Connectedness of Markets with Heterogeneous Agents and the Information Cascades

Avijit Ghosh*[1], Aditya Chourasiya†[2], Lakshay Bansal‡[3], and Abhijeet Chandra§[4]

[1,2,3]Financial Engineering Program, IIT Kharagpur
[1,2,3,4]Vinod Gupta School of Management, Indian Institute of Technology, Kharagpur

November 06, 2020

Abstract

Macroeconomic integration of global financial markets is often characterized as complex systems where ever-increasing interactions among a vast number of agents make it difficult for the traditional economic theory to provide a realistic approximation of market dynamics. Economic systems are increasingly interdependent through cross-country networks of credit and investment, trade relations, or supply chains, and highlight the need for an integration of network theory and economic models to reduce the risk of global failure of financial systems. Our aim is to study the cross holdings of entities in terms of input-output and look at a time varying feature to examine the changes in the network. We also study the ripple effects caused due to the failure of entities inside the model. Using the WIOD (World Input Output Database) dataset covering 28 countries from the European Union and 15 other major countries across 56 industries for the period from 2000 to 2014, we present evidence on the nature of interconnectedness that global markets exhibit in terms of their input-output representing the cross-holdings. The interdependence of some markets in a global network is strongly correlated with not only the size of the markets, but also the direction of trades/cross-holdings, and the type of industries that dominate in their input-output data. With growth model estimation, we are able to project the cascades of failures in the network significantly. Our findings employ innovative approaches such as network formation approach and graph theory to explain the interconnectedness of markets across the world, and contribute significantly to the theoretical issues related to market integration and risk spill-over.

Keywords— Network theory, Interconnectedness, Financial systems, Ripple effects

JEL Codes: D85, F36, G15, G33.

*Email: avijitg22@gmail.com
†Email: adityachourasiya142@gmail.com
‡Email: lakshayb5@gmail.com
§Email: abhijeet@vgsom.iitkgp.ac.in

1 Introduction

Macroeconomic integration of global financial markets is often characterized as complex systems where ever-increasing interactions among a vast number of agents make it difficult for the traditional economic theory to provide a realistic approximation of market dynamics. Schweitzer et al. (Sci., 325: 2009) emphasize that economic systems are increasingly interdependent through cross-country networks of credit and investment, trade relations, or supply chains, and highlight the need for an integration of network theory and economic models to reduce the risk of global failure of financial systems.

The diversification argument suggests that price fluctuations attributed to macroeconomic shocks tend to average out over time and, therefore, have little aggregate effects on the system. However, this argument ignores the fact that economic agents operating in financial markets are interconnected. This connectedness might propagate idiosyncratic shocks throughout the financial system. Such "ripple effects" or "cascade effects" are observed during the global financial crisis of 2007-08 (Mulally (2008) 5).

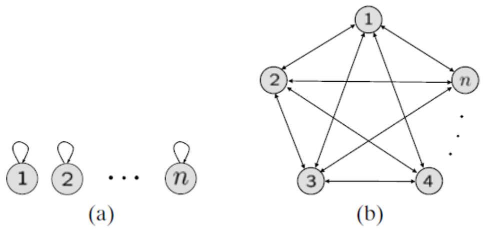

Figure 1: Sample representations of the network of two financial systems that are symmetric. (a) A financial system with no economic agent depending on other agents. (b) A financial system with each agent relying equally on all other economic agents (Adopted from: Acemoglu et al., Econometrica, 2012.)

Connectedness among firms in a financial market becomes more prominent an issue with respect to risk management and its key aspects such as market-level risk in terms of return connectedness and portfolio concentration, credit risk in terms of default connectedness, and systemic risk in terms of interconnectedness among firms (Diebold (2014) 3). It is, therefore, a central issue to understand how different agents in a financial market are connected to each other and how they share risks. The dependence among the agents could be either flat-structured where each agent acts independently and in the process contribute to the overall system in unique ways (see Fig 1(a)), or interconnected as a web where each agent contributes not only to the overall system but also to the shocks caused by other agents (Fig 1(b)). The connectedness of the economic agents is therefore important to study as it helps to identify potential weak agents and understand the source of cascading defaults and failures well in advance and thereby ensure that the system operates well.

In this paper, we develop a model for the diffusion of shocks across heterogeneous yet interconnected macroeconomic agents in terms of a basic growth-based network. Specifically, our model provides new evidence regarding the co-integration of select major world economies and sharing of risks in terms of cascades of failures across the network of the economies. The interdependence of firms and institutions in a network can be explained with the help of cross-holdings of assets and liabilities. Suppose a firm loses its economic value for certain reasons, intrinsic or extrinsic, and touches a downside threshold that further propagates a fall in economic value of the firm, it will have economic implications for other firms operating in the network. Since the firms operating within a network directly or indirectly cross-hold assets and liabilities, the losses in economic value of one (or more) firm(s) will propagate loss in economic value of other firms as well. Even though some firms might not transact directly with the firm(s) that loses economic value, it will be affected as a result of being part of the broader network. By this way, risks of firms in a network are shared and propagated by other firms operating in the network. Interestingly, at every stage, some firm may touch a threshold and lose value discontinuously. This may, at macro level, even amplify the risks in the network substantially.

In our work, we consider forty three major world countries covering about 85 percent of world gross domestic product (GDP) as heterogeneous economic agents that hold economic assets (e.g., any factor of production or other investment) as well as liabilities. The primitive holdings of these agents are represented in terms of input-output of these countries obtained from World Input-Output Database (WIOD: Trimmer et al., Rev. Int. Eco., 2015). Our network model shows that cascades of failures spread rapidly in the network and that large markets with values above certain threshold are able to sustain the cascades of failure much longer compared to the smaller markets even though these smaller markets have value slightly below the threshold. The information about the threshold of economic value, below which the cascade of failure starts in the network, for different countries can help us avoid failure of the network as a whole. We also show that the connectedness of markets are well represented in the WIOD datasets over time. Our backbone network model narrows down the connectedness of the markets to show the dynamic impact of industry-specific input-output on the network formation in our sample.

The remaining of the paper is organized as follows. Section 2 discusses the relevant and recent literature on the applications of networks in finance and macroeconomic research. Section 3 presents the details pertaining to the data, their characteristics, sources, and mathematical and empirical methods to implement the network approach to macro-finance issues in the context. Preliminary results obtained through the analyses of the data are provided in Section 4, followed by detailed discussions and the implications of the results in Section 5. The paper ends with a summary and concluding remarks along with the issues that are left unaddressed in this work in Section 6.

2 Related Work

Financial markets in general and stock markets in particular act as complex systems consisting of several agents that interact with each other in a stochastic manner. The level of complexity is attributed to many factors including the structure of micro and macro environments, the heterogeneity of the participating agents and their interactions with each other.

Economic agents such as firms at micro level and countries and/or markets at macro level are interconnected by way of international trade relations, eco-political integration, and information spill-overs. They share risks and shock as well as get shocked by each entity in the system. Recent literature dealing with issues such as contagion and cascades of failures across multiple agents in a system highlights the context in which agents are ex ante heterogeneous. In such cases, the risk characteristics of the shocks in the system hit the projects of the various agents. Because of the increase in interconnections among firms and/or markets (Diebold (2014) 3), we argue that it is inadequate to consider the regulation of capital requirements and macro prudential investigation as reliable. Some researchers have suggested that a policy that allows modulation exposures within a network can act as an effective tool (Stiglitz, 2010) 7 that are evident in a concrete empirical framework as well (Degryse and Nguyen, 2007) 8.

One customary way of addressing the problem of macro-prudential regulation is to rely on stress tests. Local macroprudential policy in a core country tend to affect the cross-border transmission of local macroeconomic policies by way of lending abroad, by restricting the increase in lending by less strongly capitalized banks in the country. This essentially requires the researchers and policy makers to carry out empirical studies that examine the outcomes for a system in which institutions that are interconnected are subjected to large shocks (see, for example, ESMA 2006; Kara, Tian, and Yellen 2015). This, however, does not consider that a well-connected network will likely collapse after subjected to a sufficiently large shock. It is argued that, such connectedness at times offer the benefit of forestalling problems when the network experiences smaller yet frequent shocks. It is, therefore, not feasible to achieve a certain level of the optimality of a particular connection structure unless we incorporate the impact of the whole distribution of shocks in the system. An alternative approach for assessing the risks in the banking systems is to hypothetically simulate the impact of stock drawn from the empirical distribution of the historical returns under the connectedness as seen in the actual network (Elsinger, Lehar, and Summer 2006 9).

Moreover, examining the information spill-overs across markets/firms can highlight similar insights. Preliminary research within the domain of risk spillover and market contagion in the debt markets emphasizes on an examination of primary determinants of debt markets. These studies use structural, financial, institutional indicators as micro factors, and macroeconomic characteristics that explain the dynmaic movements of the yields of a sovereign bond. In this context, seminal works by Eichengreen and Luengnaruemitchai (2004), Claeys and Vašíček (2014), and Burger and Warnock (2006) for the Asian and European markets; Eichengreen et al. (2008) empirical work in the Latin American markets; Adelegan and Radzewicz-Bak (2009) and Mu et al. (2013) for the African markets. These studies argue that the volatilities in the exchange rate and the fiscal characteristics typically hinder the development of both sovereign and corporate bond markets across most of the emerging economies. On the contrary, institutional, firm-specific, and structural characteristics, such as trade openness and bureaucratic qualities provide a positive nudge for the growth of both sovereign and corporate bond markets. In this context, the application of network approach to understand the contagion and risk sharing attributes of different markets is studied by Ahmed et al. (2018).

The literature on financial contagion, cascades of failures and systemic risk spans across markets and economies and appears to be emerging steadily in the recent past. It captures the imagination of researchers across disciplines including those primarily working in financial economics, mathematics and other computational domains, and engineering disciplines. Hence we present only a brief summary of some of the more closely related and recent research works.

The research on interconnectedness was pioneered by Allen and Gale (2000) who studied the stability in interconnected financial systems in a developed market. They propose a model in line with Diamond and Dybvig (1983), where a network structure has a single and completely connected component. This structure is always optimal. Such a network minimizes the extent of default. We show in our model the contrasting results. We find that a richer shock structure generates a genuine trade-off between the risk shared within the network and the contagion effect and that both segmentation and lower dispersion of connections may be optimal for the network.

Some more recent, related research on the issue are by Elliott et al. (2014), Diebold (2014) 3, Glasserman and Young (2015), Acemoglu et al. (2015), and Ahmed et al. (2018). The nature and form of the financial linkages among firms (and in some contexts, markets) examined in these works are seemingly different, as they consider both the asset side and the liability side of the firms' (country's) balance sheet. Such a framework, in turn, entails the presence of a mechanism that amplifies the shocks hitting a firm (a country), and subsequently spreading across the network in unique manners.

In a multi-firm context, literature suggests the presence of the trade-off between the risk distribution enabled by stronger interconnection and the increased exposure to cascades as an outcome of larger components in the financial network (Cabrales, Gottardi, and Vega-Redondo, 2013). Cabrales et al. (2013) study selected benchmark networks that are minimally interconnected and complete, to identify the best for different distributions of shocks.

Another unique approach that our work focuses on is related to the implementation of network formation in growth model framework and the related analysis. Elliott et al. (2014) characterizes conditions for the macroeconomic structure of the network under which the default cascades might occur. We, however, aim to characterize the optimal and dynamic structures of financial and economic networks in diverse scenarios and also investigate if the industry-context matter for the network to sustain the shocks. In an earlier examination, Shaffer (1994) too suggests a moderated relationship between risk spillovers and systemic failures of economies. Although entities hold diversified portfolios to reduce risk, they also face the risk of owning similar portfolios in the market and being in a system that might be susceptible to contemporaneous failures. Acemoglu et al. (2015) highlights the optimal structure of financial networks, but they focus on examining the shock distributions that are concentrated within a system for a given shock magnitude. More recent works, on the contrary, presents the properties of the curvature of the function of the risk exposure and the cumulative distribution of shocks (Cabrales et al., 2017). These more recent evidences with regard to the network formation among heterogeneous economic agents allow us to incorporate in our analysis a rich set of possible shock distributions. We can then show different ways of variations in an optimal financial structure, in response to the characteristics of those shock distributions. This also enables us to examine the dynamic properties of the networks over time and other inputs such as industry category. This uniqueness of our work is a significant contribution to the theoretical and empirical work on the issue.

Another line of the literature highlights how financial contagion and cascades of failures are affected by imperfect information about the shocks hitting the system. This is studied widely in econometrics and financial economics literature on information spill-over and market co-integration to certain extent. Some recent work, for example, Allen et al. (2012), studies the effects of the arrival of a signal on segmented and unsegmented structures of the network. These signals indicate that a firm in the system will have to default. This argument can further be extended to the networks of markets from different countries.

Finally, it is important to discuss the empirical and policy-oriented evidence that has been the main objective of bringing in the summary measures for the network connectedness. These measures are derived from the network of relationships among business entities (mostly financial firms) with the aim of predicting the probabilities of systemic failures. Some studies, for example propose different measures of centrality in networks (Battiston et al. (2012); Wang & Ng (2011); Denbee et al. (2011)). A significant contribution in this respect is the work by Elsinger, Lehar, and Summer (2006), who uses data from the Austrian market and show that a correlation in banks' asset portfolios can be considered as the main source of systemic risk.

3 Research Objectives

The above mentioned review of relevant research examining twin issues of the interconnectedness of heterogeneous economic agents and the contagion and cascades of failures across firms and markets, information and risk spill-over, and macro prudential regulations in the context of financial and economic entities such as firms and markets has brought out the following research issues to be examined:

- Since the theories emphasize that the economic entities such as firms and/or markets, whether homogeneous or heterogeneous, are interconnected to certain extent, how do these entities form networks? It would be of empirical interest to investigate how these entities connect to each other in terms of the directional spill-over of risks and cascades of failures.
- With a growth model framework, the network formation tends to evolve with change in underlying attribute(s), such as time, values, and so on. We propose to examine how industry specific inputs affect the formation of networks of economic entities. This would suggest the interconnectedness of economic entities at the micro-level where firm/market characteristic(s) becomes an important input to identify the potential risk in the network.

4 Methodology

Our aim is to study the cross holdings of entities in terms of input-output and look at a time varying feature to examine the changes in the network. We also hope to study the ripple effects caused due to the failure of entities inside the model. It is hypothesized that the ripple effects in the network should be caused once an identified entity(-ies) touches or crosses the threshold indicating the cascade of failures.

4.1 Data Source and Details

To measure the value of cross-holdings of different economic entities, our study focuses on tracking the flows of products across industries and countries. Our main measure is the the World Input-Output Database (WIOD). This data, available at the database website (http://www.wiod.org), which provides for the data on input-output for several countries, has been specifically constructed for studying the relationship among countries through trade flows (see Timmer et al. 2014, 2015; Wang & Ng, 2011; Dietzenbacher et al. 2013). The database also provides world input-output data for each year starting from 1995 of more than forty countries. The countries included in the database are all twenty seven countries of the European Union (as of January 1, 2007) and 15 other major countries, namely, China, Brazil, India, Australia, Canada, Mexico, Japan, Indonesia, Russia, Taiwan, Turkey, South Korea, and the USA. These 43 countries are economically significant in the world trade ecosystem as they represent more than 85 percent of world GDP. In addition, we also incorporate a model for the remaining non-covered part of the world economy. This model is designed such that the decomposition of final output is complete for value addition. This model captures thirty five industries spanning across the overall economy, including sectors such as, agriculture, utilities, construction, and mining, fourteen manufacturing industries, and seventeen services industries. Our sample dataset comprises the WIOT data for all years between 2000 and 2014 for all the 43 countries and industries available in the database.

4.2 Estimation Framework

Our framework proposes that there are n organizations (as economic agents such as, countries, financial firms, or other business entities) making up a set $N = 1, ..., n$, with $n = 43$. The values assigned to these sample organizations are ultimately based on the economic value of asset holdings or factors of production — henceforth, simply assets $M = 1, \ldots , m$. For consistency, an asset holding may be taken as a project that is expected to generate a series of cash flows over time. The present value (or the current market price) of asset k is denoted p_k. Further, let $D_{ik} \geq 0$ be the share of the value of asset k owned by an organization i that receives the cashflows and let $\mathbf{D}$ denote the matrix whose (i, k)th entry is equal to D_{ik}.

An organization can also hold shares (here we have an amount of debt held by one country from another country) of other organizations in the sample. For any $i, j \in N$ the number $C_{ij} \geq 0$ is the fraction of the organization j owned by the organization i, where $C_{ii} = 0$ for each i. The matrix $\mathbf{C}$ can be proposed to be a network with a directed link from i to j, if i holds a share of j with a positive value, so that $C_{ij} > 0$.

After we account for all these cross-holding shares across sample organizations, we are left with a share $\widetilde{C_{ii}} := 1 - \sum j \in N_i C_{ij}$ of organization i that is not owned by any organization in the system. This component of the share is assumed to be of positive value. Theoretially, this is the part that is held by outside shareholders of the organization i, and is external to the system of cross-holdings. The off-diagonal entries of the matrix $\widetilde{\mathbf{C}}$ are defined to be 0.

The equity or book value V_i of an organization i is the total value of its shares. The value is obtained by adding the value of the shares owned by other organizations and the shares owned by outside shareholders. This value equals to the value of organization i's asset holding plus the value of its claims on other organizations in the system:

$$V_i = \sum_k D_{ik} p_k + \sum_j V_j C_{ij} \tag{1}$$

In matrix notation the above equation can be written as

$$\mathbf{V} = \mathbf{Dp} + \mathbf{CV} \qquad or \qquad \mathbf{V} = (\mathbf{I} - \mathbf{C})^{-1}\mathbf{Dp} \tag{2}$$

As shown in both Brioschi, Buzzacchi, and Colombo (1989) and Fedenia, Hodder, and Triantis (1994), the market value reflects the external asset holdings. The final non-inflated economic value of an organization to the economy is well-captured by the equity value of that organization that is held by its outside investors. This economic value captures the flow of real assets that is expected to accrue to the ultimate investors of that organization. The market value, denoted by v_i, and equals to $C_{ii}V_i$, and therefore:

$$v = \widetilde{\mathbf{C}}V = \widetilde{\mathbf{C}}(\mathbf{I} - \mathbf{C})^{-1}\mathbf{Dp} = \mathbf{ADp} \tag{3}$$

where,

$$\mathbf{A} = \widetilde{\mathbf{C}}(\mathbf{I} - \mathbf{C})^{-1} \tag{4}$$

Here $\mathbf{A}$ is the *dependency* matrix. Suppose in our system, every organization holds the ownership of exactly one unique asset, so that $m = n$ and $\mathbf{D} = \mathbf{I}$. We further propose that A_{ij} describes the dependence of the value of the organization i upon the organization j's unique asset holding. It is then logical to propose that $\mathbf{A}$ is column-stochastic, so that the total economic values of all organizations supposedly adds up to the total economic values of all underlying assets - then for all $j \in N$, we have

$$\sum_{j \in N} A_{ij} = 1 \tag{5}$$

If the market value v_i of an organization i in the system, for any reason, drops below a threshold μ, then i is said to fail, in economic sense, and incurs failure costs $\beta_i(p)$. These failure costs are then subtracted from the cash flows received by the failing organization. In such scenario, these organizations can propose to push the diversion of cash flow to deal with the failure. They can also hope a decrease in the returns that the organization generates from the unique assets that they hold. Either way, the proposed approach introduces critical nonlinearities, or rather discontinuities, into the system of organizations.

We have calculated a *fractional ownership* matrix which represent the fraction of GDP produced by the country using its own resources and debt taken from other countries. Here GDP is the total output from all industries, where each industry might or might not have borrowed money from other countries. We have taken the base year as 2000. We have normalized the GDP values with the GDP of India.

So, if we consider all the diagonal elements of a *fractional matrix* as zero we get a $\mathbf{C}$ matrix and by forming a matrix with the diagonal elements of the *fractional matrix* gives a $\widetilde{\mathbf{C}}$ matrix (non-diagonal elements are filled with zeros). Using equation 4 we can calculate matrix $\mathbf{A}$.

We define parameter $\theta \in [0, 1]$, which is used to calculate the fractional decrease in GDP values of base year which can cause the country to fail, numerically threshold is defined as:

$$\Upsilon = \theta * (\mathbf{A}.\mathbf{p}_t) \tag{6}$$

Here p_t is the normalized GDP of base year (2000). So, if the normalized GDP of any country goes below this threshold we consider that country to be a failure. If any country fails we subtract 50% of the threshold value from its normalized GDP of the present year and repeat the process again until no country fails.

Mathematically steps can be visualized as:

1. $\mathbf{A} = \widetilde{\mathbf{C}}(\mathbf{I} - \mathbf{C})^{-1}$ (nXn matrix)
2. $\mathbf{p} = GDP$ (Normalised nX1 matrix)
3. $\mathbf{p}_t = GDP$ (Normalised base year (2000) nX1 matrix)
4. $\Upsilon = \theta * (\mathbf{A}.\mathbf{p}_t)$
5. If $\mathbf{A}.\mathbf{p} < \Upsilon$ (compared elementwise) follow step 6 else all countries are safe at that .
6. $p = p - \Upsilon/2$ (elementwise, subtract $\Upsilon/2$ only from countries which has failed)
7. Repeat step 5 until no country fails.

To get a qualitative idea of the accuracy of our network, we run the cascading model on the WIOT dataset from 2000 to 2014, and try to see if there are economic explanations for failure of the countries reported by the algorithm. Once the veracity of the algorithm is ascertained, we will look into simulating a large amount of trading and then repeatedly apply our failure model to find the most ideal trading scenarios for the least failures.

5 Preliminary Results

The WIOD dataset provides the input-output in current prices, and denoted in millions of dollars. The WIOD database covers twenty-eight countries from the European Union and fifteen other major countries (totaling to 43 countries) from across the world for the sample period from 2000 to 2014. The data is sorted industry-wise for 56 industries in total. For a preliminary analysis, we have condensed the data to only the inter-country input-output table. The interlink, with respect to trade, between the countries is given in the Fig. 2.

6 Discussions

Traditional approach to understand the way in which an economic agent's – an individual or a firm in particular and a market or an economy in general – behavior depends on what other economic agents do involves insights from cognitive and mathematical sciences, such as psychology and game theory among others. Researchers carry out controlled and non-controlled experiments to observe and analyse the reaction of economic agents as a response to shifts in behavior of other players. This mechanism explains the nature of interconnectedness of agents in a system where the agents are believed to be part of the network and hypothesized to be homogeneous. Recent research focuses on heterogeneity characteristic of these economic agents to understand the nature of interconnectedness in the network.

In finance, the interconnectedness becomes more significant as it helps understand the contagion of risk, the flow of information (that eventually explains the price discovery process and existence of arbitrage opportunities), and overall the ability of the system to absorb the shocks caused by one or more agents (Diebold (2014) 3). During the 2008 global financial crisis, several firms belonging to the finance industry

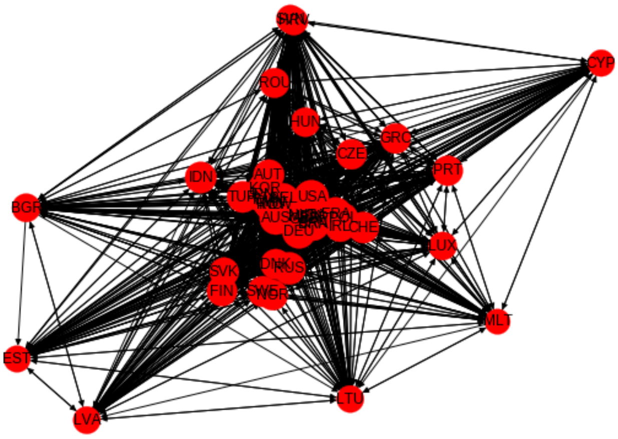

Figure 2: A representative network diagram of the sample countries based on the WIOT dataset for the year 2016.

across the globe were so deeply interconnected that one failure in one part of the world would result in tremors across several players in the industry. For example, the fall of Lehman Brothers caused few big finance firms to become susceptible to bankruptcy that led the government to swing into action and bailout many other financial institutions to save the entire economy (or, probably several economies around the world). In this context, examining the interconnectedness of the markets should explain the vulnerability of the system and pinpoint the weak nodes in networks so that regulators and governments among others take corrective actions well in time.

7 Concluding Remarks

Our research presents the evidence on the nature of interconnectedness that global markets exhibit in terms of their input-output representing the cross-holdings. It shows that the interdependence of some markets in a global network has strong correlation with not only the size of the markets, but also the direction of trades/cross-holdings, and the type of industries that dominate in their input-output data. With growth model estimation, we are able to project the cascades of failures in the network significantly. Our results as exhibited in the graphs corroborate with the empirical research on the failures of the markets. It is shown that markets having more connections with other markets in the network are likely to sustain the shocks and cascades of failures for longer time. This evidence is aligned with the argument of diversification as a strategy to mitigate risk. Our findings employ innovative approaches such as network formation approach and graph theory to explain the interconnectedness of markets across the world, and contribute significantly to the theoretical issues related to market integration and risk spill-over (Diebold (2014) 3; Cabrales et al., 2017 2; Ahmed et al., 2018 1).

Acknowledgement

The authors are grateful to the reviewers and the editor for their comments and suggestions. The financial support of Indian Institute of Technology Kharagpur through the Challenge Grant (CFH ICG 2017 SGSIS/2018-19/090) towards this research is hereby acknowledged. Usual disclaimers apply.

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8 Appendix

	2001
0.1	[[]]
0.775	[[]]
0.78	[[’TUR’] []]
0.785	[[’TUR’] []]
0.88	[[’TUR’] []]
0.885	[[’BRA’ ’TUR’] [’TWN’] [’JPN’] []]
0.89	[[’BRA’ ’JPN’ ’TUR’ ’TWN’] []]
0.91	[[’BRA’ ’JPN’ ’TUR’ ’TWN’] []]
0.915	[[’BRA’ ’JPN’ ’TUR’ ’TWN’] [’MLT’] []]
0.92	[[’BRA’ ’JPN’ ’TUR’ ’TWN’] [’KOR’ ’MLT’] []]
0.925	[[’BRA’ ’JPN’ ’TUR’ ’TWN’] [’KOR’ ’MLT’] []]
0.93	[[’BRA’ ’JPN’ ’TUR’ ’TWN’] [’KOR’ ’MLT’] []]
0.935	[[’BRA’ ’JPN’ ’KOR’ ’TUR’ ’TWN’] [’AUS’ ’MLT’] [’IDN’] []]
0.94	[[’BRA’ ’JPN’ ’KOR’ ’MLT’ ’TUR’ ’TWN’] [’AUS’ ’IDN’ ’SWE’] []]
0.945	[[’BRA’ ’JPN’ ’KOR’ ’MLT’ ’SWE’ ’TUR’ ’TWN’] [’AUS’ ’IDN’] []]
0.95	[[’BRA’ ’JPN’ ’KOR’ ’MLT’ ’SWE’ ’TUR’ ’TWN’] [’AUS’ ’IDN’] []]
0.955	[[’BRA’ ’JPN’ ’KOR’ ’MLT’ ’SWE’ ’TUR’ ’TWN’] [’AUS’ ’IDN’] [’ROW’] [’FIN’ ’LUX’] []]
0.96	[[’AUS’ ’BRA’ ’JPN’ ’KOR’ ’MLT’ ’SWE’ ’TUR’ ’TWN’] [’FIN’ ’IDN’ ’ROW’] [’CYP’ ’LUX’] []]
0.965	[[’AUS’ ’BRA’ ’JPN’ ’KOR’ ’MLT’ ’SWE’ ’TUR’ ’TWN’] [’FIN’ ’IDN’ ’ROW’] [’CYP’ ’LUX’] []]

Table 1: Name of countries failed at that threshold and the cascade impact in 2001

	2002
0.1	[[]]
0.95	[[]]
0.955	[[’JPN’] [’BRA’] []]
0.96	[[’BRA’ ’JPN’] []]
0.975	[[’BRA’ ’JPN’] []]
0.98	[[’BRA’ ’JPN’] [’ROW’] []]
0.985	[[’BRA’ ’JPN’] [’ROW’] [’TWN’] [’USA’] [’CAN’ ’MEX’] []]
0.99	[[’BRA’ ’JPN’] [’ROW’] [’TWN’ ’USA’] [’CAN’ ’MEX’] []]
0.995	[[’BRA’ ’JPN’ ’ROW’] [’CAN’ ’TWN’ ’USA’] [’MEX’] []]

Table 2: Name of countries failed at that threshold and the cascade impact in 2002

	2009
0.1	[[]]
0.725	[[]]
0.73	[[]]
0.735	[[’LTU’] []]
0.74	[[’LTU’] []]
0.745	[[’LTU’] []]
0.75	[[’LTU’ ’LVA’] []]
0.755	[[’LTU’ ’LVA’] []]
0.76	[[’LTU’ ’LVA’] [’EST’] []]
0.765	[[’EST’ ’LTU’ ’LVA’] []]
0.77	[[’EST’ ’LTU’ ’LVA’] []]
0.775	[[’EST’ ’LTU’ ’LVA’] []]
0.78	[[’EST’ ’LTU’ ’LVA’] []]
0.785	[[’EST’ ’LTU’ ’LVA’] []]
0.79	[[’EST’ ’LTU’ ’LVA’ ’POL’ ’RUS’] []]
0.795	[[’EST’ ’LTU’ ’LVA’ ’POL’ ’RUS’] [’HUN’] []]
0.8	[[’EST’ ’HUN’ ’LTU’ ’LVA’ ’MEX’ ’POL’ ’RUS’] []]
0.805	[[’EST’ ’HUN’ ’LTU’ ’LVA’ ’MEX’ ’POL’ ’RUS’] [’CZE’ ’SWE’] []]
0.81	[[’EST’ ’HUN’ ’LTU’ ’LVA’ ’MEX’ ’POL’ ’RUS’ ’SWE’] [’CZE’] [’SVK’] []]
0.815	[[’CZE’ ’EST’ ’HUN’ ’LTU’ ’LVA’ ’MEX’ ’POL’ ’RUS’ ’SWE’] [’FIN’ ’SVK’] []]
0.82	[[’CZE’ ’EST’ ’HUN’ ’LTU’ ’LVA’ ’MEX’ ’POL’ ’RUS’ ’SWE’] [’FIN’ ’SVK’ ’TUR’] [’ROU’ ’SVN’] []]
0.825	[[’CZE’ ’EST’ ’HUN’ ’LTU’ ’LVA’ ’MEX’ ’POL’ ’RUS’ ’SWE’] [’FIN’ ’ROU’ ’SVK’ ’SVN’ ’TUR’] [’ESP’] [’DNK’] [’NOR’] []]
0.83	[[’CZE’ ’ESP’ ’EST’ ’HUN’ ’LTU’ ’LVA’ ’MEX’ ’POL’ ’ROU’ ’RUS’ ’SWE’ ’TUR’] [’DNK’ ’FIN’ ’ITA’ ’NOR’ ’SVK’ ’SVN’] [’HRV’ ’IRL’ ’LUX’] [’GBR’] [’BEL’ ’DEU’] [’AUT’ ’BGR’ ’MLT’ ’PRT’] []]
0.835	[[’CZE’ ’ESP’ ’EST’ ’FIN’ ’HUN’ ’LTU’ ’LVA’ ’MEX’ ’POL’ ’ROU’ ’RUS’ ’SVN’ ’SWE’ ’TUR’] [’DNK’ ’HRV’ ’ITA’ ’NOR’ ’SVK’] [’BGR’ ’DEU’ ’GBR’ ’IRL’ ’LUX’] [’AUT’ ’BEL’ ’MLT’ ’PRT’] []]
0.84	[[’CZE’ ’ESP’ ’EST’ ’FIN’ ’HUN’ ’ITA’ ’LTU’ ’LVA’ ’MEX’ ’POL’ ’ROU’ ’RUS’ ’SVN’ ’SWE’ ’TUR’] [’BGR’ ’DEU’ ’DNK’ ’GBR’ ’HRV’ ’IRL’ ’LUX’ ’NOR’ ’PRT’ ’SVK’] [’AUT’ ’BEL’ ’MLT’ ’TWN’ ’USA’] [’CAN’ ’FRA’ ’NLD’] []]
0.845	[[’CZE’ ’ESP’ ’EST’ ’FIN’ ’HRV’ ’HUN’ ’ITA’ ’LTU’ ’LVA’ ’MEX’ ’POL’ ’ROU’ ’RUS’ ’SVK’ ’SVN’ ’SWE’ ’TUR’] [’BEL’ ’BGR’ ’DEU’ ’DNK’ ’GBR’ ’IRL’ ’LUX’ ’NOR’ ’PRT’ ’TWN’] [’AUT’ ’FRA’ ’MLT’ ’NLD’ ’USA’] [’CAN’] []]
0.85	[[’CZE’ ’DNK’ ’ESP’ ’EST’ ’FIN’ ’GBR’ ’HRV’ ’HUN’ ’IRL’ ’ITA’ ’LTU’ ’LUX’ ’LVA’ ’MEX’ ’NOR’ ’POL’ ’ROU’ ’RUS’ ’SVK’ ’SVN’ ’SWE’ ’TUR’] [’AUT’ ’BEL’ ’BGR’ ’DEU’ ’FRA’ ’MLT’ ’PRT’ ’TWN’ ’USA’] [’CAN’ ’NLD’] []]
0.855	[[’CZE’ ’DNK’ ’ESP’ ’EST’ ’FIN’ ’GBR’ ’HRV’ ’HUN’ ’IRL’ ’ITA’ ’LTU’ ’LUX’ ’LVA’ ’MEX’ ’NOR’ ’POL’ ’ROU’ ’RUS’ ’SVK’ ’SVN’ ’SWE’ ’TUR’ ’TWN’ ’USA’] [’AUT’ ’BEL’ ’BGR’ ’CAN’ ’DEU’ ’FRA’ ’MLT’ ’PRT’] [’KOR’ ’NLD’] []]
0.86	[[’BGR’ ’CZE’ ’DNK’ ’ESP’ ’EST’ ’FIN’ ’GBR’ ’HRV’ ’HUN’ ’IRL’ ’ITA’ ’LTU’ ’LUX’ ’LVA’ ’MEX’ ’NOR’ ’POL’ ’PRT’ ’ROU’ ’RUS’ ’SVK’ ’SVN’ ’SWE’ ’TUR’ ’TWN’ ’USA’] [’AUT’ ’BEL’ ’CAN’ ’DEU’ ’FRA’ ’KOR’ ’MLT’] [’CYP’ ’NLD’] []]
0.865	[[’BEL’ ’BGR’ ’CZE’ ’DEU’ ’DNK’ ’ESP’ ’EST’ ’FIN’ ’GBR’ ’HRV’ ’HUN’ ’IRL’ ’ITA’ ’LTU’ ’LUX’ ’LVA’ ’MEX’ ’NOR’ ’POL’ ’PRT’ ’ROU’ ’RUS’ ’SVK’ ’SVN’ ’SWE’ ’TUR’ ’TWN’ ’USA’] [’AUT’ ’CAN’ ’FRA’ ’KOR’ ’MLT’ ’NLD’] [’CHE’ ’CYP’] []]

Table 3: Name of countries failed at that threshold and the cascade impact in 2009

	2010
0.1	[[]]
0.93	[[]]
0.935	[['GRC' 'IRL'] []]
0.94	[['GRC' 'IRL'] []]
0.945	[['GRC' 'IRL'] []]
0.95	[['GRC' 'HRV' 'IRL'] []]
0.955	[['GRC' 'HRV' 'IRL'] ['CYP'] []]
0.96	[['GRC' 'HRV' 'IRL'] ['CYP'] []]
0.965	[['GRC' 'HRV' 'IRL'] ['CYP'] []]
0.97	[['GRC' 'HRV' 'IRL'] ['CYP' 'ESP'] []]
0.975	[['CYP' 'ESP' 'GRC' 'HRV' 'IRL'] ['BGR'] []]
0.98	[['CYP' 'ESP' 'GRC' 'HRV' 'IRL'] ['BGR'] []]
0.985	[['BGR' 'CYP' 'ESP' 'GRC' 'HRV' 'IRL'] []]
0.99	[['BGR' 'CYP' 'ESP' 'GRC' 'HRV' 'IRL'] ['PRT'] []]
0.995	[['BGR' 'CYP' 'ESP' 'GRC' 'HRV' 'IRL'] ['PRT'] []]
1	[['BGR' 'CYP' 'ESP' 'GRC' 'HRV' 'IRL'] ['PRT'] []]

Table 4: Name of countries failed at that threshold and the cascade impact in 2010

	2013
0.1	[[]]
0.85	[[]]
0.855	[['JPN'] []]
0.86	[['JPN'] []]
0.965	[['JPN'] []]
0.97	[['JPN'] ['AUS'] []]
0.975	[['JPN'] ['AUS'] []]
0.98	[['GRC' 'JPN'] ['AUS'] []]
0.985	[['AUS' 'GRC' 'JPN'] ['IDN'] []]
0.99	[['AUS' 'GRC' 'JPN'] ['IDN'] []]
0.995	[['AUS' 'GRC' 'JPN'] ['IDN'] ['TWN'] []]
1	[['AUS' 'GRC' 'IDN' 'JPN'] ['IND' 'TWN'] ['BRA'] []]

Table 5: Name of countries failed at that threshold and the cascade impact in 2013

	2014
0.1	[[]]
0.935	[[]]
0.94	[[]]
0.945	[['JPN'] []]
0.95	[['JPN'] ['AUS'] []]
0.955	[['JPN'] ['AUS'] []]
0.96	[['JPN'] ['AUS'] []]
0.965	[['AUS' 'CYP' 'JPN'] ['RUS'] []]
0.97	[['AUS' 'BRA' 'CYP' 'JPN'] ['RUS'] []]
0.975	[['AUS' 'BRA' 'CYP' 'JPN' 'RUS'] []]
0.98	[['AUS' 'BRA' 'CYP' 'JPN' 'RUS'] ['CAN' 'IDN'] ['TUR'] ['GRC'] []]
0.985	[['AUS' 'BRA' 'CAN' 'CYP' 'JPN' 'RUS'] ['GRC' 'IDN' 'TUR'] ['HRV' 'ITA' 'SWE'] ['AUT' 'EST' 'FIN' 'NLD' 'NOR' 'SVK'] ['BEL' 'CZE' 'DEU' 'DNK' 'FRA' 'LTU' 'LVA' 'MLT' 'SVN'] ['CHE' 'ESP' 'HUN' 'POL' 'PRT' 'ROU'] ['BGR' 'IRL'] ['LUX'] []]
0.99	[['AUS' 'BRA' 'CAN' 'CYP' 'GRC' 'JPN' 'RUS' 'TUR'] ['FIN' 'HRV' 'IDN' 'ITA' 'NOR' 'SWE'] ['AUT' 'CZE' 'DEU' 'DNK' 'EST' 'FRA' 'LTU' 'LVA' 'NLD' 'SVK' 'SVN'] ['BEL' 'CHE' 'ESP' 'HUN' 'MLT' 'POL' 'PRT' 'ROU' 'TWN'] ['BGR' 'IRL' 'LUX' 'ROW'] ['KOR' 'MEX'] []]
0.995	[['AUS' 'BRA' 'CAN' 'CYP' 'GRC' 'HRV' 'IDN' 'ITA' 'JPN' 'RUS' 'TUR'] ['AUT' 'CZE' 'DEU' 'FIN' 'FRA' 'NLD' 'NOR' 'SVK' 'SVN' 'SWE'] ['BEL' 'CHE' 'DNK' 'ESP' 'EST' 'HUN' 'LTU' 'LVA' 'MLT' 'POL' 'PRT' 'ROU' 'TWN'] ['BGR' 'IRL' 'LUX' 'ROW'] ['KOR' 'MEX'] ['GBR'] []]

Table 6: Name of countries failed at that threshold and the cascade impact in 2015