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Research on Risk Spillover Measurement of Fintech System Based on DCC-GARCH and Generalized Variance Decomposition Network Model

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Abstract: Using daily data from September 26, 2007 to July 13, 2023, this paper uses DCC-GARCH model and generalized variance decomposition network model to analyze the systemic risk spillover effects of fintech on banking, securities and insurance industries. The study quantifies the systemic risk impact of fintech on the traditional financial industry by calculating VaR (value at risk) and ΔCoVaR (change in conditional value at risk). The results show that while the risk of fintech has decreased after P2P lending has been phased out, it has increased during the COVID-19 pandemic. Fintech has the greatest risk spillover to the securities industry and the least impact on the banking industry. In addition, the correlation between fintech and various financial sectors increased significantly during the pandemic, indicating its high systemic importance. Based on these findings, this paper puts forward policy recommendations to strengthen risk monitoring and supervision, emphasizing the construction of a sound regulatory network for systemic risk contagion, real-time monitoring, and timely response to potential crises.

1. Introduction

With the increasing frequency of global warming and extreme weather events, the importance of green finance in environmental protection is becoming increasingly prominent, especially in the green stock and green bond markets. According to the Climate Bonds Initiative, global green bond issuance has reached $513 billion by 2022. Although China's green finance system started a little later, its speed and scale of development are among the highest in the world. In 2020, China issued $68.2 billion in green bonds with no defaults, while the green equity market raised $8.1 billion, demonstrating its growing importance in environmental investment.

The concept of green finance was first proposed in the 1980s, and although there are different interpretations in the academic world, the core goal is still to support sustainable development and low-carbon environmental protection. At present, China's green financial instruments mainly include green stocks, green bonds and green trusts. Despite the late emergence of the green stock market, research focus has gradually shifted to its portfolio and risk characteristics. As the green stock market has higher liquidity risk than the traditional financial market, the transmission of this risk becomes more significant when the connection between the two is deepened.

2. Relevant Literature

Based on the spillover index model and the DCC-GARCH model, this paper comprehensively analyzes the risk spillover effect and its temporal and spatial characteristics of the seven major financial markets in China from July 22, 2005 to August 27, 2021. The results show that in the time dimension, the risk spillover index fluctuates between 18% and 52%, the dynamic correlation coefficient varies between 0.09 and 0.31, and the risk spillover is significantly enhanced and asymmetrical when the policy and event shocks occur. In spatial dimension, there is asymmetric spillover effect among financial markets. The net risk spillover index of real estate, commodities and stock markets is positive, while that of gold, currency, foreign exchange and bond markets is negative, and the risk correlation between commodities and gold, stocks and real estate, bonds and gold markets is relatively high [1].

Based on the data of gold AU9999 and ten industry indices of Shanghai Stock Exchange from 2015 to 2023, DCC-GARCH model was used to analyze the dynamic correlation and calculate the optimal investment weight and hedging ratio. The results show that there is a dynamic correlation between gold and the industrial stock market, and the hedging and hedging effects are different. In extreme markets, gold is highly negatively correlated with the industry index; In a bear market, gold has a negative correlation with nine industries and a sustained negative correlation with seven industries over the long term. Gold has the highest weighting in major consumer sectors and the highest hedging ratio in the raw materials sector. It is recommended to include gold in your portfolio and continuously assess industry risks [2].

In the complex international economic environment, it is very important to study the dynamic correlation of financial risks for the risk prevention of China's financial system. Based on the DCC-GARCH model, this paper analyzes the yield data of the four industry indexes of banking, insurance, securities and diversified finance. The results show that there is a high positive correlation between the sub-industries, and the volatility is negatively correlated with the economic stability, and the correlation coefficient is significantly time-varying [3].

In recent years, financial technology has become an important tool for Chinese banks to control risks. Based on the data of 16 A-share listed banks, GARCH-EVT-Clayton-Copula-CoVaR model was adopted to measure their fintech development level and systemic risk spillover value. Research shows that fintech can reduce systemic risk spillover, and factors such as bank size, return on total assets, deposit liability ratio, leverage ratio and non-interest income ratio have an impact on systemic risk spillover [4].

This paper uses quantile regression and conditional value at risk model to analyze the risk spillover effect of fintech on 24 listed commercial banks. The results show that fintech increases the systemic risk of banks, with greater impact on shareholding and regional banks and less impact on state-owned banks. It is recommended to establish a fintech risk early warning mechanism, improve regulations, and strengthen "functional supervision." [5]

Under the background of rising global economic policy uncertainty, this paper studies the spillover effects and transmission channels of systemic financial risks in China by using the high-frequency data of 64 financial institutions and the TVP-FAVAR model. The results show that global economic policy uncertainty will significantly increase China's systemic financial risk, and the spillover effect is stronger when the uncertainty is high, showing nonlinear characteristics [6].

The development of digitalization provides new opportunities for cooperation in the technology and finance ecosystem. This paper discusses the impact of digitization on ecosystem symbiosis and its spatial spillover effect. Using the panel data and spatial Durbin model of 31 provinces in China from 2003 to 2020, the results show that the digitalization level has a significant spatial spillover effect on ecosystem symbiosis, which is represented by the U-shaped nonlinear influence of the digitalization level of neighboring provinces on the local ecosystem, and there is regional heterogeneity [7].

Using TVP-VAR and Copula methods, this paper analyzes the risk spillover effect between the financial sub-market and the real industry. The results show that the risk spillover of banking and bond market to the real industry is large, the banking industry affects the traditional industry, the bond market affects the emerging industry. The spillover effect of foreign exchange on the energy sector is small. The bond market, especially Treasury bonds, has the strongest impact on real sector tail risk. Financial market risks need to be regularly monitored and controlled [8].

The coronavirus outbreak and falling oil prices have increased the downward pressure on global financial markets, increasing the interconnectedness among financial markets and potentially amplifying the level of risk, triggering concerns about a financial crisis in the United States. In this paper, an early warning system with 9 markets and 15 indicators is constructed, and the spillover effect is analyzed with generalized prediction error variance decomposition and complex network technology, which is integrated into the KLR model [9].

This paper establishes a DCC-GARCH model on the stock returns of the four major state-owned banks from July 15, 2010 to December 18, 2020, and finds the dynamic correlation of systemic risk among the four major state-owned banks in China. The empirical analysis shows that the stock returns of China's four major state-owned banks have the characteristics of volatility aggregation, and there is a positive risk dynamic correlation. Banks should continuously strengthen their systemic risk management capabilities, improve their internal risk prevention and control mechanisms, and improve their anti-risk capabilities, so as to reduce the losses caused by risks to banks [10].

3. Research on Risk Spillover Measurement of Fintech System Based on DCC-GARCH and Generalized Variance Decomposition Network Model

3.1. Theoretical Framework and Model Construction

3.1.1. Impact of Fintech on Systemic Risk and Spillover Transmission Characteristics

The development of fintech has had a profound impact on the financial system, bringing both new opportunities and new risks. Technological innovation has increased financial efficiency, but it has also introduced new risks such as technical failures and cyber security. The highly leveraged operations and high-frequency trading of fintech companies have increased market volatility and liquidity risks, and complex systems may also face the risk of operational error and fraud, affecting financial stability. Effective risk management measures include improving technical security, optimizing liquidity management, increasing market transparency, and establishing cross-institutional risk monitoring and collaboration mechanisms. Studying the impact and spillover characteristics of fintech on systemic risks can help to better identify and address these potential risks, which are not limited to a single market or institution, but may spread to the entire financial system through a variety of pathways.

3.1.2. Construction and Related Explanation of DCC-GARCH Model and Generalized Variance Decomposition Network Model

The DCC-GARCH model is a tool for analyzing dynamic correlations between financial markets, which extends the power of the traditional GARCH model by allowing it to process data from multiple markets simultaneously and track the time-varying characteristics of correlations between markets. The working principle of this model is to use the GARCH model to calculate the volatility data of each market to estimate the dynamic correlation matrix between markets. This method can more accurately capture the interaction between markets, especially when the market is volatile, this method can better identify the transmission path of risks. Simplifying the complexity of correlation calculations across multiple markets is a major advantage of the DCC-GARCH model, which reveals the dynamic relationships between markets. The model also has some limitations, such as its high positive qualitative requirements for conditional variance matrix, which may be difficult to satisfy completely in practical applications. The computational complexity and resource requirements of this model are high, and although the DCC-GARCH model shows significant potential in financial market risk and correlation analysis, in practical applications it is often necessary to combine other methods to achieve a more comprehensive and accurate risk assessment.

The generalized variance decomposition network model considers financial institutions as network nodes, calculates the risk contribution of each node, and then draws a weighted directed network graph. This network demonstrates the detailed path and intensity of risk propagation in the system, providing a comprehensive understanding of the dynamics and spillovers of systemic risk. For financial regulators, this risk spillover network map provides valuable insights to identify and monitor critical risk transmission pathways, by identifying and managing these pathways, regulators can adopt more effective risk management policies, and the spread of systemic risk can be reduced. The impact of different financial policies and market events on systemic risk can also be assessed. The generalized prediction error variance decomposition method solves the problem of the traditional Cholesky decomposition method in the stability of the results, and the GVD method has been widely used in financial risk analysis, especially in the construction of the risk spillover network between financial technology and traditional financial institutions. The model reveals the risk transmission relationship between variables by calculating the contribution of each variable to the total impact, and the risk transmission path and intensity between different financial institutions are also described in detail here.

3.2. Data and Methods

3.2.1. Data Processing

The data in this study are mainly from Wind database and China Securities Index Company. The Wind database provides financial data such as stock prices, trading volumes and company financial statements, while the China Securities Index Company provides industry classification standards. To ensure data integrity and accuracy, this study selected data from 2010 to 2023 as a sample. Before data analysis, it is necessary to preprocess the original data to ensure data quality and consistency.

In the data cleaning process, missing values are processed by means filling, interpolating, or deleting records with a large number of missing values, while outliers are detected and processed by boxplot and the 3σ principle. Data standardization adopts Z-score standardization method to eliminate the dimensional influence between different variables. Time series alignment ensures that each variable has a data record at the same time node. According to the industry classification standard of the CSI Index Company, the companies in the sample data are classified by industry in

order to distinguish the characteristics of different industries in the subsequent analysis.
After data preprocessing, descriptive statistical analysis was carried out on the sample data to understand its basic characteristics. The sample data covers a total time span of 14 years from 2010 to 2023 and contains financial data of 500 listed companies, including traditional financial institutions and fintech companies. The main variables include daily closing price, daily trading volume, asset-liability ratio, current ratio and return on equity. Through descriptive statistical analysis of these variables, such as mean, median, standard deviation, maximum and minimum values, the results show the distribution and dispersion of each variable. These steps ensure the quality and reliability of the research data, and lay a solid foundation for the subsequent risk spillover measurement analysis of fintech systems based on DCC-GARCH and generalized variance decomposition network model.

3.2.2. Construction and Risk Measurement of DCC-GARCH and Generalized Variance Decomposition Network Models

The DCC-GARCH model can effectively reveal the risk transmission and interaction between assets, which helps to fully understand the overall risk situation of the financial market. The model also estimates the conditional variance and correlation between assets through the dynamic conditional correlation method, which can depict the correlation structure of assets over time. While exercising these, the generalized variance decomposition network model uses the generalized prediction error variance decomposition technique to decompose the variance of the prediction error into the risk shock borne by each variable, and calculates the contribution of these variables to the overall risk (Figure 1). This model provides a detailed view of risk transmission, and the risk spillover effect between variables in the financial system can also be visually displayed through the variance decomposition matrix. Researchers can combine DCC-GARCH and GVD models to more comprehensively assess risks in fintech systems, thereby developing more effective risk management strategies, which not only improves the accuracy of risk identification, but also optimizes risk warning and management measures.

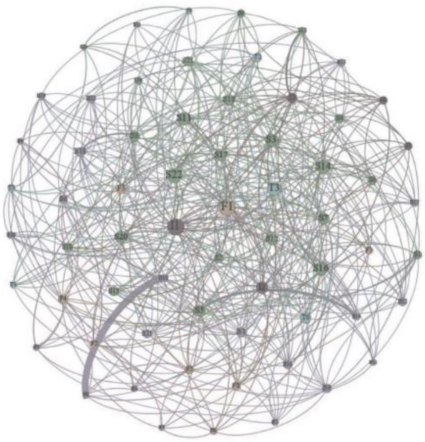

Figure 1: System risk overflow network diagram

3.3. Empirical Analysis

3.3.1. Results of DCC-GARCH Model

The DCC-GARCH model is outstanding in capturing the dynamic conditional correlation between different assets or institutions in the financial market, which can accurately quantify the risk spillover effect in the fintech system and reveal the risk transmission mechanism among fintech institutions. The results of this model show that the risk spillover effect among fintech institutions is significantly enhanced when market volatility intensifies, and its dynamic characteristics are reflected. When markets move sharply, models show increased correlations between fintech institutions and increased transmission of systemic risk. The analysis of time series data reveals the reaction of market participants to external shocks and the changes in their behavior, thus providing an important reference for financial risk management and policy making. These findings can help financial regulators identify key risk transmission nodes and paths, and they will then implement targeted monitoring and management measures, so as to effectively prevent the spread of systemic risks and improve the stability and security of the financial system (Figure 2).

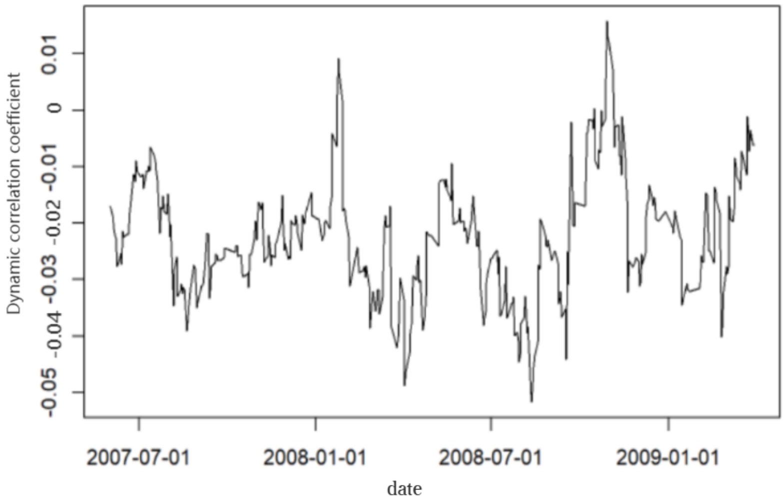

Figure 2: Sequence of dynamic correlation coefficients

3.3.2. Network Model Results

The GVD model helps us understand the role of each institution in the risk transmission process by breaking down the risks of the whole system into specific risks borne by each financial institution. Through this method, we can identify important risk nodes and edge nodes in the financial system, and clarify the role and influence of these institutions in risk transmission. This allows us to gain a clearer understanding of the internal structure of the financial system and the mechanisms by which risk is transmitted, so that when we develop risk management strategies, we can focus on those institutions that have a greater impact on systemic risk.

The central institution is generally subject to a greater risk impact and its risk can be passed on to multiple other institutions, thus forming a backbone of risk transmission within the system. Compared to this, the risk impact of fringe institutions is relatively small, but they can still be subject to risk spillover from central institutions. By establishing the risk spillover network diagram, the path and structure of risk transmission can be clearly described, and the main risk sources and vulnerable links in the system can be identified. These analysis results provide data support for the formulation of targeted risk management measures and policies, and help to improve the stability and resilience of the financial system.

3.3.3. Result Comparison

Through dynamic analysis of financial market volatility, DCC-GARCH model can reveal conditional correlations in time series, thus helping to identify transient changes in systemic risk. However, this model mainly focuses on the dynamic behavior of volatility, and has limited description of the specific transmission path of risk in the financial system and the interaction between institutions. The generalized variance decomposition network model uses variance decomposition technology to describe the risk interaction and transmission among financial institutions in detail. The model calculates the contribution of each financial institution to the prediction error variance by disassembling the total risk within the system. The model also reveals the role of each institution in the overall risk and shows how risk flows between different institutions. This process not only helps to identify key risk nodes in the system, but also quantifies the intensity of risk transmission between nodes, providing valuable information for the development of risk management strategies and early warning systems.

4. Results and Discussion

In theory, this study proposes a new risk assessment method combining DCC-GARCH and generalized variance decomposition network model, which enriches the theoretical framework of fintech risk management. In practice, it is recommended that regulators focus on fintech institutions that play a key role in the risk transmission process and take effective regulatory measures to prevent the spread of systemic risks. Limitations of the study include that model selection and parameter Settings may affect the accuracy of the results, and the limited sample data is also an issue. Future studies can verify the stability of the model under different market environments, expand the sample data, improve the comprehensiveness and representativeness of the study, and add more variables and indicators to improve the risk assessment model and enhance the understanding of the risk transmission mechanism in complex financial markets. The combination of the two improves the accuracy of systemic risk identification and can accurately quantify the risk spillover effect.

5. Conclusion

The DCC-GARCH model reveals the volatility dynamics in the fintech system and the changes in its conditional correlation, showing the risk volatility of the market in the short term. However, the model is limited in the elaboration of risk transmission paths and comprehensiveness. To supplement this shortfall, generalized variance decomposition (GVD) network models are introduced to provide an in-depth analysis of risk transmission and network structure in fintech systems. This model not only maps the flow of risk between financial institutions, but also helps identify key risk points within the system. Combining the advantages of these two models allows for a more comprehensive understanding of risk dynamics and transmission mechanisms in the fintech system, with the DCC-GARCH model suitable for short-term risk volatility analysis, while the GVD model provides in-depth insight into the long-term risk network. This integrated application enhances the understanding of financial risks and provides a scientific basis for risk management and policy making. Future research could further explore the performance of these models under different market conditions and integrate more data and variables to improve the accuracy and comprehensiveness of risk measures.

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