Macroeconomic and Financial Networks: Review of Some Recent Developments in Parametric and Non-parametric Approaches

Anindya S. Chakrabarti, Anirban Chakraborti, and Suryansh Upmanyu

1 Introduction

Networks are ubiquitous in the natural and social worlds. In social lives, networks of peers (friends, families, colleagues, and so on) influence the decisions that people make and are simultaneously impacted by the decisions made by people. As the world becomes more connected in the digital age, it becomes more and more likely that any decision-making entity will be impacted by the network it belongs to, and it has to gauge the impact of its decision on its neighbors in the network. Evidently, financial markets have become increasingly more complex and entangled with time. Economies have become more interdependent, both within and across countries, due to natural growth processes and globalization. Therefore, an interesting question to ask is "While it is correct that the nature of linkage across economic entities are granular, does it really impact the economic behavior in a substantial manner?" In other words, while the network description of an economy might be more realistic than the earlier homogeneous and representative single entity paradigm, does it provide any new insights into the working of the economy? In this review article, we would argue that indeed the network view goes beyond descriptive accuracy and provides a more complete and useful view of the economic mechanisms.

A. S. Chakrabarti (✉)
Indian Institute of Management, Ahmedabad, Gujarat, India
e-mail: anindyac@iima.ac.in

A. Chakraborti
School of Engineering and Technology, BML Munjal University, Gurugram, Haryana 122413, India
e-mail: anirban@jnu.ac.in

S. Upmanyu
School of Computational and Integrative Sciences, Jawaharlal Nehru University, New Delhi, India

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At the outset, we would like to mention that there are already some very well-written books and reviews on networks in economics. For example, [87, 97] provide applications of networks in the context of microeconomics; [1] reviewed macroeconomics and financial implications of networks. Textbooks on networks are abounded —for different treatments in the domains of economics and finance, interested readers can refer to [66, 86, 96] for a microeconomics-oriented description; [63] considers a more financial econometrics-oriented viewpoint. This list is merely indicative and by no means exhaustive. Though there has been substantial developments in different facets of economic networks, we could not find a single reference that brings both microeconomic and macroeconomic (and financial) networks in one place; this provided us the motivation for writing this review. However, this review should be seen more as a compendium than a stand-alone complete reference. We have also included in this review, some recent developments in the statistical physics literature that found applications in high-dimensional financial data. These are mostly non-parametric in nature, as opposed to more standard parametric economic and finance models. In our view, such non-parametric approaches provide useful and complementary methods of analyzing the underlying network structures.

Network description of a system is more computationally intensive than a representative agent description, owing to the heterogeneity displayed by the constituent parts. Even a couple of decades back, the computational burden was too much to gain reasonable magnification of an economic system into the nodes and linkages between them. A tremendous improvement in computational power in the last few decades and the need to develop more realistic models have contributed to the current state-of-the art knowledge in networks. Across all the topics that we will discuss below, a common thread that ties the significant developments due to this approach is the explicit modeling and analysis of “externalities” or “spillovers”. The outcome for a particular node may depend on multiple external factors other than its own decision. Using networks, we are able to analyze the effect of these external factors. It is important to note that the spillover effects might often be of second-order importance, whereas the aggregate dynamics of a system can potentially have first-order importance. As we will emphasize below, that in both macroeconomics and finance, the network architecture at the macro-level does influence the aggregate behavior of the economy as well.

The article is organized as follows: we start by discussing the recent literature on production networks in Sect. 2. Firms typically rely on other firms in the supply chain for inputs for the production process. These dependencies manifest themselves in the form of a production network, where firms across different industries are linked with each other (either directly or indirectly) as sellers or buyers of products that each firm produces. The study of production networks focuses on the role that these connections play in shock transmission across the network, i.e., it studies the impact of an exogenous shock to a particular firm on the rest of the firms in the network to which it is connected directly or indirectly. Next, we explore the connections between different countries in the form of international trade networks. With the advent of globalization, local industries have benefited due to the possibility of cheaper production technologies abroad. Similar to the field of production networks, international trade networks study linkages between economies through the sale and purchase of goods, although in different countries. An important question in this field studies the dynamics of link formations, i.e., how agents decide whether to form or remove a link with other agents. These decisions are taken in a cost-minimizing way and affect the efficiency of the equilibrium outcome and distribution of surplus among market participants.

Section 3 focuses on the propagation of risk through financial networks. Financial networks are formed when there is a transfer of funds (or assets) between agents, either due to a lack of funds for the borrower, or as a means of insurance against future uncertainty and risk. Ever since the 2007–08 financial crisis, there has been a rising interest in the study of the role of networks in transmitting shocks throughout the financial system. This strand of literature focuses on the reasons for the formation of different network structures, and the analysis of shock propagation through them. A complementary approach to study financial network focuses on inferring linkages based on time series properties of multiple financial assets.

In Sect. 4, we analyze social networks. Given the situation, a person may interact with others through different media, thus forming a social network. These kinds of networks can be seen all around us. We find information about our friends, and the friends of our friends, through online social media platforms like Facebook. Interaction with the people in our neighborhood leads to a transmission of information. We rely on our contacts, and online job portals, to search for new employment opportunities. All the above-mentioned situations explore the concept of different forms of social networks based on their use. As people become more connected with the rapid growth in technology, social networks emerge as powerful and useful tools, as a means of communication and information transmission. This section discusses the impacts of social networks on mechanisms including informal risk-sharing and information transmission across economic agents.

Next, we present some empirical work on networks in Sect. 5, where we discuss some recent developments in econometrics-based network approaches to networks, which are mostly parametric in nature. Finally, we end our discussions with non-parametric approaches to networks in Sect. 6.

2 Macroeconomic Networks

We discuss a benchmark model used in production networks, popularized by Ref. [3]. We then discuss a few extensions of this model, followed by the role of production networks in competition policy. For a discussion on recent empirical work on these topics, we refer the reader to Ref. [43].

2.1 Input–Output Networks

The baseline model is a variant of the model developed in Ref. [108]. Following Ref. [3], the model considers a static economy with n granular industries, each producing a distinct good. The production function for the ith industry is assumed to be a constant returns to scale Cobb–Douglas function:

$$y_i = z_i \tau_i h_i^{\alpha_i} \prod_{j=1}^{n} x_{ij}^{a_{ij}}, \tag{1}$$

where h_i denotes the amount of labor hired by industry i, x_{ij} is the quantity of good j used to produce good i, α_i gives the share of labor in industry i's production technology, $a_{ij} \geq 0$ is a measure of the importance of good j as an input for good i, z_i is a Hicks-neutral productivity shock, and τ_i is a normalization constant. Similarly, the economy consists of a representative household providing an inelastic supply of 1 unit of labor. The utility function of the representative household over the n goods produced by the industries is given by

$$u(c_1, \ldots, c_n) = \sum_{i=1}^{n} \beta_i log(c_i/\beta_i), \tag{2}$$

where c_i is the amount of good i consumed and β_i gives good i's share in the utility function of the household. In equilibrium, quantities, and prices are such that firms maximize their profits conditional on prices and wages, households maximize their utility, and all markets clear.

In this model, $\mathbf{A} = [a_{ij}]$ denotes the input–output matrix of this economy, where a_{ij} is defined above. The Domar Weight of an industry is given by the industry's sales as a fraction of GDP ($\lambda_i = p_i y_i / GDP$). Finally the Leontief Inverse of this economy is denoted by $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$. Given that the spectral radius of $\mathbf{A}$ is less than 1, an element of $\mathbf{L}$ - l_{ij}—shows the importance of industry j both as a direct supplier and an indirect supplier (as a supplier to i's supplier, and so on) to i.

After solving for equilibrium, Ref. [3] derived the following 2 results:

Theorem 1 *The log output of industry i (where i* $\in \{1, \ldots, n\}$*) is given by*

$$log(y_i) = \sum_{j=1}^{n} l_{ij} \epsilon_j + \delta_i, \tag{3}$$

where $\epsilon_j = log(z_j)$ *denotes a productivity shock to industry j, and* δ_i *is some constant which is independent of shocks.*

and

Theorem 2 *The real value added aggregated across the industries is given by*

$$log(GDP) = \sum_{i=1}^{n} \lambda_i \epsilon_i, \tag{4}$$

where

$$\lambda_i = \sum_{j=1}^{n} \beta_j l_{ji}. \tag{5}$$

These two theorems imply that shocks can transmit through input–output linkages across different industries. Since the matrix in consideration here is the Leontief inverse (which is dependent on the input–output matrix), it implies that along with direct effects, even the indirect effects of shocks matter across the network.

Another observation is that any shock to industry i will be propagated downstream to those industries which require i's good as an input in their own production. This effect is further propagated throughout the network. Theorem 2 also implies that the Domar Weights are a sufficient statistic for measuring how idiosyncratic shocks to different industries affect aggregate output. The downstream propagation of shocks from an industry to its customers (direct and indirect) means that the economy is more sensitive to shocks impacting industries which are important input suppliers.

2.1.1 Demand-Side Shocks

To incorporate demand-side shocks, Ref. [1] introduces government purchases for a good i as g_i, which is exogenously given. A change in government spending in this model is similar to an exogenous shock to the demand for the goods of individual industries. In this model, after solving for equilibrium output of each industry, we see that the impact of a productivity shock has an upstream effect, i.e., a shock to firm i propagates through the network by affecting i's suppliers, and further their suppliers and so on. This happens because if industry i is affected by a positive demand shock, it would increase i's input demand. This would generate a rise in demand for the products of i's suppliers, and so on.

2.2 Extensions

2.2.1 Relaxing the Cobb–Douglas Assumption

The baseline model assumes that production technologies of firms take a Cobb–Douglas form. This implies that the realization of shocks does not affect an industry's expense on inputs as a fraction of its sales. Some papers, like Refs. [21, 42] focus on nested CES production functions. They find that—up to a first-order approximation—

when elasticities of substitution are different from 1, there are 2 propagation channels for a productivity shock.

- A shock to industry i affects other industries through a downstream propagation of the shock.
- Productivity shocks can also lead to a reallocation of resources across industries which is affected by the elasticities of substitution between inputs.

2.2.2 Hulten's Theorem

Theorem 2 stated that Domar Weights are a sufficient statistic for how shocks to industries affect aggregate output. Hulten's theorem Ref. [95] makes a more general statement: In any efficient economy, the impact of a productivity shock to industry i (denoted by z_i) on aggregate output is equal to i's Domar weight, up to a first-order approximation. This can be written as

$$\frac{dlog(GDP)}{dlog(z_i)} = \lambda_i. \tag{6}$$

An important consequence of Hulten's theorem is that the effect on the economy of an idiosyncratic shock only depends on its size, and not on its location in the production network. References [41, 73] use this theorem to analyze the macroeconomic implications of idiosyncratic shocks to a production network. Generally, positive shocks to industry i would impact aggregate output in two ways. First, it leads to an outward shift of the production possibility frontier of the economy. Second, it may reallocate resources across different industries. If the original allocation is efficient, the aggregate effect due to the latter channel is second order and can be ignored in a first-order approximation. This would then imply that if economies are inefficient, then Hulten's theorem may not hold as the reallocation effect may be significant. Since Hulten's theorem focusses only on first-order approximations, if the focus is on second-order effects in a general economy, then it is seen that these second-order effects can be significant, and they depend on the structure of the network [22].

2.2.3 Frictions and Market Imperfections

The baseline model described previously assumes perfect competition. Reference [32] study the impact of productivity shocks by introducing exogenous wedges between marginal revenue and marginal cost of firms through markups. Their finding is that resource misallocation and its resulting inefficiency depends on the distribution of the firms' markups. Distortions are also studied by Ref. [23] in the form of CES production functions with exogenous wedges. They show that the first-order impact of productivity shocks in the network can be decomposed into two terms: (a) a term that accounts for the shocks' pure technology effect and (b) another term that accounts for changes in the economy's allocative efficiency. They also show that if we relax the assumption of Cobb–Douglas technology, the second effect could be substantial.

Reference [89] relaxes the perfect competition assumption, introducing oligopolistic markets in a model of production networks. In this model, shocks affect both prices and markups as the competitiveness of firms of the same industry changes in the network. Here, changes in market concentration lead to changes in the demand of industries for intermediate inputs, leading to an upstream transmission of shocks that would be absent if the markups were exogenously given.

2.2.4 Endogenous Production Networks

In the discussion above, the production networks were taken as exogenously given. One extension of the baseline model explicitly models the link formation decisions of the nodes/agents, thus making the network endogenous. Reference [14] develop a model using preferential attachment as the basis of link-creation between firms. Preferential attachment means that new edges in a network are more likely to be formed with nodes which already have more edges. Reference [44] modify the friendship model of Ref. [98] to form an industry-level network formation model. In this type of model, existing links between firms are used to search for new links to provide inputs for production. This model shows that a higher proximity in the network raises the likelihood that a firm will adopt another firm's product to use as an input in its own production.

Link formation incentives are introduced by Ref. [118] into a dynamic network formation model in which the set of suppliers to a firm keeps evolving and firms have to optimally choose one input from this randomly evolving set. Reference [2] consider an alternative model where firms in each industry select their input suppliers as a subset of other industries in the economy, knowing that each input combination would lead to a different CRS production technology.

2.3 Business Cycle from I-O Networks

We now discuss whether idiosyncratic shocks can build up in aggregate in the economy through the network structure. According to Lucas, the standard deviation of aggregate fluctuations is proportional to $\frac{1}{\sqrt{n}}$. This means that as the number of industries increases, idiosyncratic shocks get dissipated across the network, having a negligible effect on the economy. But as shown in Ref. [3], this argument breaks down if sectoral Domar weights show significant heterogeneity. These observations are also discussed in Ref. [73] through his granularity hypothesis, which states that in the presence of significant heterogeneity at the micro level, the grains of economic activity (comprised of firms or disaggregated industries) can matter for the behavior of macroeconomic aggregates. Specifically, he shows that even if there is a high level of disaggregation, aggregate volatility could be much larger than what Lucas hypothesized if the Domar weights have a heavy-tailed distribution.

Reference [3] then goes on to discuss that if the industries acting as input suppliers are sufficiently heterogeneous, they can generate very high levels of aggregate volatility, contrary to Lucas's hypothesis. This effect depends on the Leontief inverse and Bonacich centrality of the nodes of the production network. If the Bonacich centrality is high, it means that an industry is an important supplier to other central industries. Therefore, a shock to such an industry might not die down and could lead to substantial aggregate fluctuations in the economy.

Economies with heterogeneous production networks can show significant comovement as well. Reference [43] show that even if two economies have identical Domar weights distributions, the economy which is more interconnected will have a higher average pairwise correlation of output and it will be less volatile. This happens because the interconnected economy will have industries which are more diversified with respect to upstream risk from suppliers to other industries in the economy.

2.4 Policy Impact on Production Network

We now discuss the importance of considering production networks for analysis in competition policy [88]. For this, we define market power and explain how it is measured by competition authorities. A firm's market power denotes its ability to increase prices above marginal costs to raise its profits. The amount by which price can be raised over the marginal cost is referred to as a markup. As markups can be difficult to measure (since there is no reliable way to measure marginal costs), competition authorities work with concentration ratios instead to infer firms' market power. A popular way to measure concentration ratios is given by the Herfindahl–Hirschmann Index (HHI). This index is given as the sum of firms' squared market shares. To calculate HHI, only the sales data for different firms is required. Since this is readily available, the index is easy to calculate.

HHI is a good indicator of market power as it is directly proportional to Lerner's index (which is the difference in price and marginal cost of a firm, divided by the price). A higher level of concentration (denoted by a high value of HHI) would then imply a high Lerner's index, which implies that firms have the ability to increase the markup by a large margin. This can only happen if competition in the market is low, leading to some firms having significantly high market power. One specific use of HHI by competition agencies is to assess the chances of a merger being anti-competitive. For this exercise, the difference between pre-merger HHI and post-merger HHI is analyzed. If there is a significant increase in HHI, it would imply that the merger is anti-competitive, substantially increasing the market power for the newly formed firm. As discussed by Refs. [71, 112, 130], in Cournot competition (and some other market forms), such horizontal mergers can harm consumers by leading to a rise in prices and reduction in output.

Competition authorities do not usually consider the impact of a merger outside of the market where the merger takes place. Such partial equilibrium analysis could lead to an underestimation of the anti-competitive behavior of firms. This is where network analysis can play a role. Theory suggests that if a merger takes place, it would result in an increase in prices downstream because of a rise in input costs. Simultaneously, the reduction in competition in the particular market would lead to a reduction in quantities (in Cournot competition), which would imply a decrease in demand for inputs from upstream markets.

2.5 International Trade Networks

The discussion till now focused only on the linkages between industries located within the same economy. But in this era of globalization, profit-maximizing firms looking for cheaper production technologies also have the option of forming connections with industries located abroad. This leads to the formation of international trade networks. Here we discuss the model developed in Ref. [114]. This model has formed an important base for subsequent research in the field of international trade networks (some of which are discussed in Ref. [30]).

Consider an economy where firms show heterogeneity in terms of productivity and quality. These firms can buy inputs from multiple suppliers and sell the produced good either to consumers, or to other firms (as inputs). The production function for a firm i is

$$y_i = \kappa z_i l_i^{\alpha} \left(\left(\sum_{k \in S_i} (\phi_{ki} \nu_{ki})^{(\sigma-1)/\sigma} \right)^{\frac{\sigma}{(\sigma-1)}} \right)^{1-\alpha}, \tag{7}$$

where y_i is output, z_i is productivity, l_i is labor, α is the labor share, $\kappa > 0$ is a constant, ν_{ki} is the amount of inputs bought from the kth firm, and S_i is the set of firms supplying to the ith firm. Here, $\sigma > 1$ denotes the elasticity of substitution across i's suppliers. ϕ_{ki} is a measure of shift in demand that captures the idea that firms use different production technologies, affecting their demand from a particular firm. The input price index for a particular good is given by

$$P_i^{1-\sigma} = \sum_{k \in S_i} (p_{ki}/\phi_{ki})^{1-\sigma}, \tag{8}$$

where p_{ki} denotes the price that the kth supplier charges the ith firm for its product. A firm's marginal cost of production is defined as $c_i = \frac{w^{\alpha} P_i^{1-\alpha}}{z_i}$ where w denotes the wage rate. The sales of a firm are given by

$$s_i = \sum_{j \in C_i} \left(\frac{\phi_{ij}}{p_{ij}} \right)^{\sigma-1} P_j^{\sigma-1} M_j + F_i, \tag{9}$$

where M_j denotes the amount of intermediate purchases of firm j and F_i gives the amount of sales pertaining to final demand.

This model gives us two important observations. First, the marginal cost of firm i increases as the marginal costs of its suppliers increase, through P_i. This implies that a change in firm productivity (z_k) will affect marginal costs of all firms located downstream for which k acts as a direct or indirect supplier. Similarly, the set of suppliers S_i will also impact firms' production costs. Production costs are affected by international trade costs because they impact the set of suppliers, and they affect the cost of procuring from a supplier k through the price p_{ki}. Second, it is observed that the ith firm's sales s_i depend on two important factors: the set of customers C_i, and the amount which is sold to each customer (which depends on the price p_{ij} and the effective demand of the customer $(\phi_{ij} P_j)^{\sigma-1} M_j$). A change in trade costs can lead to a change in both these factors. For example, a rise in tariffs can either reduce a customer's demand or remove it from the set of customers entirely.

2.6 Matching in Trade Networks

2.6.1 Bipartite Networks

One section of the literature on international trade networks models buyer–seller relationships using bipartite graphs. For example, Ref. [31] use bipartite networks where one group of firms act as buyers (the set S_i for such firms is empty) and the other group acts as suppliers (for whom set C_i is empty). This model assumes full information for all agents, and costly link formation. As with the general theory on networks, this model also suggests that the distribution of customers per firm can be well approximated using a Pareto distribution.

This model shows a unique feature of negative degree assortativity. Low productivity suppliers are more likely to connect with high productivity buyers as only these buyers are able to incur the relatively high cost of linking with a low productivity seller. Similarly, high productivity sellers are more likely to connect with low productivity buyers. This also implies that high productivity firms are also highly connected.

In this model, high relationship-specific costs can lead to a reduction in welfare in the economy. These costs dampen trade flows and therefore reduce consumers' income. This happens because higher relation-specific costs make link formation more expensive and result in fewer links between firms. Even though having more suppliers is beneficial for each firm, these high production costs prevent them from doing so. This could reduce welfare if the firm is not able to optimally specialize in production due to a lack of suppliers. The resulting higher production costs would lead to an increase in consumer prices and subsequently reduced real wages for consumers. The introduction of tariffs also leads to adverse impacts on the economy. Tariffs increase the costs of procuring inputs from foreign suppliers and could lead to the breaking of links because of this rise in costs. Reference [28] relaxes the full information assumption by modeling costly information acquisition for firms. Therefore, an exporter engages in both production of a good, and search for consumers to link with.

2.6.2 Networks and Outsourcing

Another section of the literature aims at modeling the full production network. Reference [69] model such a network to analyze the impact of outsourcing. Here, a firm's production technology is such that its labor input and other intermediate inputs are perfectly substitutable for producing a good. Sellers meet potential buyers at random and buyers then optimally choose whether or not to outsource production. The probability of outsourcing is higher if own labor is costly (high wages) or foreign firms have low costs (due to better technology).

This paper assumes that labor is heterogeneous and consists of production and non-production workers, where only production workers can be outsourced. One observation is that trade liberalization increases the likelihood of goods getting outsourced. This is because if trade costs are reduced, it increases the probability of finding a good match abroad. It is then theoretically possible that trade liberalization can reduce real wages for production workers and increase real wages for non-production workers. This would happen since non-production workers would benefit from cheaper goods, whereas goods produced by production workers are likely to be outsourced due to liberalization. This paper suggests that the skill premium in the economy could be affected by the network structure.

Reference [118] relaxes the assumption that labor and inputs are perfect substitutes. Here firms meet possible matches randomly and decide whether to form a link with some other firm or not. Therefore, firms may not always get to match with the lowest cost supplier in the market. In equilibrium, it is seen that the distribution of customer firms asymptotically tends toward a power law distribution.

2.7 Dynamic Networks

2.7.1 Full Information

Reference [107] considers a model similar to the benchmark model presented above but extends it from a static to a dynamic setting. Using a Poisson process, firms are selected at random to decide the possible linking or dropping of matches in each period. Firms have rational expectations about the future and establish a link only if the relationship is profitable in the future. Therefore, a match may happen even if no profits are realized in the current period. Calibration of this model leads to very different shock propagation patterns compared to the static setting.

2.7.2 Search Frictions

Reference [48] develops a model where firms search for potential customers. This allows for a geographical dimension in the network model which is missing from Ref. [107]. As in the friendship model developed in Ref. [98], existing links can lower the cost of searching for new links for a firm. This implies that information flows faster through the network channels already established. Chaney's model then predicts that superstar firms will emerge in the economy, where few firms with already high number of connections grow ever larger.

Reference [68] deviate from the existing literature by allowing both sellers and buyers to search in the market. This paper models trade between producers (acting as exporters) and retailers (acting as importers), therefore allowing for many-to-many matching. In this model, the chances of a firm forming a link with a retailer are affected by multiple factors such as search intensity and the existing links of a firm. The latter feature of the model leads to the generation of fat-tailed in-degree and out-degree distributions.

2.7.3 Learning in Trade Networks

In Ref. [67], since perfect information is not available, exporters and importers engage in costly searching to form new links. Also, the firm can learn from its interaction with other firms. When a firm forms a link, it receives an imperfect signal about the attractiveness of its product in the market. The firm updates its belief about the potential of profits in a Bayesian manner, adjusting its search intensity accordingly. This implies that firms learn about their attractiveness over time. Popular firms are more likely to search more intensively, while less-popular firms will also search less.

Another type of information friction is present when firms cannot observe the productivity of a potential partner perfectly. This is analyzed in Ref. [115] where importers have the ability to learn about the reliability of potential supplier firms. Suppliers can either shirk or comply. The importer cannot directly determine the type of the supplier as contract enforcement forces myopic firms to comply with an exogenous probability. In every period after the link is formed, the importer observes a noisy signal about whether the supplier exerts effort or not. If it does, then it increases the likelihood that the supplier is reliable. If the exporter shirks, then the relationship is terminated.

There are two important observations of this model. First, the volume of trade conducted by a buyer and seller pair increases with time, since expected costs decrease as the buyer becomes more assured about the reliability of the supplier. Therefore lower prices lead to more sales and rise in intermediate input demand. Second, the likelihood of the survival of a relationship improves with time since unreliable suppliers reveal themselves early in the relationship. An important observation of this model is that learning leads to significantly higher aggregate trade than a scenario where learning does not take place.

3 Systemic Risk and Contagion in Financial Systems

In this section, we will start with a discussion of the "robust yet fragile" property commonly shown by financial networks. This will be followed by a brief explanation of the different sources of systemic risk, followed by a description of some popular measures to quantify this risk. Finally, we will discuss the increasingly important role of macroprudential stress testing for the stability of the financial network system.

3.1 Robust-Yet-Fragile Properties

We consider a simple model developed in Ref. [76] where a financial network consists of n banks forming links randomly through unsecured lending and borrowing activities. In the network, every node represents a particular bank, and each edge in the network denotes the bilateral unsecured interbank exposures between two banks. This network consists of directed edges, signifying that both lending and borrowing activities take place between banks. In the model, a bank i has j_i interbank lending links and k_i interbank borrowing links. The connectivity between the banks is given by the average degree of the interbank network which is denoted by z.

The balance sheet of a typical bank in the network looks as follows. The total assets of a particular bank i are given by its unsecured interbank assets, IA_i, and illiquid external assets, EA_i. It is assumed that a bank's total amount of interbank assets are spread evenly across its lending links.

Every interbank asset of bank i would be a liability for some other bank j. Therefore, unsecured interbank liabilities of bank i, IL_i, will be endogenously determined within the network. Each bank also has other liabilities given by exogenous customer deposits, EL_i. For each bank i in the network, the solvency condition is given by

$$(1-\phi)IA_i + EA_i - IL_i - EL_i > 0, \tag{10}$$

where ϕ denotes the fraction of banks which have taken loans from bank i but have defaulted. There is an implicit zero recovery assumption, which implies that if a counterparty defaults, all the assets of bank i held by that counterparty are lost and bank i is unable to recover anything. The solvency condition above could be simplified as $\phi < K_i/IA_i$, where $K_i = IA_i + EA_i - IL_i - EL_i$ gives us the capital buffer of bank i.

Now assume that all banks are identical. This would imply that $j_i = k_i = z$ for all banks. If some counterparty to bank i goes into default, then $\phi = i/z$ as i's assets are uniformly distributed among its counterparties. Contagion would spread beyond the first bank if another neighboring bank exists for which $z < IA/K$. This model also highlights the situations when systemic default can take place. If capital ratios are low or unsecured interbank lending is high, then it is more likely that systemic default occurs. The above equation then suggests that there exists a tipping point in the network. If the above equation is satisfied and z is sufficiently large, then an individual bank's default could induce all the other banks in the network to subsequently default as well. On the other hand, if the above condition is violated, then it implies that the bank's default has no systemic implications.

Reference [75] simulate the model with the assumption that links in the network are distributed uniformly, where the probability that a link exists between two banks is independently given by the probability p (a Poisson network). Their aim is to analyze the impact of the failure of a bank on the whole network. They specifically study (i) the probability of contagion across the network and (ii) the proportion of the network which is impacted by contagion, given different values of z (which gives the average connectivity of the network). Simulation results show that an increase in connectivity z does not have a monotonic effect on the likelihood that system-wide contagion will occur in the interbank network, since benefits of sharing risk eventually dominate the cost of risk-spreading. But even though the probability of contagion reduces as z increases, its impact is felt throughout the network. Therefore, the system exhibits a robust-yet-fragile tendency.

3.2 Sources of Contagion

3.2.1 Default Contagion

The line of work focusing on default contagion was first explored by Refs. [10, 70, 145]. Default contagion is described as follows. An exogenous shock to bank i's asset value could reduce its net worth and reduce its ability to repay its lenders. If the shock is large enough, it could lead to a default by bank i. If the loss due to bank i's default is large enough, it could lead to bank i's lenders defaulting as well, and so on. Recent work was accelerated after the emergence of the 2008 financial crisis [4, 74, 75, 111].

3.2.2 Distress Contagion

One stream of work explores distress contagion, where financial distress can spread even though an actual default by a borrower may not take place [24, 137]. This could happen if the market value of bank i declines due to a reduction in its net worth, even though it remains solvent. Even if a default does not happen, this could lead to a loss for bank j if the value of i's obligation to j is "marked to market".

3.2.3 Common Asset Contagion

Another line of work explores common asset contagion and fire sales. Banks can be connected indirectly if they have investments in the same assets. If a shock leads to change in asset prices, a bank might sell a significant amount of this asset so that its price falls significantly. If this asset was held by other banks too, they would be affected by the secondary shock (due to the sale of asset) as well, causing them to sell the asset. This would trigger a devaluation spiral [40, 59, 100].

3.2.4 Funding Liquidity Contagion

Contagion could also spread from the liability side. Institutions may be affected adversely if creditors start hoarding liquidity [6, 72, 74, 77]. This could lead to a funding run if a liquidity shock occurs unexpectedly, as in Ref. [58].

3.3 Systemic Risk: Measurements and Impact

3.3.1 MES and SES

Suppose there are N financial firms in the economy. Let r_{it} denote the return on firm i's equity in time period t. Therefore, we can calculate market return or index return as the weighted average of the asset returns across all the individual firms, $r_{mt} = \sum_{i=1}^{N} w_{it} r_{it}$. Here, the weight w_{it} assigned to each return series signifies the value of relative market capitalization of the ith firm. MES is calculated as each individual firm's marginal contribution to systemic risk, which in turn is evaluated by the system's expected shortfall, ES. This measure was introduced in Ref. [7].

Given the available information till time $t-1$, the ES in time period t is calculated as

$$ES_{mt}(C) = E_{t-1}(r_{mt} | r_{mt} < C) = \sum_{i=1}^{N} w_{it} E_{t-1}(r_{it} | r_{mt} < C), \tag{11}$$

where C is some threshold value (Ref. [7] takes $C = -VaR_\alpha$, where VaR_α is defined as the largest amount that an institution loses with confidence $1-\alpha$, that is, $P(r_{it} < -VaR_\alpha) = \alpha$). The MES is then given by calculating the partial derivative of the system's ES with respect to firm i's relative market capitalization in the economy [131]:

$$MES_{it}(C) = \frac{\partial ES_{mt}(C)}{w_{it}} = E_{t-1}(r_{it} | r_{mt} < C). \tag{12}$$

Intuitively, MES is a measure of the increase in risk due to an infinitesimal change in the relative market capitalization of the ith firm. The SES modifies this measure and signifies the level by which the equity of a bank can drop below a particular threshold (which is given as k, a fraction of the bank's assets) during a crisis, conditional on aggregate capital being less than k times the value of aggregate assets:

$$\frac{SES_{it}}{W_{it}} = kL_{it} - 1 - E_{t-1}\left(r_{it}|\sum_{i=1}^{N} W_{it} < k\sum_{i=1}^{N} A_{it}\right). \tag{13}$$

Here A_{it} gives the total assets of firm i in time t, W_{it} denotes the market value of firm i's equity, and L_{it} gives a measure of the firm's leverage, which is equal to A_{it}/W_{it}.

3.3.2 SRISK

$SRISK$ was introduced in Refs. [5, 39]. It extends the MES to allow for the consideration of a financial firm's size and liabilities. $SRISK$ is defined as a firm's expected shortfall in capital, when the entire system is affected by a crisis. When a firm has a larger capital shortfall, it has a higher likelihood of contributing to a financial crisis. Therefore, such a firm is systemically riskier. $SRISK$ is calculated as

$$SRISK_{it} = max\,[0, k(D_{it} + (1 - LRMES_{it})W_{it}) - (1 - LRMES_{it})W_{it}], \tag{14}$$

where k denotes the prudential capital ratio, $LRMES$ is defined as the long-run MES and the book value of aggregate liabilities is denoted by D_{it}. Intuitively, $LRMES$ provides us a measure of the expected future drop in a firm's equity value, conditional on the market falling below a specific threshold within a given time period (taken as 6 months here). Substituting $L_{it} = (D_{it} + W_{it})/W_{it}$, the above expression can be modified as:

$$SRISK_{it} = max\,[0, [kL_{it} - 1 + (1 - k)LRMES_{it}]W_{it}]. \tag{15}$$

3.3.3 CoVaR

$CoVaR$ is a systemic risk measure given by Ref. [8]. Let $CoVaR_{it}^{m|C(r_{it})}$ be a term related to the value at risk (VaR) of the realized market return, conditional on the observation of some event for firm i (denoted by $C(r_{it})$):

$$P(r_{mt} \leq CoVaR_{it}^{m|C(r_{it})}|C(r_{it}) = \alpha. \tag{16}$$

$CoVaR$ for the ith firm is then calculated as the difference of two terms: (i) the VaR of the entire system when the ith firm is in financial distress, and (ii) the VaR of the system when firm i is at the median state. Here, we can define distress in multiple ways depending on the definition of $C(r_{it})$. Reference [8] assumes that the loss is equal to its VaR and subsequently uses a quantile regression approach to analyze this situation:

$$CoVaR_{it}(\alpha) = CoVaR_{it}^{m|r_{it}=VaR_{it}(\alpha)} - CoVaR_{it}^{m|r_{it}=Median(r_{it})}. \tag{17}$$

3.3.4 Debtrank

Reference [25] developed a measure called DebtRank to find systemically important financial institutions. Debtrank is similar to PageRank by Google, and it is an eigenvector centrality measure which can be used to assess the influence of a bank on the interbank network as a whole. Suppose a bank i is connected to other highly connected banks in the network, then bank i would have a higher centrality. Therefore, a bank would have a higher DebtRank value when it is connected to other banks which have high values of DebtRank themselves.

3.4 Macroprudential Stress Testing

Central banks around the world regularly conduct stress tests aiming to measure the robustness of financial firms (e.g., banks) to adverse shocks. But it is also necessary to analyze the impact of network contagion as well in potentially amplifying systemic risk. As mentioned before, evidence suggests that most of the observed interbank networks show a core-periphery structure [51, 54, 106]. Such network structures showcase the robust-yet-fragile tendency described before.

Reference [70] describe a model which—under certain assumptions- proves the existence of a unique clearing vector after at least one bank in the network defaults. A particular assumption of the EisenbergNoe model is the absence of deadweight losses after a bank defaults. This leads to the clearing mechanism redistributing existing assets among the surviving banks with the aim of maximizing payments. Reference [127] relax this assumption, allowing for default costs after the failure of banks. Their model leads to multiple clearing vectors which includes a Pareto-dominant clearing vector. This clearing vector is found by allowing banks to fail one by one till there is only a single solvent bank remaining.

Reference [76] states that most of the models used for macroprudential stress testing mainly focus on post-default contagion. Recent developments in this literature show extensions where other sources of risk are also considered. For example, Ref. [99] study liquidity risk and contagion, focusing on the cash-flow constraint of banks. Reference [52] explore the theory of fire sales. In their model, portfolios are constrained by leverage or capital considerations, resulting in shocks to asset values leading to a rapid sale of the asset. The fire sale that follows leads to further deleveraging. Reference [53] attempt to analyze counterparty credit risk, liquidity hoarding, and fire sales in the same framework.

An important question for stress testing in the future could be to analyze the impact of contagion, not just on financial networks, but on the real economy as well. During the 2008 financial crisis, a debt overhang and reduction in credit supply led to both a rise in unemployment and a significant decrease in GDP growth rates. Reference [88] explore input–output networks as an alternative channel for shock propagation throughout the economy.

4 Social Networks

In this section, we first discuss the applications of social networks in labor markets, specifically focusing on job referrals by individuals for employment opportunities. We then explore different network models of information flows among people. The last part of this section focuses on the importance of social networks in the domain of informal risk sharing. For a detailed discussion on labor markets and social networks, see Ref. [140]. For information flows and risk sharing, see Ref. [37].

4.1 Labor Markets and Referrals

Job seekers frequently rely on their social networks to obtain information on possible employment prospects and recommend them for job opportunities, either formally or informally. Here, we discuss the role that social networks play for recommendations (or referrals) in the labor market. The literature presents various types of models to analyze referrals. The model of *asymmetric information* (analyzed by Refs. [45, 116]) argues that referrals reduce the information asymmetry between the candidate and employer about the candidate's quality. A person tends to have like-minded people in his network, so it is likely that high-quality workers will provide referrals for people who are themselves highly skilled. This would act as a signal for a prospective employer to gauge the quality of a candidate. Moreover, since the referrer's reputation is also at stake, he would only refer good quality candidates.

The model of *symmetric uncertainty* suggests that both the employer and job-candidate are uncertain about their match. Therefore, referrals can provide better information to both parties compared to other employment channels. This model is explored in Refs. [65, 78, 135]. According to this theory, employers would be more willing to provide referred hires with a higher wage subject on getting hired (since referrals would provide a better indication of the candidate's quality). Additionally, as match quality becomes apparent over time, referred hires would have lower separation rates than non-referred hires.

Another set of models discussed in Refs. [90, 101] focuses on the *moral hazard* aspect of referrals. The moral hazard interpretation explains that employers may not be able to monitor a newly hired worker properly. In this case, the referrer can act as a monitor, since the performance of the new worker affects his reputation as well. This allows the employer to motivate better performance from the worker. Empirical work on referrals studies the impact of this hiring channel on hiring probabilities, wages, and employee performance, compared to other hiring channels. References [93, 94] study the employee side of the market and find that hiring probabilities are higher when candidates use personal contacts rather than using other formal hiring channels. Similarly, using data obtained from employers' referral systems, Ref. [38] find that even though only 6 percent candidates use referrals, they make up 30 percent of all eventual hires in the dataset analyzed. References [26, 91, 92, 132] find that referrals lead to a greater likelihood of getting high wages compared to other hiring channels. References [38, 65, 92] state that candidates coming through the referral channel also tend to stay longer at their jobs. This would imply that referrals are associated with lower turnover rates. There is also some heterogeneity of referral effects. Referrals are more likely to be used by the younger demographic, ethnic and racial minorities, and individuals with lower socio-economic status. But this does not imply that the probability of getting hired for these groups is high as well. A study by Ref. [93] observes that conditional on usage of referrals, probability of getting hired is higher for whites than for blacks. Reference [27] find a similar result when comparing women to men.

The impact of business cycles on social networks is still largely unexplored. Local labor market conditions depend on business cycles, subsequently affecting the formation of social networks and their use in providing referrals. The change in composition of employed and unemployed contacts in an individual's network at different phases of a business cycle would impact the individual's decisions about the people he forms links with and the use of his network for different job prospects. Papers which have started addressing these questions include the works of Refs. [78, 80, 82, 105]. The study of social networks has been greatly hindered by a lack of good quality data. This has changed in recent years with the availability of social media and professional networking data. Recent studies like Refs. [15, 83] use data from Facebook to study the impact of social networks in decisions related to housing investment and employment prospects respectively. References [20, 110] utilize data obtained from online search portals to analyze employment prospects of workers. The use of referrals to improve a person's employment outcomes leads to a role for government policy as well. Even though referrals lead to many benefits, for both job candidates and employers, they also have some disadvantages. Referrals can lead to rising inequalities between different socio-economic groups as people tend to refer like-minded individuals. Reference [38] find significant evidence for assortative matching between referrers and referred individuals based on race, gender, and education in their dataset. This suggests a role for government intervention.

4.2 Information Flows

Information transmission is an important aspect of many programs, whether it is the marketing of a new product by a consumer brand, or a policy intervention by the local government. An important question in information transmission is the selection of groups (or specifically, individuals) to be targeted (or seeded) so that the program has maximum impact. Reference [29] observe that if peer farmers are provided incentives to transfer information regarding a new technology, the technology's adoption is 10–14 percent greater relative to a control group. Similarly, Ref. [12] provide evidence of higher adoption of a new product or trend if viral campaigns are used.

This implies that whether the use of networks can improve information transmission is important and has relevance in multiple areas. Networks can potentially provide huge benefits, but they incur a cost as well. Identifying whether networks do provide substantial advantage over traditional information transmission channels, and the subsequent identification of individuals (or seeds) can be an expensive and time-consuming process. Reference [18] show that a microfinance scheme's adoption depends heavily on the initial individuals chosen as seeds. Reference [9] find a similar result for the transfer of messages in the environment of an online social network.

We now consider different models which are used to study information transmission in networks. In a *viral process*, an informed individual (infected node) in a network transmits information to all the nodes it is connected to. This form of transmission is deterministic and irreversible and is called diffusion. This is a fairly simple model and thus, may not be of much use in explaining real-world phenomena. In *aggregation models*, the object of study is the change in intensity of beliefs as information spreads through a social network. The DeGroot model (used by Ref. [56]) is one such aggregation model. In this model, everyone receives signals at the initial stage. In subsequent stages, communication takes place among individuals and their beliefs are updated by averaging their and their neighbors' beliefs. This goes on until a steady state is reached where beliefs are not changed further and everyone reaches a consensus. One important fact about this model is that the consensus in the steady state is a weighted average of initial opinions, where the weights are given by the eigenvector centrality of each individual (Ref. [84]). In other words, a person is influential if he is connected to other influential individuals, and such a person would have a large impact on the final consensus which is reached.

The DeGroot model analyzes the speed of convergence toward a consensus in a given social network. Reference [85] discuss that networks showing homophily show a very slow rate of convergence. In such networks, people similar to each other reach a consensus within themselves first, and only then start moving toward a group consensus. References [17, 113] document this type of behavior when networks consist of different castes, religions and ethnicities. This model also provides an insight on good candidates to select as seeds. If a policymaker can persuade individuals to spread the correct information and he cares about the speed of transmission, then individuals with higher eigenvector centrality would be better candidates to act as seeds.

Reference [16] generalizes the DeGroot model to merge both diffusion and aggregation. Initially, the chosen seeds transmit information to inactive neighbors through the diffusion process. In each subsequent period, this process continues as active nodes spread information to their inactive neighbors. Simultaneously, the process of aggregation takes place in each period as individuals update their beliefs as in the DeGroot model. Therefore, this model leads to the existence of domains of influence, where an individual is influenced more by seeds which are closer to him (in a network sense).

Other models also discuss the role of strategic interactions in the process of information transmission. Reference [129] explores the presence of strategic complementarities in networks. These can accelerate diffusion. For example, a person who hears about Whatsapp for the first time is more likely to use it if he knows that his friends and relatives use it as well. Reference [79] study strategic substitutes, where adoption is less likely if more people in one's network are adopting.

4.3 Risk Sharing

In communities where formal insurance is not prevalent, the role of social networks is important to reduce risk through informal insurance channels. This is seen in multiple countries, as documented in References [19, 50, 128], among others.

Informal insurance allows risk-averse individuals with uncertain future incomes to opt for state-contingent monetary transfers which leads to a Pareto improvement. In the benchmark model [147], individuals are uncertain about their future incomes, there is perfect information about individuals' characteristics, and all agents can commit to contracts. In this case, the equilibrium consumption is distributed with the aim of maximizing expected utilitarian welfare along with Pareto weights to account for the heterogeneity among people. Therefore, this model fully insures agents against all diversifiable risks.

One extension of the benchmark model focuses on understanding how a given risk-sharing network is formed. If maintaining links between agents entails a social cost, then the efficient network is one which satisfies full risk sharing and in which every individual forms connections in a cost-minimizing way. It is possible that the equilibrium network is different from the efficient one. The equilibrium network is said to be stable [96] if no agent wants to deviate from the existing network by removing one of his links. Reference [36] give an alternate definition of stability by requiring that no pair of agents should profit by creating a link between themselves. Stable networks are usually smaller than the efficient network as individual agents do not consider the positive externality of a better diversification of risk in the network when they form links.

Another possible network structure is the bargaining model studied in Ref. [11]. In this model, agents with existing links can renegotiate between themselves by threatening to break the connection if their demands are not met. In case the connection is broken, it would have a significant adverse impact on the agent who is less well connected in the network, thus reducing his risk-sharing prospects. Therefore well-connected individuals are in a better position to negotiate and get a higher surplus. This implies that individuals tend to over-invest in the formation of links, to allow for better prospects of renegotiation with others. As costs of link formation increase, the star network is the only stable network structure left, where one central individual is connected to all other individuals, and no other link is present. Therefore high costs would imply high inequality in relationship patterns as well.

A different extension of the benchmark model relaxes the commitment assumption and looks at limited commitment risk sharing. Reference [33] study such a model, where the network is given exogenously. In this model the same network structure is used for risk sharing as well as the transmission of information about the deviation of agents. They find that the stability of the network first decreases, and then increases with the density of the network. In sparse networks, deviation is less likely as agents have few connections, so the breaking of a link leaves less opportunities for a person to undertake risk sharing. On the other hand, there are ample risk-sharing opportunities in dense networks, but information about deviations travels fast as well, leading to reduced incentives for an agent to deviate.

5 Econometric Modeling of Networks

In this section, we discuss the framework described in Ref. [63], a method developed by Diebold and Yilmaz in a series of articles to study the interdependence between multivariate time series.

5.1 Variance Decomposition and Connectedness Measures

The Diebold–Yilmaz (DY) approach tries to measure volatility spillovers in the economy given by the impact of an idiosyncratic shock to a firm on the rest of the firms. The main question that this framework seeks to answer is this: *How much of an entity i's future uncertainty at horizon H can be explained by shocks arising with entity j?* The foundation of this approach lies in the concept of Variance Decomposition. Given a Vector Autoregression (VAR) model, the variance decomposition matrix measures the proportion of forecast error variance explained by idiosyncratic shocks to other variables.

Formally, suppose we define an N-variable p lag VAR model as

$$x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \epsilon_t, \tag{18}$$

where $\epsilon_t \sim (0, \Sigma)$. The equivalent moving average representation of this model is given by $x_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i}$. It is assumed that the matrices satisfy the recursive relationship: $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_p A_{i-p}$, where A_0 is an identity matrix.

In general, the shocks to entities in the economy can be correlated. To account for the correlation while calculating the Variance Decomposition matrix, the DY approach discusses two methods which allow us to work with correlated shocks. Reference [61] uses Cholesky Factorization to orthogonalize the shocks. One particular disadvantage of this approach is that it may give different results if the ordering of variables changes. To deal with this issue, later papers use the Generalized Variance Decomposition (GVD) framework for orthogonalization. This approach accounts for correlated shocks, assuming that the shocks follow a normal distribution. The GVD approach is described as follows: Suppose an element in the ith row and jth column of the Variance Decomposition matrix is given by $\theta^g_{ij}(H)$, where H specifies the horizon for which the forecast is made. Following the GVD approach, the Variance Decomposition matrix is given by

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj^{-1}} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_j)}, H = 1, 2, \ldots \tag{19}$$

where Σ denotes the covariance matrix of ϵ, the standard deviation of the disturbance in the jth equation is given by σ_{jj}, and e_i is a vector of zeros with a one in the ith entry.

Usually, $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$. So each entry is normalized by the row sum to determine pairwise directional connectedness from firm j to firm i:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}. \tag{20}$$

Let $\tilde{\theta}_{ij}^{g}(H)$ be written as $C_{i \leftarrow j}^{H}$. Then we say that $C_{i \leftarrow j}^{H}$ gives us the *pairwise directional connectedness* from firm j to firm i. Additionally, the value $C_{ij}^{H} = C_{i \leftarrow j}^{H} - C_{j \leftarrow i}^{H}$ gives us the *net* pairwise directional connectedness between i and j. Henceforth, we call the Variance Decomposition matrix as the Connectedness matrix. The Connectedness matrix allows us to answer other relevant questions as well. Suppose we wanted to know the impact of exogenous shocks to other firms on firm i's forecast error variance. This can be calculated from the Connectedness matrix by adding all non-diagonal entries in the ith row of the matrix, which gives us the *Total directional connectedness* to firm i from all other firms j

$$C_{i \leftarrow \cdot}^{H} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N}. \tag{21}$$

On the other hand, if we wanted to calculate the impact of an exogenous shock on i to other firms in the economy, we can take the sum of all non-diagonal entries in the ith column of the Connectedness matrix. This gives us the *Total directional connectedness* from firm i to all other firms j:

$$C_{\cdot \leftarrow i}^{H} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N}. \tag{22}$$

As before, *net* Total directional connectedness is given by $C_i^H = C_{i \leftarrow \cdot}^{H} - C_{\cdot \leftarrow i}^{H}$. Finally, the *Total Connectedness* can be calculated as

$$C^{H} = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N}. \tag{23}$$

Total Connectedness can be calculated as the ratio of the sum of the non-diagonal entries of the connectedness matrix to the sum of all the entries of the matrix. The Variance Decomposition matrix is a useful tool to analyze the impact of shocks on the entities in an economy. It allows us to measure not only the impact of an entity's own shock, but also the spillover from a shock affecting some other entity in the economy. Similarly, the Variance Decomposition matrix also helps us to estimate the transmission of shocks between a firm and the rest of the economy as whole. Moreover, it gives us the degree of connectedness in the economy, which can be very useful for policymakers.

5.1.1 Variance Decomposition Matrices as Networks

The Connectedness Matrix is a network adjacency matrix with some modifications. First, the elements of the Connectedness matrix are not restricted to 0 or 1, but instead can take any value between these 2 numbers. This implies that the links are *weighted*, i.e., they show the strength of the bonds between two entities. Secondly, the matrix is *directed*. Lastly, the entries of the Connectedness matrix are *dynamic*, so that they may change over time. The observation that the Connectedness matrix can be defined as a network means that the total directional connectedness measures are equivalent to node in-degree and out-degree. Similarly, total connectedness is given by the mean degree of the network.

5.2 *Empirical Results*

In this section we will discuss a few recent applications of the Diebold–Yilmaz approach. For each application, we will state the dataset used, explain the methodology and then discuss the important results.

5.2.1 Global Bank Networks

Reference [57] uses data for 96 banks across 29 countries provided by Thomson–Reuters for the period September 12, 2003–February 7, 2014. These banks are among the world's largest 150 banks (by assets) which were publicly traded during the given time period. These banks include all the "globally systemically important banks" which were publicly traded in this time period.

To measure volatility from returns, daily range-based realized volatility is calculated using the data on stock returns. Using the methodology introduced by Ref. [81], this is measured as

$$\begin{aligned}\hat{\sigma}_{it}^2 =& 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) \\ & - 2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2,\end{aligned} \tag{24}$$

where H_{it}, L_{it}, O_{it} and C_{it} are the log values of daily high, low, opening, and closing prices for bank stock i on day t. The high dimensionality of global bank networks can lead to difficulties in estimating the connectedness in these networks. To mitigate this problem, the paper uses LASSO methods [138] which allows for both shrinkage and selection of variables, thus reducing the dimensionality of the problem. Formally, a penalized estimation problem is given as

$$\hat{\beta} = \arg\min_{\beta} \left[\sum_{t=1}^{T} \left(y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} |\beta_i|^q \right]. \tag{25}$$

This problem puts a penalty on the calculated β, depending on the value of q. For LASSO methods, $q = 1$, which leads to both selection and shrinkage of parameters. This paper uses a variant of the LASSO, called the adaptive elastic net [148]. This method has the "oracle property", which means that the generated model is consistent for the best KullbackLiebler approximation to the true data generating process. It is given as

$$\hat{\beta}_{AENet} = \arg\min_{\beta} \left[\sum_{t=1}^{T} \left(y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} w_i \left(\frac{1}{2}|\beta_i| + \frac{1}{2}\beta_i^2 \right) \right], \tag{26}$$

where $w_i = 1/|\hat{\beta}_{i,OLS}|$ and λ is selected using tenfold cross validation. The weights allow the shrinking of the smallest OLS coefficients toward 0. The paper then proceeds as follows. The adaptive elastic net method is used to estimate the VAR model for log volatilities at horizon $H = 10$. This provides us with the Variance Decomposition matrix through which the different connectedness measures are calculated.

We first discuss the full sample static analysis. The main result is that the network graph shows strong clusters within and across countries. This is an important observation as it is not entirely obvious that location (rather than other factors like bank size) would be a dominant factor in the formation of the network. Another important observation from the Connectedness matrix is that North America and Europe are net transmitters of future volatility uncertainty. Moreover, looking at the country bank network (where each node denotes a particular country), it is seen that USA is highly connected, with links showing a strong connection from USA to Canada, Australia, and UK.

For dynamic analysis, the paper uses rolling estimation, analyzing the data for a 150-day window at a time. Analyzing the impact of the collapse of Lehman Brothers on the US banks, we see a sharp increase in the connectedness of these banks with others. This could explain the global spread of volatility, leading to a crisis worldwide. A similar observation is seen for the European Debt Crisis in 2011. Taking the static analysis network as a benchmark, the network for October 7, 2011 shows a marked difference. This network is much more tightly clustered, indicating a rise in volatility connectedness compared to the full sample benchmark.

The paper then discusses system-wide connectedness. First, we decompose the connectedness measures into its trend and cyclical variation. The cycles show a sharp increase in connectedness during the 2008 Recession and 2011 European Debt Crisis. The trend line first increases, hitting its peak during the Lehman bankruptcy, and then decreases, although at a slower rate. Alternatively, decomposing the connectedness measures into cross-country and within-country variation, it is observed that cross-country variation dominates the movements in system-wide connectedness. The authors also try to observe the relation between bank size and eigenvector centrality. Using a rank regression, it is seen that bank eigenvector centrality is highly correlated with bank size. But this relation weakens during the 2008 financial crisis and 2011 European debt crisis. This implies that during bad times, smaller banks can become central to the network, leading to idiosyncratic volatilities generating system-wide fluctuations.

5.2.2 Equity Volatility Network

Reference [64] uses stock return data for 35 major financial institutions for the time period January 2004–June 2014. 17 financial institutions are from USA and include 7 commercial banks, 2 investment banks, and 1 credit card company. The other institutions are those which were either acquired, went bankrupt, or were taken in government custody after the 2008 Financial Crisis. Commercial banks located in Europe form the rest of the sample. First, the full sample analysis shows the formation of 2 clusters based on whether the banks are located in USA or Europe. This means that location has an important role to play in volatility transmissions between banks. At the national level, the highest pairwise connectedness is observed between USA and UK, probably because these countries are home to the London Stock Exchange and the New York Stock Exchange. Comparing net connectedness measures, Belgium has the highest negative net connectedness, while France and USA have the highest positive net connectedness.

For dynamic analysis, a 200-day rolling sample was used for estimating connectedness measures. Plotting the values for total connectedness over the given time period, we see sharp increases in connectedness during the 2008 Financial Crisis and 2011 European Debt Crisis. The most important result of this paper is based on Total Directional Connectedness. Before Lehman Brothers collapsed, US financial institutions were net transmitters of volatility to European financial institutions. After a full-blown global crisis emerged due to the collapse of Lehman Brothers, net connectedness from USA to Europe declined. Finally, net connectedness from US to Europe went below zero as the European Debt Crisis intensified. The paper further analyses connectedness at the country and institution level, specifically comparing volatility transmissions to and from nodes at different periods of time.

5.2.3 Commodity Network

Reference [60] studies 19 different sub-indices provided by the Bloomberg Commodity Price Index. These sub-indices are for the following commodities: precious metals (silver, gold), livestock commodities (lean hogs, live cattle), energy (natural gas, heating oil, unleaded gasoline, crude oil), grains (soybeans, wheat, soybean oil, corn), industrial metals (nickel, copper, zinc, aluminum) and "softs" (sugar, cotton, coffee). Data is collected daily (except for weekends and holidays) from May 11, 2006 to January 25, 2016. Ordering the commodities from largest to smallest (first according to to-degrees and then according to from-degrees), it is observed that the rankings are almost similar, implying that the commodities transmitting significant volatility to others also receive significant volatility from others. The network itself shows low system-wide connectedness, but clusters are formed according to the traditional industry groupings. These clusters show high within-group connectedness. At the industry level, industrial metals, energy, and precious metals are close together, and energy has a high value of total directional connectedness to the other groupings in the network.

A dynamic analysis of connectedness measures is also conducted using a rolling window of 150 days. It is observed that commodity return volatilities have a lower connectedness compared to global stock market returns, global bank returns, and bond yield volatilities. There is a sharp rise in total connectedness during the 2008 Financial Crisis. This also led to a fall in commodity prices till 2009. Post—2009, connectedness dropped as markets recovered. It is also seen that system-wide connectedness was heavily affected by oil price volatility. This volatility was largely due to demand and supply shocks over the world. The paper also analyzes the total directional connectedness of each commodity over the specified time period. It is again confirmed that energy commodities (especially oil) are major transmitters of volatilities to others.

5.2.4 Global Business Cycle Network

Reference [62] studies business cycle connectedness using monthly seasonally—adjusted industrial production (IP) for G-7 countries excluding Canada. the time period for which data is considered is January 1958–December 2011. Firstly, the data is tested for any possible cointegration. Testing for unit roots using augmented Dickey–Fuller tests, there was no evidence against the unit root in any log IP series, and substantial evidence against the unit root in every differenced log IP series. To test for cointegration status, Johansen's maximum eigenvalue and trace tests are conducted. These show the possibility of at most one cointegrating relationship among the IP series. Therefore, a vector error-correction (VEC) model is used for approximation purposes.

Calculating the connectedness measures from the VEC model, the total connectedness is found to be 29.1 percent. Japan and USA are found to be the largest net transmitters of industrial production shocks. Similarly, Italy and Germany are the largest recipients of business cycle shocks. Using 5-year rolling windows to analyze dynamic connectedness, the paper shows that almost all US recessions were related to an increase in connectedness. The same is observed for recessions in Germany, France, Japan, and Italy ending in 1993–94. Late 1980s onwards, the rise of globalization led to an increase in connectivity among all countries. This also led to the upward movement of the band within which the connectedness index fluctuates. During this period, each subsequent cycle was longer and had a larger bandwidth than the previous one, showing that the business cycles have become more synchronized due to globalization. This behavior culminated with a sharp rise in connectedness during the 2008 Financial Crisis. Finally, it is shown that trade balance can be used to determine if a country is a net transmitter or receiver of business cycle volatility. If a country has a trade surplus, then it would have a tendency to be a net receiver of shocks. On the other hand, countries with trade deficits are more likely to be net transmitters.

5.3 Ripples on Financial Networks

Reference [102] analyzes the impact a volatility shock may have across a financial network by providing an algorithm characterizing ripples on financial networks. In the discussion below, we briefly discuss the algorithm. The paper uses data for the largest $N = 100$ stocks based on market capitalization at the New York Stock Exchange over the time period 2002–2017. The stocks were selected so that data was available for them throughout the given time period. The paper divides this period into four equal length intervals—2002–05, 2006–09, 2010–13, and 2014–17. During the first window, the US economy was experiencing a boom, the second window was marked by the 2008 financial crisis, the third period contains the phase of recovery after the crash, and the fourth period was marked by a period of relative stability.

The paper then constructs the return series using the first difference of log price series for each stock. To construct the conditional volatility series from returns, the paper uses the GARCH framework. The paper then aims to construct the maximally connected component of the network. Using the adaptive Lasso technique developed by Ref. [148], the maximally connected component is constructed by removing those stocks for which in-degree and out-degree is less than 10 percent. Hierarchical networks are then constructed using sample correlation matrices calculated using return and volatility series. Since correlations can be negative, distance matrices are calculated instead using the metric $d_{ij} = \sqrt{2(1 - \rho_{ij}}$ discussed by Ref. [109], where ρ denotes the correlation between firms i and j. Minimal Spanning Trees are filtered out from the network to provide maximum information from a minimal sized network. Using eigenvector centrality as an exogeneity criterion over the return correlation matrix, the stocks are ordered so that Cholesky decomposition can be used to derive orthogonalized impulse response functions from a VAR model for the volatility series. These impulse response functions are then used to study shocks across the network.

This approach is different from the Diebold–Yilmaz approach where they use Generalized Variance Decomposition (GVD) instead. Since GVD requires the assumption of normality, it could be a strong and incorrect assumption in many settings. Therefore, this paper gives an alternative approach to analyze spillovers.

6 Non-parametric Approaches

Finally, we briefly summarize findings from some recent works on non-parametric approaches to economic and financial networks that have mainly originated from the "econophysics" literature [35, 47, 109, 136].

6.1 Correlation-Based Networks

In order to gain insight about the co-movements among price returns in a stock market, correlation-based networks are constructed from the empirical correlation matrix. Such networks provide a visual representation of the co-movements as well as information about the underlying market dynamics [126]. By continuously monitoring the structure of the correlation-based network, one can find different patterns that appear time and again, and reveal the underlying trends in the system. Multiple methods have been proposed to construct networks [13, 142–144] from the empirical correlation matrices, such as the minimum spanning tree [34, 46, 103, 117, 119–122, 139], planar maximally filtered graph [141], threshold network [49], etc.

To initiate the discussion, below we describe the network construction algorithm and a standard filtering method. Readers are requested to consult [123] for a very nice detailed exposition of this methodology. Consider N number of daily return series being constructed from N asset prices for T days: $r_{it} = \log(p_{it}) - \log p_{i,t-1}$ for the ith series where $i = 1, \ldots, N$ and tth day where $t = 1, \ldots, T$. From these N number of return series, one can construct a correlation matrix of size $N \times N$ that we denote by $\Sigma_{N\times N}$ where σ_{ij} is the correlation coefficient between assets i and j. One can conduct an eigendecomposition of this typically large-dimensional matrix to analyze the corresponding eigenspectra:

$$\Sigma = \sum_{i=1}^{N} \lambda_i e_i e_i', \tag{27}$$

where λ_i denotes the ith eigenvalue and e_i is the corresponding eigenvector (e_i' is the transpose of e_i). Then the correlation matrix can be decomposed into three parts:

$$\Sigma = \Sigma^{market} + \Sigma^{group} + \Sigma^{random}, \tag{28}$$

where the *market* mode corresponds to the top eigenvalue, *group* mode corresponds to all deviating eigenvalues except the top one, and the *random* mode corresponds to the remaining eigenvalues. A natural question arises as to how to find the *deviating* eigenvalues? The method popularized by [126] is to apply Marcenko–Pastur distribution to decide the cut-off. Essentially, all eigenvalues above the cut-off given by Marchenko–Pastur distribution are statistically significant and can be taken as *deviating eigenvalues*. In practice, the top eigenvalue seems to capture the market dynamics quite well, and the ones in the *group* mode seems to represent sectoral dynamics [123]. However, some recent work shows that one needs to look further deep into the core-periphery structure of the implied networks for sectoral dynamics [104].

An important consideration in computational finance is the time period over which the computation of empirical cross-correlation matrix takes place. In general, incorrect choices of time periods could lead to non-stationarity issues or too much noise in the correlation matrices. Reference [124] applies random matrix theory in financial markets to address this problem. Random matrix theory is used to analyze the eigenvalues derived from random matrices, and had its original application in nuclear physics. Pharasi et al. [124] use the power mapping method where short epoch correlation matrices are subjected to non-linear distortions. Following the literature [126], this paper also conducts an eigenvalue decomposition of the empirical cross-correlation matrix. Resultant modes can be classified as the market mode, group mode, and random mode; the bulk of the eigenvalues constitute the random modes and is described by a Marcenko–Pastur distribution. In another paper, Pharasi et al. [125] utilized random matrix theory to find correlation patterns that may emerge during times of crisis vis-a-vis relatively stable periods. They attempted to categorize different "market states" and to find evidence for long-term precursors to the market crashes (see also, [104]).

While most research on network properties typically focus on individual networks in isolation from the rest of the world, there are many large-scale networks which show interdependence [55, 146]. In [146], the authors analyzed the foreign exchange and stock market networks for 48 countries based on complex Hilbert principal component analysis to quantify lead-lag relationships across the markets. They also constructed a coupled synchronization network to identify the formation of stable network communities.

6.2 Mesoscopic Networks

This paper [134] analyzes the economy at the mesoscopic (sectoral) level. An important finding of this paper is that the core of the return networks mainly consists of sectors of the economy which are relatively large. On the other hand, the periphery of such networks mostly consists of sectors which are relatively smaller in size. This observation hints at a connection between sector-level nominal return dynamics and the real size effect. Data for sectoral price indices collected for 65 sectors across

27 countries is analyzed over the time periods: Jan. 08–Dec. 09, Oct. 12–Sept. 13, and Oct. 14–Sept. 16. Data for the real variables (such as number of employees in each sector, revenue , and market capitalization) are available at the company level. Therefore, these are aggregated to get sectoral level data.

Return series is constructed using the first difference of log price series for each sector. The return series is first used to calculate the pairwise Pearson correlation coefficients which are then used to construct the distance matrix using the transformation $d_{ij} = \sqrt{2(1 - \rho_{ij})}$, where ρ denotes the correlation between firms i and j. Clustering algorithms of Multi-Dimensional Scaling (MDS) and Minimum Spanning Tree (MST) are used to study the network structure in all the countries considered in the sample. Both methods indicate that the network is in the form of a core-periphery structure.

This paper shows that the structure of the network derived from the return correlation matrix has a robust relationship with the measures of sectoral size. For this exercise, the eigenvector centrality is regressed on sized, where size is defined by either market capitalization, revenue, or employment, aggregated across all firms within a sector. On analyzing the results from twenty-seven countries, there is an indication that the variation in the dispersion of sectoral centralities in the sectoral return a correlation matrix can be explained by the dispersion in economic size.

6.3 *Multi-layered Economic and Financial Networks*

Reference [133] studies the empirical connections between financial networks and macroeconomic networks using the concept of multi-layered networks. This paper finds that the different network structures considered here take the form of a core-periphery structure, where the core consists of similar countries in each network. The paper also shows that if a country has high trade connectivity, it is more likely to have higher financial return correlations as well.

Moreover, the paper shows that the Economic Complexity Index is positively related to the equity markets. To reveal the dynamics and structure of the global market indices, the paper studies minimum spanning tree. It is observed that geographical proximity is an important factor in determining the correlation structure across different markets.

7 Concluding Remarks

In this article, we have reviewed a number of different approaches to describe, analyze, and study economic and financial networks. Future developments in the digital economy will usher in further interconnectedness in our existing economic system, leading to creative destructions and disruptions in the economic and financial networks along with new forms of networks being formed. Probably, theory of networks is going to take the center stage in economic analysis in such a world.

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