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Review Article

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Review on the Innovation of Investment Banks' Credit Risk Assessment System in a Highly Volatile Market

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Abstract
In highly volatile markets, traditional credit risk assessment systems for investment banks face critical limitations, including reliance on outdated data, linear assumptions, and inadequate integration of non-financial factors. This study proposes a machine learning-driven framework to address these gaps, leveraging real-time multi-source data (e.g., macroeconomic indicators, market sentiment, transactional behavior) and nonlinear algorithms to enhance predictive accuracy. Case analysis, including JPMorgan Chase's post-2008 reforms, validates the system's effectiveness in mitigating risks during extreme market fluctuations. Results highlight significant improvements in real-time risk identification and adaptability to dynamic environments. Challenges such as model interpretability and data quality persist, necessitating future research on explainable AI and ESG integration. The findings provide actionable insights for modernizing risk management practices, offering a robust pathway to bolster financial stability in increasingly unpredictable markets.

1. Introduction

In the era of global economic integration, the stability of the financial market is crucial for the economic development of countries. As emphasized in the "Global Financial Stability Report 2023" released by the International Monetary Fund (IMF), financial market disruptions can have far - reaching consequences for national economies [1]. In recent years, the outbreak of the COVID - 19 pandemic and the frequent adjustments of the Federal Reserve's monetary policy have significantly disrupted the financial market. These factors, when combined, have made the financial market environment increasingly complex and volatile, leading to large - scale and frequent fluctuations in asset prices [2]. However, the traditional credit risk assessment system has shown its limitations in the highly volatile market environment [3]. For example, the traditional assessment system often lags, failing to accurately and promptly evaluate the credit risk of investment banks [3]. This poses a significant potential threat to investment banks' risk management and the stability of the financial market. Thus, innovating the credit risk assessment system for investment banks has become a pressing issue in the financial field.

Currently, in the research on the innovation of investment banks' credit risk assessment systems, most studies mainly propose improvement suggestions based on the existing risk assessment system, lacking an in - depth reconstruction of the underlying logic and structure of the entire assessment system. When faced with extreme market volatility, the improvement proposals based on the existing system are often ineffective. Therefore, this research aims to deeply analyze the innovation path of investment banks' credit risk assessment systems in a highly volatile market. By exploring the introduction of new data and technologies and analyzing the limitations of the traditional assessment system, it endeavors to construct a more scientific and efficient credit risk assessment system.

The specific research plan is as follows: First, systematically clarify the definition of a highly volatile market, its formation reasons, and its impact on investment banks' credit risk. Second, thoroughly analyze the limitations of the traditional credit risk assessment system. Then, explore the feasibility and specific methods of constructing a new credit risk assessment system using machine learning and other technologies. Finally, verify the effectiveness of the new assessment system through case - study analysis, summarize the research findings, and propose future research directions.

2. Characteristics of Investment Banks' Credit Risk in a Highly Volatile Market

2.1. Definition of a Highly Volatile Market

A highly volatile market refers to a financial market state where asset prices fluctuate significantly and frequently within a certain period [2]. Quantitatively, the Volatility Index (VIX) and Beta are commonly used as references. The VIX, such as the Chicago Board Options Exchange (CBOE) VIX index, measures the market's expectations of stock market volatility in the next 30 days. A higher index value indicates that market participants expect greater future market volatility. The Beta value is used to measure the sensitivity of individual assets or asset portfolios relative to the overall market volatility [4]. When the Beta value is greater than 1, it means the volatility of the asset or portfolio is higher than the market average; when it is less than 1, the volatility is lower. Generally, when the VIX index remains consistently above a certain threshold (e.g., 20) and the Beta values of numerous assets in the market show large fluctuations, the market can be considered highly volatile [5].

2.3. Causes of Highly Volatile Market

2.3.1. Macroeconomic Factor

The Federal Reserve's monetary policy adjustments have a far - reaching impact on the global financial market. When the Fed raises interest rates, global funds flow to the United States, causing capital outflows from other countries' financial markets and a decline in asset prices. Conversely, when the Fed cuts interest rates and injects a large amount of liquidity, asset prices rise. These fluctuations exacerbate the volatility of the financial market. Inflation changes also play a role [4]. During high - inflation periods, prices soar, business costs increase, profit expectations decline, and investor confidence is shaken, leading to market fluctuations. In deflationary periods, low consumption and investment willingness and weak economic growth also cause market volatility [6].

2.3.2. Geopolitical Factor

Geopolitical conflicts not only disrupt the local economic order but also trigger significant fluctuations in the global energy and food markets. For example, during the Russia - Ukraine war, as a major global energy exporter, Russia's unstable energy supply led to sharp oil price fluctuations, which in turn affected the prices of various global assets. Trade wars also impact the financial market [7]. The increase in trade barriers disrupts enterprises' import and export businesses, disturbs the global industrial and supply chains, and makes investors pessimistic about the economic outlook, thus triggering market turbulence [8].

2.3.3.Contingency Factor

The outbreak of the COVID - 19 pandemic is one of the emergencies that have had a huge impact on the financial market in recent years. The pandemic brought the global economy to a standstill, halted business operations and production, shrank the consumer market, and plunged the financial market into panic. The embargo measures implemented by countries in response to the pandemic increased the risk of corporate cash - flow disruptions and investment banks' credit risk. Similarly, financial crises and other events can also cause high market volatility. During a financial crisis, the asset quality of financial institutions deteriorates, investors sell assets in large quantities, market liquidity dries up, and asset prices plummet [8].

2.4. Impact of Highly Volatile Markets on Investment Banks' Credit Risk

2.4.1. Increased Correlation Between Market Risk and Credit Risk

In a highly volatile market, market risk and credit risk are highly correlated. Large - scale asset price fluctuations directly affect the value of financial assets held by investment banks. For instance, a significant drop in stock prices can cause a substantial shrinkage of investment banks' proprietary business assets, reducing their solvency and increasing credit risk. At the same time, the rise in credit risk further exacerbates market risk [9]. When the market is concerned about an investment bank's credit status, it triggers investor panic, leading to massive capital outflows. Investment banks then face greater financing and asset - selling pressures, which further drive down asset prices, forming a vicious cycle [9].

2.4.2. Failure of Traditional Credit Risk Identification Models

During the 2020 COVID - 19 pandemic, the global financial market was severely hit, and investment banks faced huge credit risk challenges. Traditional credit risk identification models showed significant shortcomings. Many investment banks' credit risk assessment models based on historical data failed to predict the pandemic's massive impact on companies and the market in a timely manner [6]. In the early stage of the pandemic, the corporate default risk soared. However, due to their reliance on past stable data, traditional models could not accurately assess the rapid changes in credit risk, leading to a significant underestimation of risk by investment banks [8]. As a result, some investment banks suffered substantial losses. For example, a large number of corporate bonds held by some investment banks defaulted due to corporate operational difficulties, and the traditional credit risk model failed to issue early warnings, causing huge losses in their bond investments.

3. Limitations of the Traditional Investment Bank Credit Risk System

3.1. Outdated Models

Most traditional investment bank credit risk assessment systems use linear regression models, assuming a linear relationship between risk factors and credit risk. In a highly volatile market environment, this assumption is far from the actual situation. The complexity of the market makes risk factors interact and entangle, presenting a complex non - linear relationship. The normal distribution assumption in traditional models is also overly idealized [1]. In highly volatile markets, asset price fluctuations often exhibit characteristics of sharp peaks and thick tails, which are quite different from the normal distribution. This means that models based on the normal distribution assumption cannot accurately measure credit risk in extreme situations. When the market experiences large fluctuations, the model's prediction results deviate significantly from the actual risk situation. Some studies pointed out that the limitations of traditional assumptions in real - world volatile markets were first recognized [10].

3.2. Obsolete Data

The traditional credit risk assessment system is highly dependent on historical financial data, which is usually updated quarterly or annually, with a low update frequency. In a highly volatile market, an investment bank's financial position and risk characteristics can change dramatically in a short time, and historical data cannot reflect the latest market changes promptly. When unexpected market events occur, such as major policy adjustments or natural disasters, an investment bank's asset - liability structure and cash - flow position can change instantly [11]. However, assessments based on historical data cannot capture these changes in a timely manner, resulting in a delay in risk assessment and failing to provide timely and effective decision - making support for investment banks' risk management. Furthermore, the traditional system mainly focuses on financial indicators such as the asset - liability ratio, liquidity ratio, and net profit margin, and does not adequately consider non - financial factors such as market risk factors, industry competition dynamics, and macroeconomic policy changes. In a highly volatile market, these non - financial factors have an increasingly significant impact on investment banks' credit risk. Macroeconomic policy adjustments can directly affect an investment bank's business and profitability, and intensified industry competition may lead to a decline in market share and customer loss, thereby affecting its creditworthiness. The traditional system cannot fully capture the impact of these non - financial factors, which greatly reduces the accuracy of credit risk assessment [12].

4. Using Machine Learning in Credit Risk Assessment System

As there are a range of problems with traditional systems and also today is the era of big data and information technology. Therefore, new technologies, such as machine learning, are perfectly suited to help optimise the system in a range of ways.

4.1. Definition of Machine Learning

Machine learning is a technology based on artificial intelligence. It uses big data and computers to predict or classify the latest market developments through a series of data analysis. By constructing algorithmic models, it enables computers to automatically learn laws and patterns from a large amount of data and use this learned knowledge to make predictions and decisions on new data [1]. Unlike traditional rule - based methods, machine - learning models can automatically adapt to data changes and continuously optimize their performance, thus more accurately reflecting market dynamics [13].

4.2. Advantages of Machine Learning

4.2.1. Higher Real - Time Performance

Machine learning models can acquire and process the latest market data in real - time, timely capture market trends, and quickly update risk assessment results. In a highly volatile market where information changes rapidly, the real - time advantage of machine learning can help investment banks identify potential credit risks promptly and provide timely support for risk management decisions [14].

4.2.2. Integration of the Latest Data

Machine learning can integrate a vast amount of internal and external data, including trading data, market sentiment data, macroeconomic data, and industry data. These rich data sources offer a more comprehensive perspective for credit risk assessment and help uncover potential risk characteristics and patterns. For example, by analyzing social media sentiment related to investment banks, machine - learning models can detect changes in market confidence in investment banks in advance, providing forward - looking information for credit risk assessment [15].

4.2.3. Use of Non-Linear Models

Machine learning can construct non - linear models such as random forests and neural networks, which can better capture the complex non - linear relationships between risk factors. In highly volatile markets, the relationships between risk factors are intricate, and non - linear models can more accurately describe these relationships, improving the accuracy of credit risk assessment. For example, the random forest model can effectively handle data noise and outliers. By constructing multiple decision trees and comprehensively analyzing their results, it can enhance the model's stability and predictive power [13].

4.3. The Process of Using Machine Learning to Construct a New System

4.3.1.Collecting the Latest Data

To build an accurate and effective credit risk assessment system, it is essential to collect a large amount of the latest data first. This data includes an investment bank's internal financial data, transaction data, and customer data, as well as external data such as macroeconomic data, market quotation data, industry data, and social media data [11]. Multiple - channel data collection ensures data comprehensiveness and timeliness, providing a solid data foundation for subsequent analysis and modeling. The UCI Machine Learning Repository serves as a great example of a rich data source for such studies, which is continuously updated since 2017.

4.3.2. Data Pre-processing

The collected data often contains noise, missing values, and outliers, which require data pre - processing. Data pre - processing includes operations such as data cleaning, data filling, and data standardization. Data cleaning is used to remove noise and outliers to ensure data quality; data filling methods are employed to handle missing values to maintain data integrity; and data standardization is used to unify different types of data to the same scale, facilitating subsequent model training and comparison [12].

4.3.3. Selecting the Optimal Model

Based on the data characteristics and the objectives of credit risk assessment, an appropriate machine - learning model needs to be selected. Common machine - learning models include logistic regression, decision trees, random forests, support vector machines, and neural networks [10]. Each model has its own advantages, disadvantages, and applicable scenarios. Through experiments and comparisons, the model with the best performance on the current data and problem can be selected. Methods like cross-validation can be used to evaluate different models, and the model with high accuracy, high recall, and a large F1 value can be chosen as the final credit risk assessment model.

4.3.4. Model Training and Optimization

After selecting the model, it is trained using pre-processed data. During the training process, the model's performance is optimized by adjusting its parameters, such as the number of layers and nodes in a neural network or the number of trees in a random forest. Regularization techniques are also used to prevent overfitting and improve the model's generalization ability. Algorithms like gradient descent can be used to continuously adjust the model parameters to minimize the model's loss function on the training data, thereby obtaining the optimal model parameters.

4.3.5. Real-Time Monitoring

After constructing a credit risk assessment system, it is necessary to monitor investment banks' credit risks in real-time [8]. By continuously inputting new data into the model, the model can update the credit risk assessment results in real - time and issue timely risk warnings [8]. When the model detects that an investment bank's credit risk indicator exceeds the set threshold, it promptly notifies the risk management department to take corresponding measures, such as adjusting the investment portfolio or increasing guarantee measures, to reduce credit risk.

5. Case Study of Innovative Practices

5.1. JPMorgan Chase

JPMorgan Chase, as a leading global financial institution, faces the limitations of traditional credit risk assessment models. Traditional models mainly rely on historical financial data and credit scores (e.g. FICO scores), which are difficult to fully reflect the credit status of customers, especially for those who lack credit history (e.g. young people and emerging market customers). To improve the accuracy and coverage of credit risk assessment, J.P. Morgan has introduced machine learning technology.

JPMorgan Chase has developed a machine learning-based credit risk assessment platform that uses supervised and unsupervised learning algorithms to analyse a diverse set of data about its customers, including their financial data, transaction data, and changes in wealth. And the machine learning model extracts key variables through feature engineering and uses algorithms such as Random Forest and Gradient Boosted Tree (GBM) for training and prediction. The credit score output from the model is used to dynamically adjust the customer's credit limit and lending rate. Ultimately, JPMorgan's machine learning model managed to reduce credit defaults by 15 per cent by identifying high-risk customers, which significantly improved the accuracy of credit scoring, especially when assessing customers who lacked a credit history.

5.2. Citibank

Citibank faces the challenge of credit risk assessment in its small and medium enterprise (SME) lending business. Traditional models rely on a company's financial statements and credit history, making it difficult to fully reflect the actual operating conditions and risk level of SMEs. By introducing machine learning technology, Citibank has successfully improved the accuracy and efficiency of risk assessment.

The bank uses machine learning models, such as logistic regression, support vector machines (SVMs) and neural networks, and other algorithms, to quickly assess how much lending is appropriate for the business by extracting key variables such as the business's balance sheet, income statement, and cash flow statement through feature selection and data preprocessing. Ultimately, with the machine learning model, Citibank was able to quickly process and analyse a large amount of data, reducing the loan approval time by 30%.

6. Conclusion

This study systematically explores the innovation of credit risk assessment systems for investment banks in highly volatile markets, addressing critical gaps in existing research and proposing a machine learning-driven framework to enhance risk management efficacy. The analysis reveals that traditional credit risk models, reliant on historical financial data and linear assumptions, exhibit significant limitations in dynamic environments characterized by rapid asset price fluctuations, geopolitical uncertainties, and macroeconomic disruptions. These models fail to capture nonlinear interactions among risk factors, integrate real-time data, or account for non-financial variables such as market sentiment and policy changes, leading to delayed or inaccurate risk evaluations.

The proposed machine learning-based system demonstrates substantial advantages, including real-time data processing, integration of multi-source datasets (e.g., macroeconomic indicators, transactional behaviour, and social media sentiment), and the ability to model complex nonlinear relationships through algorithms like random forests and neural networks. However, due to space constraints, this paper does not use a model from machine learning to specifically operationalise the identification of credit risk, and therefore cannot visualise where the advantages of the model lie over traditional models. Therefore, future research can further demonstrate the advantages of machine learning in credit risk identification based on the above shortcomings and provide more effective recommendations for investment banks, regulators and policy makers, among others.

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