Utilization of the Markov Chain Model for Credit Rating Migration Analysis

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Abstract. Credit rating migration is an important link in financial risk control. Dynamic forecasting is of great significance to investor decision-making and the credit management of financial institutions. The Markov chain model has become an important tool for rating status migration forecasting because it has no aftereffects. This paper takes credit rating migration prediction as the research theme, and uses the rating data of listed companies and bond issuers in the CSMAR credit rating database to establish a Markov chain model for empirical research. Through data cleaning, migration matrix construction, and model prediction using Python, a reasonable migration matrix is obtained, and the model's accuracy is higher for medium-term and long-term rating prediction. After the robustness test, in which the data, time, and indicators were replaced, the model's prediction results remain reliable. The Markov chain model established in this paper provides a feasible method for credit rating migration forecasting, which can provide practical reference for investors' risk avoidance, credit decision-making, and bond pricing of financial institutions, and enriches the quantitative research paradigm in the field of credit risk management.

Keywords: Markov Chain Model, Credit Rating, Risk Management.

1 Introduction

Credit rating is an important component of the financial risk control system and the main indicator for evaluating the debt repayment capacity and credit status of enterprises and financial institutions. Migration behavior directly reflects the dynamic changes in the credit quality of the credit subject, which plays an irreplaceable role in investor decision-making, credit management of financial institutions, and risk monitoring of regulatory authorities. The financial market is becoming more and more complex, and the fluctuations of the economic cycle are also increasing. The upward or downward adjustment of credit ratings will cause fluctuations in asset prices and the adjustment of risk premiums. Accurately predicting the trend of credit rating migration has become the prerequisite for preventing and resolving credit risks and making scientific decisions. The traditional credit rating migration forecast relies on expert experience and subjective judgment [4]. There are poor consistency,

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systematic deviation, and other conditions, which cannot meet the requirements of risk management in the era of big data. Due to the advantages of no aftereffects, easy calculation, and strong interpretability, the Markov chain model has good applicability in the field of state migration prediction and has been applied to credit rating migration research. Through in-depth research on the applicability of the Markov chain model in credit rating migration prediction, it can effectively reveal and answer various problems encountered by enterprises in practical applications.

Existing research has carried out a lot of researches on the application of the Markov chain model in credit rating migration, and has formed rich research results. A rating migration model based on the Markov chain was proposed for the first time, which laid the foundation for research in this field [1]. The model holds that rating migration is only related to the current state and does not consider the impact of historical states. The model was extended to a semi-Markov process, making up for the deficiency of the traditional model in ignoring state residence time [2]. It is believed that the Markov chain model has an efficient modeling ability in credit rating forecasting, but the prediction effect will be affected by the economic cycle [3]. On the domestic side, China's short-term financing coupon data were used to verify the applicability of the Markov chain model in the domestic market. The successful combination of Markov chain models with other analytical techniques in various financial application scenarios, such as precision marketing, has demonstrated the flexibility and practical utility of this methodology, offering a valuable reference for its extension to credit risk measurement [5]. The construction and estimation of state transition matrices, a core component of Markov chain modeling, have been well established in the analysis of financial time series data, providing solid methodological support for the calculation of credit rating migration matrices [6]. Advanced Markov chain variants, such as Bayesian Markov switching models, have been successfully applied to classify and predict financial states in currency markets, offering sophisticated methodological tools that can be extended to credit scoring and credit risk ranking systems [7].

The existing literature mainly analyzes the application of the Markov chain model in credit rating migration from the aspects of model construction, theoretical verification, and model application, but there are still gaps in local data systematic testing, model practical optimization, and multi-dimensional robustness verification. This article focuses on filling the above gaps. This paper takes Chinese listed companies and bond issuers as the research objects. Based on the rating data of the CSMAR credit rating database from 2010 to 2025, it uses the Markov chain model and Python to realize data cleaning, migration matrix construction, predictive effect evaluation, and robustness testing. Through division, analyze the rate migration law and model prediction performance, and derive the applicability and optimization path of the Markov chain model in China's credit rating migration prediction. In terms of theory, the applicability of the Markov chain model in the Chinese market is systematically verified, the heterogeneous characteristics of the credit rating migration prediction effect are found, and the theoretical results of credit rating migration prediction are enriched. In a practical sense, investors, financial institutions,

and regulators are provided with an operable credit risk forecast and tools to improve the level of credit risk management.

2 Theory and Model

The data in this paper is sourced from the CSMAR credit rating database, which contains complete credit rating information of Chinese listed companies and bond issuers, including subject ID, rating time, original rating, target rating etc. The data from 2010 to 2025, with a total of 16 complete years, is complete and accurate, which can meet the requirements of model establishment and empirical analysis in this paper. Credit rating refers to an objective evaluation conducted by professional rating agencies on the debt repayment willingness and ability of credit subjects based on factors like enterprises' debt repayment capacity, profitability, operational capacity, development prospects, macroeconomic environment, and industry trends. It is generally expressed as a grade. The core grades include AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, BBB-, BB+, BB-, B+, B, B-, CCC, CC, D, etc. Different grades are related to different credit risk levels. Credit rating migration refers to the upward, downward, or stable dynamic changes in the credit rating of credit subjects over time. The factors affecting it include enterprise fundamentals, macroeconomic cycle, industry competition pattern, regulatory policy adjustment, etc. The core value of credit rating migration forecasting is to discover the changing trend of credit risk in advance and provide a scientific basis for the risk exposure adjustment of financial institutions, investor portfolio optimization, and capital supervision of regulatory institutions.

The Markov chain model is a random process with no aftereffect, whose core principle is to describe the state transfer law of random variables [8]. The core assumption is that there are no aftereffects, that is, given the current state, the probability distribution of the future state is only related to the current state and has nothing to do with the state evolution process in the past [9]. The status in the credit rating migration forecast is the credit rating level, and the status migration is the change in the rating level. There is no post-effect hypothesis. The rating of the next period of the credit subject is only related to the current rating and has nothing to do with the historical rating changes. The non-post-effect hypothesis simplifies the model calculation and conforms to the dynamic change characteristics of the credit rating. The application logic of the Markov chain model in rating migration prediction is to first construct a migration probability matrix according to the historical rating data to test whether the data meets Markovity, and then use the migration probability matrix power operation or matrix index operation to predict the credit rating distribution in various periods of time in the future, and finally use more. The predictive effect of dimensional indicators is evaluated, and the application of the model is optimized.

3 Markov Chain Model Construction

This paper selects the relevant data of listed companies and bond issuers in the CSMAR credit rating database as research samples, and the data span is from 2010 to 2025. Two main considerations underpin the selection of 2010 as the starting point of the data. On the one hand, after 2010, China's financial market has experienced many rounds of complete economic cycle fluctuations, including the 2014-2016 commodity and energy market crisis, the Sino-US trade friction in 2018-2020, and the 2020 COVID-19 pandemic. During critical periods, it can provide the model with rich and representative observation samples. On the other hand, the CSMAR database has only had relatively complete credit rating historical data since 2010, ensuring the availability and integrity of the data. This paper adopts the deletion method to exclude observations with missing key variables, preventing missing values from interfering with subsequent matrix operations and model results. For abnormal migrations such as short-term multi-level jumps in rating data, the Z-score of state transfer frequency is used to identify and handle extreme outliers, ensuring the rationality of rating migration data. Considering the inconsistency of rating observation time, all rating data are converted into annual observation dimensions, and the rating status on December 31 of each year is used as the final rating of the year to solve the contradiction of time dimensions of discrete observation and continuous evolution. At the same time, 20 credit rating grades such as AAA, AA+, and AA are represented by numerical codes from 0 to 9, which not only simplifies the process of matrix calculation but also retains the ordinal characteristics of the rating level itself, laying the data foundation for the construction of a subsequent transfer matrix.

This paper uses standardized annual rating data to realize credit rating migration prediction with a discrete-time Markov chain model [10]. First, count the annual transfer frequency between each rating level, and obtain an 8×8 transfer frequency matrix C, including default status D, which intuitively reflects the distribution of the number of transfers between each rating status. On this basis, the transfer frequency matrix is standardized, and the transfer probability matrix P is calculated. Each element in the matrix represents the probability of transferring from the rating state i to state j. In order to test whether the rating migration meets the non-post-effect hypothesis of the Markov chain, the Martens test is done. If the p-value of the test result is greater than 0.05, that is, the test result is not effective, it is considered that the data conforms to the Marten characteristics, and the model construction process can continue. After completing the test, the transfer probability matrix P is used for matrix power operation to obtain the future rating distribution prediction, which can accurately calculate the distribution of the initial rating state after n years.

This paper also establishes a continuous-time Markov chain model to solve the discrete observation and continuous evolution. The model first uses historical rating conversion data to estimate the generator matrix by the maximum likelihood estimation method. After that, the matrix index is used to calculate the transfer probability matrix in a specific time interval. This paper sets the time interval t to 1 year, which is consistent with the DTMC model, to ensure that the results of different models are comparable. Finally, using the generated matrix Q, the matrix index

operation is used to predict the situation of different initial rating states after n years, which is more in line with the characteristics of the continuous evolution of credit ratings. In order to measure the prediction effect of the model in a full and objective way, this paper uses multiple quantitative indicators to evaluate. The mean square error is used to measure the overall difference between the predicted rating distribution and the actual rating distribution. The smaller the value is, the more accurate the prediction is. The accuracy rate focuses on the degree of coincidence of the predicted rating and the actual rating, which can intuitively reflect the accuracy of the prediction of the direction of rating migration. Harrell's C statistics are used to measure the model's predictive ability to predict the order of rating migration. The value range is between 0.5 and 1, and the closer to 1, the stronger the prediction ability. The accuracy ratio is used to evaluate the accuracy of the model's prediction of default time. The value is equal to the area under the AUC-ROC curve, which can well reflect the ability of the model in default prediction.

4 Analysis of Model Prediction Effect

4.1 Rationality Analysis of Migration Matrix

The credit rating migration matrix established in this paper, based on the sample data from 2010-2025, has a migration law that conforms to the realistic characteristics of China's credit market. Highly rated subjects exhibit obvious downgrade inertia. The probability of AAA rating downgrading to AA+ within a year is about 2.3%, and the probability of AA+ rating downgrading to AA is about 3.5%. The overall trend is a high probability of moving to a low rating. In contrast, the likelihood of the low-rated subject improving is typically low. The probability of the BBB+ rating subject upgrading to A- within a year is 1.2%, and the probability of the B+ rating subject upgrading to BB+ is only 0.8%, indicating that the credit repair ability of the low-rated debt-issuing subject is generally not high. At the same time, the default state D has a typical absorption state characteristic. Once it enters the default state, the transfer probability is 0, and there is no further state change, which is consistent with the actual evolutionary characteristics of credit risk. The results of the chi-square test show that China's credit rating migration data from 2010 to 2025 satisfy the Markov property. The test statistics $\chi^2=12.45$, $p=0.072>0.05$, which provides a reliable theoretical basis for the Markov chain model of credit rating migration prediction.

According to the further classification of the rating level, it can be found that there are obvious differences in the migration characteristics of different categories of subjects, and the average annual default probability of the investment level, that is, the AAA to BBB+ range, is about 0. As shown in Fig. 1, in order to visually show the distribution of credit rating migration probability, the core rating level is drawn and simplified into 8 categories. The migration probability matrix heat map, the darker the color, the higher the migration probability. The average annual default probability of investment-grade, speculative-level, and high-speculative-level is 0.3%, 4.5%, and 15.6%, respectively.

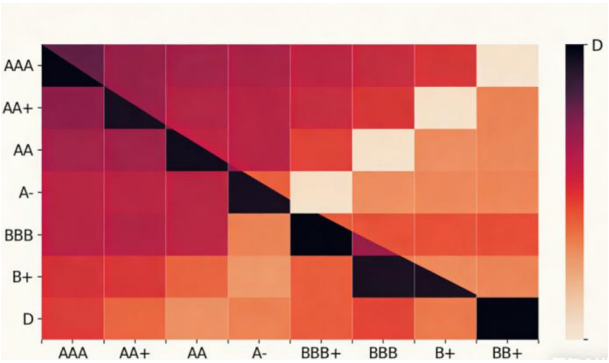


Fig. 1. Heat map of credit rating migration probability matrix (Picture credit: Original).

4.2 Prediction of the Rating Migration

Based on the established migration matrix, this article makes an out-of-sample forecast of the credit rating migration in 2021-2025, and then compares it with the actual migration results in many aspects. The prediction accuracy of the discrete-time Markov chain model is 68.7%, and the prediction accuracy of the continuous-time Markov chain model is 66.2%. The difference between the two is not significant, with a p-value of 0.12. In terms of mean square error, the MSE of the DTMC model is 0.023, and the MSE of the CTMC model is 0.025, so the short-term rating distribution prediction of the discrete time model is better. According to Harrell's C statistics, the DTMC model is 0.698, and the CTMC model is 0.685, both of which are greater than 0.5 random levels, indicating that both models strongly discriminate the order of rating migration. In terms of accuracy, the DTMC model is 0.732, and the CTMC model is 0.715, which shows that the two models have a better effect on the prediction of default time.

The results of the sub-rating level comparison show that the prediction effect of the investment-level subject is the best. The accuracy of the DTMC model and the CTMC model is 72.1% and 70.5%, respectively. The error and sorting indicators are better than those of other groups, which can better capture the credit stability characteristics of the high-rated subject. The predictive effect of speculative subjects is at a moderate level. The accuracy rate of the DTMC model is 64.3%, and the accuracy rate of the CTMC model is 62.7%. The models have a certain ability to identify the changing trends of credit risk for such subjects. The prediction accuracy of high-speculative subjects is low. The accuracy rate of the DTMC model and the CTMC model is 58.6% and 57.3%, respectively, but the model can still distinguish its high default risk attribute, providing an important reference for risk identification. To intuitively compare the differences in the prediction effect of DTMC and CTMC models under each rating category, draw a combination comparison chart as shown in Fig. 2, and display the two main indicators of accuracy and MSE.

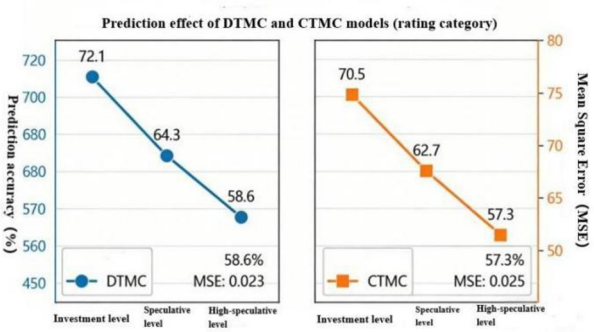


Fig. 2. The prediction effect of DTMC and CTMC models (Picture credit: Original).

4.3 Practical Application

The model prediction results have multi-faceted application value in the practice of credit risk management. First, in the calculation of the probability of default, the cumulative probability of default of each rating subject within different periods can be directly obtained with the help of the migration matrix, which provides important parameters for the calculation of the capital adequacy ratio under the framework of Basel III. For example, the probability of default of AAA-rated subjects in 1 year is about 0.2%, the 5-year period is about 1.1%, and the 10-year term is about 2.3%. Second, in terms of risk weight determination, the probability of default output by the model can be combined with the exposure of default risk and the loss rate of default, which can be used for economic capital measurement and risk-weighted asset measurement. Investors can adjust the allocation ratio of bonds with different ratings based on rating migration probabilities to achieve a dynamic balance between risk and return. Financial institutions can use the model to warn the subjects at high risk of moving in advance, and take risk mitigation measures such as credit enhancement and quota control in a timely manner. Third, in bond pricing, embedding the rating migration probability in the pricing model can improve the accuracy of risk premium measurement and provide a more scientific pricing basis for the issuance and trading of bonds. To clearly present the cumulative default probability of different rating subjects under different periods, draw a line diagram as shown in Fig. 3.

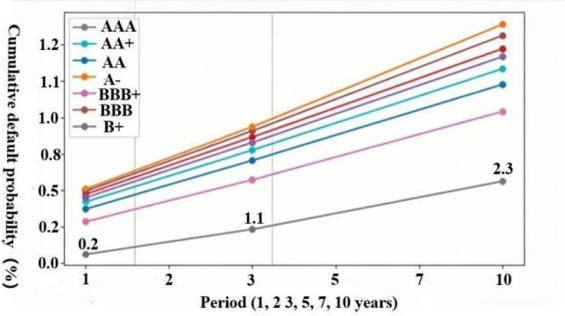


Fig. 3. Cumulative default probability for various rating categories (Picture credit: Original).

5 Conclusion

Through the establishment of discrete and continuous time Markov chain models, this paper makes empirical predictions of China's credit rating migration, and draws the following conclusions: China's credit rating migration data meets the Markov nature, and the overall prediction effect of the model is better. The discrete-time model is slightly better than the continuous-time model in short-term prediction. The prediction results of the two models are not significantly different. There is heterogeneity in the prediction effect of different rating levels. The prediction accuracy of the investment-level subject is the highest, and the high-speculative level is the lowest, reflecting the characteristics that the credit risk of the high-rated subject is relatively stable and the credit repair of the low-rated subject is difficult. The models' predictive ability is affected by the economic cycle: prediction accuracy is higher during crisis periods, decreases during recovery periods, and exhibits strong robustness to data sources and rating systems. Therefore, it is recommended that financial institutions take different risk management measures for different rating subjects, mainly for high-speculative subjects to do a good job of default risk warning, dynamically adjust the forecasting method in combination with changes in the economic cycle, improve the relevance of risk control, and use the default probability parameters given by the model to increase capital adequacy and risk Power assets, etc. are calculated and measured, to improve the allocation of the portfolio.

The main contribution of this paper is to verify the applicability of the Markov chain model in predicting China's credit rating migration, build a whole-process framework for the model and evaluation, reveal the heterogeneity characteristics of the model prediction effect, prove the reliability of the model through robustness test, and calculate the capital adequacy ratio under Basel III. Technical support has been provided. It fills the gap of a lack of systematic empirical verification and a whole-process application framework in relevant domestic fields, provides investors with quantitative analysis tools, and provides a reference for regulatory agencies to improve the regulatory system. At present, there are still certain shortcomings in the research. The influence of historical status and macroeconomic indicators is not considered, and the model structure is relatively fixed. Future research can relax the Markov hypothesis, establish a macro-micro integrated joint model, attempt deep learning methods, design a dynamic transfer matrix, and expand application scenarios for micro-investment decision-making to improve the model's adaptability and application value.

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