ENHANCED VOLATILITY SPILLOVER NETWORK PREDICTION OF CHINESE FINANCIAL INSTITUTIONS USING GCN-LSTM MODEL

QI-NEN GU[1]

[1] School of Economics and Management, Southeast University, Nanjing 211189, China
E-MAIL: qinen_gu_926@163.com

Abstract:

By constructing the volatility spillover network based on LASSO-VAR and generalized variance decomposition method, this study develops the graph convolutional network and long short-term memory (GCN-LSTM) model to predict the volatility spillover network of 31 listed Chinese financial institutions between 2014 and 2022. Our findings confirm the volatility spillover of bank, security and insurance sectors exhibits heterogeneity and during the stock market crash, the volatility spillover network among institutions is enhanced, and the spillover from security to bank and insurance acts a crucial role in accumulating systemic financial risk. The empirical results demonstrate the proposed GCN-LSTM model yields promising predictive performance than models including ARMA, SVM, RF, and LSTM.

Keywords:
Volatility spillover network; GCN-LSTM model; LASSO-VAR model; Prediction

1. Expand abstract

The core characteristic of systemic financial risk lies in its transmission and amplification effects through institutional interconnectedness networks (Belcaid et al., 2024; Benoit et al., 2017; Kumar et al., 2024). While financial integration enhances market efficiency, it concurrently establishes risk contagion channels through cross-border linkages and institutional interdependencies (Gavronski and Ziegelmann, 2021). Under the international consensus of financial risk management, complex network theory has introduced a new paradigm for systemic risk research, overcoming limitations of linear models by quantifying non-linear connectivity structures (Hautsch et al., 2015). And volatility spillover networks represent a crucial manifestation for mapping risk transmission pathways and their evolution (Wu and Jiang, 2023; Yousaf et al., 2020).

Based on the·5-minute data of 31 listed Chinese financial institutions between: January 1 2014 and July 31 2022, we· construct volatility, spillover networks using LASSO-VAR·and generalized·variance decomposition, then develop a graph convolutional network and long short-term memory (GCNLSTM) model to predict network. features. Finally, a comparative analysis among ARMA, SVM, RF and LSTM models and further robustness tests are performed to·demonstrate·GCN-LSTM model's superior predictive accuracy and robustness. Our findings show the volatility spillover of three sectors exhibits heterogeneity and during the stock market crash, the spillover from banking to securities act as crucial role in accumulating systemic financial risk, For prediction, the·GCN-LSTM model has highest accuracy rate compared to baseline models.

Our study contributes to financial risk modeling, systemic risk early warning, and real-time monitoring tools. First, the GCN-LS'TM model proposed in this study advances risk prediction by combining graph convolutional layer to aggregates neighborhood information with LSTM units to track risk evolution (Kou et al., 2020; Kumar et·al, 2024; Li and Qin, 2023). Second, we·establish·volatility spillover networks as empirically validated early warning indicators, expanding graph neural networks' use in systemic risk detection. Third, GON-LSTM's outperformance provides regulators and investors with a practical monitoring tool, demonstrating how, network-based deep learning can enhance financial stability oversight.

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