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Systemic importance analysis of chinese financial institutions based on volatility spillover network

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ABSTRACT

From the perspective of volatility spillover, this paper investigates systemic importance and its influential factors of Chinese financial institutions by complex network modeling method. We first construct the volatility spillover networks by vector autoregressive models-multivariate generalized autoregressive conditional heteroscedastic models (VAR-MGARCH) in a BEKK form, and then construct a comprehensive network centrality index based on five network centralities (degree centrality, closeness centrality, betweenness centrality, modified Katz centrality and information centrality) to measure the financial institutions' systemic importance. The results indicate that the larger comprehensive network centrality index is, the higher corresponding ranking for the node of networks is and the greater systemic importance of financial institution will be. Finally, we identify the major factors which affect systemic importance of the financial institutions with panel data regression analysis. We find that compared with the market factors, the accounting factors are more advantageous to identify important financial institutions. Specifically, financial institutions with lager size and higher assets growth rate tend to be associated with greater systemic importance.

1. Introduction

Chaos theory is a general theory of non-linear dynamics and complexity theory is a subset of chaos [1]. The sciences of complexity deals with the often complex or chaotic collective behavior of systems made up of large numbers of relatively simple entities. Very often such systems exhibit nonlinear dynamical behavior [2]. The theory of complex networks seems to offer an appropriate framework for such a large-scale analysis in a representative class of complex systems, with examples ranging from cell biology and epidemiology to the Internet. Along with the study of purely structural and evolutionary properties, there has been increasing interest in the interplay between the dynamics and the structure of complex networks [3]. In these contexts, time-dependent phenomena are intimately related to the performance of the system, as exemplified by cascading failures. The nodes could be nonlinear dynamical systems, and the state of each node can vary in time in complicated ways.

It has also focused the attention of researchers on the use of complexity theory to understand the behavior and dynamics of financial markets, because the financial system has shown itself to be a complex system with a great number of interactive agents. In the financial system, network science has also emerged as a useful tool for describing the interconnectedness between financial agents, such as the financial institutions. Connectedness among financial institutions would appear central to modern risk measurement and management, and indeed it is. Financial institutions are connected to each other via a complicated network of multilateral relations. Through these linkages, the failure of a financial institution will trigger the subsequent failure of others, thereby generates a failure cascade. The transmission can take place through a multitude of channels, balance sheet exposures, portfolio rebalancing, payment system, equity cross-holdings and asset prices [4]. The presence of risk externalities is the essence of systemic risk, and requires the regulator to take a macro-prudential approach to financial institution regulation and supervision [5,6]. The potentially high social costs of systemic risk and the need to develop readiness for crisis management make it vital to identify the financial institutions that transmit risk to other financial institutions with which they are connected by multilateral relation networks. To guide policy, it is necessary for regulators to measure and analyze the systemic importance of individual financial institutions, i.e. characterizing the systemic impact when an institution fails, and identifying influential factors of systemic important institutions is the foundation for creating regulations, supervisory policies, and infrastructure that will rein in the associated systemic risk [7,8].

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A few measures of systemic importance have been proposed in recent empirical studies. The related studies are classified as two approaches. The first class relies directly on joint distribution of asset returns, and tries to describe co-dependence at the tails of the distribution of returns. The measures can provide informative estimates of correlated losses. The most popular measures of this class include Conditional Value-at-Risk (CoVaR) [9], Marginal Expected Shortfall (MES) [10], SRISK [11] and so on. The main advantage of this approach is data availability. However, What becomes clear from these works is that both the number of affected financial institutions and the financial system' s volume of losses depend not only on the aggregate volume of risk exposures but also on their distribution within the system and the structure of that system [6,12–15]. Thus, not only the size of an institution matters its systemic importance, but also its connectedness. Naturally, the second approach is from the perspective of network analysis. Our understanding of systemic importance and our ability to measure it will be greatly enhanced by taking a close look at the topological properties of the network that link financial institutions together. Three main tools for network analysis are used: centrality analysis [16,17], cluster analysis [18], and balance sheet simulation methods [4,6,19–21]. The starting point of the analysis is the construction of network. However, on one hand, the bilateral exposures of financial institutions to each other either are not reported or are strictly classified [22]; on the other hand, the alternative estimation methods (maximum entropy, minimum density) create unrealistically networks, and therefore fail to capture all of the dynamics [14,23,24].

As we know, return and/or volatility spillover effects are usually investigated to measure the extent of the linkages between different financial markets [25–32]. Although the existing literature focuses on financial markets, it is important to extend spillover effect analyses to financial institutions as they develop fast and are part of the financial market. In contrast with asset returns, the above second approach, taken in this paper as well as in other papers studying systemic importance of financial institutions based on volatility spillover, a network link is based on some measure of the impact of the stock price of each institution on the stock prices of all other institutions [7,33]. As a result, in our volatility spillover network, vertices represent financial institutions, and edges represent the stock volatility of the starting institution contribute to the stock volatility of the ending institution. Volatility propagates across financial institutions via spillovers that exert greater impact when financial institutions are more connected. Specifically, an individual financial institution may be the source of volatility spillover that can be transmitted to the whole system. The systemic importance of a financial institution is the influence of stock returns on other institutions in the volatility spillover network, which could be represented as its network connectedness.

We first analyze the volatility spillover effects among financial institutions by vector autoregressive models-multivariate generalized autoregressive conditional heteroscedastic models (VAR-MGARCH) in a BEKK form. Secondly, the volatility spillover networks are constructed. Thirdly, we calculate several network centralities, including degree centrality, closeness centrality, betweenness centrality, modified Katz centrality and information centrality, to analyze systemic importance of financial institutions. Then, because different centrality measures are correlated with each other, we use the principal component analysis method to obtain comprehensive information about systemic importance. Finally, we use panel regression to identify the factors affecting systemic importance of the financial institutions based on network analysis. Our paper makes two main contributions. First, our measures directly consider the interconnectedness of institutions. Second, the links are estimated by volatility spillover among financial institutions. It avoids the difficulty of lack of bilateral exposure data availability. This paper is organized as follows. Section 2 discusses relevant literature. Section 3 constructs volatility spillover network and outlines the network centrality measures. Section 4 is the empirical study. The last section presents conclusion.

2. Related literature

First, we discuss systemic risk measures based on asset prices distributions. Adrian and Brunnermeier [9] proposed a measure for systemic risk contribution,ΔCoVaR, defined as the Conditional Value-at-Risk (CoVaR) of the financial system conditional on an institution being under distress in excess of the CoVaR conditional on the median state of the institution. Considering more severe distress events of institution that are farther in the tail, Girardi and Ergun [30] modified CoVaR defined in [9] and changed the definition of financial distress from an institution being exactly at its VaR to being at most at its VaR. While CoVaR looked at the returns of the financial system when an institution is in financial distress, Acharya et al [10] did the opposite and proposed Marginal Expected Shortfall (MES) measure, which is an institution's average loss when the financial system is experiencing losses. Acharya et al [11] introduced SRISK to measure the systemic risk contribution of a financial institution. SRISK measures the capital shortfall of an institution conditional on a severe market decline. These conditional loss-probability-based measures are not from the perspective of complex interdependences among financial institutions, which are the origin of systemic risk.

Second, we want to mention the literature on network analysis of financial institutions' systemic importance. The analyzed networks include interbank exposure network and interbank payment network. Links in these networks are estimated by bilateral transactions [34,35]. The transactions are transfer process, and traditional centrality measures which have been developed with other types of processes (parallel duplication, serial duplication) are not applicable. Battiston et al [16] proposed a metric DebtRank to quantity the systemic importance of banks. DebtRank is based on the network structure of an interbank exposure network. For interbank payment system, Soramaki and Cook [17] developed a robust measure SinkRank to estimate the magnitude of disruption caused by the failure of a bank. Aldasoro and Angeloni [22] developed several metrics that highlight different aspects of systemic importance based on network balance sheet contagion. A lot of researches resorted to simulation methods to investigate the possibility and the severity of contagion in the interbank networks [4,6,19–21]. The possibility refers to the whether or not contagion can take place if a given bank fails, and the severity refers to the extent to which the bank failure disrupts the financial system. As information on bilateral exposures in the interbank market is scarce and often of limited quality, the networks are usually estimated from balance sheet or payments data.

Third, this paper contributes to a vast literature on volatility spillover effects among financial markets. The studies analyzed volatility spillovers in context of developed markets [26,29,30], developing or emerging markets [31,32], developed and developing markets [25,27,28]. Majority of studies in the literature applied ARCH (Auto Regressive Conditional Heteroskedasticity) and GARCH (Generalized Auto Regressive Conditional Heteroskedasticity) family of models with slight variations such as AR(1)-GARCH [29], GARCH model and ARCH-LM tests [30], VAR-BEKK [31], GARCH-BEKK [25–27], Fractionally Integrated GARCH model [32]. Some others apply error variance decompositions from a vector autoregressive (VAR) model [28]. Some studies incorporated the impact of financial crisis on the spillover effects among financial markets [26,36]. The literature almost unanimously concluded that crisis accentuated volatility spillover across global equity markets. The