The Empirics of Macroeconomic Networks: A Critical Review

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Abstract This chapter critically surveys the recent empirical literature applying complex-network techniques to the study of macroeconomic dynamics. We focus on three important macroeconomic networks: international trade, finance and migration/mobility. We discuss both the empirical evidence on the topological properties of these networks and econometric works that identify the impact of network properties on macroeconomic dynamics. Results indicate that a detailed knowledge of macroeconomic networks is necessary to better understand the dynamics of country income, growth and productivity, as well as the diffusion of crises.

Keywords Complex networks • Diffusion of economic shocks • International finance • International migration • International trade • Macroeconomic networks

1 Introduction

In the last two decades, the empirical and theoretical research on economic networks has boomed.[1] Economists have indeed become increasingly aware that the dynamics of economic systems may be strongly influenced by the patterns of interactions among their constituent units (e.g., firms, consumers, institutions, industries, countries). Understanding how the structure of social and economic interactions is shaped and evolves across time, and how it affects—and it is influenced by—economic dynamics, becomes therefore crucial in order to describe, predict and control fundamental economic phenomena such as, among others, country growth, economic development, and the diffusion of global crises.

[1] See Schweitzer et al. (2009), De Martí and Zenou (2009), Jackson (2010), Easley and Kleinberg (2010), and Jackson and Zenou (2015).

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Using an admittedly coarse-grained criterion, existing studies addressing from a complex-network perspective the study of economic and social interactions can be classified in three main classes: (1) micro; (2) meso; and (3) macro. Micro studies address economic networks where nodes (i.e. vertices in the graph) are microeconomic agents, such as firms, banks, financial institutions and consumers.[2] Links in microeconomic networks may represent, depending on the context, buying/selling or borrowing/lending relationships, knowledge and information exchanges, and so on. Meso-economic networks deal instead with interactions among economic entities (nodes) located in-between the micro and the macro layer of the economy. These can be products, technologies and industries (Hidalgo et al. 2007; Acemoglu et al. 2012), connected by links assessing, e.g., their technological similarity or their input-output relations, both within countries and at the level of global value chains (Cerina et al. 2015).

Macroeconomic networks—the topic of this chapter—focus instead on interactions among world countries, which play the role of nodes in the graph. Links in macro-networks describe the ways in which world countries may interact. These range from international trade, financial/banking relations, and foreign direct investment (i.e. mergers and acquisitions or green-field investment) all the way to permanent cross-border human migration and temporary international mobility.[3]

The starting point of this literature is that the study of macroeconomic linkages from a complex-network perspective is important to understand macroeconomic dynamics. For example, macroeconomic linkages may be responsible in transmitting internationally economic fluctuations and other types of shocks occurring at the country level (Galvão et al. 2007). In presence of non-linear transmission mechanisms, understanding the topology of these interaction structure becomes crucial to predict how a shock hitting a certain country may be amplified and diffused to other regions of the world economy. Furthermore, the position of a country in the macroeconomic network at a certain point in time may impact the trajectories of its subsequent growth and development. For instance, the relative centrality and embeddedness of a country in the network of international financial relationships may act either as a shield against (or an amplifier of) shocks transmitted from other countries, thus influencing its subsequent economic performance.

In this chapter we shall critically survey some of the recent literature on macroeconomic networks. In particular, we will focus on three classes of bilateral international linkages, i.e. trade, finance and human migration/mobility. We will organize the discussion in such a way to answer two main questions, namely: (1) How do macroeconomic networks look like? (2) Can we employ the knowledge of the topology of macroeconomic networks to better understand and predict

[2]Cf., among others, May et al. (2008), Guerrero and Axtell (2013), and Saito et al. (2007).

[3]A parallel line of research, which we will not discuss here, has explored infrastructure networks connecting world countries, which facilitate how people and goods move across space and borders (e.g., air, cargo and maritime transportation networks; cf. Barrat et al. 2004; Hua and Zhu 2009; Kaluza et al. 2011; Woolley-Meza et al. 2011).

macroeconomic dynamics? In other words, we are not only interested in empirically characterizing the shape of macroeconomic networks, but also to use this information as predictor for the behavior of world countries in the macroeconomy.

This rest of this chapter is organized as follows. Section 2 sets the stage and formally defines macroeconomic networks using complex-network concepts. In Sect. 3, we discuss the existing empirical evidence on the structure of macroeconomic networks. Section 4 presents some examples dealing with the impact of network structure on macroeconomic dynamics. Finally, Sect. 5 concludes and sketches out some topics for future research.

2 Macroeconomic Networks

Macroeconomic networks are graph-based descriptions of bilateral linkages among pairs of world countries. More formally, at any given point in time t (e.g., a year), consider the graph where nodes are the elements of the set $C^t = \{1, 2, \ldots, N^t\}$ of world countries[4] and links between any pair of countries (i,j), $i,j \in C^t$, and $i \neq j$, represent an existing "type of interaction" between them (e.g., international trade, finance, migration/mobility). Links may be directed if one can in principle differentiate between the effect of i on j and that of j on i; and weighted if directed or undirected links may be associated to their intensity. In the most general terms, a macroeconomic network for a given interaction type ι is defined as a sequence of network snapshots:

$$MN(\iota)^t = \{C^t, W(\iota)^t\}, \quad t = 1, \ldots, T \tag{1}$$

where $W(\iota)^t$ is a weighted, possibly asymmetric, $N^t \times N^t$ matrix fully representing the structure of weighted (directed) links in place among world countries at time t for the interaction type ι, and T is the number of time periods which we have information about.[5]

This chapter mainly discusses three interaction types, which we will shortly describe in the following sections.

[4] Of course, the number of world countries to be considered in the analysis at time t may depend not only on those actually existing at t but also on data availability at that period of time.

[5] Due to data availability, misreporting and the presence of zero flows, C^t may also depend, in principle, on the type of interaction ι. In what follows, we will focus on cases when one restricts the analysis on the minimal set of countries present in all interaction layers, so that $C^t(\iota) = C^t$.

2.1 The International-Trade Network

In the second half of the last century, the volume and value generated by the exchange of goods and services across international borders (aka international trade) have boomed. During the "second wave of globalization"[6] the share of world trade to GDP has more than doubled, increasing from 25 to 60 %.[7] Such a spectacular trend has been achieved not only *intensively* (i.e., through increases of trade flows between countries already trading in the past), but also *extensively* (i.e., via newly created trade relationships). Indeed, according to the estimates in Felbermayr and Kohler (2006), about 40 % of world trade growth after 1950 came from newly-established bilateral trading relationships.

This process has generated an intricate web of trade linkages, which currently connects the great majority of world countries, channels a huge economic value, and facilitates cross-border technological diffusion (Keller 2004) and global human mobility (Egger et al. 2012). It is therefore of a paramount importance to understand its structure, as well as its socio-economic, political and geographical determinants.

Research addressing the properties of international trade from a complex-network perspective has flourished in the last years (Fagiolo et al. 2009).[8]

The object of analysis is the International-Trade Network (ITN), aka World Trade Web (WTW) or World Trade Network (WTN), which is the graph representation of bilateral trade flows among world countries across the years. In its simplest form, the ITN is binary and undirected, that is a link represent the existence of a positive trade relationship (import and/or export) between any two countries. Differentiating between the existence of import vs export relationships makes the graph directed. If any existing (directed or undirected) link is associated to the (deflated) value expressed in a common currency (e.g., USD) the ITN becomes a weighted graph. In the directed case, it is customary to weight each directed link with the value of exports (or imports). If the graph is undirected, links between countries (i, j) may typically represent total trade (i.e. the sum of imports and exports).

Data to study how the ITN is shaped and evolves are easily available, both at the aggregate level and at the commodity-specific one.[9] This chapter mostly deals with

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[6] By "second wave of globalization" we mean the period from 1945 onwards, as opposed to the "first wave of globalization" (1800–1914). The two waves are separated by a slump in international trade occurred between the two world Wars (Baldwin and Martin 1999).

[7] World Development Indicators Online (WDI) database, see http://data.worldbank.org/data-catalog/world-development-indicators.

[8] Quantitative approaches to the study of trade in terms of networks have been pioneered in sociology and political sciences. For instance, the seminal paper by Snyder and Kick (1979) triggered a fruitful literature mostly aimed at testing some flavor of "world system" or "dependency" theories using social-network analysis techniques, see e.g. Nemeth and Smith (1985), Sacks et al. (2001), Breiger (1981), Smith and White (1992), Kim and Shin (2002) and Mahutga (2006), and the discussion in Fagiolo et al. (2010).

[9] See for example COMTRADE (comtrade.un.org), the BACI dataset at CEPII (cepii.fr) or data on trade in goods and services at UNCTAD (unctadstat.unctad.org). Additional data are available

aggregate representations of the ITN, i.e. where linkages describe aggregate export and import flows. However, data allow one to construct as many interaction layers of the network as data on trade about specific commodities become available. This permits to correlate the properties of different product-specific layers of the ITN to understand potential complementarities and substitutability (Barigozzi et al. 2010; Dalin et al. 2012; D'Odorico et al. 2014). We will also focus on approaches that do not discriminate between trade for goods and trade for services. Indeed, as discussed in De Benedictis et al. (2014), service trade is still poorly analyzed from a complex-network perspective, mostly because of a lack of reliable data that cover a large number of countries for a sufficiently long period of time.[10] Finally, due to space constraints, we will not be able to properly account for the vast literature on trade networks and international relations (Wilkinson 2002; Hafner-Burton et al. 2009), including conflicts and military alliances (Polachek 1980; Dorussen and Ward 2010; Kinne 2012; Jackson and Nei 2015).

2.2 The International-Financial Network

Despite its undeniable economic importance, merchandise trade represents only one of the many possible economic linkages existing between world countries. Another substantial role is played by financial relationships, which typically channel a much higher value than what merchandize trade does. For example, in 2012, the dollar value of world merchandise exports was close to US$18.5 trillion,[11] whereas total cross-border holdings of securities reached US$43.6 trillion.[12] It is therefore extremely important quantify and explore the network of such bilateral financial relationships, and possibly compare them with those of the ITN.[13]

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from individual researchers, e.g. Andrew Rose (http://faculty.haas.berkeley.edu/arose/), Kristian Gleditsch (privatewww.essex.ac.uk/~ksg/), Robert Feenstra (cid.econ.ucdavis.edu), and Arvind Subramanian and Shang-Jin Wei (users.nber.org/~wei/data.html), among others. See also De Benedictis et al. (2014) for a tutorial-like presentation of the main properties of the ITN using the BACI dataset. See also the WIOD dataset (wiod.org), which provides time-series data of world input-output tables for 40 countries worldwide.

[10] See, however, Egger et al. (2016) for a recent attempt bridging trade in goods and trade in services.

[11] See wto.org/english/news_e/pres14_e/pr721_e.htm.

[12] To this figure, one should also add the value of total foreign-direct investments (FDIs) flows, which in 2012 reached US$ 1.4 trillion, cf. oecd.org.

[13] Due to space constraints and the focus on macroeconomic relations, we cannot survey here the extremely interesting and influential literature on micro and meso financial networks, especially the contributions addressing systemic risk (Cf. e.g. the work of Stefano Battiston and co-authors: See for instance Battiston et al. 2012a,b). The interested reader is referred to the reviews by Hasman (2013) and Chinazzi and Fagiolo (2013).

Financial data that can be used to build a network representing cross-border financial relationships among world countries is provided by the IMF in its Coordinated Portfolio Investment Survey (CPIS). Data include cross-border portfolio investment holdings of equity securities, long-term debt securities and short-term debt securities listed by country of residence of issuer. Overall, one has complete bilateral data for roughly 70 countries for the period 2001–2010 (Schiavo et al. 2010; Chinazzi et al. 2013), which can be employed to define a multi-graph representation of the International Financial Network (IFN), with three disaggregated layers and an aggregate one.

More precisely, existing data allow to build the IFN in five different cases: (1) all financial investments (Total Portfolio Investments, TPI); (2) equity securities (ES); (3) debt securities (TDS); (4) long-term debt securities (LTDS) and (5) short-term debt securities (STDS). More formally, one can build a 5-layer weighted-directed multigraph, where each directed link is weighted by the value of security—in millions of current dollars—issued by the origin node and held by the target. This involves aggregating first the debt layers (iv) and (v) to generate an aggregate debt layer; and then merging equity and debt to get the TPI layer. At any level of aggregation, the generic entry $w_{ij}^t(k)$ of the corresponding weight matrix $W^t(k)$ for layer k at time t represents the actual stock of assets k issued by country j, and held by country i at time t.

Notice that data used to build the IFN record year's end holdings of securities reported at the economy level, from the asset side (more reliable than liability side), like equity, long-term and short-term debt instruments, securities held as reserve assets and securities held by international organizations. Data do not record instead FDIs,[14] loans, holdings of domestic securities (issued and held by residents of the same country) and securities acquired under reverse repurchase agreements.

An additional source of network data that can be employed to study financial relations among countries comes from the Bank for International Settlements (BIS) locational statistics on exchange-rate adjusted changes in cross-border bank claims. Data record flows of financial capital channeled through the banking system in every country, and are well-suited for an analysis of geographical patterns in financial linkages across countries (Reyes and Minoiu 2011). Using these data, one may build a network representation of the global banking network (GBN), where weighted links describe estimates of flows, obtained as changes in cross-border banking stocks (aggregated at the country level) including loans, deposits, debt securities, and other bank assets.

[14]FDIs are another important channel of interaction between world countries. Typically a large part of cross-border FDIs are done in terms of direct M&A between firms of two countries. Using alternative data sources (e.g., Thomson Reuters Mergers and Acquisitions database, see http://thomsonreuters.com/en/products-services/financial/hedge-funds/mergers-and-acquisitions.html), one may build, for each given time window, an international M&A network where nodes are countries and (direct) links represent acquirer-target M&A operations (in number of in total value). Interesting issues that can be addressed with this network concern, e.g., the geographical localization of clusters of countries engaged in M&A activities and the persistency over time of investment flows.

2.3 The International Networks of Permanent Migration and Temporary Mobility

Beside commercial and financial transactions, world countries interact also through cross-border movement of people. If one considers legal permanent migration alone, existing statistics show an unprecedented level of cross-border flows in the last years, leading to an overall migrant world population of about 190 million in 2010.[15] Current estimates predict that in 2050 the population of migrants will achieve 405 million, more than twice the figure for 2010. Quantifying international migration in a globalized world becomes therefore crucial in order to provide policy makers with the right tools.

A network approach to international migration must however face the fact that finding detailed bilateral data is extremely difficult. Data problems are especially acute when compared to higher-frequency data on international trade and finance flows. Nevertheless, thanks to the combined efforts by the United Nations Population Division, the Statistics Division of the United Nations, the World Bank and the University of Sussex, a reliable source about bilateral international *permanent* migration compiled using the United Nations Global Migration Database has been made available to the community of researchers (Ozden et al. 2011).

Starting from about 3500 individual census and population register records from more than 230 destination countries and territories from across the globe, the final database comprises five origin-destination 226×226 matrices for each decade in the period 1960–2000. For each year $t = 1960, \ldots, 2000$, the generic element (i, j) of each matrix records the stock of migrants (corresponding to the last completed census round) originating in country i and present in destination j. One can therefore employ these five origin-destination 226×226 matrices W^t to build a time-sequence of weighted-directed networks describing bilateral migration stocks among $N = 226$ countries. Therefore, the International-Migration Network (IMN) at time $t = 1960, \ldots, 2000$ is defined by a weighted matrix whose generic element (i, j) represents the stock of migrants originated in country i and present at time t in country j.

Permanent (legal) migration does not of course account for all existing cross-border people movements. In addition to illegal migration, which is almost by definition not measurable, people move also temporarily across borders for business or leisure purposes. Data about temporary international human mobility do actually exist and allow for a complex-network analysis of the phenomenon. In particular, the World Tourism Organization (UNWTO, www2.unwto.org) collects data about arrivals and departures of people traveling to a different country with respect to their usual place of residence, and stay there for less than one consecutive year. Outbound data are based on incoming visitors registered by the destination country and encompass both leisure and professional travelers, excluding border and seasonal

[15] See http://publications.iom.int/bookstore/free/WMR_2010_ENGLISH.pdf.

workers as well as long term students. Data are available for $N = 213$ countries from 1995 onwards, and allow for the construction of the international human temporary mobility network (IHTMN). This is defined as the network characterized in each year t by the $N \times N$ weight matrix W^t, whose generic entry w_{ij}^t records the number of travellers who left from country i and arrived in country j during year t.

3 Empirical Evidence

This section surveys some of the empirical evidence on macroeconomic networks. In particular, we will discuss differences and similarities in the observed topology of the ITN, IFN and IMN. We shall begin describing research on the ITN, as historically most of the efforts have been initially addressed towards the exploration of the web of international trade.

3.1 Topological Properties of the ITN

Despite the ITN is a very dense graph as compared to other real-world networks (its density is close to $\frac{1}{2}$), from an international-trade perspective one is left with the puzzle that half of all possible bilateral relations are not exploited. In other words, most countries do not trade with all the others, but they rather select their partners. In the period 1950–2000, the ITN has shown a marked increase in the number of directed linkages and a (weak) positive trend in density (De Benedictis and Tajoli 2011; Garlaschelli and Loffredo 2005). This occurs irrespective of whether one factors in or not any increase in the number of countries in the sample, due e.g. to improvements in data collection or new-born countries. Therefore, trade globalization has not only increased the connections among countries that were already trading back in 1950, but it did so by embedding in the trade web the newcomers over the years, inducing a stronger trade integration.

The ITN is also a very heterogenous network. For example, the distribution of the number of export and import partners of each country (i.e., in-degree and out-degree in network jargon) has become more and more bimodal over the years, with a group of very tightly connected countries co-existing with another group holding a smaller number of inward and outward links, thus preventing one to talk of a representative country in terms of trade patterns. Furthermore, the distribution of country imports, exports and total trade all follow log-normal densities (Fagiolo et al. 2008), implying that a few countries exporting and importing a lot exist side-by-side many countries characterized by very low trade levels.

Another relevant feature of the ITN is its disassortative nature: countries that hold many trade partners typically trade with countries holding a few links (Fagiolo et al. 2010). This is relatively less true from a weighted perspective: countries that import or export a lot tend to do so from and to countries characterized by low export and import levels, but there is a small number of very intensively connected countries trading with very similar partners.

Despite trade globalization, the ITN is still a strongly modular network. Due to geographic, economic and political reasons, countries have been forming over time relatively stable modular patterns of multilateral trade relations, possibly interacting among them, which can be easily identified through network analysis. A first interesting property is that countries that trade more tend to form intense trade triangles in their neighborhoods (i.e., clustering patterns, cf. Fagiolo 2007). This hints to the presence of a core of tightly connected countries in the ITN (Fan et al. 2014). Indeed, at least in year 2000, it turns out that the ten richest countries in terms of total trade are responsible of about 40 % of the total trade flows, a quite strong indication in favor of the existence of a rich club in the weighted ITN. More generally, community-detection techniques (Fortunato 2010) allow to identify several clusters of countries forming tightly-connected trade groups, each one relatively disconnected with respect to others (Barigozzi et al. 2011; Piccardi and Tajoli 2015). These groups tend to mimic geographical partitions of the world in macro areas but are less overlapping with existing preferential trade agreements (PTAs), confirming previous findings hinting to an ambiguous role of PTAs in explaining trade (Rose 2004). Despite communities of countries in the ITN are easy to identify, their statistical significance is still an open issue (Piccardi and Tajoli 2012). Indeed, inter-community linkages are far from being irrelevant, providing support for the ITN as a globalized trading system.

As mentioned above, the ITN has undergone some structural changes over the second decade of the last century. Trade globalization has occurred through intensive and extensive processes leading to denser but more bimodal network, with a stronger core. This does not mean, however, that the periphery of the network has become more and more marginal (De Benedictis and Tajoli 2011). Indeed, both the overall betweenness centralization of the network (Vega Redondo 2007) and the average path length between the countries (Albert and Barabási 2002) have been decreasing over time, meaning that hubs have become less important and countries formerly located in the periphery moved closer to the core, not necessarily through exclusive trade connections made with the hubs.

Notwithstanding trade globalization has induced structural changes in the ITN in the period 1950–2000, one can still learn from the past evolution of the network to project its future evolution. Indeed, as shown in Fagiolo et al. (2009), the Markovian nature of the ITN dynamics allows to predict its long-run state. Their analysis suggests that the architecture of the ITN will probably evolve towards a more polarized (Pareto) distribution for link weights (i.e., export flows), implying an increasingly large majority of links carrying moderate trade flows and a small bulk of very intense trade linkages.

3.2 Finance, Migration and Trade

We now discuss differences and similarities between the ITN and other two macroeconomic networks that we have introduced so far, namely the IFN and the IMN.

3.2.1 IFN vs. ITN

Comparing the IFN with the ITN can give interesting insights as to the degrees of integration of real vs. financial world markets. The existing contributions (see e.g. Schiavo et al. 2010) stress the fact that real markets are typically more integrated than financial ones, and that the international movement of financial assets tends to be mediated by a small number of financial centers. Indeed, the IFN is much less dense than the ITN. Furthermore, the vast majority of countries have a very large number of partners in the ITN, whereas the IFN has a more core-periphery structure, where an elite of countries connected with everybody else coexists with a second group of nodes characterized by average connectivity, and a peripheral group featuring poorly-connected countries. Another interesting difference between the ITN and the IFN concerns the heterogeneity of country portfolios of link weights. Results suggest that the intensity of financial links is less homogeneous than in the ITN. Once again, this is consistent with the fact that trade in financial assets is channelled through a few large financial centers, whereas trade for goods occurs more directly.

The IFN and the ITN share a strongly disassortative nature (as measured e.g. by the correlation between node degree or strength and node average nearest-neighbor degree or strength). In the case of the IFN this hints to the presence of financial centers intermediating a large fraction of trades in financial assets, or with the existence of benchmark securities entering almost every portfolio. The fact that disassortativity is much lower in the weighted case suggests that the bulk of capital flows occurs between a small subgroup of financial centers: since the connections between hubs and spokes are not very strong, the resulting correlation between node strength and average nearest-neighbor strength is likely to decrease.

Both networks exhibit a strong rich-club effect, especially when one explicitly considers link weights. Indeed, as mentioned, the top ten countries in terms of node strength account for more than 40 % of world trade in goods. This share grows to above 60 % in the case of the IFN. In general, countries belonging to the core appear to be those with higher per-capita GDP in both networks. Interestingly, these countries are also the most central in the network, e.g. according to measures of random-walk betweenness centrality (Fisher and Vega-Redondo 2006).

3.2.2 IMN vs. ITN

When comparing the IMN with the ITN over the period 1960–2000, several differences stand out (Fagiolo and Mastrorillo 2014). First, despite both networks are extremely dense, the ITN has gone through a steady density increase over the years, and became more dense than the IMN in 2000. As expected, the ITN is also more symmetric than the IMN, as testified, for instance, by the percentage of reciprocated directed links. This is because a trade channel is easier to reciprocate than a migration corridor. Second, as already noticed in Fagiolo and Mastrorillo (2013), the IMN features a much more marked small-world and modular structure, with average-path lengths smaller than in the ITN.

As far as weighted topology is concerned, a very strong and positive correlation is typically observed between ITN and IMN link weights: if any country *i* exports a higher trade value to country *j*, in *j* there is also a larger stock of migrants originated in *i*. This positive association, however, is far from being perfect, as the cloud of points describing ITN-IMN link weights displays a lot of noise. Nevertheless, such a variation can be explained by larger country economic/demographic sizes and smaller distances in a gravity-like fashion. This suggests that traditional country-level explanatory variables such as real GDP and population, as well as geographical distance, may drive much of the observed correlation in the two networks.

A positive correlation also emerges when one compares node-specific network statistics (e.g., node degree and strength, average nearest-neighbor degree and strength, node clustering coefficients, etc.) between the two networks. For example, if a country has more trade channels (respectively, trades more), it also carries more migration channels (respectively, holds larger immigrant/emigrant stocks). Again, it is easy to see that this positive relation is mostly explained by country demographic and economic size. Furthermore, countries trading with countries that either trade with many other partners or trade a lot are also connected to countries that hold a lot of migration channels or stocks, i.e. both average nearest-neighbor degree and strength are positively correlated in the two networks.

However, unlike what happens for degrees and strength, smaller levels of average nearest-neighbor degree and strength are associated to larger demographic and economic country sizes. This is because both networks display a marked (binary and weighted) disassortative behavior: the partners of more strongly connected nodes are weakly connected. However, larger countries (i.e. with higher levels of real GDP and population) also hold larger degrees and strengths. Therefore, countries with larger levels of average nearest-neighbor degree and strength are smaller, in both economic and demographic terms.

4 Impact on Macro-Economic Dynamics

In the previous section, we have discussed some empirical evidence related to the topological properties of macroeconomic networks describing country linkages concerning international trade, finance and migration. We now ask whether the structure of these networks can affect macroeconomic dynamics. More precisely, we are interested in investigating if the overall position and embeddedness of world countries in these networks, as well as their direct and indirect connectivity, can constrain and influence the processes going on *over* the networks. Such processes may include, for example, economic growth and development of countries and macro-regions, as well as diffusion of shocks that originate locally and possibly percolate globally.

As we shall see, the answers to these questions are in generally encouraging, indicating that networks matter in explaining macroeconomic dynamics. However, the identification of causal linkages going from network structure to dynamic processes over the network can be strongly limited by endogeneity issues. Indeed, network structure can affect macroeconomic dynamics, but the latter is likely to impact, in turn, the structure of the network over time. This conceptual issue poses several methodological hurdles to both theoretical and empirical research trying to single out the net effect of network structure on node behaviors.[16]

4.1 Diffusion of Shocks in the International Trade Network

Since international trade is one of the most important channels of interaction among world countries, and data are easily available at a sufficient level of commodity disaggregation for a long time span, the ITN has been often used as a testbed to understand how locally-originated shocks diffuse throughout the system.[17] The idea is very simple. Suppose that countries are connected via weighted trade links, as proxied by a time-snapshot of the ITN, and that a negative shock hits a given country. Assume a set of rules that govern the way in which this initial shock is possibly transmitted to the neighbors of the shocked country, to the neighbors of neighbors, and so on. By shocking one after the other all world countries, and observing each time how shock diffusion evolves, impact other countries, and possibly dies away, one may understand the relative importance of each country as a crisis propagator.

Following this intuition, Lee et al. (2011) study a simple dynamic model of shock diffusion over the ITN. In the model, countries are characterized by their capacity (proxied by their GDP). Every time a negative shock hits a country, all its incoming and outgoing link weights are decreased by a certain percentage. If the decrease in total country trade exceeds some fraction of its capacity, the shock is transmitted

[16]Another subtle and potentially important issue arising in dealing with econometric models involving networks is the existing interdependency between dyadic observations. This might bias results in e.g. gravity-like estimations due to the omissions of higher-level correlation between triads and, more generally, cliques; see, e.g., Ward et al. (2013).

[17]See also Foti et al. (2013). They study a simple model of diffusion where, after the system is shocked, a local rebalancing of supply and demand is assumed to occur in order to mitigate the effects of the shock.

to all its trade neighbors. This may initiate an avalanche of shocks, as also some of the neighbors can then transmit it to their neighbors. The process terminates when all countries hit by the shock do not transmit it to any other additional country. An interesting statistic describing the diffusion process is the number of countries that are eventually hit by an initial shock originated from a given country (call it “avalanche size”). Interestingly, the Authors show that there exist a certain range of model parameters that allow the avalanche-size distribution to become a power law (i.e., a Pareto distribution). This implies that countries play very heterogeneous roles in their ability to propagate local crises to the system, and there exists a small but not irrelevant number of countries that, once hit by a shock, are able to diffuse it worldwide. Big countries (in terms of GDP) tend to be the most disruptive, but this is not the end of the story. Indeed, the position of the country in the ITN and its local embeddedness in the web of indirect connections plays a very crucial role in explaining avalanche size. This is because the way in which countries may be hit by a shock and transmit it to their neighbors may be either direct or indirect. It is direct if the link with the neighbor that has transmitted the shock is so strong, as compared to its GDP, that the capacity threshold is exceeded right away. Conversely, the shock transmission may be indirect if, for example, country A withstands a first shock transmitted by neighbor B, but then it is hit by a second shock transmitted by neighbor C, who is also neighbor of B, which was hit by the shock transmitted by B, and did not withstand it, thus transmitting it to its neighbors, among which there is A. All countries belonging to any single avalanche can then be associated to a direct vs indirect chain of diffusion. By repeating this exercise for all major avalanches generated in the simulations, Lee et al. (2011) show that indirect patterns account for a very large percentage of chains of reaction. This confirms that second and third order effects in the ITN are crucial to understand how shocks propagate in the system (Abeysinghe and Forbes 2005).

4.2 Embeddedness in the IFN and Post-crisis Country Performance

The recent financial crisis has clearly stressed the potential problems arising from increasing financial market interconnectedness. However, the impact of higher degrees of connectivity on the players in a financial network is far from being straightforward. On the one hand, indeed, a more connected network may favor diffusion of small shocks and therefore be conducive to systemic crises. On the other hand, players that are more connected and central in the network may more easily dissipate the shocks that hit them thanks to a sort of portfolio-diversification effect. Furthermore, despite the probability of contagion is small when connectivity is high, the system-level consequences of defaults may be widespread and difficult to isolate (Gai and Kapadia 2010).

In order to understand the interplay between player connectivity and network embeddedness in the macroeconomic financial network, Chinazzi et al. (2013) have performed an econometric study to examine the ability of network-based measures to explain cross-country differences in the way countries in the IFN have been hit by the recent financial crisis. More specifically, two indicators of country "crisis intensity" are considered, one real (i.e., the 2009–2008 Change in real GDP) and the other financial (i.e., volatility-adjusted stock-market returns between Sep 15, 2008 and Mar 31, 2009). These measures, following the literature on early-warning systems (Lane and Milesi-Ferretti 2011), are regressed against a number of country controls (e.g., credit market regulation, real GDP per capita, bank credit to private sector over GDP, current account over GDP) and a set of network-based measures controlling for country position in the IFN, including node degree and strength, clustering coefficients and centrality indicators. The Authors perform two sets of regression exercises. In the first one, a cross-section specification is fitted to the data, where crisis measures (referring to the post-crisis period) are regressed against controls and network measures in year 2006. Despite the timing chosen for the cross-section regression, this exercise may still suffer form omitted variable biases and endogeneity issues. Therefore, a second set of regressions is performed, this time in a dynamic panel framework, using a Generalized Method of Moments (GMM) estimator to reduce endogeneity biases.

Overall, the results of these two sets of econometric exercises are consistent. To begin with, country network indicators exert a significant, nonlinear, and stable role in explaining both real and financial impact of the crisis on a country. Higher local connectivity seem to shield countries from severe impact via a risk diversification effect. However, a higher global embeddedness in the IFN (e.g., a higher binary clustering or centrality) exposes a country to a higher vulnerability, especially if the country is not within the rich-club of the IFN. This result also indicates that first (e.g., node degree) and higher (e.g., clustering or centrality) order network indicators are both important to fully characterize the position of a country in the network, and can offer interesting insights about the way local and global network properties interact in influencing node behavior.

4.3 Temporary Human Mobility and Country Income

Distinguishing between local and global network properties is very important to understand the effect that network topology can have on macroeconomic dynamics. In graphs characterized by a sufficient heterogeneity, e.g. in the way link weights are distributed across pairs of nodes, local node connectivity (e.g., measured by node degree or strength) and global node importance (e.g., measured by centrality indicators) can indeed strongly differ. For instance, a node that is not strongly connected locally, may be indeed linked with very globally important nodes in the network, thus becoming itself very important despite holding a few connections.

Conversely, very locally connected nodes may end up being not that central from a global point of view in the network.

From an econometric perspective, this means that global centrality indicators may increase the explanatory power of regressions where country characteristics like income, growth or productivity are described in terms of country-specific characteristics and local country connectivity in the network. This intuition is exploited in Fagiolo and Santoni (2015), who explore the network determinants of country per-capita income and labor productivity. Traditional explanations have stressed the importance of physical and human capital, the efficiency with which capital is used, and international technological diffusion. In particular, the latter is known to be enhanced by cross-border flows of trade, people and ideas. Therefore, net of trade openness and other factors, the level of integration of world countries in the international network of human mobility is a good candidate to explain country income and productivity. How can such an integration level be measured? Starting from temporary human mobility data (see Sect. 2.3), one can consider countries in the IHTMN and define two related set of integration indicators. The first one is simply country *mobility openness* in the network, i.e. the sum of arrivals and departures from and to a given country, divided by its population.[18] Mobility openness is a local network proxy for foreign technology exposure, as it considers only first-order links with direct partners, and has been shown to significantly explain the variation in country income and productivity, net of trade openness and other factors by Andersen and Dalgaard (2011). The second integration measure is a set of country *global centrality indicators* (i.e., eigenvector and Katz centrality) that assign to each country a score that is increasing in its overall relative connectivity with respect to the whole network. These are global integration measures insofar the importance of a country is defined in terms of how much it is connected with other countries that are themselves important, and so on. Therefore, country openness takes into account only a limited subset of all the information contained in the network, which is instead fully accounted for by global centrality indicators.

Including global centrality measures in regressions explaining country income and productivity—together with standard country controls, and trade/mobility openness—gives interesting insights. Indeed, once all potential endogeneity problems are dealt with, either with an instrumental-variable approach or via a GMM estimation, one finds that, net of country mobility openness, being more globally central in the IHTMN consistently induces higher income and productivity. This implies that the impact of human mobility in the international technological-diffusion process depends not only on how many direct partners a country has (and how strongly it is connected with them), but mostly on whether such a country is embedded in a web of relationships that connect her with other influential partners in the network.

[18]This parallels trade openness, defined as the sum of import and exports divided by country GDP.

4.4 International Migration and Trade

In the previous examples, we have discussed econometric frameworks wherein one can identify, net of possible endogeneity issues, the impact of first and higher order network properties on country-specific performance indicators. More generally, similar methodological techniques can be employed to single out the causal effect that the position of a country in a certain macroeconomic network may have on the behavior of countries in other macroeconomic networks.[19]

An interesting application of such an approach concerns the relationship between international migration and trade. Several studies, indeed, find quite a robust evidence suggesting that bilateral migration affects international-trade flows (Gaston and Nelson 2011; Egger et al. 2012). As argued in Gould (1994), for example, trade between any two countries (i, j) may be enhanced by the stock of immigrants present in either country and coming from the other one (m_{ji} and m_{ij}). This is because migrants originating in j and present in i (and vice versa) may foster imports of goods produced in their mother country (bilateral consumption-preference effect) or reduce import transaction costs thanks to their better knowledge of both home- and host-country laws, habits, and regulations. Again, such a *bilateral information effect* only takes into account the direct impact of migrants from either countries present in the other one to explain bilateral trade, i.e. a first-order effect. However, in line with the discussion in the previous section, one may posit that trade between any two countries can be fostered not only by bilateral-migration effects, but also thanks to migrants coming from other "third parties" and, more generally, by the overall connectivity and centrality of both countries in the IMN (Rauch 1999; Felbermayr et al. 2010; Felbermayr and Toubal 2012). This is because the better a pair of countries is connected in the IMN, the larger the average number of third countries that they share as origin of immigration flows and the more likely the presence of strong third-party migrant communities in both countries. This may further enhance trade via both preference and information effects. Moreover, it may happen that two countries are relatively well connected in the IMN (in both binary and weighted terms) even if they share a very limited number of non-overlapping third parties. In such a case, one may ask whether a cosmopolitan environment engendered by the presence of many ethnic groups in both countries can be trade enhancing—and if so why.

To test this idea, Fagiolo and Mastrorillo (2014) fit a battery of gravity models of trade where country centrality in the IMN is added as a further explanatory factor.[20] They find that pairs of countries that are more central in the IMN also trade more. This mainly occurs through a third-country effect: the more a pair of countries is

[19]Of course here causality is exogenously assumed by means of theoretical arguments, and not tested econometrically.

[20]See Sgrignoli et al. (2015) for a complementary analysis that explores similar issues using a product-specific trade perspective.

central in the IMN, the more they share immigrants coming from the same third-country, and the stronger the impact of forces related to consumption preferences and transaction-cost reduction. Furthermore, results suggest that also inward third-party migrants coming from corridors that are not shared by the two countries can be trade enhancing, in addition to common inward ones. This can be due to either learning processes of new consumption preferences by migrants whose origins are not shared by the two countries (e.g. facilitated by an open and cosmopolitan environment) or by the presence in both countries of second-generation migrants belonging to the same ethnic group.

5 Concluding Remarks

This chapter has surveyed some of the recent literature on macroeconomic networks, with particular emphasis on the networks of international trade, finance, permanent migration and temporary mobility. We have argued that describing interactions among world countries using a complex-network approach offers several empirical and theoretical insights. Overall, considering world countries as embedded in a complex web of relationships allows one to identify a wealth of additional and non-trivial empirical facts concerning the patterns of interactions at the macroeconomic level. Furthermore, econometric exercises show that these higher-order structures, and more generally the relative positions of countries in the networks, have substantial implications as to the dynamics of country performance and shock diffusion. In other words, macroeconomic networks do matter: direct and indirect connections among countries are indeed relevant to better understand macroeconomic dynamics.

Despite these very promising results, research on macroeconomic networks is still in its infancy and much remains to be done. A first important area that requires more efforts concerns the theory behind empirically-observed properties and econometric evidence. Indeed, theoretical models, possibly micro-founded, delivering as their (equilibrium) outcomes predictions about the topology of the networks should be developed and taken to the data, in order to validate the internal mechanisms proposed as explanations for the observed network regularities. Some effort in this direction has been made in the case of the ITN. Examples are the work on null statistical network models (Squartini et al. 2011a,b; Fronczak and Fronczak 2012) and stochastic models of trade network evolution (Riccaboni and Schiavo 2010), as well as the contributions by Fernando Vega-Redondo and co-authors on the dynamics of globalization (Dürnecker and Vega-Redondo 2012).

Another interesting avenue for further research is the integration of multi-layer network techniques (Kivelä et al. 2014) in the study of macroeconomic networks. Indeed, existing contributions have so far investigated the properties of different macroeconomic networks as they were independent from each other. In reality, world countries are connected at the same time through different types of linkages, including international trade, finance, investment, migration and mobility, infrastructures. From a complex-network perspective, considering all these interaction dimensions together means building a time-sequence of multi-layer networks where every time snapshot of the multi-layer is composed of a fixed number of nodes (i.e., countries) that may be connected by several different types of links, each representing a different interaction channel. Studying how multi-layer macroeconomic networks evolve over time would allow to better understand how different interaction channels correlate among them and cause each other, and eventually to dig deeper into the relationship between the role of a country in the global macroeconomic network and its economic performance.

Finally, a very promising line of research attempts to go beyond the spatial disaggregation of nodes in terms of countries by providing a finer level for the geographical breakdown of spatial units. For example, instead of building networks where nodes are countries, one may think, data permitting, to study macro networks where nodes are sub-national entities such as regions or other administrative units (see, for example, other chapters in this volume dealing with complex networks and geographical economics). If data about both intra-national and across-country links are available, such a perspective could greatly enhance our understanding of community structures and shock diffusion mechanisms.

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