Information Systems and Economics (2024)
Clausius Scientific Press, Canada

DOI: 10.23977/infse.2024.050503
ISSN 2523-6407 Vol. 5 Num. 5

Research on Credit Debt Liquidity Risk Measurement and Early Warning Based on Machine Learning Model

Yunpeng Zhao

Treasury Department, Bank of China, New York, NY 10018, USA
JackZ20241@outlook.com

Keywords: Credit Debt, Liquidity Risk, Tail Correlation, Risk Factor System, Neural Network, Machine Learning Model, Risk Measurement, Risk Warning, Noise Trading, Maturity Impact

Abstract: This study focuses on the liquidity risk management of credit debt, aiming to explore effective measurement and early warning methods to reduce the potential threat of systemic financial risks to security. This study by analysing the monthly data of China's credit debt from January 2009 to December 2020, this paper evaluates the liquidity risk of credit debt using tail correlation, and constructs an early warning factor system from three perspectives: financing constraints, credit risk and noise trading. Furthermore, 11 kinds of machine learning models, including neural networks, are used for early warning analysis of credit debt liquidity risk. The results show that the neural network with a hidden layer shows high warning accuracy under various bonds and different environmental conditions, especially can effectively capture the market liquidity crunch signal. The maturity of bonds has a significant impact on liquidity risk. Newly issued bonds face higher risk due to noisy trading. With the increase of maturity, this risk gradually decreases, but the weakening speed tends to be gentle. It is also found that the formation of liquidity risk is closely related to the synergistic effect of multiple risk factors, especially the nonlinear interaction between economic situation, monetary policy changes, cross-market shocks and bond age, which plays an important role in promoting the evolution of liquidity risk. This study deepens the understanding of credit debt liquidity risk and provides a new theoretical basis for risk management practice.

1. Introduction

With the rapid development of economy, the credit bond market has accumulated significant risks. In the context of regulatory pressure, a wave of defaults and external "black swan" events, market liquidity drying up occurs from time to time, which impedes the normal functioning of markets. For example, the systemic selling triggered by the "Yongcoal bond default" event at the end of 2020 has sharply worsened the liquidity of the bond market. Liquidity risk mainly includes liquidity commonality, the sensitivity of asset return to market liquidity and the sensitivity of asset liquidity to market return. Liquidity commonality describes the synergistic changes in asset liquidity and market liquidity that can lead to widespread liquidity depletion under negative shocks. From the perspective of the commonality of tail liquidity, this paper uses machine learning model to measure the liquidity risk of credit debt, and explores the mechanism of key risk factors. The research not only enriches the theoretical framework of liquidity risk measurement, but also applies machine learning technology to credit debt liquidity risk early warning for the first time, revealing the core risk factors and their non-linear impact mechanism, and providing new ideas and practical basis for financial supervision and systemic risk prevention.

2. Related Research

The theoretical measurement of liquidity risk includes many types, such as liquidity fluctuation, systemic liquidity fluctuation, downward systemic liquidity fluctuation and tail systemic liquidity fluctuation. At present, the liquidity risk measurement of China's credit bond market is mostly concentrated on the liquidity fluctuation level, and has not covered more detailed market microstructure characteristics. It is particularly important to develop a liquidity risk measurement index that can fully reflect the market microstructure. Although liquidity risk has been explained in detail, the application of machine learning technology in the early warning of credit debt liquidity risk is still in its infancy. This paper aims to establish a credit debt liquidity risk measurement and early warning framework based on machine learning to fill the gaps in the existing research, and improve the identification and management level of credit debt liquidity risk by enhancing the early warning ability. This not only helps to improve the theoretical system of liquidity risk measurement, but also promotes the practical application of machine learning technology in credit debt risk management, providing new ideas and tools for preventing systemic financial risks. H Chen, Y Yang, C Shao proposed a multi-task learning method to realize efficient spatio-temporal modeling of data. A hierarchical Bayesian inference structure based on Gaussian process is constructed for knowledge transfer between multiple similar but not identical measurement tasks[1]. Varatharajah's team discusses the potential use of reinforcement learning (RL) -based human-in-loop recommendation systems to support the clinical management of COVID-19[2]. X Zhang's team innovatively used the distortion degree of vortex optical interference pattern to build a regression prediction model based on superposition ensemble learning algorithm to achieve high-precision measurement of small angles[3]. The Z Wei team made a detailed comparative analysis of the differences in volatility characteristics among various factors and proposed the optimal forecasting and early warning framework for the A-share market.

3. Establish and Optimize Credit Debt Liquidity Risk Early Warning Factor System

This paper constructs a comprehensive early-warning factor system of credit debt liquidity risk, including 84 potential factors, which are screened from three dimensions: financing constraints, credit risk and noise trading. We select a variety of indicators related to financing constraints, including the Shanghai Composite index of the stock market, the total full price index of the national bond market, the total full price index of the policy financial bond market and the total full price index of the local bond market. It also includes various interest rates in the interbank market, such as Shibor overnight interest rate, 7-day interest rate, January interest rate, etc., as well as pledged repo rates between banks and exchanges.

In terms of credit risk, this paper introduces the transformation of credit rating into orderly integers and rating changes as key factors to reflect the fluctuation of credit risk. To capture the impact of noise trading, we selected factors associated with noise trading, combined with illiquidity indicators and measures of credit market sentiment, where credit market sentiment is quantified by the proportion of credit bond issuance with a rating of AA- and below[4].

Based on the identification of risk factors, the work developed an advanced machine learning model specifically designed to prevent liquidity risks, in which liquidity risks were identified as response variables to help predict scenarios of potential liquidity depletion in the future. The model's effectiveness in forecasting liquidity risk has been confirmed by its high correlation with actual events of liquidity depletion, which indicates that the projected increase in liquidity risk is consistent with the increased likelihood of such adverse events. This complex approach provides a comprehensive, data-driven structure that can better predict and resolve liquidity problems, greatly increasing the accuracy of liquidity risk forecasts. The model provides an innovative technical framework and practical guidance for effective credit and debt liquidity risk management, providing stakeholders with the necessary tools and strategies to mitigate liquidity vulnerability and enhance the reliability of their overall risk management practices.

This paper uses a variety of machine learning models to give early warning to credit debt liquidity risks in order to improve the prediction accuracy of future liquidity depletion events. Liquidity risk is treated as a continuous variable at the bond level and input as a response variable of the model. In order to establish the baseline model, this paper adopts linear regression (OLS) and introduces the penalty term to construct the Elastic Net (ENET) model to alleviate the overfitting problem. Principal component analysis (PCA) and partial least squares regression (PLS) models were also used to reduce the dimensions of risk factors.

Due to the limitations of linear models in dealing with nonlinear relationships, this paper further introduces regression tree models such as random forest (RF) and extreme gradient lifting regression tree (XGB), and adopts neural network (NN) model for more complex nonlinear analysis. The design of the neural network varies from single layer to multi-layer hidden layer structure, by adjusting the number of neurons to optimize the performance of the model, combined with regularization methods such as learning rate contraction and early stop, to prevent overfitting.

In the model training stage, this paper divides the data from January 2009 to December 2020 into training set, verification set and test set, accounting for 65%, 10% and 25% of the total samples respectively, to ensure the integrity of the time series structure. This way of data partitioning helps to improve the generalization ability of the model. Through the construction and training of a series of models, this paper systematically analyzes the effects of different machine learning models in the early warning of credit debt liquidity risk, which provides an important decision-making basis for the risk management of credit debt market.

4. Analysis on the Mechanism of Credit Debt Liquidity Risk Factors

4.1 Identification and Evaluation of Key Liquidity Risk Factors

In this study, the redistributive importance method is used to assess the relative importance of various risk factors in determining liquidity risk associated with credit bonds and to assess their impact through a multi-stage process. The calculation coefficients that determine the external coefficient of the model shall establish the base line of performance. Then, using random risk factors that were censored, were replaced by random noise concentrations of training data to recalculate model performance to monitor changes in results. This iterative process allows for accurate quantitative measurements of how the removal or change of each risk factor affects the accuracy of the projection in order to assess its relative importance. Comparing these performance changes before and after the introduction of accidental noise into the system and normalizing these differences, the study identifies risk factors depending on the impact of risk factors on liquidity. Such a comprehensive approach provides a strong basis for clarifying the relative contribution of individual risk factors, facilitating better decisions and strengthening the risk management strategy by better understanding the most significant factors affecting liquidity risk.

The analysis revealed that the main drivers of liquidity risk are noise transactions, credit risks and financial constraints, all of which operate in different but interrelated ways. Noise trade was caused by market information asymmetries and lack of transparency, which led to serious market distortions; This distortion exacerbates market volatility and liquidity risk, as investors respond to incomplete or misleading information and engage in a volatile trading model that may cause a number of liquidity problems. Credit risks systematically weaken investors' risk appetite through multi-channel channels such as industry, geography, bond ratings; This general decline in confidence often leads to massive bond sales, which in turn exacerbates the liquidity crisis. Financial constraints have significantly exacerbated the liquidity problem in the market, forcing investors facing financing constraints to liquidate bonds in order to meet their debt obligations or to convert collateral into cash, which has led to a sharp deterioration in market liquidity through a surge in bond sales. These factors interact, creating complex dynamics that seriously undermine liquidity stability in credit bond markets.

In various estimation factors, the influence of the age of the percentage vote is particularly noticeable, accounting for almost 50% of the total, mainly due to the complex relationship between the age of the percentage vote and the risk of interest rates and asymmetry of information; In particular, long-term liabilities show high sensitivity to interest rate fluctuations, which in turn can trigger large noise deals, especially during sharp interest rate fluctuations. The spread of structural bonds by less creditworthy organizations has exacerbated the existing information asymmetry in the market, increasing the relative importance of ticket age as a risk factor. This growing importance highlights not only the acute sensitivity of markets to changes in interest rates, but also the complexity arising from different levels of transparency of information, indicating that the interaction between interest rate risk and information asymmetry profoundly determines liquidity and affects market dynamics.

4.2 Analysis on the Influence of Liquidity Risk Factors on the Liquidity Risk of Credit Bond Market

This article USES the partial correlation card (PDP) as a complex analytical tool that deepens the complex relationship between major risk factors and liquidity risk by clearly and intuitively describing the impact of specific risk factors on liquidity risk. This approach specializes in isolating the influence of one unit of change in a given risk factor, retaining all other risk factors on average and facilitating a controlled and detailed analysis of the impact of each of them. Thus, the analysis explains how changes in individual risk factors can lead to liquidity risk fluctuations, providing valuable insights into their unique role and significance in the broader liquidity risk profile. By focusing on the partial impact of specific risk factors, the PDP helps to understand in detail its contribution to improved liquidity risk assessment and management strategy in general.

The analysis shows that there is a clear non-linear relationship between successive risk factors and liquidity risk and that the impact of classification risk factors on liquidity risk is relatively limited; The maturity of bonds has become a particularly influential determinant of liquidity risk. As bond maturities increase, investors tend to keep them in long-term storage, which helps reduce the frequency of noisy transactions, leading to reduced liquidity risk. Liquidity risk reduction does not follow a linear path; On the contrary, as the number of votes increases, the risk decreases. This indicates that while long-term liabilities have some advantage in mitigating liquidity risk, their effectiveness in this regard is significantly impaired once they exceed a certain threshold. While extending the maturity of debt has significant advantages in reducing liquidity risk, the improvement in the rate of risk reduction becomes increasingly small after a certain maturity level has been exceeded.

This analytical approach clarifies the complex non-linear relationships between various risk factors and liquidity risk, providing a solid empirical basis for strengthening the liquidity risk early warning model and helping to develop more accurate and effective risk management strategies. If the complex mechanisms that influence liquidity risk on the various risk factors were carefully considered and explained, this approach would be explored more thoroughly, supporting the creation of a strategy aimed at creating multidimensional dynamic adjustment strategies to address these risk factors. This comprehensive analysis not only improves the accuracy and reliability of liquidity risk forecasts, it plays an important role in optimizing early warning systems and enhancing the overall impact of liquidity risk management. This approach provides an operational understanding of the delicate relationship between risk factors and liquidity risk, facilitating wiser and strategic approaches to managing liquidity risk in difficult financial circumstances.

5. Conclusion

Based on the monthly data of China's credit debt from January 2009 to December 2020, this paper evaluates liquidity risk through tail correlation analysis, and constructs an early warning factor system that comprehensively considers financing constraints, credit risk and noise trading. 11 kinds of machine learning models, including neural networks, are used to predict and evaluate credit debt liquidity risk and identify the mechanism of important risk factors. The main findings of the study are as follows: The neural network model (NN1), especially the single hidden layer model, shows the best early warning performance. In different types of bonds and multiple market environments, the model shows high stability and reliability, and can effectively track changes in liquidity risks and predict potential liquidity crises.

Noise trading, credit risk and financing constraints have significant effects on credit debt liquidity risk. Coupon age was identified as the most important risk factor. The new and old degree of bonds has a key impact on liquidity risk. New bonds are more likely to cause noisy transactions due to information asymmetry and interest rate risk, which increases liquidity risk. With the increase of bond holding time, the decline of liquidity risk gradually decreases.

Liquidity risk is not determined by a single risk factor, but the result of synergistic action of many factors. The complex nonlinear relationship between the change of economic conditions, the adjustment of monetary policy or the market shock and the maturity of bonds is the main factor driving liquidity risk.

Based on these conclusions, the following policy recommendations are proposed: Regulators should prioritize the use of advanced machine learning methods, such as neural networks, when establishing credit debt liquidity risk early warning systems to address the challenges of high-dimensional data and complex non-linear relationships. In view of the dynamic relationship between financing constraints, credit risk and noise trading, regulatory policies should be adjusted to mitigate liquidity risks. Specific measures include: first, pay close attention to the money market capital flow and its structural changes, especially when the inter-bank chain is broken, through timely expansion of money supply to ease the short-term capital shortage; Second, strengthen the monitoring of credit risks, establish a risk management mechanism during the duration of bonds, crack down on debt defaults, and improve the debt transfer mechanism; Third, in the process of the transformation of the net worth of financial products, the policy should be adjusted according to the change of investors' interest rate risk, the issuance process should be standardized, and the market distortion caused by structured issuance should be strictly monitored.

References

[1] Chen H, Yang Y, & Shao C. Multi-task learning for data-efficient spatiotemporal modeling of tool surface progression in ultrasonic metal welding [J]. Journal of Manufacturing Systems, 2021, 58, 306-315.
[2] Varatharajah Y, Chen H, Trotter A, & Iyer R K. A Dynamic Human-in-the-loop Recommender System for

Evidence-based Clinical Staging of COVID-19 [J]. In HealthRecSys@ RecSys, 2020, 21-22
[3] Zhang X, Zhao D, Ma Y, et al. Research on high-precision angular measurement based on machine learning and optical vortex interference technology [J]. IOP Publishing Ltd, 2024. DOI:10.1088/1361-6501/ad6207.
[4] Wei Z, Dong J, Dong Z. Research on Prediction and Early Warning of A-Share Market Volatility Based on HAR-Type Models [J]. Journal of Systems Science and Information, 2023, 11(6): 671-690.