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Research on the Explainable Early Warning Model and Decision-Making Path of Corporate Bond Default Risk

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Abstract: With the development of the times, the market-oriented reform of the capital market has been continuously deepened. As a key channel for direct corporate financing, the scale of the corporate bond market continues to expand. However, the frequent occurrence of default events has also significantly impacted market stability and investor interests. Traditional bond default risk early warning models often focus on improving prediction accuracy but generally suffer from the "black box" problem, making it difficult to clearly explain the formation logic of risk warning results. This greatly restricts the application value of the models in practical decision-making. In view of this, this paper analyzes the explainable early warning model and decision-making path for corporate bond default risk and proposes relevant strategies.

Keywords: Corporate bond default risk; Explainable early warning model; Decision-making path; Risk influencing factors

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1. Significance of research on corporate bond default risk early warning

Carrying out research on the explainable early warning model and decision-making of corporate bond default risk helps promote the in-depth application of explainable methods in the field of financial risk early warning. Explainable methods were initially mainly applied in fields such as computer science, and their application in the financial field is still in the exploration stage [1]. By analyzing the characteristics of corporate bond default risk to adaptively adjust and integrate explainable methods, we can gradually build an explainable model framework suitable for bond risk early warning scenarios, which also provides theoretical reference and practical examples for the application of explainable methods in the field of financial risk management and control.

For regulatory authorities, the explainable early warning model and decision-making research on corporate bond default risk can clearly present the core driving factors and transmission paths of bond default risk, helping regulatory authorities accurately locate risk sources, identify high-risk industries, regions, and enterprises, thereby formulating differentiated regulatory policies and improving regulatory efficiency and pertinence [2]. At the same time, a clear decision-making path can provide regulatory authorities with standardized risk disposal process guidelines, enabling rapid response when risk events occur and effectively preventing the spread and spillover of risks.

In addition, for investors, the explainable early warning model and decision-making research on corporate bond default risk have better interpretability. Its early warning results can help investors deeply understand the risk level and potential risk points of different corporate bonds, get rid of dependence on a single credit rating, and provide more comprehensive and reliable basis for investment decisions, thereby reducing investment risks and protecting the legitimate rights and interests of investors [3].

For issuing enterprises, the explainable early warning model and decision-making research on corporate bond default risk can help enterprises identify potential risks in their own operation and management, financial status, and financing structure, clarify the key links for risk improvement, provide guidance for enterprises to formulate precise risk management and control strategies, and help enterprises improve their credit level and enhance financing capacity [4].

2. Current problems in corporate bond default risk early warning and decision-making

2.1. Lack of interpretability of early warning models

At present, mainstream bond default risk early warning models can be divided into traditional statistical models and machine learning models, but both types of models have obvious deficiencies in interpretability. Although traditional statistical models can intuitively present the direction and degree of influence of each variable on default risk through coefficients and have a certain degree of interpretability, such models are often based on strict assumptions. However, corporate bond default risk is comprehensively affected by multiple factors such as the macroeconomic environment, industry cycle, and corporate operating conditions, and its influence mechanism presents significant nonlinear and asymmetric characteristics. Traditional statistical models are difficult to accurately fit these complex relationships, resulting in limited early warning accuracy and difficulty in meeting the needs of actual risk management and control [5].

In recent years, machine learning models represented by neural networks have been widely used in bond default risk early warning due to their strong nonlinear fitting ability and adaptive learning ability, and their early warning accuracy has been significantly improved compared with traditional statistical models. However, the internal operation process of such models is highly complex, and users cannot clearly understand the specific influence degree and mechanism of each input variable on the early warning results. The early warning results output by the model lack effective logical support, forming a typical "black box" problem [6]. This "black box" problem makes it difficult for model users to trust the early warning results, and they cannot carry out subsequent risk analysis and management and control work based on the early warning results, which greatly restricts the application value of machine learning models in practical decision-making.

2.2. Incomplete identification of risk influencing factors

Corporate bond default risk is the result of the combined action of multiple factors such as the macroeconomic environment and industry development cycle, and has the characteristics of multi-dimensionality and complexity. At present, most bond default risk early warning models do not comprehensively identify risk influencing factors in the construction process. They often over-rely on corporate financial data, taking financial indicators such as asset-liability ratio as core early warning variables, while ignoring the impact of non-financial factors such as the macroeconomic environment and industry development trends [7]. Fluctuations in the macroeconomic environment will directly affect the operating performance and solvency of enterprises. For example, during an economic downturn, enterprises' profitability declines and cash flow is tight, and the risk of bond default will increase significantly.

The industry development cycle also has an important impact on the survival and development of enterprises. Enterprises in declining industries face problems such as shrinking market demand and intensified competition, and their default risk is much higher than that of enterprises in growing and mature industries. The improvement of corporate governance structure is related to the decision-making efficiency and risk management and control ability of enterprises. Enterprises with unreasonable equity structures and lack of internal control are more likely to have operational risks and moral hazards, which in turn trigger bond defaults [8]. The lack of non-financial factors leads to the failure of early warning models to fully capture the formation mechanism of bond default risk, and the single early warning dimension makes it difficult to accurately identify potential risk hazards. Especially for enterprises with seemingly healthy financial data but serious non-financial risks, the model often fails to issue early warnings in a timely manner, resulting in early warning failure.

2.3. Disconnection between early warning and decision-making

The ultimate purpose of risk early warning is to provide support for risk decision-making to achieve effective risk management and control. However, most current studies only stay at the level of model construction and early warning accuracy verification, lacking effective connection for transforming early warning results into decisions, leading to a serious disconnection between early warning and decision-making. The reason for this problem is that many early warning models have the "black box" problem, which makes it impossible for model users to clarify the core crux and key influencing factors of risks based on early warning results, and it is difficult to formulate targeted risk management and control measures [9]. In addition, current studies have not constructed a decision-making path system based on early warning results.

For corporate bonds of different early warning levels, there is a lack of clear decision-making guidelines. For example, for high-risk bonds, what stop-loss strategies investors should adopt, what regulatory measures regulatory authorities should take, and how issuing enterprises should carry out risk rectification all lack standardized processes and methods. This disconnection between early warning and decision-making makes risk early warning lose its due practical value. Early warning results are only an identifier of risk level and cannot provide effective action guidelines for market participants. Investors are often at a loss when facing early warning results and find it difficult to make scientific investment decisions; regulatory authorities cannot carry out precise supervision based on early warning results and can only adopt a "one-size-fits-all" regulatory method with low regulatory efficiency; issuing enterprises cannot find the direction for risk improvement based on early warning results, and risk management and control work is blind and disorderly.

3. Construction of explainable early warning model and optimization strategy of decision-making path for corporate bond default risk

3.1. Construct a multi-dimensional system of risk influencing factors to lay a solid model foundation

To solve the problem of incomplete identification of risk influencing factors in current early warning models, we should construct a multi-dimensional system of risk influencing factors covering the macroeconomy and industry characteristics. In the macroeconomic dimension, we can select indicators such as economic growth rate and inflation rate to reflect the overall impact of the macroeconomic environment on bond default risk. In the industry characteristic dimension, we can select indicators such as industry growth rate and industry concentration to reflect the impact of industry development cycle and competitive pattern on corporate default risk [10]. Moreover, we can conduct an analysis in the corporate financial dimension, selecting indicators from solvency and profitability, such as asset-liability ratio and current ratio, to more accurately depict the financial health of enterprises.

In the corporate governance dimension, we can select indicators such as ownership concentration and the proportion of independent directors to better measure the governance level and risk management and control ability of enterprises. In the credit status dimension, we can select indicators such as enterprises' historical default records and credit rating adjustment to reflect their credit level and potential risks. On the basis of constructing a multi-dimensional system of risk influencing factors, we can use feature selection methods to screen variables, removing some redundant variables and noise variables, which can greatly improve the operational efficiency and early warning accuracy of the model. In addition, we can combine the advantages of filtering methods, wrapper methods, and embedded methods: initially screen variables highly correlated with default risk through filtering methods, then further optimize variable combinations based on model performance through wrapper methods, and finally integrate variable selection into the model construction process through embedded methods to ensure that the selected variables not only have strong predictive ability but also can clearly reflect the risk formation mechanism [11].

3.2. Integrate explainable methods to construct an explainable early warning model framework

To solve the "black box" problem of early warning models, we can try to combine explainable methods with machine learning models to build an early warning model framework with both predictive performance and interpretability. According to the different implementation levels of interpretability, we can divide explainable methods into intra-model explainable methods and post-model explainable methods. In terms of intra-model interpretability, we can select machine learning models with a certain degree of interpretability as the base models, such as Gradient Boosting Decision Trees (GBDT) and Light Gradient Boosting Machine (LightGBM). Such models perform integrated learning by constructing multiple decision trees, which can intuitively present the influence degree of each variable on the early warning results through feature importance scores, and the splitting process of decision trees also provides certain support for explaining the early warning logic [12]. In the model training process, we can control parameters such as the depth of decision trees and the number of leaf nodes to avoid excessive model complexity, thereby further enhancing the inherent interpretability of the model.

In terms of post-model interpretability, we can attempt to introduce explainable methods such as Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) to supplement the explanation of the early warning results of the base model. LIME approximates the prediction results of complex models by constructing simple linear models locally, which can clearly show the formation reasons of early warning results for individual samples, helping users understand the core driving factors of default risk for specific corporate bonds [13]. The integration of intra-model interpretability and post-model interpretability not only ensures the prediction accuracy of the model but also realizes a comprehensive explanation of the early warning results, effectively solving the "black box" problem.

3.3. Establish a dynamic update mechanism to improve model adaptability

To enhance the adaptability of the early warning model to the complex and dynamic risk environment, we can establish a dynamic model update mechanism to better realize the dynamic adjustment of model parameters, variable systems, and early warning thresholds. At the data level, we can build a real-time data collection and update system to more timely collect the latest information such as macroeconomic data and corporate financial data, providing data support for model updates. In terms of variable updates, we need to regularly evaluate the risk influencing factor system, add important risk variables and eliminate redundant variables that no longer have predictive ability in combination with changes in the market environment and the evolution of risk formation mechanisms to ensure the timeliness and effectiveness of the variable system [14]. In terms of model parameter updates, we can adopt a rolling training method to regularly retrain the model using the latest data to better adjust model parameters and make the model adapt to changes in risk characteristics. In terms of early warning threshold updates, we can regularly optimize the early warning threshold in combination with changes in the market default rate, adjustments in regulatory requirements, and changes in investors' risk preferences to ensure the accuracy and applicability of the early warning results.

3.4. Construct a closed-loop decision-making path of "early warning-analysis-decision-making- feedback"

To solve the disconnection between early warning and decision-making, a closed-loop decision-making path of "early warning-analysis-decision-making-feedback" is constructed based on the explainable early warning model to realize the effective transformation of early warning results into decision-making actions. We can use the constructed explainable early warning model to evaluate the default risk of corporate bonds, output the risk level, and provide a preliminary basis for subsequent decision-making. While outputting the risk level, a risk early warning report is generated synchronously to clarify the early warning logic and core risk variables of the model. At the same time, we can conduct in-depth analysis of early warning risks based on the interpretability results of the model, use SHAP values to analyze the marginal contribution of each risk variable to default risk, and identify the core driving factors of risks. We can use the LIME method to locally explain individual high-risk bond samples to further clarify the risk crux of specific enterprises. Through risk analysis, precise guidance is provided for formulating targeted decision-making measures [15]. Furthermore, we can formulate differentiated decision-making paths for different market participants according to the risk level and risk analysis results. By tracking the implementation effect of decision-making measures, we can collect subsequent change data of corporate bond default risks, which can greatly improve the accuracy of the evaluation early warning model and the effectiveness of the decision-making path.

3.5. Improve supporting guarantee mechanisms to promote the implementation of models and decision-making paths

To ensure the effective implementation and application of the explainable early warning model and decision-making path, we need to improve relevant supporting guarantee mechanisms. In terms of data guarantee, strengthen data standardization construction, unify the statistical caliber and disclosure standards of data from various dimensions, break data barriers, and build a cross-departmental and cross-institutional data sharing platform to ensure the data quality and timeliness of model construction and dynamic updates. In terms of system guarantee, regulatory authorities can introduce relevant policies to encourage financial institutions and enterprises to apply explainable risk early warning models, standardize the construction and application standards of models, and clarify the risk management and control responsibilities of various market participants.

Disclosure statement

The author declares no conflict of interest.

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