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A financial network perspective of financial institutions' systemic risk contributions

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HIGHLIGHTS

- We measure systemic risk contribution by dynamic conditional correlation multivariate GARCH model.
- We construct minimum spanning trees (MSTs) from dynamic conditional correlations (DCC).
- We show the dynamic evolution of systemic risk contribution and financial network structure.
- We investigate quantitative relationships between systemic risk contribution and financial network structure.

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ABSTRACT

This study considers the effects of the financial institutions' local topology structure in the financial network on their systemic risk contribution using data from the Chinese stock market. We first measure the systemic risk contribution with the Conditional Value-at-Risk (CoVaR) which is estimated by applying dynamic conditional correlation multivariate GARCH model (DCC-MVGARCH). Financial networks are constructed from dynamic conditional correlations (DCC) with graph filtering method of minimum spanning trees (MSTs). Then we investigate dynamics of systemic risk contributions of financial institution. Also we study dynamics of financial institution's local topology structure in the financial network. Finally, we analyze the quantitative relationships between the local topology structure and systemic risk contribution with panel data regression analysis. We find that financial institutions with greater node strength, larger node betweenness centrality, larger node closeness centrality and larger node clustering coefficient tend to be associated with larger systemic risk contributions.

1. Introduction

The financial crisis has raised questions about the adequacy of financial regulation to ensure stability of the financial system. A particular feature was the threat of systemic risk [1]. According to the Bank for International Settlements, systemic risk in the financial system is the risk that a failure of a participant to meet its contractual obligations may in turn cause other participants to default, with the chain reaction leading to broader financial difficulties [2]. The related studies mainly focus

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on the measurement of financial institutions' systemic risk contributions, influence factors of systemic risk contribution, and risk contagions among financial institutions [3–8,1].

Measuring the contribution of each financial institution to overall systemic risk can help identify the institution that contributes more to systemic risk. Stricter regulatory requirements for institutions with larger systemic risk contributions would break the tendency to generate systemic risk. Adrian and Brunnermeier [3] proposed CoVaR measure for systemic risk, namely the value at risk (VaR) of the financial system conditional on institutions being under distress. The authors defined an institution's contribution to systemic risk as the difference between CoVaR conditional on the institution being under distress and the CoVaR in the median state of the institution. Other systemic risk contribution evaluations include Shapley value methodology and systemic expected shortfall (SES) [4,5]. The influence factors of financial institutions' systemic risk contribution mainly include institutional characteristics, such as size, leverage, maturity mismatch, etc. [3].

The failure of one institution spreading to other institutions results from financial links between them. These financial links include interbank loans, payment systems or OTC derivatives positions. Such an intricate structure of linkages can be captured by a network representation of the financial system. More recent studies explicitly model the financial links between institutions as networks and employ empirical or simulation techniques to assess the propagation of institution failures [1,9–11]. These networks include interbank networks, payment networks, counter party exposures in credit default swaps, or trade credits between companies [12–15]. However, the network analysis literature only concentrate on the effects of overall network structure on systemic risk. The relationships between institutions' local network structure and systemic risk contributions are neglected. Furthermore, the stock price cross-correlations among financial institutions evaluate the systemic risk [16]. Such correlations are frequently used to construct financial networks. The research includes basic topology characteristics and intrinsic hierarchical structure of stock correlation network, etc. [17–21]. But the stock price cross-correlation network analyses rarely relate systemic risk contributions to financial institutions' local structure.

Our aim is to investigate the relationships between systemic risk contributions and institutions' local topology structure in the financial networks. We first measure dynamic systemic risk contribution of financial institutions by estimating the change of CoVaR denoted by $\triangle$CoVaR. Then dynamic minimum spanning trees (MST) of stock price cross-correlation are constructed from the dynamic conditional correlations (DCC). Finally, we use panel data regression, and relate these time-varying $\triangle$CoVaRs to measures of each institution's local network structures like node strength, node betweenness centrality, node closeness centrality, node occupation layer, and node clustering coefficient. This paper is organized as follows. Section 2 discusses relevant literature. Section 3 outlines the systemic risk contribution measures. Section 4 constructs financial networks and studies properties of the local network structure. Section 5 is the empirical study. The last section presents conclusion.

2. Related literature

First, we discuss the measurement methodology literature of systemic risk contribution. Closest to the present paper is the approach in Ref. [3]. The authors introduced the Conditional Value-at-Risk (CoVaR) and defined it as the VaR of financial system conditional on an institution being in financial distress. Lopez-Espinosa et al. [6] identified main factors driving systemic risk in a set of international large-scale complex banks using the CoVaR approach. They found that the short-term wholesale funding is a key determinant in triggering systemic risk episodes. Girardi and Ergun [7] modified CoVaR from Ref. [3], and changed the definition of financial distress from an institution being exactly at its VaR to being at most at its VaR. Tarashev et al. [4] proposed Shapley value methodology to attribute systemic risk to individual institutions. The systemic expected shortfall (SES), i.e., the financial institution's propensity to be undercapitalized when the system as a whole is undercapitalized, was also proposed as a systemic risk contribution measure in Ref. [5]. Billio et al. [22] proposed direct and unconditional econometric measures of connectedness based on principal components analysis and Granger-causality tests. These two measures of connectedness complement the conditional loss-probability-based measures (CoVaR, SES) in providing direct estimates of the statistical connectivity of a network of financial institutions' asset returns.

Second, we want to mention the literature on financial network models and systemic risk. The literature mainly focuses on empirical structure of interbank network and risk contagion. The investigated networks include interbank payment network [10,23], interbank exposure network [24–27] and bipartite bank-asset network [28–30]. Empirical studies showed that the connections between banks exhibit a power-law tail for US FedWire system, Austrian interbank market, Brazilian banking system, UK and Italian market [23,31,32]. The literature on risk contagion in networks is vast. Here we mention some of the closest works to our own research. Allen and Gale [33] suggested that a more interconnected architecture enhances the resilience of the financial system to the insolvency of any individual institution. However, other studies showed that the financial contagion exhibits a form of phase transition as interbank connections increase [8]. The size of the bank initially failing is the dominant factor whether contagion occurs, but for the extent of its propagation the characteristics of the network of interbank loans are most important [1]. In contrast to this literature, we consider the effects of local network structure of financial institutions on their systemic risk contribution.

Third, this paper contributes to a vast literature on network modeling analyses studying the correlations of stock prices. In the considered networks, the vertices are stocks and edges between vertices are price fluctuation relationships of stocks [34–41]. The resulting networks are usually very large and their analysis is rather complex. In much of the previous work, specific filtering processes were applied to reduce the complexity, such as the threshold method [34–36], Minimum Spanning Tree (MST) [37–40] and Planar Maximally Filtered Graph (PMFG) [41–43]. Kenett et al. [44] introduced