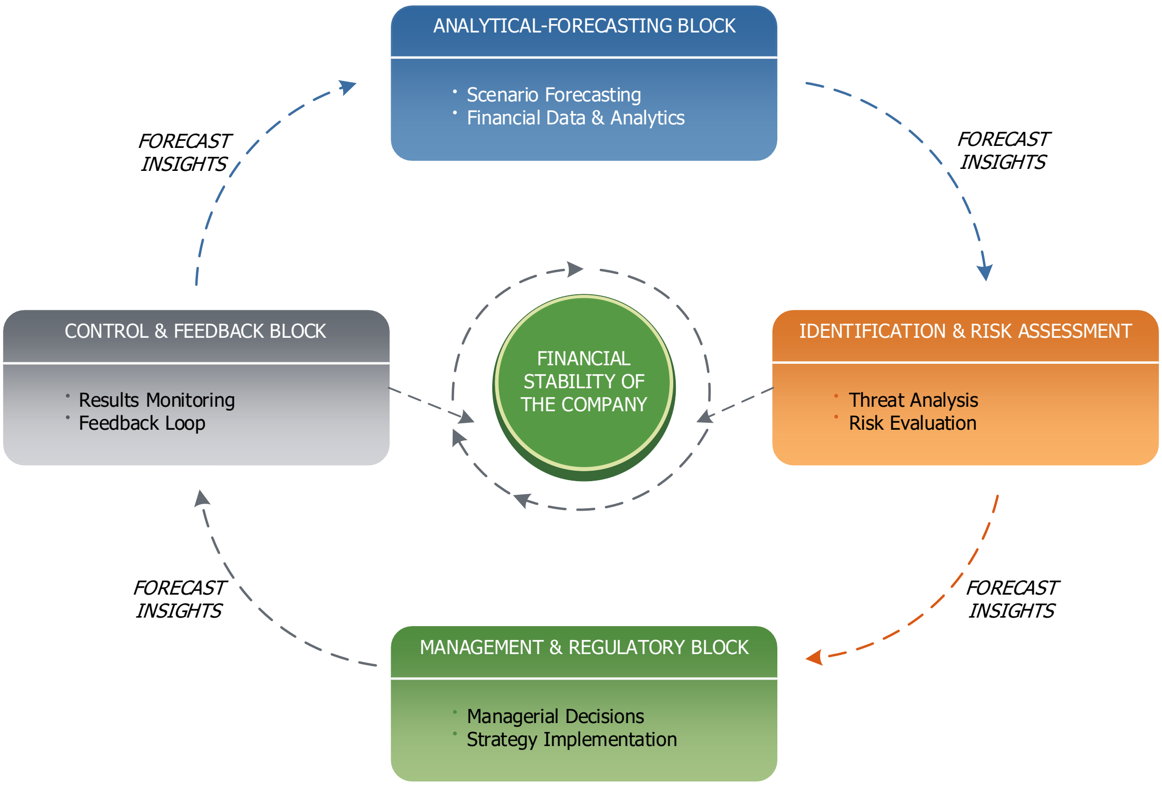

Figure 2. Conceptual model for integrating financial forecasting into processes of financial risk management.

The proposed model is grounded in process-based and system-oriented approaches and treats financial forecasting not as an isolated stage of financial analysis, but as a dynamic information and analytical module integrated into all key phases of risk management. Its conceptual novelty lies in shifting the focus from reactive responses to risks toward proactive management of financial stability based on forecasting signals.

Within the author's model, the integration of financial forecasting is implemented through the sequential interaction of four interrelated blocks:

- The first block – the analytical and forecasting block – involves the systematic collection of financial data, their structuring, and the development of alternative forecasting scenarios for key financial indicators. At this stage, forecasting performs an early diagnostic function by identifying potential deviations and creating an information basis for detecting latent financial risks.
- The second block – the identification and assessment block – is the stage at which forecasting results are transformed into risk-oriented information. Here, forecasting insights serve as a basis for identifying areas of increased financial vulnerability, assessing the potential consequences of risk realization, and determining their criticality for the company's financial stability.
- The third block – the managerial and regulatory block – involves the integration of forecasting conclusions into the managerial decision-making process. At this stage, forecasting performs a navigational function by guiding managerial actions aimed at selecting appropriate financial risk mitigation instruments, adjusting financial strategy, and adapting operational activities to expected changes in the financial environment.
- The fourth block – the monitoring and feedback block – ensures continuous monitoring of the outcomes of implemented managerial decisions and the updating of forecasting assessments. The presence of a feedback mechanism allows the model to maintain flexibility and adaptability, as well as to support the continuity of financial risk management processes under conditions of uncertainty.

Thus, the proposed conceptual model forms a closed management cycle in which financial forecasting serves as an integrating link between analysis, risk assessment, and strategic managerial decisions. Unlike traditional approaches, the model is oriented not only toward minimizing the negative consequences of risks but also toward strengthening corporate financial stability through proactive management.

The proposed approach creates a methodological foundation for further empirical testing of the model and its adaptation to the specific characteristics of companies operating in different industries and at different scales.

The developed conceptual model for integrating financial forecasting into financial risk management processes provides a basis for assessing its practical relevance from the perspective of managerial effectiveness and corporate financial stability. The transition from fragmented use of forecasts to the systematic application of forecasting insights changes the logic of managerial decision-making, shifting it toward anticipatory responses to potential financial threats.

The practical value of using forecasting insights lies primarily in the extension of financial risk management time horizons. Through forecasting, companies gain the ability not only to record existing financial imbalances, but also to timely identify trends that may lead to disruptions in financial stability in the medium and long term. This facilitates a shift from reactive managerial decisions to proactive ones, which is particularly important in an unstable financial environment.

The use of forecasting insights within risk management systems also improves the soundness of managerial decisions. Forecast-based scenarios make it possible to assess alternative development paths, compare the potential consequences of managerial actions, and select optimal tools for mitigating financial risks. As a result, the likelihood of intuitive or delayed decisions that negatively affect corporate financial stability is reduced.

These managerial effects are summarized in Table 4, which presents a comparative characterization of key parameters of financial risk management under conditions of fragmented use of forecasting and its systematic integration into risk management processes. The results reflect expected changes in management time horizons, decision-making quality, the level of adaptability of the financial system, and the overall state of corporate financial stability.

In addition, the integration of forecasting insights contributes to enhancing the adaptability of a company's financial system. The presence of feedback between the outcomes of implemented managerial decisions and updated forecasting assessments enables flexible adjustments of financial strategy in response to changes in internal and external conditions. This approach makes it possible to maintain the stability of key financial parameters even under conditions of increased uncertainty.

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Table 4. Practical managerial effects of using forecasting insights within corporate financial risk management practices.

Impact direction	Characteristics of risk management without forecasting insights	Anticipated effects of integrating forecasting insights
Risk management time horizon	Predominantly short-term, focused on risks that have already emerged	Extension of the management horizon through early recognition of potential threats
Quality of management decision-making	Decisions are mainly reactive and are made with limited information	Improved quality of decisions based on scenario analysis and forecasting results
Stability of financial indicators	Significant volatility of the impact of external shocks on financial results	Reduced volatility of key financial indicators
Risk management efficiency	Uncoordinated management of individual types of financial risks	An integrated forecast-oriented framework for risk management
Financial system adaptability	Restricted ability to quickly adjust financial strategy	Improved flexibility and the ability to respond quickly to changes in the financial environment
Level of financial stability	Proneness to periodic financial imbalances	Strengthened financial stability through preventive risk management

In summary, the practical significance of using forecasting insights is reflected in the strengthening of corporate financial stability through improved risk management quality, reduced financial vulnerability, and the development of sustainable managerial mechanisms for responding to future risks. This confirms the relevance of integrating financial forecasting as an essential component of modern financial risk management systems.

The results of the study indicate that financial forecasting plays a system-forming role in ensuring corporate financial stability by creating an information and analytical foundation for effective financial risk management. The theoretical generalization of the role of forecasting, the substantiation of the importance of forecasting methods, the author's interpretation of the relationship between forecasting, risk management, and financial stability, as well as the developed conceptual model of their integration, allow forecasting insights to be viewed as an active element of the managerial framework. The assessment of the practical relevance of this approach confirms its ability to improve the quality of managerial decisions, enhance the adaptability of the financial system, and strengthen corporate resilience to risks, thereby providing a basis for further academic discussion and empirical validation of the findings.

DISCUSSION

The obtained results confirm that financial forecasting plays a system-forming role in ensuring corporate financial stability, serving not only as a tool for estimating future financial indicators but also as a key element of the information support for risk management processes. Unlike traditional approaches that are mainly focused on retrospective analysis of financial performance, the forecast-oriented approach proposed in this study enables a transition toward proactive financial risk management and extends the time horizons of managerial decision-making.

The findings are consistent with previous studies that interpret financial stability as a dynamic characteristic shaped by liquidity, financial flexibility, and companies' ability to adapt to external shocks (Ross et al., 2022; OECD, 2020). At the same time, unlike most existing research that examines these factors in isolation, this article emphasizes the mechanisms through which forecasting results are transformed into concrete managerial actions within the risk management system. This perspective allows financial stability to be viewed as the outcome of a closed management cycle rather than as a static financial condition.

The results also contribute to the literature on enterprise risk management. While studies by Gatzert and Martin (2015) and the COSO framework (2017) stress the importance of integrating risk management into corporate strategy, the role of forecasting in these approaches remains secondary. The conceptual model proposed in this article extends these frameworks by demonstrating that forecasting insights can serve as a central link connecting risk analysis, managerial decisions, and financial outcomes, thereby supporting higher levels of corporate financial resilience.

Special attention in the study is given to comparing different groups of forecasting methods and their impact on the effectiveness of financial risk management. The results are consistent with the classical conclusions of Jorion (2006) regarding the importance of VaR and CVaR for assessing tail risks, as well as with recent empirical studies that confirm the superior predictive performance of machine learning methods in credit and financial risk tasks (Chang et al., 2024; Shi et al., 2022). At the same time, the findings refine these conclusions by emphasizing that the advantages of machine learning methods become most evident when they are embedded within managerial triggers and risk management procedures, rather than applied as standalone forecasting tools.

An important contribution of the study is the justification for combining different forecasting approaches within a single management framework. In contrast to studies that oppose classical statistical models to machine learning algorithms (Hyndman & Athanasopoulos, 2021; Wasserbacher & Spindler, 2021), the results support a hybrid approach that integrates the interpretability of traditional models with the ability of ML algorithms to detect nonlinear relationships and latent risks. This approach is consistent with the recommendations of international financial institutions regarding the use of forward-looking tools in stress testing and financial supervision systems (Tressel & Ding, 2021; Baudino et al., 2024).

At the same time, the results of the study should be interpreted in light of certain limitations. First, the proposed conceptual model of forecasting integration has a generalized nature and does not account for industry-specific characteristics, which may significantly influence the structure of financial risks and data availability. Second, the effectiveness of forecasting methods largely depends on the quality of historical data, which limits their applicability under conditions of structural changes or unprecedented shocks. Third, the use of complex machine learning algorithms increases model risk and requires additional mechanisms for interpretation, validation, and control, which may complicate their practical implementation in corporate governance.

These limitations outline directions for future research, including empirical testing of the proposed conceptual model using data from companies across different industries and countries, the development of industry-specific forecast-oriented risk management tools, and further investigation into model interpretability and the management of risks associated with the use of machine learning methods in financial forecasting.

CONCLUSIONS

This article substantiates the role of financial forecasting as a key element in ensuring corporate financial stability under conditions of increasing economic uncertainty. The study demonstrates that traditional approaches to financial risk management, which are mainly based on retrospective analysis, are insufficient for timely responses to contemporary financial challenges. In contrast, the integration of forecasting insights into risk management processes creates the basis for a shift toward a proactive model of managing corporate financial stability.

The results show that corporate financial stability is dynamic in nature and depends on a company's ability to maintain liquidity, meet debt obligations, and preserve investment capacity in the presence of internal and external shocks. Within this framework, financial forecasting performs preventive, adaptive, and stabilizing functions by providing an information base for well-grounded managerial decisions in the field of risk management.

The significance of forecasting methods for the identification and quantitative assessment of financial risks is confirmed. The study shows that the application of scenario analysis, risk metrics such as VaR and CVaR, early warning systems, and machine learning methods enables potential threats to be detected at an early stage and reduces the likelihood of crisis scenarios. At the same time, the highest effectiveness is achieved when forecasting models are used systematically within management processes rather than applied in isolation.

The key scientific contribution of the research is the development of an original conceptual model for integrating financial forecasting into financial risk management processes. The proposed model forms a closed management cycle in which forecasting insights are transformed into managerial decisions and, in turn, influence subsequent forecasting assessments, thereby contributing to the strengthening of corporate financial stability.

The practical significance of the findings lies in improving the quality of managerial decisions, extending the time horizons of risk management, reducing the volatility of financial indicators, and increasing the adaptability of companies' financial systems. At the same time, the results are subject to certain limitations related to the generalized nature of the proposed model, the dependence of forecasting effectiveness on data quality, and the need to ensure the interpretability of complex analytical algorithms.

Future research should focus on empirical testing of the proposed model using data from companies across different industries and countries, the development of industry-specific forecast-oriented risk management tools, and further investigation into model risk management and the transparency of forecasting methods.

DOI: 10.55643/ser.4.58.2025.639

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All authors have contributed equally.

FUNDING

The Authors received no funding for this research.

CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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ФІНАНСОВА СТАБІЛЬНІСТЬ КОМПАНІЙ: ІНТЕГРАЦІЯ ПРОГНОЗНИХ ІНСАЙТІВ У ПРОЦЕСИ УПРАВЛІННЯ РИЗИКАМИ

В умовах зростання економічної невизначеності, підвищеної фінансової волатильності й частоти зовнішніх шоків проблема забезпечення фінансової стабільності компаній набуває особливої актуальності. Традиційні підходи до управління фінансовими ризиками, які здебільшого ґрунтуються на ретроспективному аналізі фінансових показників, не завжди дозволяють своєчасно ідентифікувати потенційні загрози та адекватно реагувати на них. У цьому контексті фінансове прогнозування виступає важливим інструментом формування проактивної моделі управління фінансовою стабільністю компаній.

Метою дослідження є обґрунтування ролі фінансового прогнозування в забезпеченні фінансової стабільності компаній і розробка концептуального підходу до інтеграції прогнозних інсайтів у процеси управління фінансовими ризиками. Дослідження базується на використанні загальнонаукових і спеціальних методів, зокрема системного та процесного підходів, структурно-логічного моделювання, аналізу сучасних прогнозних методів і ризик-менеджерських інструментів.

У статті показано, що фінансове прогнозування виконує превентивну, адаптивну та стабілізаційну функції, забезпечуючи ранню ідентифікацію фінансових ризиків і підвищення якості управлінських рішень. Доведено, що застосування сценарного аналізу, метрик ризику, систем раннього попередження та методів машинного навчання дозволяє своєчасно виявляти потенційні фінансові дисбаланси та знижувати ймовірність реалізації кризових сценаріїв. Обґрунтовано, що найбільший ефект досягається за умов системної інтеграції прогнозних моделей в управління фінансовими ризиками.

Основним науковим результатом дослідження є розробка авторської концептуальної моделі інтеграції фінансового прогнозування в процеси управління фінансовими ризиками, яка формує замкнений управлінський цикл і сприяє зміцненню фінансової стабільності компаній. Отримані результати мають теоретичну й практичну значущість і можуть бути використані в системах корпоративного фінансового менеджменту.

Ключові слова: фінансова стабільність, фінансове прогнозування, управління фінансовими ризиками, прогнозні інсайти, проактивне управління ризиками, сценарний аналіз, системи раннього попередження, машинне навчання у фінансах, корпоративні фінанси, фінансова стійкість

JEL Класифікація: C53, G17, G31, G32, M21

 DOI: 10.55643/ser.4.58.2025.639