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ABSTRACT: The world has become more interconnected over the past few decades. Against this backdrop, economic and financial contagion following adverse shocks can have a severe impact on the global economy. How systemic can the effects of contagion be? What specific transmission channels are involved? What is their relative importance? We address these questions using a multilayered global network model of contagion that simulates the impact of sovereign debt default on the global economy. We also develop a measure of global systemic risk and use bank stress testing techniques to quantify the systemic impact of the shock and the extent of contagion on the global economy. Our model shows that economic and financial contagion are highly non-linear, and many bystander economies can experience significant negative effects as the initial default is spread through the network. This suggests that many economies might be systemically more important than what conventional measures of size or openness might suggest.

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Contents

I. Introduction

The world economy has become highly interconnected, largely reflecting the rapid expansion of cross-border trade and financial operations. Over the past 40 years global trade has increased about tenfold, while international financial flows have increased about 45 times.[1] The increased interconnectedness has delivered substantial benefits. It has helped improve efficiency in production—as reflected by the integration and prevalence of global value chains (GVCs)—and supported the expansion of research and investment activities across economies. It has also prompted the broad availability of goods and services nearly everywhere and allowed individuals and firms to diversify risks. In doing so, it has helped spur innovation and growth throughout the globe.

However, interconnectedness comes with trade-offs. Its benefits in terms of diversification and growth have come along with greater vulnerabilities. Economies and economic agents have become more exposed to each other, thus increasing the risk of contagion when idiosyncratic shocks hit the global economy. These vulnerabilities stem from the same diversification channels through which benefits spread across the globe. For example, it is widely acknowledged that the collapse of Lehman Brothers in 2008 triggered distress across the global financial system, with significant adverse effects on the real economy, resulting in what is now known as the *global financial crisis*. Subsequent episodes of turmoil, including the so-called *taper tantrum* in 2013, also triggered chains reactions in financial markets across the globe (Sahay et al., 2014). More recently, the COVID-19 crisis and its global economic and financial impact has made evident the cost of interconnectedness.

The Global Financial Crisis (GFC) and the COVID-19 pandemic, along with the required policy responses, have brought to the fore the vulnerabilities arising from debt sustainability concerns and the challenges of creditors to finance them in an interconnected world. Policymakers have expressed concerns regarding the peak debt levels reached globally (Figure 1a) and the large number of countries determined by the International Monetary Fund (IMF) as being in high risk of debt distress or in debt distress (Figure 1b). These developments have increased the likelihood of debt defaults and underscore the importance of better understanding the implications of these potential events.[2]

This paper applies network analysis techniques to examine how economic and financial contagion can spread across economies once an economy or group of economies incur debt default. Building on the dynamic model outlined in IMF (2017), we incorporate cross-border network structures of trade, interbank lending, and portfolio and FDI positions for 63 economies that as of 2018 represent about 80 percent of global GDP. The model uses this network structure to simulate the dynamics of international reserves for each individual economy following a debt default in an economy or group of economies. In the model, the realization of an exogenous shock can force an economy to default on all its cross-border obligations.[3] Contagion thus emanates from the *direct* impact that the debt default has on the capacity of other economies to fulfill their cross-border obligations. *Cascading effects*

[1] Authors' calculations based on Oxford University and Bank for International Settlements data.

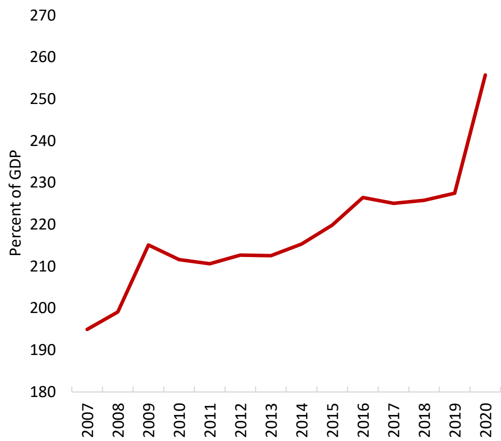
[2] On April 2020, supported by the IMF and the World Bank, the G20 allowed the world's poorest economies to temporarily suspend repayment of official bilateral credit. See G20 (2020).

[3] The nature of the shock that triggers a debt default is not the focus of this paper. However, the COVID-19 pandemic has made evident that an exogenous (and non-economic) shock can trigger debt defaults.

can materialize as other creditor economies see their reserves decline due to the losses triggered by the initial debt default, in some cases forcing them to follow suit.

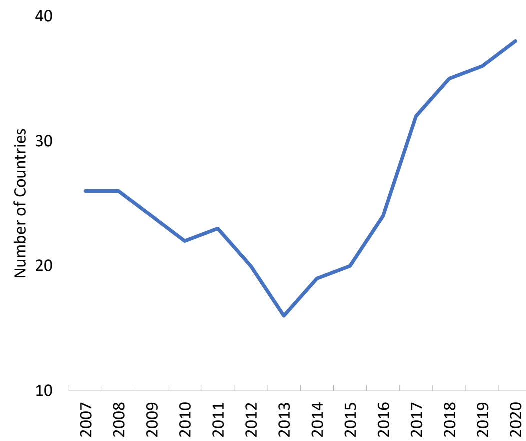
Figure 1. Selected Debt Indicators

a. Global Debt to GDP



Source: WEO and IMF Staff calculations.

b. Debt Distress: Low-Income Countries



Source: Low-Income Countries Debt Sustainability Analysis Database and IMF Staff calculations.
Note: The chart shows the number of countries at high risk of debt distress or in debt distress.

This paper makes several contributions to the literature on contagion. First, it models global contagion taking into account the observable trade and financial linkages across economies. Second, building on the financial literature, it helps to assess the systemic vulnerability of the global economy by drawing an analogy to bank stress-testing metrics and techniques (Battiston et al., 2016). Third, while we report the impact of idiosyncratic debt default shocks, the model is flexible enough to allow for more complex shock scenarios, and the simulated impact of this model could be interpreted as reflecting broader shocks due to limited access to international capital markets (e.g., inability to roll over debt). Beyond this, the model can, for example, simulate the effects of simultaneous debt defaults across the world. It also allows to assess the impact of different policy responses (e.g., exchange rate adjustment or fiscal consolidation), additional amplification mechanisms such as asset price co-movements (Papamichalis et al., 2022, Ramadia et al., 2022), or the effectiveness of the global financial safety net (IMF, 2017; and Papamichalis et al., 2022).[4]

Our results suggest that debt defaults can have large and highly non-linear systemic effects on the global economy—as captured by indexes of economy- and global-level vulnerability (reserve losses). The topological structure of cross-economy interconnectedness plays an instrumental role on aggregate outcomes, underscoring the importance of understanding the role of networks, and how they influence contagion. Ultimately, the results indicate that many economies might be systemically more important than what conventional measures of size or openness might suggest.

[4] The model has also been applied to stress the global economy to climate change shocks in large and highly interconnected economies. See Jung et al., 2022.

The rest of the paper is organized as follows. Section II presents an overview of the literature on networks and its applications to trade, financial and real activities. Section III discusses the model setup and how contagion through direct exposures can lead to global vulnerabilities. Section IV discusses the data, coverage, and the various elements of the network. Section V presents a stress-testing measure of systemic vulnerably of the global economy building on the literature on financial/banking literature. Section VI concludes.

II. Trade, Financial, and Real Networks

There is rising interest among policy makers and academics in understanding how economic and financial interconnectedness affect the transmission of shocks across the global economy. Network analysis techniques have become a powerful tool to analyze such interconnections, help assess its benefits and costs, and understand their aggregate implications, particularly for policy design and implementation (Jackson, 2008, Newman, 2010).[5]

Despite the growing research on network analysis, there is still a limited understanding of how interconnectedness, through the topological configuration of a network,[6] may influence the resilience to, and the contagion from adverse shocks. Moreover, due to the intrinsic complexity associated with networks—including its data requirements—the literature has mainly examined these issues from a relatively 'narrow' perspective. That is, one in which interconnectedness and contagion arise from production chains, trade linkages, or financial interactions, and that involves a narrow set of economic agents, such as firms, banks, or economies.[7]

The literature on contagion through production channels builds on intersectoral input-output linkages where microeconomic idiosyncratic shocks can lead to aggregate fluctuations (Acemoglu et al., 2012, and Carvalho, 2014). In traditional macroeconomic models, microeconomic idiosyncratic shocks tend to average out, resulting on negligible aggregate effects. However, the new macroeconomic literature that builds on network analysis, shows that the presence of interconnections between firms and sectors serves as a propagation mechanism. The configuration of the economic structure (i.e., the network) is thus key in determining whether and how shocks propagate, and their aggregate implications (Acemoglu et al., 2014).

The literature on networks has also started to help fill gaps in the understanding of how trade shocks may have broader macroeconomic effects.[8] Network analysis of production and international trade allows a gauge of the potential effects of shocks in a manner not possible with classical trade theory or with gravity models (Bernard and Moxnes, 2018; Korniyenko et al., 2017). This is evident, for example, in the shift away from bilateral trade analysis toward global trade linkages (Fagiolo et al., 2008; De Benedictis et al., 2014). In doing so, network analysis can help better determine whether international trade integration makes an economy more vulnerable

[5] There is an extensive literature on contagion that does not build on network analysis. For an overview, see for example, Allen and Gale, 2000; Kaminsky et al, 2003; or Claessens and Forbes, 2001.

[6] We refer to the topological space to differentiate it from the physical or geographical space. That is, an economy's (node) might be small geographically but may be important in terms of the number and strength of interconnections with the global economy.

[7] These agents are usually represented in the network literature as *nodes*, and the interconnections among them as linkages. See a full discussion on the representation and measurement of networks in Jackson (2008).

[8] See an overview of the role of trade in the global economy in IMF (2015) and an overview of firm-to-firm connections in trade in Bernard and Moxnes (2018).

to financial crises (Kali and Reyes, 2010) or the extent to which systemic risk is embedded in an economy's import basket (Korniyenko et al., 2017).[9] Addressing these questions is not trivial, as production and trade integration can either help diversify or amplify the impact of shocks. Nonetheless, the literature has shown that idiosyncratic shocks tend to have a greater impact on those economies with the most connected industries (or with industries heavily involved in the global value chain), and that highly interconnected economies that produce easily substitutable goods are better positioned to withstand disruptions in trade (Korniyenko et al., 2017).[10]

Work on contagion stemming from financial interconnections is possibly the most extensive strand of literature relying on network analysis. This largely reflects the academic and policy interest that emerged after the global financial crisis. Work in this area has focused on the interaction between interconnectedness and the propagation of contagion across financial institutions—mostly in the banking sector—both within economies (Glasserman and Young, 2016, Diebold and Yilmaz, 2015, and Demirer et al., 2016), and across the globe (Arellano et al., 2017, and Garas et al., 2010).

A key finding of this financial literature is that direct contagion channels arising from counterparty linkages or exposures can be compounded by interconnections across individuals, as well as by the location of the initial shock. These features are common where liquidity effects, leverage levels, heterogeneity of size, capitalization (distance to default), and asset price co-movements reinforce the effects from default through direct exposures (e.g., Glasserman and Young, 2015; Gai and Kapadia, 2010; Gai et al.., 2011, and Minoiu and Reyes, 2013).

The financial network literature also finds that high connectivity can help reduce the probability of contagion through diversification of exposures. However, conditional on a shock that leads to a default, increased connectivity can amplify the contagion effects and lead to further defaults.[11] This has important implications for the potential effects of debt default going forward, and for the role of bilateral and multilateral institutions that make up the global financial safety net, such as the IMF.

The financial literature has also shown that considering a 'single' network does not provide a complete view of underlying vulnerabilities. This may lead to an inadequate assessment of such vulnerabilities and their aggregate implications, as well as the failure to capture all the relevant contagion and distress channels (Battiston and Martinez-Jaramillo, 2018). However, research that combines multiple sources of contagion (multilayered networks) is less common. Some studies have developed a network model of trade and financial interconnectedness to estimate the size of the global financial safety net and, more specifically, the role of regional financing arrangements (RFA) in mitigating contagion (IMF, 2017). The relative scarcity of work using

[9] The role of network structures on production and trade, in particular of firm-to-firm connections, also raises new questions about market structure, returns to different factors of production, and the role of trade in increasing welfare (Bernard and Moxnes, 2018).

[10] Korniyenko et al. (2017) use network analysis to show how global trade is adversely affected by temporary negative supply shocks, such as a natural disaster (e.g., hurricane or earthquake), armed conflict, or political turmoil.

[11] This has important implications for policy design and implementation. For example, Espinosa-Vega and Sole (2010) illustrate how network analysis can be used for cross-border financial sector surveillance by simulating different credit (default) and funding (rollover) shocks. They incorporate risk transfers in addition to direct exposures across banks, that is, the effects that contingent liabilities stemming from credit guarantees or derivatives can have on other banks' balance sheets. Their analysis focuses on the identification of systemic and vulnerable banking institutions/systems to illustrate the importance of maintaining an effective perimeter of prudential regulation.

multilayered network models is not surprising, given its more complex structure (Estrada, 2014) significant data constraints and challenges from integrating and consolidating global databases across different markets (e.g., trade or financial) and market segments (e.g., debt vs. equity),[12] and limited tractability of the underlying analytical framework (Acemoglu et al., 2012).

A perennial issue in the literature is understanding whether the structure or configuration of a network by itself dampens or amplifies contagion. This is a non-trivial issue, largely due to the trade-offs arising from interconnectedness. It is natural to think that the extent of contagion is directly linked with the number of connections an individual or 'node' has with others, that is, fewer links imply less contagion and more links more contagion (e.g., Jackson, 2008, Newman, 2010, Carvalho, 2014). However, this is not necessarily the case. A more interconnected network may allow to diversify risks and hence have a stabilizing effect (Allen and Gale, 2000 and Freixas et al., 2000). But it is also possible to have a network configuration that amplifies risk and destabilizes the system, thus resulting in more contagion. Moreover, conditional on the nature of the shock and channels involved, contagion can be more severe, and its effects could be amplified (Papamichalis et al., 2022; Glasserman and Young, 2016).

The tensions in determining whether interconnectedness increases or decreases the vulnerability of a system are most evident in the context of financial intermediation. In this stream of research, the likelihood of cascading contagion effects increases with interconnectedness, but so does the opportunity to lend to others (Elliott et al., 2014). Moreover, while a less connected network reduces the likelihood of contagion cascades, financial intermediaries also become more dependent on just a few counterparties, thus increasing their vulnerability due to more concentrated exposures. This makes evident the tradeoffs that can emerge in the financial system (e.g., contagion vs. profitability or mitigating contagion vs. concentrated exposures) and the importance of understanding the extent to which an intermediary is exposed to others, or the extent to which the overall exposure is spread throughout the network. The financial literature also suggests that high connectivity can deter the emergence of shocks. However, once a shock takes place, high connectivity may exacerbate contagion (Gai and Kapadia, 2010).[13]

Finally, monitoring and quantifying systemic risks has become central to network analysis of (financial) interconnectedness. The traditional approach to measuring systemic risk overlooks cascade effects arising from interconnectedness across banks. To tackle this shortcoming, Battiston and others (2016) have developed a framework that considers not only the immediate effect of a shock through direct exposure, but also distress propagating both within the network, and from bank failure/fire sales. This framework accounts for the changes in the value of an individual's assets even in the absence of a default/failure. Battiston and Martinez Jaramillo (2018) argue that indirect linkages could matter more than direct exposures in a contagion model, and interconnectedness can have ambiguous effects on financial stability, through asset prices and leverage. This could be extended to multilayered networks to assess the extent to which the interaction between interconnections and other propagation mechanisms could, on the extreme, jeopardize the prevalence of the network itself. To quantify systemic risks in the financial system, the literature has explored different indicators, such as the number of defaults, the total loss of capital, the cost of liquidating long-term assets to cover short-

[12] For instance, the global financial crisis made evident that regulators and market participants had limited information about the network of obligations between institutions. This lack of information, by itself, can induce contagion and contagion cascades that could otherwise not occur (Glasserman and Young, 2016).

[13] This study uses the degree of a node, a measure of connectivity for each individual within a network and assigns a probability distribution over this measure.

term liabilities, or the deadweight costs of bankruptcy proceedings. While some of these factors may not necessarily affect cross-border sovereign exposures, they can have implications for setting policies that limit contagion in the financial system (Glasserman and Young, 2016).

III. A Network Model of Contagion

The underlying dynamics of the model presented in this paper builds on the multilayered network model described in IMF (2017). Taking an initial multilayered network structure as given, we stress test the systemic vulnerability of the global economy by analyzing the impact of an exogenous shock that triggers a default on an economy's external liabilities, thus affecting its balance of payments position. Specifically, the shock can trigger reserve losses that force an economy to fail to repay its debt service payments on all its external obligations. Contagion and cascading effects occur if other creditor economies suffer large enough reserve losses due to the original non-payment on their loans, forcing them to also default on their interest payments to others. By modelling the dynamics of an economy's balance of payments, the framework *endogenously* determines the propagation of the shock, with the level of international reserve losses becoming a summary statistic for an economy's vulnerability. When aggregated at the global level, these losses allow to quantify the systemic impact of the shock.

A. Multi-layered Network

Economies are interconnected through bilateral (net) asset and trade positions, measured in U.S. dollars.[14] Each economy, or node, *i* is endowed with foreign exchange reserves at *t* = 0 in an amount of R_{i0} dollars. Balance of payments dynamics—and hence the stock of foreign exchange reserves at any moment in time—in economy *i* are given by its trade and net foreign asset and liability positions against all its counterparts. Formally, the change in foreign exchange reserves of economy *i* at time *t* ($\Delta R_{i,t}$) is determined by the following expression:

$$\Delta R_{i,t} = \underbrace{\sum_{j\neq i} TB_{ij}\left(e_{ji,t-1}\right)}_{Trade\ revenues} + \underbrace{\sum_{j\neq i}^{\in ND_t} a_{ij}\, r_{j,t}\, e_{j,t}}_{Return\ on\ net\ foreign\ Assets} - \underbrace{\sum_{j\neq i} a_{ji}\, r_{i,t} e_{i,t}}_{Return\ on\ net\ foreign\ liabilities}$$

where a_{ij} denotes economy i's asset holdings against economy j, $r_{j,t}$ is economy *j*'s specific interest rate on its liabilities, $e_{i,t}$ is the nominal effective exchange rate. Given the multilayered network model, and without loss of generality a_{ij} captures various aspects of each economy's balance sheet position (see Section IV). In the model, a liquidity crisis, and hence the possibility of a solvency crisis, emerges when economy *h* (or a set of economies) is unable to fulfill payments due on its external liabilities, $a_{ih,t}r_{h,t}$ and *defaults*.[15] For all economies with direct exposure to economy *h,* this implies an external revenue loss and increased external financing pressures as their own international reserves decline. It must be noted that for an economy that remains

[14] A detailed description of the data and the various layers of the network is provided in Section IV below.

[15] The size of the shock is determined by the implied quarterly interest payments due based on total outstanding liabilities and a "relevant" interest rate. In the baseline model, repayments of principal are excluded. Including principal repayments would require a detailed debt profile for each economy, including amortization vis-à-vis its creditors over time—this disaggregation of the data is not available.

current on its obligations ($i \in ND_t$)—where ND_t denotes the set of non-defaulting economies—the initial loss of international reserves is equivalent to its exposure to the 'defaulted' amount, that is, $\Delta R_{i,t} = -a_{ih,t} r_{ht} e_{h,t}$.[16] If reserves are depleted, then the exposed economy *defaults* ($h \in D_t$), triggering a cascading effect on others.[17,18] In particular:

$$\forall\, i \in ND_t \; if \sum_{h \in D_i} r\, a_{hi} > R_i \rightarrow Country\ i\ defaults: i \in D_{t+1}$$

It is worth noting that direct exposures, although necessary for contagion cascades, do not result in the amplification of the original shock. This implies that the outcome in this setting constitutes a minimum level of possible aggregate losses.[19]

IV. Data

To construct the various network layers, we use 2018 data for 63 economies representing about 80 percent of global GDP (see Appendix Table 1). Specifically, we use cross-economy imports and exports as reported by *Direction of Trade Statistics* (DOTS), and each economy's balance sheet position against the rest of the world from: (*i*) interbank asset and liabilities positions as reported by the *BIS Locational International Banking Statistics;* (*ii*) portfolio investment positions from the International Monetary Fund's *Coordinated Portfolio Investment Survey* (CPIS); and (*iii*) foreign direct investment positions from the International Monetary Fund's *Coordinated Foreign Direct Investment Survey*. These components constitute the multiple layers of the network. Figure 2 provides a visualization of these layers, where each node represents an economy. The exposures across economies in each layer of the network is displayed by the connecting lines between nodes. Greater exposures are depicted by wider lines.

A. Measuring Interconnectedness and Assessing Contagion

In order to assess interconnectedness, we compute centrality measures for each layer of the network (Table 1 and Appendix Table 2). These measures are crucial for identifying the most systemic economies and, hence, assess the extent to which a default can induce a contagion cascade. Economies with higher centrality measures are the most efficient channels through which a shock is transmitted to the global economy. We focus on four centrality measures:
degree, *strength*, *alpha* (the geometric average of the previous two), and *eigenvector centrality*.[20]

[16] As in IMF (2017), we assume for simplicity that the trade balances of all countries are in equilibrium initially, consistent with stable net foreign asset positions and reserves. This implies that a default does not trigger additional reserve losses through the trade channel. This assumption is relaxed once we introduce endogenous policy responses through exchange rate and fiscal adjustment (see Papamichalis et al., 2022).

[17] Reserve adequacy is thus an indicator of an economy's ability to remain current on its obligations.

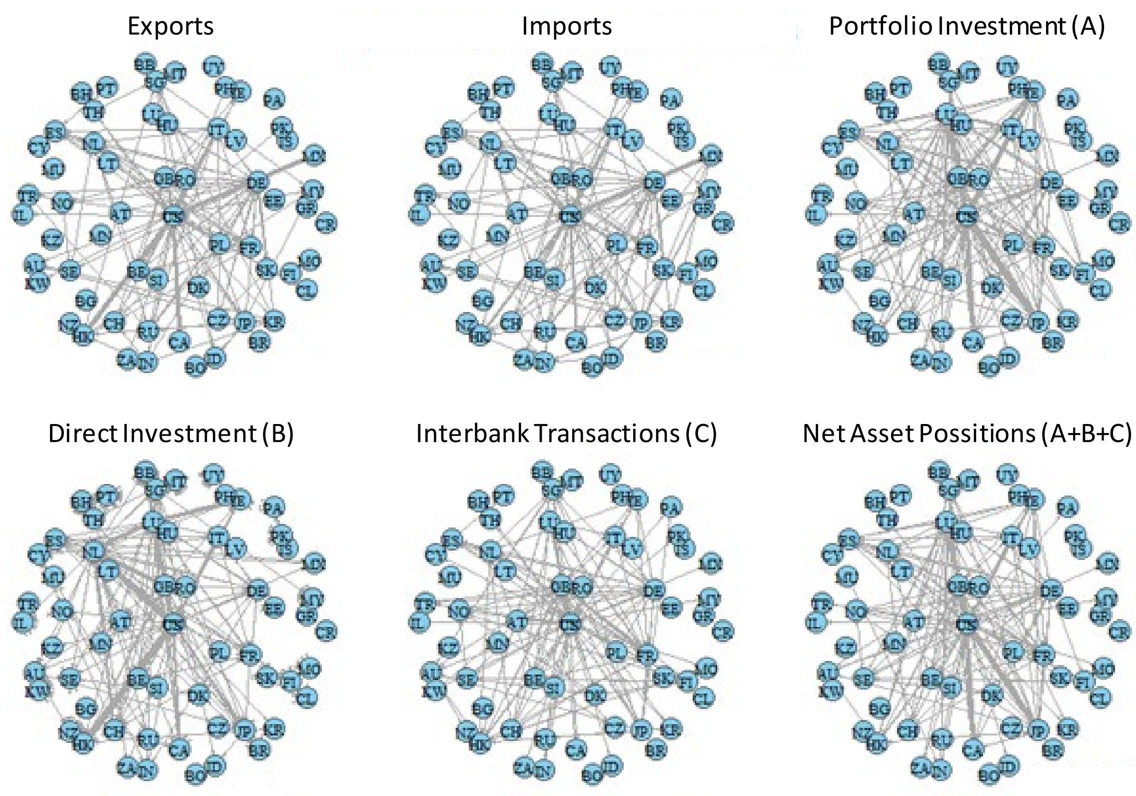
[18] For simplicity, we assume that once an economy defaults, it cannot regain access to the network in subsequent periods.

[19] See Papamichalis et al. (2022) and Jung et al. (2022) for an extension of this framework to a more complex setting and Ramadiah et al. (2022) for a setting in which the exogenous shock is not triggered by a default event.

[20] See Jackson (2008) for a thorough description and Opsahl et al. (2010) for applications of these measures.

Degree is the simplest centrality measure of a node. This is computed by counting the number of links for each node. As shown in Table 1, the average node in the imports layer is almost fully connected, with about 60 links or connections (of a total of 62 available nodes).[21] Conversely, the average node in the interbank positions layer is the least connected, with about 34 links. Continuing with these two variables, the economy with the minimum number of import linkages is Mongolia (52 linkages),[22] while 29 economies are fully connected (62 linkages) through this channel—Pakistan or Uruguay, for example, resemble the average economy. Similarly, Bolivia has the minimum number of linkages through interbank operations (13 linkages). In this case, only 12 economies are fully connected—Greece resembles the average economy.[23]

Figure 2. The Multilayered Network Model



Source: Author's calculations.
Note: For simplicity, only the top 5 percent strength linkages are shown (see main text and Appendix Table 2).

Strength is a measure of centrality that accounts for the *level* of interaction between nodes, or the "weight" of a linkage. In our analysis, the weight represents the dollar amount of an economy's transactions with another to

[21] Note that this measure can be normalized between zero and 1 by dividing by the maximum number of nodes (63 in our case) minus 1.

[22] Mongolia is also the least connected through exports, with 35 linkages.

[23] Details on economy-specific measures are provided in Appendix Table 2.

which it is connected to. Strength for economy *i* is defined as the sum of all weights of links connected to any given node:

$$C_D^S(i) = \sum_j^N w_{ij},$$

where w_{ij} is the value associated with the link between economy *i* and economy *j*. As Table 1 illustrates, the strength of the average node is largest for portfolio investment transactions, and lowest for exports. This means that the value of a given transaction for the average node is largest for the former than for the latter. Australia is the closest economy to the average Exports strength, while Italy is the closest for the case of portfolio investment. Exports strength is lowest in Barbados and highest in China. Kuwait and the U.S. are the economies with the minimum and the maximum portfolio investment strength, respectively.

Table 1. Global Network Centrality Measures
(Average, 2018)

	Degree	Strength	Alpha	Eigenvector
Exports	59.0	235,500.2	2,978.1	0.117
Imports	60.1	236,393.5	3,034.5	0.100
Portfolio Investment (CPIS)	46.8	663,002.4	4,160.2	0.095
Direct Investment (CDIS)	40.9	507,928.7	3,656.8	0.126
Interbank Positions (BIS)	34.4	400,328.6	2,892.1	0.080

Source: Authors' calculations.

Alpha centrality is a geometric average of degree and strength. It is mainly used in networks where both links and weights are important, as in our analysis. The average is weighted by introducing an exogenous tuning parameter, called alpha (we take a geometric mean, hence a is set to 0.5):

$$C_D^{wa}(i) = C_D^S(i)^a C_D(i)^{1-a}$$

where $C_D(i)$ is the degree of node *i*. Alpha centrality is highest in portfolio investment and lowest in interbank transactions. It is worth noting that this measure suggests that the portfolio investment channel appears to be the most important one, even though, on average, economies are more connected through trade—particularly via imports, as captured by the degree measure.

Finally, *eigenvector centrality* measures the influence of each node on the network. This indicator captures the importance of neighbors for each node. The logic behind this measure is that high eigenvector 'scores' are assigned to nodes connected to other nodes that have high scores themselves. The centrality of each node is proportional to the sum of the centralities of its neighbors:

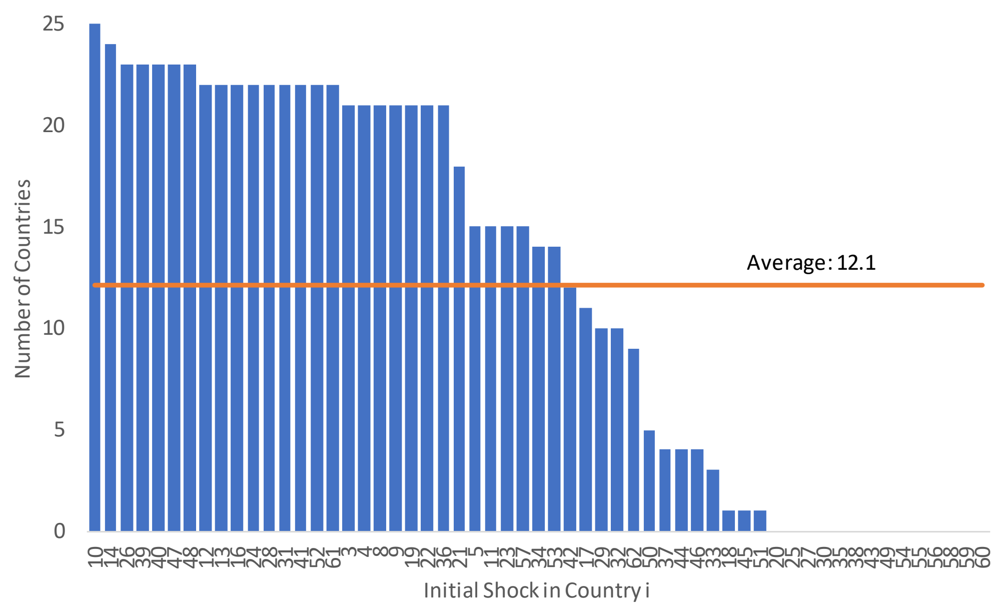
$$C_E(i) = \frac{1}{\lambda}\sum_j^N C_E(j)x_{ij}$$

where *i* is the node of interest, *j* is every other node that *i* is connected to, and *N* is the number of nodes. In this case, *x* takes the value of 1 if nodes *i* and *j* are connected, and 0 otherwise. The larger value for direct investment (Table 1) indicates that the average node for that layer of the network is more interconnected that that for the other layers. This could reflect the importance of global value chains across the world.

V. Stress-Testing the Global Economy

We now stress-test the global economy to assess the systemic impact of the shocks. We do this by examining how an exogenous shock forcing an economy to default on its debt obligations reverberates through the network and generates losses across the global economy.[24] Simulations are calibrated and run for a 5-year horizon. Due to the sensitivity of the analysis, we do not report the names of economies subject to a shock. Our exercise is comprised of multiple scenarios, each analyzing an initial default in each of the 63 economies, taken one at a time, and calculates, for each of these scenarios, the systemic impact conditional on the network structure, that is, through other economies' direct exposures.[25] Building on the stress-testing literature we compute measures that summarize the vulnerability of the network arising from contagion, and the systemic importance of different economies (Battiston et al., 2016).

Figure 3. Number of Subsequent Economies Falling into Debt Default



Source: Authors' calculations.

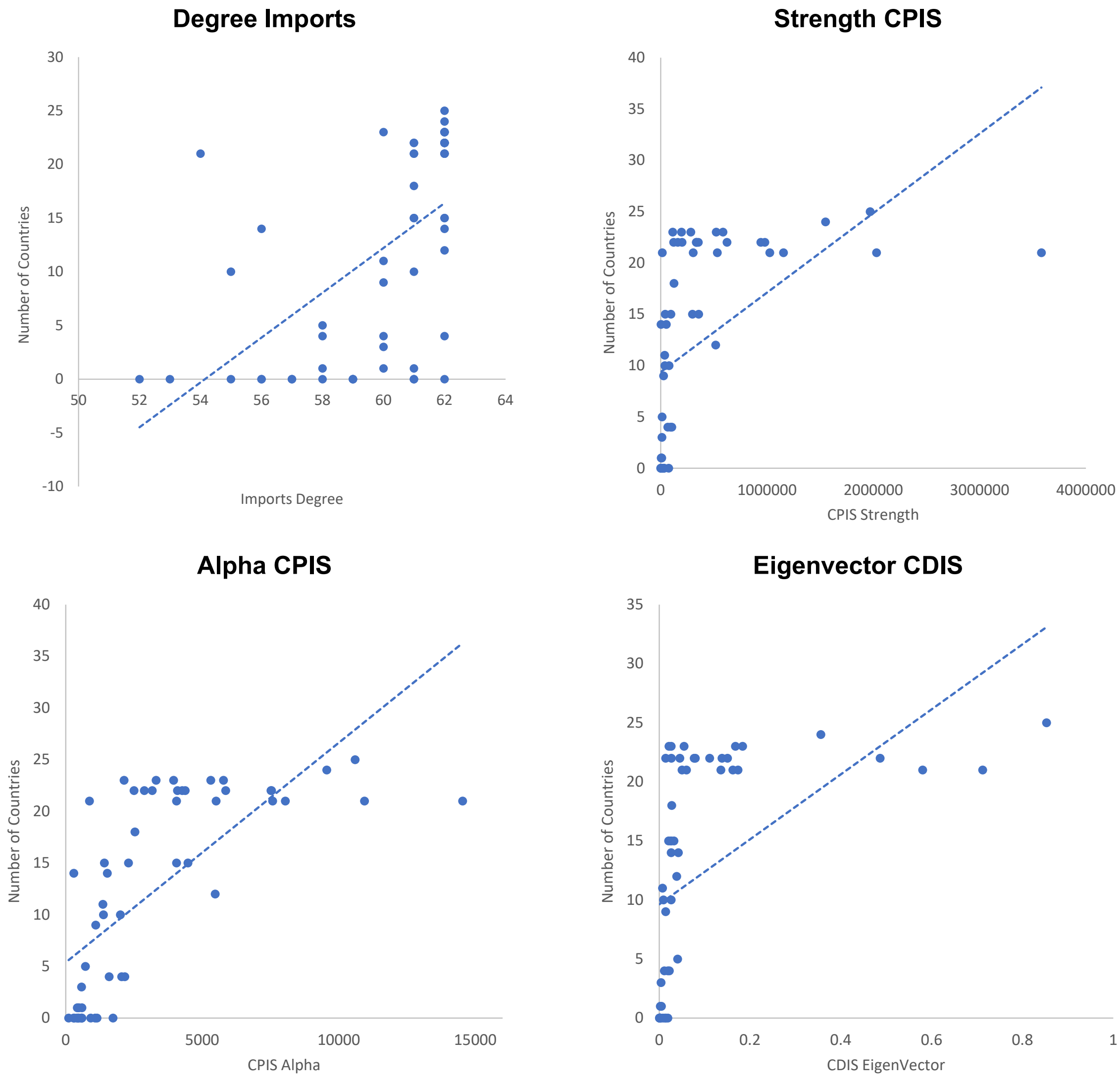
Note: Each scenario is initially triggered by a single economy falling into default. The number of subsequent defaults excludes the initial economy in default.

The *extent of contagion* is summarized by the number of economies falling into 'debt default' following the initial shock (each bar corresponds to different scenario). As shown in Figure 3, contagion may affect as many as 25 economies following a default in economy number 10. The average number of defaults is around 12.1. Not surprisingly, economies that induce the largest number of defaults, for the most part, correspond to those that are more interconnected (Figure 4).

[24] The analysis assumes that 6 economies are reserve-currency issuers (France, Germany, Japan, United Kingdom, United States, and People's Republic of China) and hence do not incur default.

[25] As described in Section III-A, a liquidity, and hence the possibility of a solvency crisis, emerges when a given economy defaults on its interest payments due to all its counterparts. This is the initial shock in the model.

Figure 4. Interconnectedness and Default—Selected Centrality Measures and Economies in Debt Default



Source: Authors' calculations.
Note: The scatter plots depict the correlations of the indicator with the highest average on Table 1

We capture the *systemic importance* of an economy by the *aggregate reserve losses* it induces on other economies within the simulated horizon. For simplicity, we account for reserve losses including those from both defaulting and non-defaulting economies. Due to the market sensitivity, we do not report dollar amounts. Instead, we build on the stress testing literature and compute a *vulnerability index* for each economy. Given the initial level of international reserves, $R_i(0)$, the vulnerability index $V_i(t)$ of economy i at time t can be defined as the reserve loss that it would experience at each moment in time. Intuitively, if an economy is exposed to a shock that induces a loss of all its reserves, that is $R_i(t) = 0$, then $V_i(t) = 1$. For simplicity, we maintain the assumption of full reserve depletion for an economy to default throughout the exercise.[26] This economy-specific vulnerability index $V_i(t)$ is given by:

$$V_i(t) = min\left\{1, \frac{R_i(0) - R_i(t)}{R_i(0)}\right\}$$

Where $V_i(t) \in [0,1]$. Specifically, $V_i(t) = 0$ when the country is most resilient (i.e., $R_i(t) = R_i(0)$ so the country suffers no reserve loses following the shock) and $V_i(t) = 1$, when the country is most vulnerable (i.e., $R_i(t) = 0$, that is it depletes completely its reserves). Hence, individual economies are more vulnerable the closer this index is to zero.

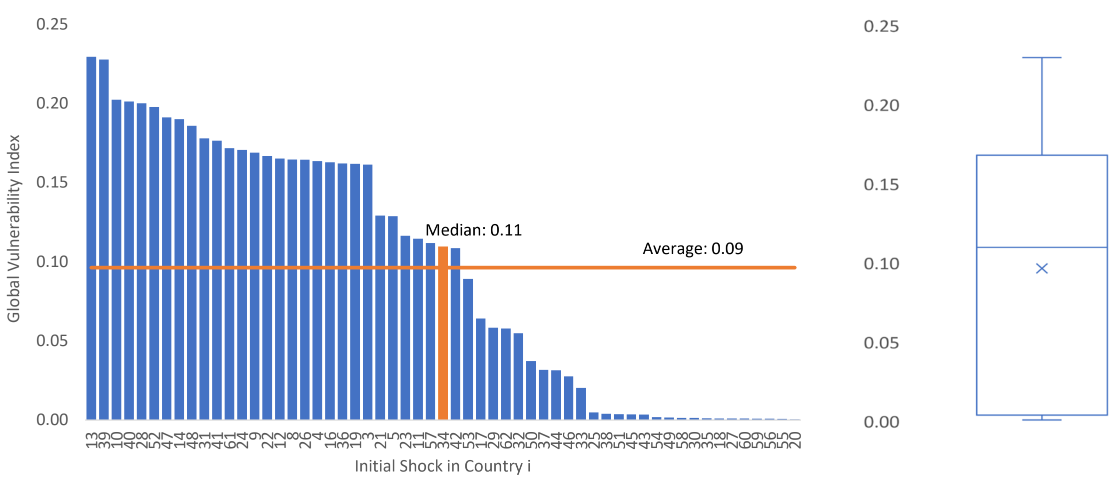
Using this expression, we can also compute a *global vulnerability index* (GV) as a weighted average of individual economies' vulnerabilities, where the weights are given by the initial level of reserves relative to the aggregate reserves in the sample. This is given by the expression:

$$GV(t) = \sum_{i=1}^{63} \left(\frac{R_i(0)}{\sum_j R_j(0)} V_i(t) \right)$$

for all $i \neq j$. Just as with the country vulnerability index, $GV(t) \in [0,1]$. That is, the closer $GV(t)$ is to zero, the less vulnerable is the global economy, and the closer it is to 1, the more vulnerable is the global economy.

Figure 5. Global Vulnerability Index

a. By Country-Specific Shock **b. Distribution**



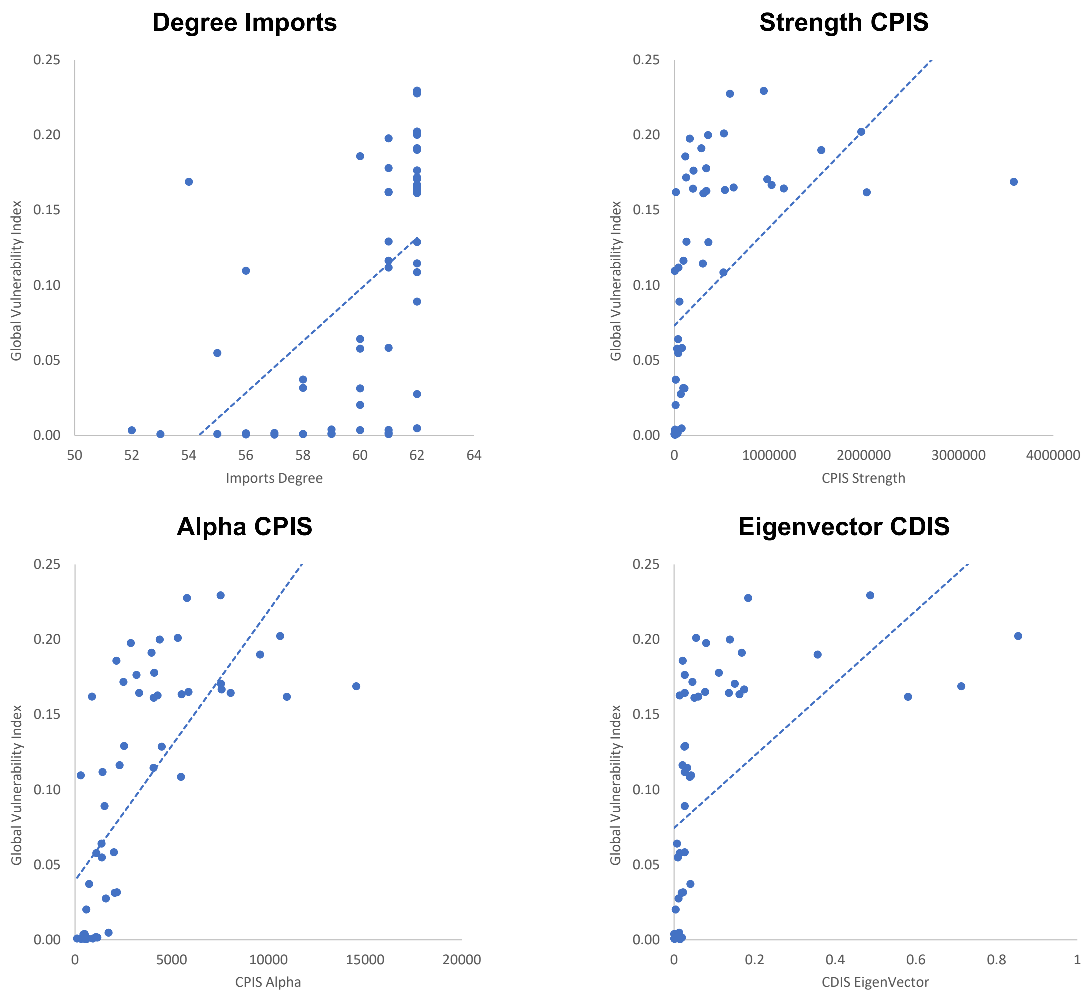
Source: Authors' calculations.

Note: In panel a, each bar corresponds to a scenario in which debt default is triggered by a single economy. Panel b shows the distribution of the global vulnerability index across all scenarios.

[26] This can be easily modified to allow for different levels of reserves at which an economy defaults Papamichalis et al. (2022) use a non-zero threshold that is in line with the IMF's reserve adequacy metric.

Figure 5a displays the *country-specific vulnerability index* following a debt default in another country. As shown, in a large number of scenarios, the global economy is highly vulnerable to contagion following a default. Figure 5b depicts the boxplot (summary distribution) of the global vulnerability index. The box shows the interquartile range, with the 75th percentile at 0.168 and median at 0.11. The distribution provides a prior on what can be considered as “normal circumstances” (economies with a vulnerability index within the interquartile range) *versus* tail risks (economies with a vulnerability index outside the interquartile range). Intuitively these results imply that there is a non-negligible set of economies for which a debt default can trigger significant loses on the global economy. As shown in Figure 6 the most systemic economies are precisely those most interconnected across layers.

Figure 6. Interconnectedness and Global Vulnerability—Selected Centrality Measures and Global Vulnerability Index



Source: Authors’ calculations.
Note: The scatter plots depict the correlations of the indicator with the highest average on Table 1.

VI. Conclusions and Possible Extensions

This paper has assessed the degree of trade and financial interconnectedness in the global economy and extended a multilayered model to analyze the systemic impact of debt default in the global economy. By allowing for contagion and cascading effects that arise from economies' direct trade and financial linkages, the model allows to stress test individual economies and the global economy.

The results have shown that contagion—once an initial default takes place—is highly correlated with the extent of interconnectedness of the economy. This has important applications for policy makers at the country and multilateral levels. At the country level, the model allows to identify the systemic importance of individual economies—which might be much larger than what conventional measures of size or openness might suggest. At the multilateral level, it allows to determine the global systemic impact of an individual or a group of economies. This for example, can help determine the role and optimal size of the global financial safety net (see IMF, 2017; Papamichalis et al., 2022, and Ramadiah et al., 2022).

The model is versatile and can be extended in several directions. One example could be to set a more realistic foreign exchange reserve threshold at which a country stops servicing its debt obligations. Also, in line with the literature, the model can be extended to include other channels of contagion, for instance, those arising from asset price co-movement and country risk premia. Including these channels can amplify the effects of a shock even if it does not necessarily induce a depletion of reserves and subsequent defaults. Moreover, the model also allows to account for endogenous policy responses, including exchange rate, monetary and fiscal adjustment, which could mitigate the impact of the shock.[27]

Including other channels of contagion and amplification effects are likely to increase the number of subsequently affected economies, the aggregate reserve losses, and the vulnerability of the global economy. This should trigger stronger domestic policy responses or call for a greater role of global safety net.

[27] See Papamichalis et al., 2022, Ramadiah et al., 2022 for extensions along several of these lines.

Appendix Table I. List of Economies

Australia	Hungary	New Zealand
Austria	Iceland	Norway
Bahrain, Kingdom of	India	Pakistan
Barbados	Indonesia	Panama
Belgium	Ireland	Philippines
Bolivia	Israel	Poland
Brazil	Italy	Portugal
Bulgaria	Japan	Romania
Canada	Kazakhstan	Russian Federation
Chile	Korea, Republic of	Singapore
China	Kuwait	Slovak Republic
Costa Rica	Latvia	Slovenia
Cyprus	Lithuania	South Africa
Czech Republic	Luxembourg	Spain
Denmark	Macao SAR*	Sweden
Estonia	Malaysia	Switzerland
Finland	Malta	Thailand
France	Mauritius	Turkey
Germany	Mexico	United Kingdom
Greece	Mongolia	United States
Hong Kong SAR*	Netherlands	Uruguay

*Special Administrative Region, People’s Republic of China.

Appendix Table II. Country-Specific Centrality Measures

	Degree Centrality				
Country Name	Exports	Imports	CPIS	CDIS	BIS
Australia	62	62	58	41	62
Austria	62	62	54	42	62
Bahrain, Kingdom of	50	59	39	20	20
Barbados	38	56	22	13	14
Belgium	62	62	57	42	62
Bolivia	50	55	18	26	13
Brazil	62	62	54	48	38
Bulgaria	62	61	37	47	20
Canada	62	62	59	49	58
Chile	62	61	51	36	40
China	62	62	56	58	26
Costa Rica	57	59	31	31	17
Cyprus	61	61	48	45	24
Czech Republic	62	62	44	43	19
Denmark	62	62	56	43	62
Estonia	61	56	31	37	15
Finland	62	62	54	39	47
France	62	62	59	49	62
Germany	62	62	59	52	62
Greece	62	60	49	45	34
Hong Kong SAR*	62	62	57	43	62
Hungary	62	61	47	45	22
Iceland	59	58	34	27	15
India	62	62	54	49	24
Indonesia	62	62	50	39	19
Ireland	62	61	59	43	59
Israel	58	58	50	33	21
Italy	62	62	56	49	57
Japan	62	62	59	37	62
Kazakhstan	54	58	39	45	19
Korea, Republic of	62	62	58	45	51
Kuwait	50	59	31	17	19
Latvia	60	58	33	37	15
Lithuania	61	56	34	36	17
Luxembourg	62	54	59	50	61
Macao SAR*	35	52	22	22	30
Malaysia	61	60	40	36	21
Malta	55	57	44	38	21
Mauritius	50	57	40	43	19
Mexico	61	61	50	51	24
Mongolia	37	53	22	30	15
Netherlands	62	62	57	51	43
New Zealand	62	62	40	32	23
Norway	62	62	55	42	23
Pakistan	61	60	34	23	18
Panama	41	55	47	35	22
Philippines	62	62	38	35	57
Poland	62	62	51	50	22
Portugal	62	61	51	35	24
Romania	60	60	43	48	20
Russian Federation	60	61	51	52	23
Singapore	62	62	55	50	23
Slovak Republic	61	61	37	39	18
Slovenia	62	61	42	40	18
South Africa	62	62	56	47	49
Spain	62	62	56	53	62
Sweden	62	62	55	43	56
Switzerland	62	62	60	46	62
Thailand	60	60	40	47	22
Turkey	61	61	55	53	25
United Kingdom	62	62	61	55	62
United States	62	62	59	57	62
Uruguay	58	60	29	24	21
Average	59.0	60.1	46.8	40.9	34.4
Max	62	62	61	58	62
Min	35	52	18	13	13
Median	62	61	50	43	24

*Special Administrative Region, People's Republic of China

	Strength Centrality				
Country Name	Exports	Imports	CPIS	CDIS	BIS
Australia	227,093.0	214,784.8	979,729.8	554,447.0	655,748.0
Austria	174,914.7	180,997.6	305,573.1	266,979.0	160,165.0
Bahrain, Kingdom of	8,888.8	11,131.8	8,699.1	9,876.0	40,301.1
Barbados	156.7	1,533.2	3,979.2	135,134.0	44,433.0
Belgium	430,428.7	420,960.2	532,873.4	619,096.0	311,638.0
Bolivia	6,076.3	7,659.4	640.4	6,615.0	1,399.7
Brazil	189,605.1	150,499.3	355,237.2	532,019.0	101,089.0
Bulgaria	28,220.4	33,616.2	4,968.0	32,962.0	9,761.4
Canada	434,450.5	455,121.5	1,550,464.9	1,001,364.0	549,564.0
Chile	67,961.5	61,875.3	78,638.4	127,912.0	31,373.0
China	2,079,022.4	1,472,918.1	930,047.8	1,593,884.0	1,257,258.3
Costa Rica	8,879.7	14,452.5	5,257.1	10,236.0	10,277.1
Cyprus	2,207.8	9,098.7	15,884.1	385,510.0	51,731.2
Czech Republic	193,985.2	176,112.3	52,770.9	138,898.0	81,995.6
Denmark	83,408.2	95,193.3	358,380.1	133,821.0	158,315.0
Estonia	15,886.7	18,112.0	3,051.5	16,546.0	6,615.0
Finland	70,553.0	76,513.6	337,271.4	81,000.0	366,035.1
France	517,993.9	617,287.0	2,940,446.0	899,811.0	2,713,233.0
Germany	1,466,372.3	1,222,628.4	2,184,276.6	1,059,291.0	877,862.0
Greece	29,238.4	52,090.5	38,069.3	33,962.0	36,158.0
Hong Kong SAR*	525,275.6	566,524.4	586,531.3	1,361,111.0	1,081,249.0
Hungary	114,327.6	114,954.1	42,925.1	120,239.0	27,924.8
Iceland	5,016.3	7,358.0	10,458.9	12,323.0	2,275.1
India	214,415.9	329,918.8	522,777.1	392,436.0	209,826.4
Indonesia	156,602.1	162,646.8	201,130.2	184,957.0	119,495.2
Ireland	156,588.6	99,860.2	2,030,914.6	1,719,786.0	283,396.0
Israel	55,000.2	74,884.0	93,588.3	69,705.0	16,930.2
Italy	480,246.1	427,615.3	1,155,376.3	512,786.0	423,049.3
Japan	640,398.4	598,393.3	2,014,987.3	320,152.0	500,411.0
Kazakhstan	54,065.5	28,930.5	13,488.4	127,730.0	17,619.6
Korea, Republic of	496,186.4	413,024.8	517,168.8	189,766.0	208,795.0
Kuwait	54,376.0	25,550.3	7,746.9	5,131.0	28,142.2
Latvia	14,435.7	18,294.7	6,206.4	12,726.0	5,665.0
Lithuania	29,457.3	34,302.2	10,494.1	17,362.0	6,184.5
Luxembourg	15,578.7	23,727.9	3,580,806.4	2,469,519.0	366,869.0
Macao SAR*	1,266.4	10,794.2	9,291.2	24,174.0	77,021.0
Malaysia	217,548.4	186,271.8	105,458.7	121,012.0	77,195.5
Malta	2,399.0	5,802.4	7,704.7	74,269.0	23,907.5
Mauritius	1,603.5	4,957.6	32,854.7	135,600.0	28,215.3
Mexico	433,478.4	467,922.4	334,952.8	357,551.0	20,885.6
Mongolia	7,003.8	5,390.7	4,123.3	12,275.0	6,330.0
Netherlands	663,099.3	587,482.2	1,971,097.8	3,284,808.0	911,983.0
New Zealand	33,352.1	39,052.2	75,129.9	79,359.0	53,710.0
Norway	117,603.8	85,689.1	299,314.7	141,579.0	329,031.0
Pakistan	17,127.9	39,671.4	7,037.2	15,080.0	27,559.0
Panama	509.0	8,784.4	40,599.5	58,566.0	97,372.1
Philippines	62,694.0	100,466.5	66,528.1	55,822.0	21,676.0
Poland	244,232.0	251,169.6	122,913.9	211,356.0	93,522.0
Portugal	60,720.8	80,621.0	126,368.0	111,958.0	80,822.0
Romania	70,855.3	92,122.0	28,137.2	77,573.0	25,137.2
Russian Federation	368,692.1	200,345.3	162,719.5	390,655.0	90,456.8
Singapore	350,859.2	296,530.1	284,439.5	722,849.0	888,091.1
Slovak Republic	91,018.5	90,357.5	31,391.2	46,453.0	23,850.8
Slovenia	35,844.7	36,175.5	19,983.4	13,730.0	9,353.6
South Africa	58,160.3	74,696.7	195,508.3	102,327.0	28,021.0
Spain	293,416.3	325,140.2	1,026,037.6	672,259.0	360,957.0
Sweden	156,724.3	162,175.4	624,326.9	333,187.0	243,263.0
Switzerland	289,626.0	242,658.7	942,651.8	1,510,559.0	236,911.0
Thailand	200,617.8	193,586.3	114,430.5	171,192.0	70,875.4
Turkey	115,755.2	176,025.7	96,041.3	101,486.0	188,486.4
United Kingdom	435,071.1	620,750.1	3,925,556.9	3,464,711.0	3,190,713.0
United States	1,454,763.3	2,283,532.0	9,622,001.6	4,525,026.0	7,244,000.0
Uruguay	5,157.0	6,046.2	11,690.3	28,998.0	8,569.6
Average	235,500.2	236,393.5	663,002.4	507,928.7	400,328.6
Max	2,079,022.4	2,283,532.0	9,622,001.6	4,525,026.0	7,244,000.0
Min	156.7	1,533.2	640.4	5,131.0	1,399.7
Median	91,018.5	95,193.3	114,430.5	135,134.0	80,822.0

Appendix Table II. Country-Specific Centrality Measures (Concluded)

	Alpha Centrality				
Country Name	Exports	Imports	CPIS	CDIS	BIS
Australia	3,752.3	3,649.2	7,538.2	4,767.8	6,376.2
Austria	3,293.1	3,349.9	4,062.1	3,348.6	3,151.2
Bahrain, Kingdom of	666.7	810.4	582.5	444.4	897.8
Barbados	77.2	293.0	295.9	1,325.4	788.7
Belgium	5,165.9	5,108.8	5,511.2	5,099.2	4,395.6
Bolivia	551.2	649.0	107.4	414.7	134.9
Brazil	3,428.6	3,054.7	4,379.8	5,053.4	1,959.9
Bulgaria	1,322.7	1,432.0	428.7	1,244.7	441.8
Canada	5,190.0	5,312.0	9,564.4	7,004.8	5,645.8
Chile	2,052.7	1,942.8	2,002.6	2,145.9	1,120.2
China	11,353.4	9,556.2	7,216.8	9,614.8	5,717.4
Costa Rica	711.4	923.4	403.7	563.3	418.0
Cyprus	367.0	745.0	873.2	4,165.1	1,114.2
Czech Republic	3,468.0	3,304.4	1,523.8	2,443.9	1,248.2
Denmark	2,274.1	2,429.4	4,479.9	2,398.8	3,133.0
Estonia	984.4	1,007.1	307.6	782.4	315.0
Finland	2,091.5	2,178.0	4,267.6	1,777.4	4,147.7
France	5,667.1	6,186.4	13,171.4	6,640.1	12,970.0
Germany	9,534.9	8,706.5	11,352.2	7,421.8	7,377.5
Greece	1,346.4	1,767.9	1,365.8	1,236.2	1,108.8
Hong Kong SAR*	5,706.8	5,926.6	5,782.1	7,650.3	8,187.6
Hungary	2,662.4	2,648.1	1,420.4	2,326.1	783.8
Iceland	544.0	653.3	596.3	576.8	184.7
India	3,646.1	4,522.7	5,313.2	4,385.1	2,244.1
Indonesia	3,116.0	3,175.5	3,171.2	2,685.8	1,506.8
Ireland	3,115.8	2,468.1	10,946.4	8,599.5	4,089.1
Israel	1,786.1	2,084.1	2,163.2	1,516.7	596.3
Italy	5,456.7	5,149.0	8,043.7	5,012.6	4,910.6
Japan	6,301.2	6,091.0	10,903.4	3,441.7	5,570.1
Kazakhstan	1,708.7	1,295.4	725.3	2,397.5	578.6
Korea, Republic of	5,546.5	5,060.4	5,476.8	2,922.2	3,263.2
Kuwait	1,648.9	1,227.8	490.1	295.3	731.2
Latvia	930.7	1,030.1	452.6	686.2	291.5
Lithuania	1,340.5	1,386.0	597.3	790.6	324.2
Luxembourg	982.8	1,131.9	14,535.0	11,112.0	4,730.6
Macao SAR*	210.5	749.2	452.1	729.3	1,520.1
Malaysia	3,642.9	3,343.1	2,053.9	2,087.2	1,273.2
Malta	363.2	575.1	582.2	1,679.9	708.6
Mauritius	283.1	531.6	1,146.4	2,414.7	732.2
Mexico	5,142.2	5,342.6	4,092.4	4,270.3	708.0
Mongolia	509.1	534.5	301.2	606.8	308.1
Netherlands	6,411.9	6,035.2	10,599.6	12,943.2	6,262.2
New Zealand	1,438.0	1,556.0	1,733.6	1,593.6	1,111.5
Norway	2,700.3	2,304.9	4,057.4	2,438.5	2,750.9
Pakistan	1,022.2	1,542.8	489.1	588.9	704.3
Panama	144.5	695.1	1,381.4	1,431.7	1,463.6
Philippines	1,971.6	2,495.8	1,590.0	1,397.8	1,111.5
Poland	3,891.3	3,946.2	2,503.7	3,250.8	1,434.4
Portugal	1,940.3	2,217.6	2,538.7	1,979.5	1,392.7
Romania	2,061.9	2,351.0	1,100.0	1,929.6	709.0
Russian Federation	4,703.4	3,495.9	2,880.7	4,507.1	1,442.4
Singapore	4,664.0	4,287.8	3,955.3	6,011.9	4,519.5
Slovak Republic	2,356.3	2,347.7	1,077.7	1,346.0	655.2
Slovenia	1,490.8	1,485.5	916.1	741.1	410.3
South Africa	1,898.9	2,152.0	3,308.8	2,193.0	1,171.8
Spain	4,265.2	4,489.8	7,580.1	5,969.1	4,730.7
Sweden	3,117.2	3,170.9	5,859.9	3,785.1	3,690.9
Switzerland	4,237.5	3,878.8	7,520.6	8,335.8	3,832.6
Thailand	3,469.4	3,408.1	2,139.4	2,836.6	1,248.7
Turkey	2,657.3	3,276.8	2,298.3	2,319.2	2,170.8
United Kingdom	5,193.7	6,203.7	15,474.5	13,804.3	14,065.0
United States	9,497.1	11,898.7	23,826.4	16,060.1	21,192.6
Uruguay	546.9	602.3	582.3	834.2	424.2
Average	2,978.1	3,034.5	4,160.2	3,656.8	2,892.1
Max	11,353.4	11,898.7	23,826.4	16,060.1	21,192.6
Min	77.2	293.0	107.4	295.3	134.9
Median	2,356.3	2,429.4	2,298.3	2,398.8	1,392.7

*Special Administrative Region, People's Republic of China

	Eigenvector Centrality				
Country Name	Exports	Imports	CPIS	CDIS	BIS
Australia	0.17	0.11	0.18	0.15	0.20
Austria	0.07	0.06	0.03	0.05	0.02
Bahrain, Kingdom of	0.00	0.00	0.00	0.00	0.02
Barbados	0.00	0.00	0.00	0.04	0.01
Belgium	0.16	0.15	0.07	0.16	0.05
Bolivia	0.00	0.00	0.00	0.00	0.00
Brazil	0.14	0.09	0.08	0.14	0.03
Bulgaria	0.01	0.01	0.00	0.00	0.00
Canada	0.35	0.42	0.38	0.36	0.22
Chile	0.05	0.04	0.02	0.03	0.01
China	1.00	0.52	0.10	0.18	0.32
Costa Rica	0.01	0.01	0.00	0.00	0.00
Cyprus	0.00	0.00	0.00	0.06	0.02
Czech Republic	0.07	0.06	0.00	0.03	0.01
Denmark	0.03	0.03	0.05	0.03	0.02
Estonia	0.00	0.00	0.00	0.00	0.00
Finland	0.03	0.02	0.04	0.01	0.04
France	0.20	0.20	0.41	0.24	0.51
Germany	0.51	0.33	0.30	0.29	0.17
Greece	0.01	0.01	0.01	0.01	0.01
Hong Kong SAR*	0.50	0.30	0.09	0.18	0.18
Hungary	0.04	0.03	0.01	0.03	0.01
Iceland	0.00	0.00	0.00	0.00	0.00
India	0.11	0.14	0.08	0.05	0.07
Indonesia	0.08	0.07	0.03	0.03	0.04
Ireland	0.08	0.05	0.32	0.58	0.07
Israel	0.03	0.03	0.02	0.02	0.01
Italy	0.18	0.14	0.14	0.14	0.08
Japan	0.43	0.30	0.44	0.10	0.13
Kazakhstan	0.02	0.01	0.00	0.04	0.01
Korea, Republic of	0.37	0.21	0.10	0.04	0.05
Kuwait	0.03	0.01	0.00	0.00	0.01
Latvia	0.00	0.00	0.00	0.00	0.00
Lithuania	0.01	0.01	0.00	0.00	0.00
Luxembourg	0.01	0.01	0.31	0.71	0.05
Macao SAR*	0.00	0.01	0.00	0.00	0.01
Malaysia	0.12	0.08	0.02	0.02	0.03
Malta	0.00	0.00	0.00	0.02	0.01
Mauritius	0.00	0.00	0.01	0.02	0.01
Mexico	0.35	0.41	0.07	0.11	0.01
Mongolia	0.01	0.00	0.00	0.00	0.00
Netherlands	0.25	0.23	0.30	0.85	0.23
New Zealand	0.02	0.02	0.01	0.01	0.01
Norway	0.04	0.03	0.04	0.03	0.06
Pakistan	0.01	0.02	0.00	0.00	0.01
Panama	0.00	0.01	0.01	0.01	0.03
Philippines	0.04	0.04	0.01	0.01	0.00
Poland	0.09	0.08	0.02	0.05	0.01
Portugal	0.02	0.02	0.01	0.03	0.01
Romania	0.02	0.02	0.00	0.01	0.00
Russian Federation	0.16	0.08	0.03	0.08	0.02
Singapore	0.18	0.13	0.04	0.17	0.28
Slovak Republic	0.03	0.02	0.00	0.01	0.00
Slovenia	0.01	0.01	0.00	0.00	0.00
South Africa	0.03	0.03	0.04	0.03	0.01
Spain	0.10	0.11	0.13	0.17	0.07
Sweden	0.05	0.04	0.09	0.08	0.04
Switzerland	0.15	0.10	0.20	0.49	0.05
Thailand	0.11	0.09	0.02	0.02	0.02
Turkey	0.04	0.06	0.02	0.02	0.05
United Kingdom	0.19	0.25	0.68	0.96	0.66
United States	0.66	1.00	1.00	1.00	1.00
Uruguay	0.00	0.00	0.00	0.00	0.00
Average	0.12	0.10	0.09	0.13	0.08
Max	1.00	1.00	1.00	1.00	1.00
Min	0.00	0.00	0.00	0.00	0.00
Median	0.04	0.03	0.02	0.03	0.02

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