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# *Causal Inference in Financial Risk Management: Applications of Counterfactual Analysis in Credit Portfolios*

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***Keywords:*** Financial risk management; credit portfolio; counterfactual analysis; credit lending; mortgage lending

***Abstract:*** In today's complex and changing financial risk management field, the importance of accurate assessment of credit portfolio risk is self-evident, which is related to the stable operation and sustainable development of financial institutions. This study adopts the counterfactual hypothesis analysis to conduct an in-depth comparative analysis of the causal and predictive effects of three representative credit portfolio models. The results show that the p-values of all three credit portfolios are well below the 0.05 level of significance, which is usually considered statistically significant. This data result fully proves that these three credit portfolio models have strong effectiveness in coping with financial risk, and can effectively resist the impact of financial risk to a certain extent. It proves that this credit portfolio approach is well able to withstand the pressure of financial risk. This strengthens the effective management method of financial risk management and the application value of the risk management method based on the theory of causal inference in the actual financial business.

## 1. Introduction

In the field of financial risk management with its many variables, the optimization of credit portfolio management and related strategies has been a top priority issue that financial institutions and academics have been working on for a long time [1]. In recent years, credit portfolio management has become very challenging and faces unprecedented challenges, as financial markets have grown rapidly and with it credit portfolio risk management has become more complex and more thorny day by day. For financial institutions, if they want to ensure the safety of their assets in a realistic way and then pursue asset value, they need to assess the risks inherent in different types of loans in more detail and accurately, and use the assessment results to develop practical and effective risk management strategies [2]. However, traditional risk management tools often rely solely on historical data and statistical modelling. In the face of rapidly changing market dynamics, the application of traditional risk management techniques is not sufficient and it is difficult to gain comprehensive and deep insights into the broad and significant impact of these factors on credit portfolio risk. Furthermore, some studies have attempted to incorporate political factors into risk assessment models [3], but the lack of systematic and solid theoretical underpinnings or insufficient empirical support has considerably limited the application effectiveness and explanatory power of these models.

This paper aims to address the shortcomings of previous studies by introducing advanced counterfactual analysis to investigate the broader impact of fiscal and monetary policy on credit portfolio risk. By cleverly constructing counterfactual scenarios, the risk profile of the credit portfolio under different policy combinations is modelled. The aim is to reveal the subtle effects of policy changes on the implied risk of credit portfolios and to provide financial institutions with deeper and more precise guidance on their risk management strategies.

## 2. Related Works

In recent years, the application of causal reasoning in many industries has become the focus of attention, especially in industries such as banking, finance, and insurance, where its role has become increasingly important. Kumar et al. conducted a detailed study of 37 authoritative papers published between 1992 and 2023, revealing the indispensable role of causal reasoning in improving the transparency of decision-making explanations in the banking, financial, and insurance sectors [4]. Bodendorf et al. took a different approach to supply chain risk management by developing an analytical model that combines deep learning and causal learning. The model has the ability to accurately predict supply disruptions and quantify the causal impact on supply reliability, highlighting the superior benefits of data-driven strategies in solving complex supply chain problems [5]. In addition, Mauri et al. turned their attention to the field of bank stress testing and cleverly developed a predictive model that integrated professional knowledge and statistical techniques, bringing new inspiration to the industry. In particular, they used structural causal models to improve the consistency of predictions before and after, solving the problem of inferring the impact of macroeconomic changes on credit default risk[6]. Hason Rudd et al. proposed a conceptual framework that combined multiple algorithms to conduct causal analysis of customer churn and discovered key confounding features [7]. Khan et al. used a Bayesian structural time series model to study the causal impact of earthquakes on the Istanbul stock index and found that earthquakes had a significant negative impact on stock market value, emphasizing the importance of natural disaster preparation to reduce the adverse impact on stock market valuations[8].

In recent years, although the application of causal reasoning in many fields such as banking, finance, insurance and supply chain risk management has received increasing attention, there are still some shortcomings in existing research. Some research models are complex in construction and mainly focus on bank stress testing scenarios, and lack empirical support in the identification of confounding characteristics. Therefore, this paper aims to comprehensively explore the wide application and innovation of causal reasoning in the field of financial risk management, in order to propose more innovative and practical risk management strategies and methods, thereby making up for the shortcomings of existing research.

## 3. Methods

### 3.1 Credit Portfolio Application

Financial institutions analyze the economic conditions, policy environment, market potential and other factors of different geographical regions, use causal reasoning to determine the risk level of each region, and achieve precise loan allocation by regional portfolio to reduce overall risk. At the same time, through in-depth analysis of factors such as national industrial policies, industry development trends, and market competition conditions[9], financial institutions can identify the risk characteristics and profit potential of different industries and achieve reasonable allocation of loan resources by industry portfolio. In addition, financial institutions also use causal reasoning to identify high-quality customers and potential risk customers by evaluating factors such as customers' credit status, operating conditions, and repayment ability, thereby formulating more precise credit policies to meet the needs of different customers[10]. In terms of loan term, financial institutions analyze the length of loan term and use causal reasoning to assess the risk and liquidity of loans of different terms to reduce term risk while maintaining the liquidity of credit assets. Finally, by analyzing the risk characteristics and return potential of different types of loans, financial institutions can use causality to achieve a balance between risk and return and make a reasonable allocation between different types of loans.

### 3.2 Application of Counterfactuals in Credit Portfolios

In economic research, the counterfactual series generated by the components of a policy shock is usually defined as ‘policy shock-induced change’ or ‘policy shock-induced change’, emphasizing the central effectiveness of the policy instrument at the macroeconomic level. This understanding emphasizes the central effectiveness of policy instruments at the macroeconomic level. Counterfactual analysis not only has many applications in macroeconomic research, but is also important in the field of financial risk management. Credit portfolio management plays an important role in financial risk management. Counterfactual virtual analysis is an advanced and practical tool that provides practical help and important optimization opportunities for credit portfolio management. The tool allows managers to easily simulate a wide range of possible scenarios when assessing credit policy. The simulations are not limited to simple interest rate adjustments or changes in credit terms and conditions, but cover a wide range of more complex credit policy changes. By applying counterfactual hypothetical analysis, managers can visually and clearly see the specific impact of these policy adjustments on the credit portfolio, including changes in loan default rates, changes in credit quality and overall credit risk.

Similarly, counterfactual hypothetical analysis has proven its power and usefulness in forecasting market risk. Powerful simulation capabilities allow managers to visualize multidimensional market scenarios, such as interest rate fluctuations, changes in economic cycles and political adjustments. These scenarios not only reflect the complexity and volatility of the market, but also highlight the potential risks of a credit portfolio in different market environments. By analyzing these scenarios in detail, managers can more accurately assess the risk position and potential losses of their credit portfolios and develop more targeted and effective risk management strategies. These insights based on counterfactual hypothetical analysis provide managers with a valuable basis for decision-making. Such insights not only help managers gain a more comprehensive understanding of the risk profile of their loan portfolios, but also enable them to respond more effectively to market risks and ensure the smooth, orderly and safe operation of the financial institution.

### 3.3 Counterfactual Analysis Model

Counterfactual analysis is an analytical method based on causal reasoning, whose core principle is to simulate and compare the outcomes of different scenarios in order to comprehensively and accurately assess the impact of decisions and events, and has a very wide range of applications in credit portfolio management. Financial institutions can make full use of counterfactual analysis to simulate credit portfolio performance in different economic environments and select the most appropriate credit strategy. In this paper, three general types of loans have been selected for specific analysis: credit loans, mortgages and guaranteed loans. The above three objects are expressed by the following formula:

$$\tau_{jt} = Y_{jt}^{t} - Y_{jt}^{s}, t = T_0 + 1, \cdots, T \quad (1)$$

In formula (1), $Y_{jt}^{t}$ is the variable of credit loan, mortgage loan and guaranteed loan; $Y_{jt}^{s}$ is the potential result without financial risk. It is assumed that the potential results of all variables obey the following common factor model:

$$Y_{it}^{s} = \mu_i + k_i f_t + \varepsilon_{it}, i = 1, \cdots, n; t = 1, \cdots, T \quad (2)$$

In formula (2), $\mu_i$is the fixed effect; f is the K ×1-dimensional unobservable time-varying common factor; $k_i$ is a parameter that does not change over time but changes with individuals; $\varepsilon_{it}$ is the error term, satisfying $E[\varepsilon_{it}] = 0$.

Assuming that the above credit portfolio may receive the following shocks:

$$\varepsilon_{SB,h} = -\sum_{j=1}^{5} B_{3,j} x_{j,3} - \sum_{m=1}^{\min(p,h)} \sum_{j=1}^{5} B_{3,5m+j} z_{j,h-m} \ , h = 0,1,2, \cdots \quad (3)$$

$x_{i,o}, i = 1,2,\ldots,5$represents the response of variable i to financial risk shock without the intervention of counterfactual factors. Under counterfactual factors, the response of variable i to financial risk shock is:

$$z_{i,0} = x_{i,0} + \frac{\theta_{i,3,0} \varepsilon_{SB,0}}{\sigma_3} \quad (4)$$

In formula (4), $\sigma_3$ represents the standard deviation of exogenous risk.

# 4. Results and Discussion

## 4.1 Data Collection

The data are mainly sourced from the Orbis BankFocus database, Wind financial terminal, and China Financial Data Service Platform [11]. Given that there are many missing core data such as bank loan structure and loan placement areas, the study filled in this part of the data by in-depth study of the annual reports of various banks. Finally, the financial data for the five years from 2019 to 2023 were sorted out, as shown in Table 1.

Table 1: Descriptive statistics results

| Variable name | Calculation method | Observed value | Average value | Standard deviation |
|---|---|---|---|---|
| NPLs | Non performing loans/Total loan amount | 445 | 1.231 | 0.572 |
| Over | Total amount of overdue loans | 454 | 21.276 | 1.292 |
| RA | Risk weighted total assets/Total assets | 421 | 0.647 | 0.026 |
| GLoan | (Annual loan amount - year-end loan amount)/Last year's year-end loan amount | 445 | 0.289 | 0.128 |
| Ccar | (Total core capital/Weighted risk assets) * 100 | 445 | 10.29 | 1.272 |
| M1 | Narrowly defined money supply growth | 447 | 13.217 | 7.263 |
| Gua | Guarantee loan/Total loan amount | 256 | 0.208 | 0.127 |
| Credit | Credit loans/Total loan amount | 256 | 0.468 | 0.089 |
| PIe | Mortgage loan/Total loan amount | 350 | 0.086 | 0.112 |

According to the above table, the average non-performing loan ratio is 1.231 and the standard deviation is 0.572, indicating that there are fluctuations and risk differences in the credit asset quality of each entity; the total amount of overdue loans averages 21.276, indicating that credit recovery faces certain pressure. At the same time, the average risk-weighted total assets ratio is 0.647 with a small standard deviation, indicating that the ratio is relatively stable overall. The average loan growth rate is 0.289, which means that credit supply is showing a steady growth trend. In addition, the core capital adequacy ratio averages 10.29, reflecting that the core capital of banks to cope with risks is guaranteed to a certain extent. In terms of loan types, credit loans account for a high proportion (0.468), while mortgage loans account for a low proportion (0.086). This credit portfolio structure feature can be used as a basis for further analysis of credit risks.

### 4.2 Causal Analysis of Financial Events

The study used causal word matching technology to determine the causal relationship of events, and performed word segmentation, part-of-speech tagging, and dependency syntax analysis on the text. Then, according to the definition of event arguments, a total of 1,000 financial events were identified and constructed. These events were organized in the structure of attributive relation + subject-predicate relation. Figure 1 shows these statistical results in detail.

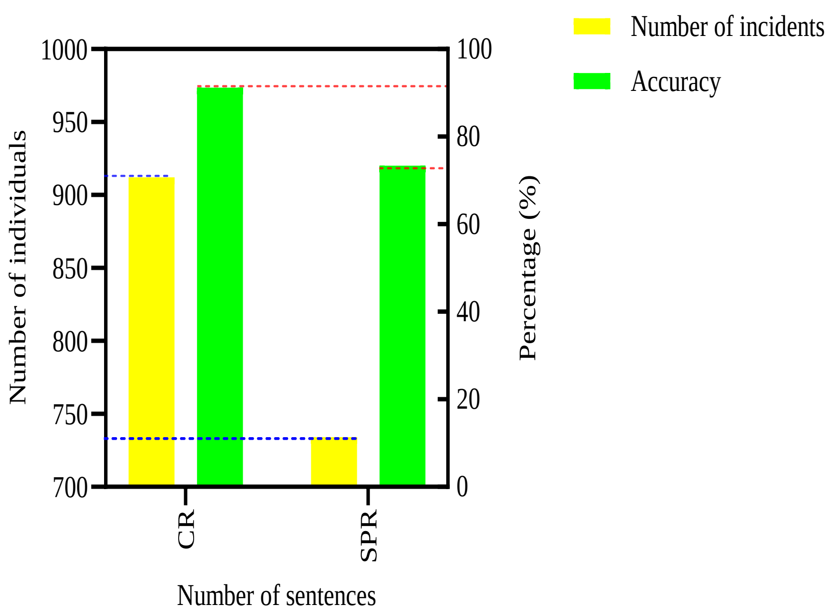



Figure 1: Causal events and relationship extraction statistics

As shown in Figure 1, the study successfully extracts 912 valid causal relationships from the text with an accuracy rate of 91.20%. This shows that the technology has high reliability and accuracy in identifying the causal relationship of financial events. The number of sentences with subject-predicate relationship reaches 734, accounting for 73.40%. This further proves the important role of subject-predicate relationship in constructing the causal relationship of financial events, and also illustrates the effectiveness of dependency syntactic analysis in the event extraction process.

The study then conducted a Granger causality test on the credit portfolio and financial risk through a unit root test. The results are shown in Table 2.

As can be seen from Table 2, at lag 2, the null hypothesis that credit loans, mortgage loans and guaranteed loans are not Granger causes of the financial risk stress index is rejected. The P values of the above three credit combination models are all less than 0.05, indicating that they have a significant impact on the financial risk pressure index.

Table 2: Causality test of the credit portfolio financial index and the financial risk stress index

| Null hypothesis | F-value | P-value | Hysteresis order | Inspection results |
|---|---|---|---|---|
| Credit loans are not granger reasons for financial risk pressure index | 4.13 | 0.0245 | 2 | Reject the null hypothesis |
| Mortgage loans are not granger reasons for financial risk pressure index | 15.23 | 0.0001 | 2 | Reject the null hypothesis |
| Ensuring that loans are not granger reasons for financial risk pressure index | 10.56 | 0.0411 | 2 | Reject the null hypothesis |

## 4.3 Counterfactual Analysis

In order to further explore the impact of financial policies on financial risks in credit portfolios, the study compared the observed values of credit portfolios before and after the issuance of financial policies with the counterfactual predicted values. The results are shown in Figure 2.

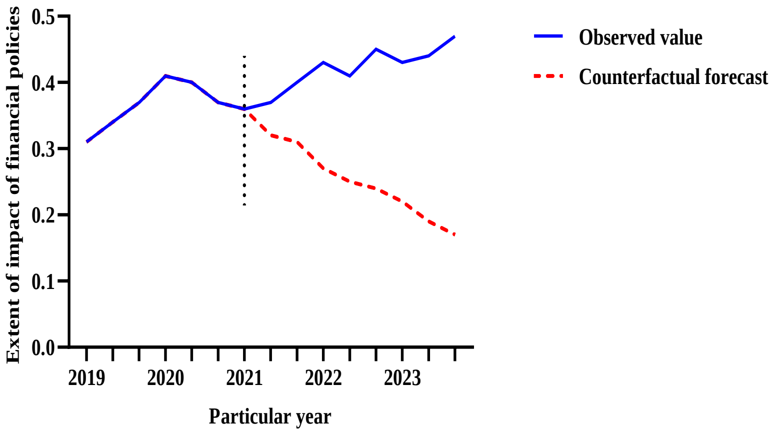
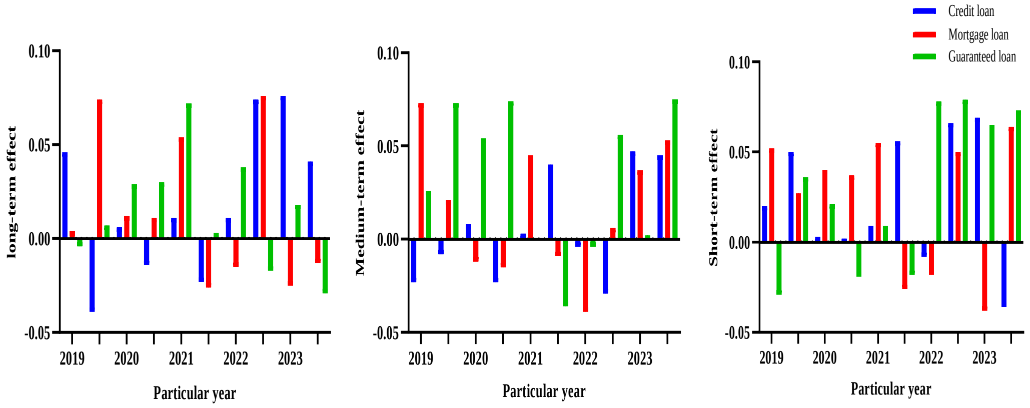



Figure 2: Observed and counterfactual predicted values of credit portfolio

In Figure 2, the vertical dashed line marks the previous period before the financial policy was enacted to avoid obscuring the treatment effect of the base period. The curves before the treatment base period show a close fit between the predicted and observed values, which indicates that the selected optimal control group effectively simulates the credit portfolio risk profile. The curve fitting after the base period reveals the impact of policy coordination on the financial risk of credit portfolios. If the predicted value and the observed value show a significant trend of separation after the treatment base period, it means that policy coordination has a significant impact on the financial risk of the credit portfolio.

In order to effectively evaluate the optimal combination of fiscal and monetary policies when banks issue credit, the study adjusted fiscal and monetary policies, observed their independent impact on the issuance of credit portfolios, and compared the results of counterfactual analysis in order to clarify the optimal combination of fiscal and monetary policies in the issuance of credit portfolios. The results are shown in Figure 3.




(a) Long-term effects (b) Medium-term effects (c) Short-term effects

Figure 3: Counterfactual effects of fiscal and monetary policy when banks issue credit

According to Figure 3, different policy combinations have different effects on the issuance of credit portfolios. The effects of different policy combinations also vary at different time scales. In the long-term effects (as shown in Figure 3a), the effect values of credit loans, mortgage loans, and guaranteed loans fluctuate differently, and credit loans have both positive and negative effects, reflecting the complexity of the impact. In the medium-term effect (as shown in Figure 3b), the effect value of mortgage loans is relatively high in some cases, indicating that it is more significantly affected by the policy. In the short-term effect (as shown in Figure 3c), the effect values of each loan type are also high and low, and the guaranteed loan has a high value of 0.078. Overall, different loan types respond differently to fiscal and monetary policies at different maturities, and it is difficult to simply determine a unified optimal combination. An in-depth analysis of various effects is needed to determine the best match.

## 5. Conclusion

The study introduced the method of counterfactual analysis to deeply explore the impact of fiscal and monetary policies on credit portfolio risk. It was found that the adjustment of fiscal and monetary policies has a significant impact on credit portfolio risk, and the risk status of credit portfolios under different policy combinations shows significant differences. These findings not only reveal the dynamic impact mechanism of policy changes on credit portfolio risk but also provide financial institutions with more accurate risk management strategies. However, this study also has certain limitations. The limitation of data samples and the simplification of model assumptions lead to a small scope of application. The study suggests that financial institutions and policymakers should fully consider the potential impact of policy changes on credit portfolio risks when formulating risk management strategies and policies, and strengthen cross-departmental and cross-field cooperation and coordination.

## References

*[1] Graetz N, Boen C E, Esposito M H. Structural racism and quantitative causal inference: a life course mediation framework for decomposing racial health disparities[J]. Journal of Health and Social Behavior, 2022, 63(2): 232-249.*

*[2] Charpignon M L, Vakulenko-Lagun B, Zheng B, et al. Causal inference in medical records and complementary systems pharmacology for metformin drug repurposing towards dementia[J]. Nature communications, 2022, 13(1): 7652-7656.*

*[3] Stimson J, Pouwels K B, Hope R, et al. Estimation of the impact of hospital-onset SARS-CoV-2 infections on length*

*of stay in English hospitals using causal inference[J]. BMC Infectious Diseases, 2022, 22(1): 922-925.*
*[4] Kumar S, Vivek Y, Ravi V, et al. Causal Inference for Banking Finance and Insurance A Survey[J]. arxiv preprint arxiv, 2023, 23(07): 16427-16428.*
*[5] Bodendorf F, Sauter M, Franke J. A mixed methods approach to analyze and predict supply disruptions by combining causal inference and deep learning[J]. International Journal of Production Economics, 2023, 256(1): 108708-108711.*
*[6] Mauri A, Rubicondo D, Polino N, et al. Advancements in Bank Stress Tests: from Bayesian Averaging to Causal AI[J]. Research Paper Series, Issue, 2023, 1(53):1-2.*
*[7] Hason Rudd D, Huo H, Xu G. Improved churn causal analysis through restrained high-dimensional feature space effects in financial institutions[J]. Human-Centric Intelligent Systems, 2022, 2(3): 70-80.*
*[8] Khan K, Cifuentes-Faura J, Shahbaz M. Do earthquakes shake the stock market? Causal inferences from Turkey's earthquake[J]. Financial Innovation, 2024, 10(1): 145-147.*
*[9] Wasserbacher H, Spindler M. Machine learning for financial forecasting, planning and analysis: recent developments and pitfalls[J]. Digital Finance, 2022, 4(1): 63-88.*
*[10] Matthay E C, Glymour M M. Causal inference challenges and new directions for epidemiologic research on the health effects of social policies[J]. Current Epidemiology Reports, 2022, 9(1): 22-37.*
*[11] Moccia C, Moirano G, Popovic M, et al. Machine learning in causal inference for epidemiology[J]. European Journal of Epidemiology, 2024, 1(1): 1-12.*