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Systemic risk management and investment analysis with financial network analytics: research opportunities and challenges

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Abstract

Recent economic crises like the 2008 financial tsunami has demonstrated a critical need for better understanding of the topologies and various economic, social, and technical mechanisms of the increasingly interconnected global financial system. Such a system largely relies on the interconnectedness of various financial entities such as banks, firms, and investors through complex financial relationships such as interbank payment networks, investment relations, or supply chains. A network-based perspective or approach is needed to study various financial networks in order to improve or extend financial theories, as well as develop business applications. Moreover, with the advance of big data related technologies, and the availability of huge amounts of financial and economic network data, advanced computing technologies and data analytics that can comprehend such big data are also needed. We referred this approach as financial network analytics. We suggest that it will enable stakeholders better understand the network dynamics within the interconnected global financial system and help designing financial policies such as managing and monitoring banking systemic risk, as well as developing intelligent business applications like banking advisory systems. In this paper, we review the existing research about financial network analytics and then discuss its main research challenges from the economic, social, and technological perspectives.

Keywords: Financial network analytics; Risk management; Investment analysis

Introduction

Nowadays the global financial system becomes increasingly interconnected in which various financial institutions such as banks, insurance companies, firms, and individual investors are linked with each other, through complex relationships such as interbank payments, stock investments, and firm board memberships. Although these relationships/networks were all studied separately, the interdependencies among them and the resulting systemic behaviors of this global financial system have rarely been investigated, making them very hard to predict, especially in extreme financial scenarios like the 2008 financial tsunami in which historical data is very limited. Moreover, the era of big data has bring the stakeholders huge amounts of data about various financial networks and thus great opportunities for studying such networks. Therefore, we need a network-based approach that can not only comprehend the complex mechanisms and dynamics of individual financial networks but also their interactions and impacts on the global financial system. We referred the needed approach as financial network analytics.

We adopted the definition of financial network in Elliott et al. (2014), in which the nodes are various organizations including banks, firms and investors that are linked through a network of financial interdependencies – e.g., cross-holdings of financial assets, inter-organization debt/liabilities, social relationships among board members. A classic example of a bank (financial) network is constructed by Hu et al. (2012) to illustrate how systemic risk (i.e., contagious bank failures) may occur through financial interdependencies among banks. As Fig. 1 shows, three banks have cross-holdings over three different financial assets - X, Y, and Z. The solid lines banks indicate interbank payment obligations between banks and the dotted lines indicate cross-holdings. In an extreme scenario like the 2008 financial tsunami, X's value may be largely reduced by a negative market shock, leading to bank A's failure and default on its payment to bank B. Then bank B, affected by both devalued X and Bank A's defaulted payment, may fail and then default on its payment to bank C, and so on, causing contagious bank failures. To understand the exact mechanisms and dynamics of financial contagion in such a bank network is critical for regulators like center banks to stop systemic meltdown of banking systems.

Previous research mainly studied financial networks from three perspectives. The first stream of financial network research adopted economics perspective and focused on network-level problems like systemic risk management. The second stream took the sociology perspective and mainly looked at relationships among individuals such as investors, mutual fund managers and firm board members. The third stream mainly studied financial networks from a technical perspective by adopting various data mining methods on large social media datasets. Research adopting these three perspectives have their roots in the reference disciplines – economics, sociology, and computer science, thereby having different pros and cons, as well as research challenges.

In this paper, we sketch several research challenges from the above three perspectives of financial network analytics. If appropriately addressed, this can dramatically improve how we understand, conceptualize and manage some key research problems in financial network analytics, including systemic risk management, investment decision support, or stock price predictions.

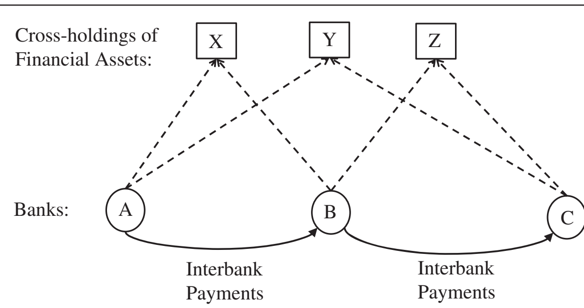

Fig. 1 An example of a bank network and possible contagious bank failures

Research challenges in financial network analytics

The economic perspective: systemic risk in banking networks

A large part of financial network research that adopt the economic perspective and methodologies focuses on studying systemic risk in banking systems/networks. Systemic risk was defined as "the propagation of an agent's economic distress to other agents that have links with the starting agent through financial transactions" in Rochet et al.(1996). In banking systems, it can be considered as the risks imposed by interbank relationships in banking systems, where the failure of a single bank or cluster of banks can cause contagious bank failures (Angelini et al. 1996; Eisenberg and Noe 2001; Hu et al. 2012). In general, existing risk management techniques or measures were mainly developed for individual financial institutions rather than systems. Therefore more effective network-based approaches are needed in managing systemic risk.

There are mainly two streams of financial network research on banking systemic risk. The first stream focused on developing and validating network-based econometric models of banking systemic risk. The other stream focuses on the development of network topology-based models of risk contagion and default spread, aiming to study the resilience of various financial networks.

Econometric models and analyses of systemic risk

The first stream that often develops econometric models of systemic risk in the context of financial networks rather than develop network (topology)-based models themselves (Acemoglu et al. 2014; Anand et al. 2014; Battiston et al. 2013; Battiston et al. 2015; Glasserman et al. 2015; Hautsch et al. 2015; Leitner 2005). Such studies are often done by economists who have their models deeply rooted in economic theories. Financial networks becomes a background rather than the environment or a set of mechanisms that drives the systemic risk. For instance,Acemoglu et al. (2015) studied the systemic risk using a financial network background framework. Their results showed that the factors that contribute to resilience against systemic risk may also function as significant sources of systemic risk under certain conditions.Hautsch et al. (2015) proposed a systemic risk beta as a measure of financial firms' contributions to systemic risk, given network interdependence between these firms' tail risk exposures. Their measure aim to monitor companies' systemic importance, enabling transparent macro prudential supervision. More recently, Glasserman et al. (2015) developed a model to estimate the extent to which interconnections increase expected losses and defaults under a wide range of shock distributions. This model assumed only minimal information of network structures and instead largely relied on information about the individual institutions.

These studies are deeply rooted in economic theories and often applied sophisticated econometric models and methods, but often largely overlooked the real-world network topologies and their impacts on systemic risk (bank failure contagion). In these studies, financial networks often serve as a background or research context in which the model is developed, while various specific network characteristics and mechanisms such as topologies are not involved. These studies excelled in their understanding of economic and financial theories but often lack of very strong capabilities in predicting how systemic may happen in various financial networks.

Network topological models and analyses of systemic risk

Network topology is an important component in financial network research and the central topic of the broader complex network research. The emergence of a specific financial network topology is resulted from certain network processes or mechanisms which are influenced by various factors. In turn, these topologies also shape the behaviors of the underlying financial networks. Thus it is important to study financial network topologies to gain a better understanding of systemic risk/bank contagious failures.

In financial network topology research, Eboli (2004) used a graph-theoretic representation of a financial network to model the flow of losses and its impacts on default contagion among firms. Elliott et al. (2014)studied cascades of failures in a network of financial institutions based on network topologies. They found that diversification connects the network initially, permitting cascades to travel; but as it increases, organizations become better insured against one another's failures. Network topology can also be used for study the resilience against systemic risk of financial networks. Amini et al. (2010) proposed a simulation-free framework for stress testing the resilience of a financial network against external shocks that affect balance sheets. Roukny et al. (2013) also investigated the stability of several benchmark topologies in bank networks. They analyzed the interplay of several crucial drivers, i.e., network topology, banks' capital ratios, market illiquidity, and random vs targeted shocks. Topology was found to have effects only when the market is illiquid. Moreover, Markose et al. (2012)) studied the credit default swaps (CDS) problem by modeling it as a financial network.

Research challenge: combining econometric-based and topology-based approaches

As reviewed in the previous two sections, existing financial network research that adopt economic perspective often focused on studying systemic risk using two main modeling and analysis approaches: econometric-based and topology-based. The first approach excels in modeling various financial mechanisms based on theories but lack of capability of reflecting the dynamics of real-world financial networks, mainly because it largely ignores the topological/physical features of such networks. On the other hand, the network topology-based approach rooted their models in analyzing the structure features of the real-world financial networks and develop the cascading models based on such features. The resulting models have strong abilities to simulate possible contagious failures in the modelled network topologies. However, oftentimes these models did not incorporate complex financial mechanisms that are often involved in the econometric models. Therefore, it is critical to develop effective systemic risk modeling and analyses approaches that can integrate both economic/financial theories with real-world network topologies, in order to take advantage of both approaches as discussed above.

The sociology perspective: investor social networks and investment decision support

Since the participants of financial markets are essentially individuals or institutes controlled by individuals (i.e., fund managers), the social networks of these individual investors become an important subject in financial network research. Studying investor social networks play a central role in understanding their decision process. Moreover, such insights can help us to design and implement more efficient decision support systems for people's investment decisions.

Investor social networks

Existing research that studied social networks of individual investors often focuses on their impacts on these people's investment decisions/behaviors. Social networks can be used for studying how information disseminates through participants in financial markets and impact the stock prices. Studying these issues could allows us to understand how stock prices respond to new information. For instance, Cohen et al. (2007) studied social networks of mutual fund managers and firm board members to identify insider information transfer. They focused on connections between mutual fund managers and corporate board members via shared education social networks. It was found that fund managers place larger bets on connected firms (i.e., they went to the same school with the board members) and perform significantly better on these holdings comparing to their non-connected holdings. Gale et al. (2007) modeled a trader network as a directed graph and found that if all possible trading opportunities are present the situation is very similar to the centralized auction market. More recently, Kinnan et al. (2012) investigated the impacts of kinship (social) networks and financial access on smoothing consumption and investment in the face of income volatility. They found that indirectly connected to the financial system through social network is as beneficial as a direct connection. In other words, not every household needs to use the banking system directly in order to benefit, if interpersonal gifts and lending are widespread in local communities.

Decision support for smart investment: the case of financial advice giving

Then client-advisor-relationship is in many ways is one of the most important and durable relationships in the financial industry and thus at the heart of any financial network. After the banks have recognized this and quite a few of them have refocused their business models on this relationship. However just as this renaissance is occurring, information technology is radically changing the clients' options and preferences and banks appear to always be one step behind. While Schwabe and Nussbaumer (2009) had found significant evidences in 2008 that the banking clients would prefer to include (suitable) IT-support in meetings, most banks regarded their client relationship to be so sensitive that any inclusion of IT would ruin it. While this fear may be appropriate for old-fashioned or poorly designed technologies (Heinrich et al. 2014a), simulations presented on tabletop or large tablet computers have shown to improve transparency (Nussbaumer et al. 2012), understanding (Bradbury et al. 2014), learning (Heinrich et al. 2014b), profiling and customer orientation, the advice giving process, documentation and compliance fulfillment. Evidence from research, the opportunities offered by new interactive devices and the expectations from clients have recently woken up banks (Nueesch et al. 2014) and the have started to seriously experiment with introducing IT in their advisory sessions.

But alas - they are coming late: While there will be a market for such an augmented advice-giving, quite of lot of the originally interested clients is moving on to new models of getting advice. Rather than relying on a professional banking advisor they rely on a social network. Already in 2008, clients reported that they typically ask their friends (and read in newspapers) before they go to a bank (Nussbaumer et al. 2009). In many cases banking advice giving served the purpose of closing the decision process by reducing remaining insecurities and recommending appropriate products. In many senses this reflected an appropriate interpretation of banking advisors as sales agents. While banks have recently struggled and (partially) succeeded in establishing true and fair advice, they are threatened to be made redundant in what is happening in the decision phases before the clients enter the bank: Clients cannot only rely on their personal social network but on special networks set up for exchanging investment-relevant financial information. Such social trading networks are either based on exchanging information (e.g. xSocial.eu?) or on sharing information on investment decision, i.e. sharing buying or selling securities (e.g. ayondo). Special support is giving for the roles such as a follower, i.e. a person who observes and maybe copies other members' investment decisions. It will be of special research interest to see what other roles and network structures evolve and to what extent the knowledge on general social networking can be applied to investment decision. While the social trading networks where originally intended for heavy traders, we see those platform becoming attractive for more conventional investors. Still, these social trading networks are for clients, who have a genuine interest in investments.

Clients who do not have this interest and believe in rational decision making in a (nearly) perfect financial market, are expected to move on to totally self-sustaining and automated services. Companies such as Wealthfront and Truewealth radically reduce the product choices (mainly to Exchange traded funds) and offer sophisticated low-cost portfolio solutions on the internet. Banks are trying to catch up to those new trends again, but they are bound to lose the competition against the rising new financial technology companies. Therefore Efma (2015) sees a new digital banking model evolve: Traditional banking companies open up and enter an ecosystem where they collaborate and compete for customers. This will again change the structure of the banking system and introduce not only new opportunities but also risks.

Research challenge: integrating the investor network analysis with the design of investment decision support systems

Although there were many studies on the impacts of social networks on individuals' investment decisions, the findings are rarely used for applications like banking advisory systems. There are two main challenges in bridging this gap. Firstly, the findings and insights derived from social network research of investors are often hard to quantify and thus transform to computing algorithms for predicting investors' decisions. To this end, research methodologies that are from interdisciplinary domains like social computing may be useful in bridging such gaps. Secondly, from the practical perspective, although IT based financial advice (investment) decision support systems are emerging in many new financial technology companies, traditional big banks are largely left behind mainly due to their concern on information security. Therefore, more research on evaluating the safety and efficacy of such systems are needed.

The technology perspective: predicting stock prices in the big data Era

There is a large stream of literature in computer science that adopt technological methods to study various financial networks. The main research goal is to predict the financial performance of firms, oftentimes using their stock prices as a proxy. There are mainly three types of studies in this literature. The first type of studies focused on studying the information diffusion in the inter-firm network. Saito et al. (2014) introduced the independent cascade model (ICM) to capture the propagation of influence in a firm network. Jin et al. (2012) developed algorithms to infer large-scale evolutionary company networks from public news during 1981 – 2009, and then predicted the profits and revenue growth for the companies within this network. Zhang et al. (2015) mined a business network from social media data, and designed an energy cascading model (ECM) for the states of the firms and the propagation of business influence among them. They used this model to predict the middle term movements the firms' stocks.

The second type of studies mainly relies on textual information from various sources such as social network platforms to analyze people's sentiments for firms/stocks. Bollen et al. (2011) adopted the sentiment analysis methods and Twitter data to analyze global public mood state for predicting stock market movement. Bouktif et al. (2013) used sentiment data from Twitter to predict stock prices using Ant Colony based Approach that integrated multiple single Bayesian classifiers. Moreover, Mao et al. (2013) investigated the correlation relationship between Twitter volume spike and stock trading, and developed a method to monitor Twitter volume spikes in stock trading. Makrehchi et al. (2013) extracted stock movements and textual information from Twitter and built a model with these labeled sentiment texts to predict the future stock movement. Arias et al. (2014) developed a public sentiment indicator from Twitter messages and investigated two domains – stock market and movie box office revenue using two forecasting models.

The third type of studies mainly use network information from financial communities for stock price prediction. De Choudhury et al. (2008) modelled financial forum communication dynamics using properties like the number of posts, the number of comments, and so on. They use them in support vector machine (SVM) to forecast stock price movements. Chen et al. (2013) developed a graph about people's online behaviors using the data from an online financial community. They studied the correlations between these graph properties and the stock trading prices and trading volumes. Lu et al. (2014) analyzed the dynamics of crowdfunding: how fundraising activities and promotional activities on social media evolve together and influence the final outcomes. The findings can help stakeholders to predict the success rate of a crowdfunding project.

Research challenge: modeling and analyzing the information diffusion in financial community networks

In the era of big data, financial network research that using technical methods, especially data mining, heavily relied on social media data like Twitter. The advantage is that such big data allows us to relate people's sentiments to stock movements in an unprecedented scale. It may accurately reflect how market participants/investors react to different news. However, these studies often focused on the textual information passed in the social media networks rather than the structure and dynamics how they propagate. We suggest that how the information is disseminated is equally important (if not more) as its content. Therefore, more research on the information diffusion patterns and mechanisms is needed, as well as proper modeling and analysis methods for information diffusion in financial networks.

Conclusion

This paper aims to extend the understanding of important financial network research problems and suggest research challenges in financial network analytics from economic, social, and technical perspectives. In particular, (1) combining econometric-based and topology-based modeling approaches for systemic risk management; (2) integrating the investor (social) network analysis with the design of intelligent decision support for investment; (3) modeling and analyzing the information diffusion in financial community networks. As various financial networks becomes more explicit via the advance of IT enabled services such as social media, online investment communities, social investing (i.e., StockTwits) services, addressing the above research challenges not only becomes possible but also more important.

Competing interests
The authors declare that they have no competing interests.

Authors' contribution
All authors contributed equally to this paper. All authors read and approved the final manuscript.

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