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Evidence from Chinese Listed Financial Institutions Shows Spatial Spillovers of Financial Risk and their Dynamic Evolution

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Introduction

The derealization of the financial industry has been accelerated by the quick development of financial innovation and internet finance, and the complexity of financial networks has been increased by hybrid operations and business crossings. Being "too big to fail" has increasingly given way to being "too connected to fail" for systemically significant financial institutions. The growth of financial technology has also increased the transfer of financial risks while strengthening domestic financial integration by improving the physical connections between financial institutions.

Risk spillovers within financial markets have been the subject of extensive scholarly study, particularly in the years following the 2008 global financial crisis. At the moment, research is concentrated on risk transmission at three different levels: spillovers of risk to global financial markets Risk spillovers across local financial submarkets, risk spillovers from foreign financial markets to domestic financial markets. To construct risk spillover indicators among financial markets, their research methodologies primarily rely on the vector autoregression (VAR), conditional value at risk (CoVaR), marginal expected shortfall (MES), and dynamic conditional correlation generalised autoregressive conditional heteroskedasticity (DCC-GARCH) models and their extensions. Copula DCC-GARCH models are especially well suited to portraying the complex dependence structure among financial assets due to the copula function's effectiveness in portraying the tail correlation of financial assets and the superiority of DCC-GARCH models in fitting time series [1].

Description

The tail correlation of financial time series can frequently be used to represent the spillover of financial risks and will dramatically rise in response to strong volatility in the financial market. DCC-GARCH was proposed by Engle. The DCC-GARCH model has been extensively employed in modelling the dynamic correlation of financial time series because it can more effectively describe the volatility spillover effect and information transmission process among financial assets. However, the DCC-GARCH model is unable to account for the non-normal, spike-back-tailed, and tail-dependent characteristics of the return distribution of financial assets. The marginal distribution is used by the copula function, a mathematical technique, to compute the joint distribution. It can be used to explain how random variables interact nonlinearly, although its primary use is to Analyze the mechanisms of dependency and correlation between random variables [2].

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The interconnectedness of tail risk between various financial time series can be efficiently described by the t-copula function, according to earlier research. The complex correlation of financial assets is best understood by combining the DCC-GARCH model and the t-copula. In order to estimate the dynamic conditional correlation coefficients which are utilised to quantify risk spillovers in financial submarkets we employ the t-copula-DCC-GARCH model. The pattern first exhibits a decline, followed by an uptick, and then another decrease in terms of the spatial spillover effects in each era. In particular, stage 4 (which covers the US-China trade dispute and the COVID-19 epidemic shock), stage 1 (which covers the financial crisis and the European debt crisis), stage 2 (which covers the money shortage and the stock market crash in China), and stage 5 are the stages where the spatial spillovers of financial risks are the strongest (which includes the post-epidemic period). The stage with the lowest probability of spillovers is stage 3 (the tranquil time) [3].

The changes in spatial spillover effects at various phases are primarily driven by government behaviour and extreme occurrences, according to the time-varying characteristics of spatial spillover effects. outbreak of COVID-19 has had a significant impact on financial markets, which prompted numerous government interventions. As a result, the fourth phase is when the spatial spillover effect is most pronounced. As a global phenomenon, the "European debt crisis" had a big effect on China's import/export industry. As a result, the third period also has a higher spatial spillover impact. The government used policy steps to restrain the excessive boom of the financial sector during the "money shortage" in 2013 and the "stock market crisis" in 2015, which caused a rapid decline of the Chinese stock market within a short period of time. The impact on big state-owned financial institutions, however, was minimal and mostly affected small and medium-sized financial institutions, which resulting in a minimal geographical risk spillover impact [4].

Despite the absence of major financial market events in the post-epidemic period, the epidemic's reappearance had a significant impact on the market. Consequently, there was no discernible drop in the spatial spillover effect. The third era saw the government behave in accordance with market expectations and no dramatic incidents, which led to a large decrease in the geographical spillover effect. The turnover rate (turnover) and the log return rate, according to the computed regression coefficients of the primary explanatory factors, are highly and positively associated, meaning that the higher the demand for stocks, the higher the return rate. While the dummy variable lvar and the log return rate do not significantly correlate, the dummy variable hvar exhibits a significant negative correlation, indicating that on the Chinese stock market, investors and traders are less sensitive to low volatility stocks and more sensitive to high volatility stocks. As a result, when stock volatility is high, investors and traders are less inclined to purchase them due to the higher risk, which results in reduced profits. This also suggests that the majority of stockholders and merchants in the rational investors in the stock market will actively steer clear of high-risk investments [5].

Conclusion

To summarise, when performing financial risk prevention, policymakers should concentrate on the following three categories. They should first distinguish between domestic and international financial dangers. When domestic financial markets are unstable, small and medium-sized diversified financial institutions need to be encouraged to improve their risk management.

Policymakers should concentrate on the risk profile of major financial institutions in the face of international financial hazards. The multidimensional spatial spillovers of financial hazards need to be taken into account, too. Comprehensive risk prevention strategies should be developed, with a focus on preventing cross-regional risk spillovers, based on the financial risks' features of cross-market, cross-industry, and cross-regional contagion. Finally, to ensure that monetary and fiscal policies can be successfully relayed, the transmission mechanism for interest rates and exchange rates needs to be opened up to the stock exchange.

References

1. Sadorsky, Perry. "Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies." *Energy Econ* 34 (2012): 248-255.
2. Diebold, Francis X., and Kamil Yilmaz. "Better to give than to receive: Predictive directional measurement of volatility spillovers." *Int J Forecast* 28 (2012): 57-66.
3. Liu, Chengcheng, Peng Song and Bai Huang. "Early-warning signals of risk contagion among global stock markets: Evidence from community-level." *Appl Econ Lett* 29 (2022): 338-345.
4. Croitorov, Olga, Massimo Giovannini, Stefan Hohberger and Lukas Vogel et al. "Financial spillover and global risk in a multi-region model of the world economy." *J Econ Behav Organ* 177 (2020): 185-218.
5. Chen, Shaowei, Long Guo and Qiang Qiang. "Spatial spillovers of financial risk and their dynamic evolution: Evidence from listed financial institutions in China." *Entropy* 24 (2022): 1549.

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