Food and Agriculture Organization
of the United Nations

The evolution of the global structure of food and agricultural trade: Evidence from network analysis

Background paper for
The State of Agricultural Commodity
Markets (SOCO) 2022

The evolution of the global structure of food and agricultural trade: Evidence from network analysis

Background paper for
The State of Agricultural Commodity
Markets (SOCO) 2022

Yaghoob Jafari and Helena Engemann
Institute for Food and Resource Economics, University of Bonn

Andrea Zimmermann
Food and Agriculture Organization of the United Nations

Food and Agriculture Organization of the United Nations
Rome, 2023

Required citation:
Jafari, Y., Engemann, H. & Zimmermann, A. 2023. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis. Background paper for The State of Agricultural Commodity Markets (SOCO) 2022*. Rome, FAO. https://doi.org/10.4060/cc4145en

ISBN 978-92-5-137589-1

Cover photograph:
©Shutterstock

Contents

Figures

Abstract

The outbreak of the COVID-19 pandemic in 2020 and the Russian–Ukrainian conflict, which began in February 2022, have tested the resilience of the food and agricultural trade network at a global level. The global dimension of these crises meets a policy landscape in which multilateral trade negotiations have largely stalled and regional approaches to trade integration are proliferating rapidly. Based on network analysis, this paper explores the evolution of the integration of the network of food and agricultural trade since the World Trade Organization (WTO) Agreement on Agriculture (AoA) in 1995, the network structure and their implications for resilience to trade shocks. Food and agricultural trade evolved rapidly and countries worldwide became more connected to global markets in the period 1995-2007, but progress has since been limited. While countries are connected globally, trade intensity is usually higher in specific regional clusters, which have become firmer over time. Increased connectivity among countries boosted their resilience to trade shocks, but vulnerabilities remain and evidence suggests slight tendencies of disintegration in recent years.

Acknowledgements

The authors thank Husam Attaallah (FAO) for support in data analysis and data visualization and George Rapsomanikis (FAO) for valuable comments on earlier drafts of the paper.

CHAPTER 1

Introduction

1 Introduction

The outbreak of the COVID-19 pandemic in 2020 and the restrictions imposed worldwide to contain the spread of the virus have tested the resilience of the food and agricultural trade network at a global dimension and almost simultaneously across all countries. The Russian–Ukrainian conflict, which started in February 2022, affects agricultural production and export capacity of two main players in the network and, in contrast to the globalized shock of the COVID-19 pandemic, poses a localized shock to the network but with a high risk of sending shock waves through the whole network through transmission effects and potentially self-propagating trade disruptions.

On average, and despite the multiple challenges, the food and agricultural trade network proved remarkably resilient to the shock posed by the outbreak of the COVID-19 pandemic. The only visible effects at global level were short-lived disruptions of trade at the beginning of the pandemic and when worldwide restrictions on movement were imposed during the March-April 2020 period (Arita *et al.,* 2022; Engemann and Jafari, 2022; FAO, 2021; Schmidhuber and Qiao, 2021). Due to high dependencies of some countries on imports of specific products, the Russian–Ukrainian conflict is expected to have more disruptive effects on food and agricultural trade. This raises questions about the stability of the network of food and agricultural trade and how to strengthen its resilience and calls for a better understanding of the structure of the current network and how it has evolved.

In the early 2000s, food and agricultural trade expanded rapidly, the share of low- and middle-income countries in global trade increased and global value chains in food and agriculture evolved (Dellink, Dervisholli and Nenci, 2020; FAO, 2020). However, this process has largely stalled since the 2008 financial crisis. One of the catalysts of the globalization process in the 2000s was the implementation of the 1995 World Trade Organization (WTO) Agreement on Agriculture (AoA), which, for the first time, ensured the explicit inclusion of agriculture as a sector in the multilateral liberalization process, reduced tariffs and other trade barriers (Daugbjerg and Swinbank, 2008; Grant and Boys, 2012). Since the 1990s, inspired by and often based on the set of rules defined by the General Agreement on Tariffs and Trade (GATT) and the WTO, a plethora of preferential and regional trade agreements (RTAs) followed or were negotiated in parallel to foster trade liberalization and deepen economic integration of countries in regional and global markets. Together, and reinforced by rapid technological progress that improved transport and communication, these trade agreements led to an unprecedented wave of globalization.

Although the WTO agreements, including the AoA, have succeeded in promoting trade, further progress in improving these rules has been limited since the latest round of multilateral negotiations, the Doha Round, stalled at the end of the first decade of the 21st century (Beghin and O'Donnell, 2021; Kerr, 2021). With limited progress in multilateral trade negotiations, RTAs have emerged more rapidly (Ahcar and Siroën, 2017). While the WTO has taken some significant steps towards behind-the-border convergence in regulations, many RTAs envisage much deeper levels of integration among their signatories (Crawford and Laird, 2001; Hofmann, Osnago and Ruta, 2019).[1]

[1] Recent trade agreements no longer emphasize market access but instead focus on behind-the-border regulatory issues, including domestic policy coordination in a much broader sense (Bown, 2017; Maggi and Ossa, 2021). These agreements are often very complex as they tend to pursue economic objectives and provisions targeting social and environmental sustainability outcomes (Maggi and Ossa, 2021; Rodrik, 2018).

Over the last decades, most countries have concluded trade agreements both within the multilateral framework of the WTO and regionally, and multilateralism and regionalism are thought to have advanced together (Baldwin, 2016). While governments come together at the WTO to negotiate the"rules of globalization"(Staiger, 2021), this process has been complemented and reinforced by an increasing number of RTAs. Since 1990, and in parallel to the multilateral trade negotiations, the number of regional trade agreements (RTAs) in force grew from fewer than 25 to more than 350 in 2022 (WTO, 2022).[2] The deadlock in WTO negotiations and the proliferation of RTAs have led to renewed interest in the question whether, after the wave of globalization in the 2000s, food and agricultural trade is now fragmenting into regional blocs.[3]

The question whether RTAs are building blocks of, or stumbling blocks to, multilateralism has generated a rich discussion in the literature (e.g. Bhagwati, 1991; Krugman, 1989; overview provided by Baldwin, 2008), but has largely focused on tariff liberalisation (Baldwin, 2008). While regionalism and multilateralism have probably both contributed to freer trade overall (Baldwin, 2008; Summers, 1991), today's deep trade agreements raise new questions about their interaction with multilateral approaches and their impact on trade. The overlapping of RTAs (Bhagwati's "spaghetti bowl"; Bhagwati, 1995) can pose challenges for compliance and transparency due to multiple rules with respect to tariffs, non-tariff measures (NTMs) and rules of origin[4], which can differ by agreement, trading partner and product, and can even lead to conflicting regulatory standards across different trading blocs, thus raising trade barriers and costs (Bhagwati, 1991, 1993; Pomfret, 2021; Thompson-Lipponen and Greenville, 2019). Negotiating and implementing an RTA requires considerable resources, which could be beyond the reach of many countries (Crawford and Laird, 2001). As a result, especially developing countries appear to have accepted provisions in RTAs that they resist at WTO level (Baldwin, 2008).

Empirical studies have found mixed evidence on the impact of RTAs on trade (Grant and Lambert, 2008; Sarker and Jayasinghe, 2007) and the effects differ across agreements (Grant and Lambert, 2008; Mujahid and Kalkuhl, 2016). The degree to which governments negotiate comprehensive and deeper trade agreements appears to be positively related to their level of economic development – the richer a country, the deeper its trade agreements. RTAs are also deeper when more WTO members are involved in the agreement, as provisions contained in RTAs usually build on existing WTO policies (Kohl, Brakman and Garretsen, 2016; Thompson-Lipponen and Greenville, 2019). The evidence of the effects of deep RTAs on trade is mixed in general and scarce in agriculture (Ahcar and Siroën, 2017; Mattoo, Mulabdic and Ruta, 2017).

In general, there is scope and reason for both global (i.e. interregional) and intraregional trade. Global trade in food and agriculture is fostered by the fact that food and agricultural production depend on agroclimatic conditions and natural resource endowments, which are unevenly distributed across the world and, together with differences in technology, shape trade flows. Both feature prominently as drivers of trade in the traditional trade theories, with the Ricardian model emphasizing technological differences and the Heckscher-Ohlin model stressing differences in factor endowments (Krugman, 1987). Demand for food is increasing fastest in regions where population and income growth are strongest, as in emerging economies

---

2 This number includes only RTAs in force that have been notified to the WTO.

3 The agricultural sector appears to be increasingly included in RTAs and is progressively being treated similarly to other sectors, although many agreements still exclude some agricultural products from specific provisions. In agriculture, RTAs may facilitate deeper integration by harmonizing NTMs, including technical and food safety standards and domestic regulations, in areas in which multilateral negotiations have made little progress as preferences across countries worldwide diverge widely. However, RTAs usually do not address (potentially trade-distorting) domestic support to agriculture (Grant and Lambert, 2008; Thompson-Lipponen and Greenville, 2019).

4 Rules of origin refer to criteria to establish where a product was made. They are important in identifying whether goods qualify for preferential treatment within an RTA because they originate in one of the RTA signatory countries and are not re-exported (FAO, 2022).

and developing countries in Africa and Asia (FAO, 2020). In many of these regions, agricultural productivity is relatively low and countries may be challenged to produce sufficient food for their growing population. Countries in these regions will depend on global imports to ensure food security. Global trade can also enhance dietary diversity and responds to consumers' 'love of variety' (Dixit and Stiglitz, 1977) as foods that cannot be produced domestically can be imported from other countries (Aguiar *et al.,* 2020; Geyik *et al.,* 2021; Remans *et al.,* 2014; Wood *et al.,* 2018). The increasing risks to agricultural production from climate change reinforce the role of global trade in ensuring food security and nutrition (FAO, 2018; Janssens *et al.,* 2020).

At the same time, most empirical evidence shows that countries that are similar in terms of economic size or are located close to each other tend to trade more among each other, as compared with countries of different relative sizes or countries that are geographically more remote (see for example Anderson and van Wincoop, 2003; Feenstra, 2015). Trade is proportional to the economic size of a country, reflecting production capacity and economies of scale, but also purchasing power and preferences associated with income levels (Anderson, 2011; Bergstrand, 1989; Krugman, 1980). Trade costs tend to increase with distance, infrastructure is linked and trade procedures, culture and preferences are often similar among neighbouring countries, favouring trade between countries that are nearer each other (Anderson and van Wincoop, 2004; Pomfret and Sourdin, 2010).

The evolution of trade patterns and their distribution over the world has implications for the resilience of the network of food and agricultural trade. Increased connectivity among countries can strengthen the buffer capacity of the global food and agricultural trade network. Countries that are well-integrated in the global market and have many trade links with other countries can benefit from trade by leveraging their comparative advantage globally. This would promote food security, a greater diversity of foods supplied and economic growth, alleviating pressure on the natural resource base. Higher connectivity would contribute to resilience to domestic production shocks and localized shocks in exporting countries.

For a country, domestic food production shocks, such as those arising from extreme weather events or geopolitical crises (Cottrell *et al.,* 2019), can be buffered by adjustments in the quantities traded, ensuring food security. In this way, shocks that are specific to individual countries or regions can be partly cancelled out at the global level, evening out supply fluctuations across the world and reducing price volatility. Nevertheless, with increasing import-dependency, greater connectivity between countries may also act as an avenue to transmit negative shocks and increase vulnerability, rather than contribute to resilience (Allouche, 2011; Remans *et al.,* 2014; Sartori and Schiavo, 2015). The effects of shocks in the trade network can be aggravated and lead to self-propagating trade disruptions if other countries in the network react by imposing export restrictions or other measures further reducing volumes in the global market, thus exacerbating price spikes (FAO, 2018; FAO *et al.,* 2011; Puma *et al.,* 2015; Torreggiani *et al.,* 2018). Still, countries with a high dependency on food and agricultural imports from only a few major trading partners are more vulnerable to shocks impacting one of their partners than countries that are better connected, allowing them to source food more easily from other places (Kummu *et al.,* 2020).

At the global level, the extent to which countries are vulnerable to external trade shocks depends on many factors, including the structure of the trade network. If the network is dominated by a few large players and many other countries are connected to these hubs, but are not connected among each other, shocks affecting these large players can easily transmit through the whole network and possibly be magnified by global value chains. A shock to the system can dissipate when all (or many) countries in the network are connected to many trade partners (Acemoglu *et al.,* 2012; Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015; Lucas, 1977; UNCTAD, 2019).

This paper sets out to describe the evolution of food and agricultural trade since the establishment of the WTO and the WTO AoA in 1995, assess globalization and regionalization tendencies and the impact on the resilience of the trade network.

The next section provides an initial exploration of major changes in food and agricultural trade at global level. This is followed by the description of methodology and data used for the main analysis. Based on network analysis, the results section first explores the integration of countries in the global network of food and agricultural trade and its evolution. Second, it analyses the evolution of the structure of integration, that is, the extent to which similar countries trade with each other along different dimensions: regional proximity, income similarities, and number of trading partners. Third, it explores the vulnerability of the trading system to shocks based on the heterogeneity in the level of countries' integration into the trade network and the way it evolved. The final section concludes.

CHAPTER 2

A glimpse of the evolution of food and agricultural trade

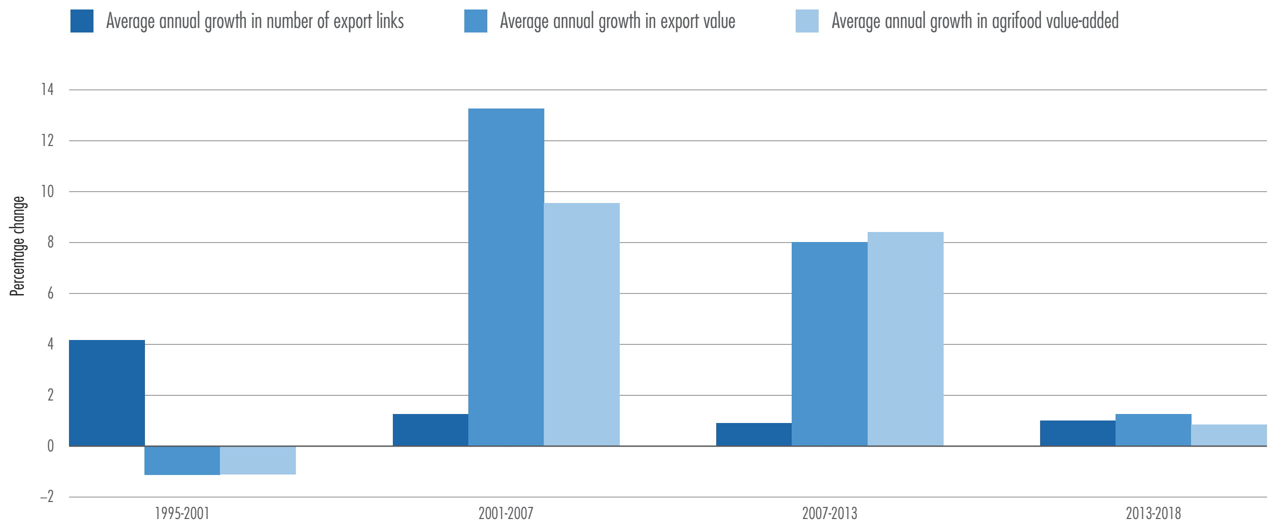
2 A glimpse of the evolution of food and agricultural trade

Since 1995, food and agricultural trade has increased in terms of volume traded and number of trade partnerships (or links) formed among countries. The total number of trade links between country pairs rapidly increased between 1995 and the early 2000s, after which newly formed trade partnerships have expanded more slowly (Figure 1). By contrast, the value of global food and agricultural trade grew strongly between the early 2000s and the early 2010s, but its growth rate has since been stagnant (Figure 1). The globalization in food and agriculture during this time period thus appears to have evolved in two steps. First, countries formed more trade links (1995-2001), followed by a rapid expansion of trade intensity through these trade links (2001-2007). As an indicator of globalization, the value of food and agricultural products traded expanded much more rapidly in the 2000s than the global value-added generated by the food and agricultural sector (Figure 1), a process that has largely stalled since the beginning of the second decade of the new millennium.

In terms of both the expansion of trade links and value traded, globalization has been mainly driven by a greater participation of emerging and developing countries in global markets. Between 1995 and 2019, the number of export links established by the group of low- and middle-income countries grew at an average annual rate of 2.1 percent, while this rate was 1.1 percent for the group of high-income economies. Low- and middle-income countries expanded their value exported at an average annual rate of 6.4 percent, while for high-income countries this rate was 4.6 percent.

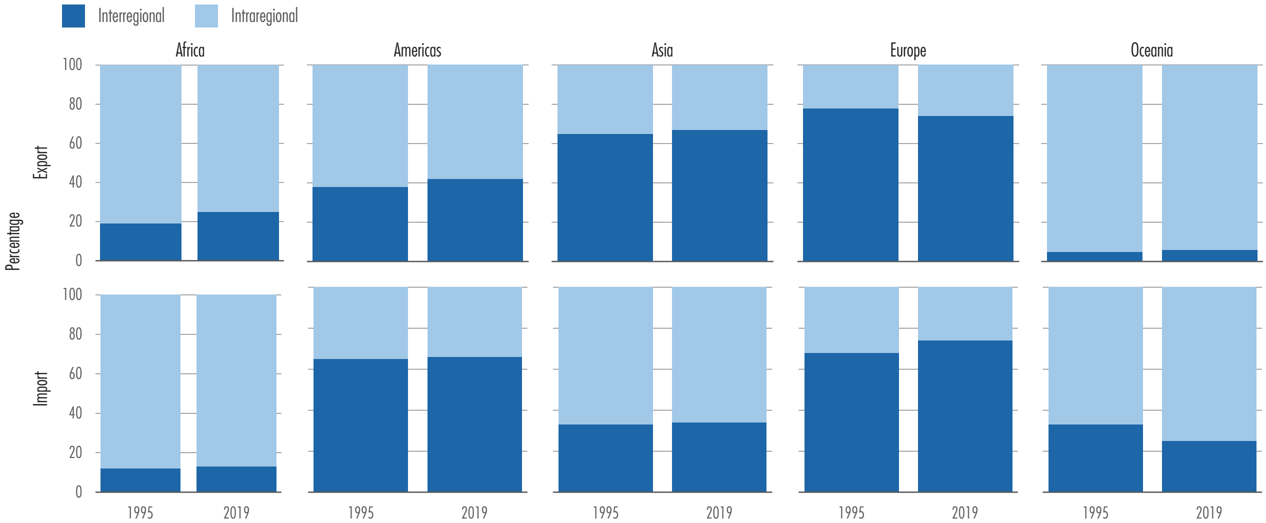
Traditionally, countries in some regions have traded more with partners within the same region, while others have been more globally oriented. At continental level, these relationships still hold, but some shifts have occurred in the global versus regional orientation of countries' trade (Figure 2). African countries tend to trade more globally, with the majority of their food and agricultural exports (almost 40 percent in 2019) destined for Europe. Still, between 1995 and 2019, the share of intra-African trade increased. The share of intra-regional trade increased also in the Americas and in Asia, while the pattern is mixed across imports and exports in Europe and Oceania.

Figure 1. Growth rates in global food and agricultural export links, export value and value-added, 1995–2018



Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

Figure 2. Food and agricultural trade within and between regions, 1995 and 2019



Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis*. Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

CHAPTER 3

Data and methodology

3 Data and methodology

3.1 Network analysis

The specific patterns in which countries trade with each other give rise to a "network" of trade which may reflect important features of the global market and interdependencies of countries through trade. An increasing number of studies rely on techniques borrowed from network analysis to analyse the patterns of trade flows and connectivity among countries. Network analysis is a well-known field of mathematics and it has a long tradition in sociology and political sciences.5 More recent examples of the application of network analysis in trade include the analysis of integration and regionalization in merchandise trade (Vidya, Prabheesh and Sirowa, 2020), the analysis of trade networks of various food and agricultural products (Chung *et al*., 2020; Gutiérrez-Moya, Adenso-Díaz and Lozano, 2021; Torreggiani *et al*., 2018) and the analysis of specialization patterns and transmission of shocks in food and agriculture (Campi, Dueñas and Fagiolo, 2021; Distefano *et al*., 2018) (a schematic overview of literature on trade networks in food and agriculture is given in Appendix D, an overview of the evolution of the merchandise trade network is given in Appendix E).

Network analysis comprises a set of techniques that are applied to analyse complex systems. It aims to depict relations among actors, in this case countries (or nodes in network terminology), and to analyse the structures that emerge from these relations (Chiesi, 2001). A multitude of network measures can be used to describe the connectivity patterns of countries, their relative importance within the network, how many other countries they are connected to, how close their relationships with other countries are, or whether they are intermediaries between others (Marsden, 2015).

In general, there exist two main approaches to analyse the trade network that complement each other: binary and weighted network analysis. Early studies investigating the properties of networks of international trade usually employed binary network analysis, where binary variables (defined as either zero or one) represent zero or non-zero trade flows (Garlaschelli and Loffredo, 2005; Serrano and Boguñá, 2003). Binary network analysis provides information on trade links (or trade relationships) between countries, but ignores trade intensity and is therefore prone to underestimate heterogeneity across trade relationships. Generally, the intensity of trade, as measured by the value of trade, is highly concentrated in a few trade links (Cepeda-López *et al*., 2019) alongside a majority of trade links with relatively low trade intensity (Bhattacharya *et al*., 2008). Weighted network analysis complements binary network analysis by weighting each trade link with its (deflated) trade value (export, import, or export plus import). The statistical properties of the weighted trade network considerably differ from the binary/unweighted network (Fagiolo, 2010). Drawing a complete picture of the trade network requires consideration of both binary and weighted approaches. However, methods that take into account both the intensity (strength) and the number of country-specific trade links are still in their early stage of development (Opsahl, Agneessens and Skvoretz, 2010). In addition to analyse trade links and values, we look at the trade network from an additional perspective, by weighting each bilateral trade link with the number of products traded through it.

[5] Social network analysis has been developing since the beginning of the 20th century, owing to the efforts of sociologist, psychologists, and anthropologists. It is built on graph theory, a well-recognized branch of mathematics since the 18th century. See Scott (2017) for the origin of social network analysis and Wasserman and Faust (1994) for a general overview.

We apply network analysis to identify the evolution of connectivity in the global network of food and agricultural trade, detect signs for a possible fragmentation of food and agricultural trade into regional blocs, and assess the resilience of the trade network to shocks to the system. The following subsections briefly introduce the network measures applied in the analysis of each of these fields. The mathematical representation of the main network measures applied in the paper is given in Appendix C.

3.1.1 Measures to assess countries' connectivity to the global network of food and agricultural trade

The overall network integration can be analysed by different measures. The density of a network is one of the simplest measures of global integration (De Benedictis and Tajoli, 2011; Kali and Reyes, 2007; Kim and Shin, 2002). It is defined as the number of observed trade links over the maximum theoretically possible trade links across countries. As this measure shows the proportion of actual connections over potential connections, it reflects the probability of the presence of a link between any two countries.[6] In a completely integrated network, the density is equal to one indicating that each country is linked to (trades with) all other countries.

We use several measures of connectivity at individual country level, each showing different aspects of country-level integration into the global trade network (see Table 1 for an overview). The most basic measure at country-level is the degree/strength of connectivity. The degree indicates the total number of trade links of a country and is identified based on binary network analysis. Strength indicates the total number of traded products or the trade value associated with each aggregate trade flow, it is derived from weighted network analysis. Outdegree/outstrength refer to export flows, indegree/instrength refer to import flows. For better comparability, these indices are often normalized.[7]

Both in- and out-degree/strength show the direct (first-order) connectivity of countries in the trade network. Countries are also indirectly linked by second or higher orders, which can constitute important ties in the economies (Bartesaghi, Clemente and Grassi, 2022). We follow Acemoglu, Akcigit and Kerr (2016) and define the second-order degree/strength as the sum of the first-order degree/strength of all direct trade partners.[8] While these measures focus on specific (first and second) orders of connectivity, other network measures consider also linkages at higher orders. The eigenvector connectivity has a similar interpretation as the first- and second-order degree connectivity measures, but also considers all higher-order degrees.[9] Eigenvector connectivity of a country thus shows its direct and indirect linkages with all countries in the network and can indicate whether a country is central or peripheral in the trade network.

Other connectivity measures focus on different aspects of the trade network. Closeness connectivity indicates how "close" a country is to all other countries in the network. The higher the closeness connectivity, the more central a country is located in the network and the "closer" it is to all other countries. Closeness connectivity of a country is defined as the inverse of the average network geodesic distance of that country to all other countries, where geodesic distance is the shortest path (definition below) of moving from one country to another in the network. The measure can be understood as a country's access efficiency to other countries. The higher

[6] This measure is primary used in unweighted network analysis.

[7] In our analysis, the in-/out-degree of a country is normalized by the total number of theoretically possible degrees. In the directed network, the total possible number of degrees (links) is: (number of countries – 1)*2. The in-/out-strength of a country is normalized by dividing by the highest observed in-/out-strength across years.

[8] Second-order degrees are calculated by multiplying the binary trade matrix with itself (Acemoglu *et al.*, 2012; Sartori and Schiavo, 2015). Product- and trade value-weighted trade matrices are multiplied by the transpose of the normalized firster-order instrength matrix. Both second-order indegree and instrength are normalized by their maximum across years.

[9] The highest order is the number of countries in the network minus one.

the closeness connectivity, the more direct the connection to other countries and the lower the number of links a country needs to take to trade with another country ("small-world property"). The computation of the geodesic distance differs in binary and weighted approaches. Referring to trade links (binary), the geodesic distance between two countries is the lowest number of links that connect two countries, i.e. the shortest path between them. There can be more than one such path. In the weighted network (either by product or by trade value), a weight is assigned to each trade link to calculate the geodesic distance. The weight for each trade link is obtained by dividing the average number of products traded per link by the number of traded products associated with each link (in case of weighting by the number of traded products) or dividing the average trade value per link by the trade value associated with each link (in case of weighting by trade value). The shortest path is defined as the strongest link, either in terms of highest number of products traded or in terms of highest trade intensity, that connects two countries.

We measure the global connectivity of the network using arithmetic averages of the individual network connectivity measures including first- and second-order indegree/instrength, eigenvector and closeness connectivity.[10]

Within the global network, individual countries can be connected (or clustered) in different forms which constitute the intermediate features or structure of integration in the network. Countries may tend to open up to trade unilaterally or engage in bilateral, trilateral, or any higher order of trade relationships such as with a group of countries (Wasserman and Faust, 1994).[11] The existence of specific types of trade relationships that occur frequently is not random (Gutiérrez-Moya, Adenso-Díaz and Lozano, 2021), and the analysis of these relationships can identify subnetworks within the global network (Chung *et al.*, 2020). We show the frequency of unilateral and bilateral trade relationships, as well as hierarchical trade relationships.[12] Bilateral and trilateral relationships can be thought of as the smallest unit on which the network builds or the micro-level connectivity. The closer these relationships, the denser the network.

3.1.2 Measures to assess the structure of the food and agricultural trade network

While the assessment of bilateral and trilateral trade relationships can give an indication of the micro-level features of countries' integration in the global food and agricultural trade network, other network measures can be used to identify broader structures, such as trade hubs, decentralization tendencies and fragmentation into trade clusters. We use a measure of "betweenness" to identify trade hubs and a clustering approach to detect important trade structures within the global network. Measures of assortativity and modularity provide additional insights into the significance of trade clusters.

The betweenness connectivity of each country in the network shows how many times a given country connects to other countries that are not directly connected with each other (Freeman, 1978). The higher the value of the betweenness measure, the more important the role of the country as a trade hub. Countries with low betweenness are peripheral countries in the network. In terms of trade links, the betweenness connectivity of each country is the total number of shortest paths in the network that go through a given country over the total possible number of

[10] Because the size of the network is constant across years we do not explicitly calculate network centralization measures that provide estimates of the normalized global connectivity with respect to the star network.

[11] In network analysis, a subgroup of countries that have local trade relationships is called motif or clique. Any type of trade relationship between two partners is called dyad; trade relationships involving three or four partners are called triad and tetrad, respectively; and so on.

[12] In a subgroup of three countries, trade relationships are hierarchical when two countries extend ties to one other country. In a sub-group of four countries, the existence of a hierarchical relationship is defined if two or three countries extend ties to one or two other countries; and so on.

shortest paths. In the weighted approaches, a weight is assigned to each shortest path, where the weight is the value of trade or the number of products that are traded through this shortest path.

Countries do not trade at the same intensity with all other countries in the world, but tend to form trade clusters/communities in which they trade relatively more. These trade clusters/communities can be of varying size, they can be regional or encompass countries in different parts of the world. Trade clusters/communities are identified by community detection algorithms and assortative mixing measures. Community detection algorithms are theory-free mechanisms to identify different trade clusters based on observed trade relationships. Assortative mixing measures show the extent to which similar countries trade with each other. These measures are consistent with the network theory of homophily[13] and a plethora of empirical studies in trade, which show that similar countries tend to trade more with each other than dissimilar ones. For example, in the empirical trade literature using the gravity model, it is often found that trade intensity is higher between countries of similar economic sizes than with other countries and that trade intensity also tends to be higher between neighbouring countries and countries with a common history (Feenstra, 2015). In contrast to the endogenous features of community detection, the calculation of assortative mixing measures requires the exogenous classification of country groups.

We use the Louvain method (Blondel *et al.*, 2008) for the identification of trade clusters, a well-known and widely applied method in the field of international trade (Bernard and Moxnes, 2018). The method endogenously identifies both clusters and the number of clusters by maximizing the density of intragroup connectivity against the density of intergroup connectivity. The significance of the detected communities is then determined based on a modularity index indicating the difference between degree of connectivity inside the detected communities and the degree of connectivity expected in a random graph.[14] A modularity index above 0.3 indicates a significant community structure. A modularity index close to zero implies that no significant community structure could be found.[15]

Assortativity indices range from 1 showing that similar countries trade with each other (assortative network) to -1 showing the reverse (disassortative network). We use the assortativity coefficient following the reasoning of Newman (2003). The similarity dimension based on which countries trade needs to be determined and was chosen based on theoretical considerations. We classify countries by income group and region for the calculation of the assortativity indices. This is consistent with trade theories that underline the importance of economic size (income) and proximity of countries in explaining trade patterns (Tinbergen, 1962). We use undirected trade matrices (see section 3.2) when detecting trade communities and assortativity because we are not interested in the direction of trade, but rather in the existence of a trade link between two partners.

---

[13] See Jackson (2010) on the related notion of homophily.

[14] The significance of a community can be measured using the Z-modularity measure. It varies from -0.5 (a non-modular clustering) to 1 (fully modular) clustering. Thus, the positive (negative) value of Z-modularity implies that the fraction of links within communities is greater (less) than the expected fraction of such links in a random graph.

[15] A negative modularity index indicates disassortativity, implying that between-community interactions are more significant than within-community interactions. The community detection method groups the observation without prior assumptions, the number of groups and the composition of groups are endogenous. It is a bottom-up approach based on the greedy optimization method that groups the nodes in successive stages to maximize the modularity and build a hierarchy of networks. At the lowest level, each node is taken as a community and then the method takes a node and adds it to a community if it increases the modularity. During the process of grouping the nodes, if joining nodes do not contribute positively to the modularity, the process starts again from the lower level and is repeated until the modularity of the overall network is maximized (Blondel *et al.*, 2008).

3.1.3 Measures to assess the resilience of the food and agricultural trade network

Changes in the stability and resilience of the trade network depend on changes in global connectivity and the distribution of connectivity across countries. We graphically analyse the distributions of countries' connectivity in terms of trade links among countries, trade links by country and product and value traded. We also show measures of tail heaviness reflecting different aspects of the distributions of country connectivity measures. The heavier (fatter) the tails of the distribution of the connectivity measures and/or the more uneven the distribution of the connectivity measures, the larger the probability of large cascade effects threatening the resilience of countries in the event of negative shocks affecting their trading partners (Sartori and Schiavo, 2015).

The comparison of the highest and lowest percentiles of a distribution provides information on the heterogeneity of the distribution and the existence of fat tails. The thickness/heaviness of the tail of a distribution can also be shown by the percentage of out-of-interval observations (observations with mean ± two standard deviations) (Sartori and Schiavo, 2015). Skewness and kurtosis provide further information on the shape of the distribution. Skewness indicates the asymmetry of the distribution relative to the symmetric bell-shaped Gaussian (normal) distribution. In a normal distribution, the skewness is zero. In presence of a right (left) fat tail, the skewness is positive (negative). Kurtosis compares the extent to which data cluster to the tails or the peak of the distribution relative to the normal distribution. A kurtosis lower than the reference level for a Gaussian (normal) distribution, which is three, suggests the presence of a thin tail.[16] The obesity index delivers additional information on the tailedness of the distribution (Cooke, Nieboer and Misiewicz, 2014). It is based on the heuristic that in the case of heavy tail distributions, larger observations lie further apart than smaller observations. Considering that the individual centrality measures $\{X_1,X_2,X_3,X_4\}$ are independent and identically distributed values that are randomly sampled from the data,[17] the obesity index is the probability that the sum of the largest and the smallest of four observations is larger than the sum of the other two observations.[18]

3.2 Data and construction of the world trade matrix

To calculate the network measures, we use data on international bilateral trade of food and agricultural products from the FAOSTAT database.[19] Our analysis considers snapshots of world trade of 190 countries[20] in the years 1995, 2007, 2013, and 2019. We select 1995 as the year in which the WTO was established, 2007 as the year when the global food price crisis started and before the financial crisis, 2013 as the year when further growth in the value of global food and agricultural trade had already plateaued, and 2019 as the most recent year for which data was available at the time the analysis was conducted.

We construct the trade matrix using data on bilateral import flows as these are often more reliable than export data (Cadot *et al*. 2011). In general, import and export links (see Figure A1 in Appendix A) and import and export values (see Figure A2 in Appendix A) are highly correlated, allowing for some generalization to overall trade patterns. Each entry of the matrix

16 Data is considered to be normal if the skewness is between -2 and +2 and the kurtosis between -7 and +7.

17 Our index is based on 10 000 random samples of four observations.

18 It is computed as $OB(X)=P(X1+X4 > X2+X3 \mid X1 \leq X2 \leq X3 \leq x4)$.

19 Our definition of food and agricultural trade products follows the definition of FAO covering 425 individual products.

20 Geopolitical changes led to variations in the number of countries over time. For the analysis, a balanced panel of 190 countries was used.

is set to one if there exists a trade flow between exporter (in rows) and importer (in columns), and zero otherwise. The constructed matrix is known as adjacency matrix. This matrix is used to analyse the trade links between countries, where each trade link indicates an aggregate trade flow (aggregated over all products) between two countries. For some results, binary values are weighted with the number of products traded on each link or with actual trade values - the matrix becomes a weighted trade matrix. A directed (asymmetric) trade matrix includes information on the direction of trade flows (from exporter to importer). An undirected (symmetric) trade matrix determines the existence of a trade relationship between two countries, regardless of its direction.

When import values were not available, but respective exports were reported by partner countries, we mirror export values to represent import values.[21] Trade values are expressed in USD and deflated using the 1995 the United States of America Consumer Price Index (e.g. Rose, 2004). We use this trade matrix for the entire analysis except for the community detection. The community detection is based on a symmetric trade matrix based on the arithmetic averages of bilateral export and import values for each trade link.

[21] See also Konar *et al.* (2011) for tackling discrepancies of import and export matrices.

CHAPTER 4

Results

4 Results

4.1 The evolution of the global network of food and agricultural trade

On average, the connectivity of countries to the global network of food and agricultural trade has increased in almost all dimensions, i.e. across several network indicators and in terms of both trade links and value traded (Table 1). The network density increased, indicating that more countries trade among each other. In terms of both trade links and trade intensity, the first-order, second-order and eigenvector connectivity increased, on average across all countries. Countries are also closer connected among each other and overall better integrated in the trade network, as indicated by the closeness connectivity. Most of the global integration took place between 1995 and 2007, with a slower rate of change between 2007 and 2019.[22]

The number of active trade relationships including both asymmetric (one-way trade links) and mutual trade relations (two-way links) between countries increased from 7 084 in 1995 to 10 454 in 2019, with the most significant changes having occurred between 1995 and 2007 (Table 2).[23] Given the same network size over years, the share of actual trade relationships over total possible trade relationships increased from 39 percent in 1995 to 58 percent in 2019. The share of asymmetric (mutual) trade relationships slightly decreased (increased), with most of the trade relationships being mutual, ranging from 60 percent to 63 percent of all trade relationships across years.

The number of trilateral trade relationships involving three countries (triads) increased significantly. The share of actual triads of all possible triads (the intensity of triads) increased from 40 percent in 1995 to 56 percent in 2007, it remained at around 60 percent in 2013 and 2019 (Table 2). Theoretically, trade relationships of three countries can form 16 different types of triads, 13 types of which involve all three countries (see Figure A 3 in Appendix A). In 1995 and 2007, the most frequent types of triads formed in the global food and agricultural trade network were intransitive triads (labelled as 201 and 111D in Figure A 3, respectively), that is triads in which countries interact through intermediaries. In 2013 and 2019 the most frequent triad type (labelled as 300 in Figure A 3) was transitive with reciprocal trade between all three countries. Overall, the share of transitive (multi-way) trade relationships increased from 19 percent in 1995 to 30 percent in 2019, while the share of intransitive trade relations decreased. This implies much stronger trade relationships between countries and between larger groups of countries in 2019 than in 1995, a clear sign of increased connectivity.

Overall, the connectivity of countries in the global network of food and agricultural trade has increased between 1995 and 2019. Most of this change happened between 1995 and 2007, while changes between 2007 and 2019 remained marginal. The network became much denser, with countries being closer connected among each other both at micro-level and from global perspective.

---

22 For the analysis, all import links have been taken into account, including those with very small trade values. Excluding links with trade values smaller than 0.5 or 1 percent of the overall trade value of a country leads to systematically lower estimates of connectivity, but general patterns regarding the evolution of connectivity hold. These results are shown in Appendix B.

23 Here, the count of trade relationships is irrespective of the type of trade links, that is, each of the mutual (two-way trade links) and asymmetric trade relations (one-way trade links) are counted as one single trade relationship. The number of trade relationships is therefore lower than the number of import links reported in Table B 1 in Appendix B.

Table 1. Global connectivity measures from different perspectives of the food and agricultural trade network

	Trade links				Trade intensity			
	1995	2007	2013	2019	1995	2007	2013	2019
Network density	0.32	0.44	0.46	0.47	-	-	-	-
First order indegree connectivity	0.33	0.46	0.49	0.5	0.67	0.72	0.74	0.75
Second order indegree connectivity	0.87	0.93	0.94	0.94	0.89	0.9	0.91	0.92
Eigenvector connectivity	0.45	0.47	0.48	0.48	0.04	0.05	0.05	0.05
Closeness connectivity	0.64	0.69	0.7	0.7	0.84	0.88	0.89	0.89

Note: Global connectivity measures are the arithmetic average of the country indicators.
Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

Table 2. Structure of bilateral and trilateral trade relationships

	1995	2007	2013	2019
Structure of bilateral trade relationships				
Active trade relationships	7 084	9 877	10 383	10 454
Share of active bilateral trade relationships over total possible ones (%)	39	55	58	58
Share of mutual relationships (%)	61	60	60	63
Share of asymmetric relationships (%)	39	40	40	37
Structure of trilateral trade relationships				
Actual number of triads	446 310	633 492	67 5494	680 616
Share of actual triads over total possible ones (%)	40	56	60	60
Most frequent type	201 (24.28%)	111D (17.70%)	300 (18.59%)	300 (20.48%)
Share of transitive (%)	19	27	29	30
Share of intransitive (%)	58	45	43	43
Share of mixed (%)	15	20	20	20
Other (021D,021U) (%)	8	8	8	7

Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

4.2 The structure of the food and agricultural trade network

The increased connectivity, the expansion of food and agricultural trade and the emergence of new players in global markets have changed the structure of the trade network. In terms of betweenness (Figure 3), we observe a heavily right-skewed distribution of both trade links and trade values (trade intensity), implying that a large part of connectivity of the network depends on a few countries. These countries serve as trade hubs that connect to many partners and through these trade hubs smaller partners (indirectly) connect to the global network. Over time, the number of hubs increased and the network depended on more but less dominant hubs in 2019 compared with 1995.

Figure 4 depicts the network of food and agricultural trade based on betweenness indices of individual countries. In terms of trade intensity, the United States of America was the most significant hub in 1995 and remained so in 2019. Following its accession to the WTO in 2001 and the rapid growth it experienced, China evolved from being a relatively small hub in 1995 to the second largest hub in 2019, moving from the periphery of the network to become one of its central players (Tombe and Zhu, 2019). Several Northern and Western European countries that were among the top ten hubs in 1995 reduced in relative importance and gave way to emerging economies such as India, the Russian Federation and South Africa (Figure 4). Emerging economies became more globalized and, at the same time, developed as important regional hubs, linking smaller countries in their regions to the global market (Chen and De Lombaerde, 2014; Iapadre and Tajoli, 2014). Indeed, as measured by the assortativity index, hub countries with many links and high trade intensity tend to trade more with countries with lower connectivity than with other hub countries (assortativity by degree/strength in Table 3), thus confirming their role in connecting peripheral countries to global markets. In 1995, the trade network had a pronounced core-periphery structure with few traders in the core and many less connected countries in the periphery. With more, though less dominant, trade hubs, there was a change to a more balanced structure, characterized by smaller core-periphery sub-networks (Figure 4). Similar structural changes and a tendency towards decentralization have also been observed by Sartori and Schiavo (2015) for food and agricultural trade and in the merchandise trade network (Vidya, Prabheesh and Sirowa, 2020).

The assortativity index by region suggests that countries within a region tend to trade more with each other than with countries in other regions (Table 3). On average, countries within the same region have relatively more trade links with each other and the intensity of trade between them is higher than with countries outside the region. Possibly reflecting regionalization tendencies fostered by RTAs worldwide, the analysis suggests that during the 1995–2019 period not only globalization, but also the tendency of countries to trade with partners within the same region increased (when measured in terms of trade intensity). When globalization came to a halt after 2008, countries appeared to trade more within their regions.

Income levels also play a role in determining trade intensity. Countries with similar income per capita tend to trade more among each other, reflecting similar tastes and preferences. High-income countries also tend to trade with rich partners due to a comparative advantage in the production of high-quality goods (Hallak, 2006). In 1995, the food and agricultural trade intensity of countries within the same income group was higher than the trade intensity of countries in different income groups (Table 3). However, with the increasing participation of low- and middle-income countries in global food and agricultural markets, this relationship between similar income levels and trade has weakened over time. In 2019, countries were much more likely to have a high trade intensity with countries of a different income group than in 1995.

Income levels, geography, differences in natural resource endowments and technology, and trade policies, all influence the choice of a trade partner. Within the global food and agricultural trade network, different trade clusters within which countries tend to trade more are identified using the Louvain method (see section 3.1.2). These clusters may be regional or can expand to include trade partners across regions. During the period 1995–2019 and in terms of trade intensity, countries traded within a pronounced cluster structure. Some clusters remained regional and stable in terms of country participation, while others expanded across regions with a country composition that changed frequently (Figure 5).

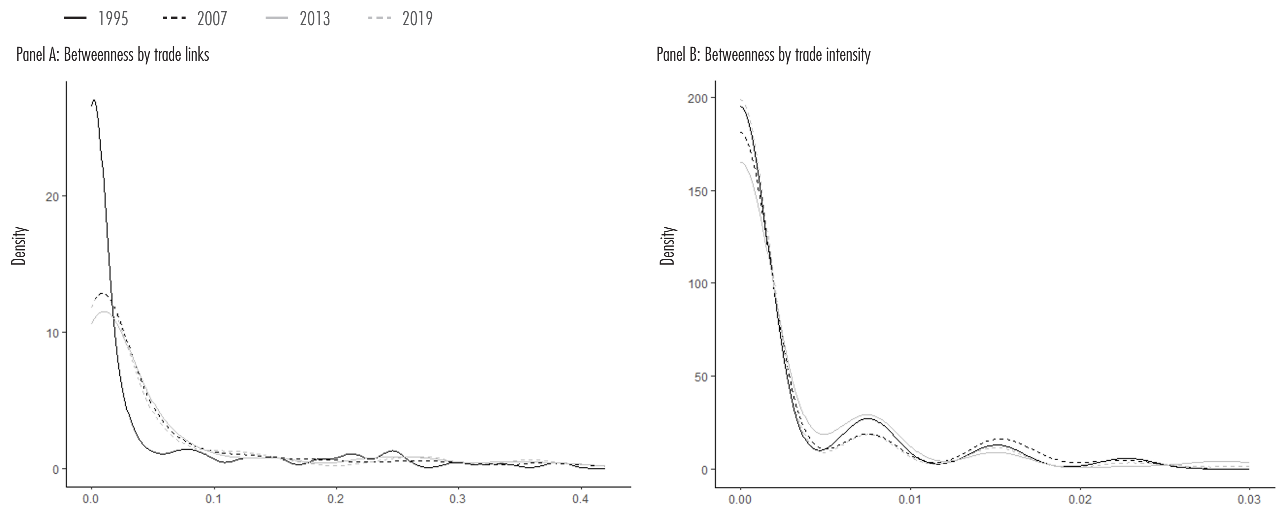
For example, a relatively stable cluster includes the signatories of the North American Free Trade Agreement (NAFTA) and its successor the United States of America–Mexico–Canada Agreement (USMCA) and some of their trade partners across Latin America and the Caribbean. Other mainly regional clusters include the European Union, where the Common Market has led to high levels of trade intensity among members and a cluster based on strong trade ties between former Soviet Union countries. The members of the Southern Common Market (Mercosur) and Eastern Asia, South-eastern Asia and Oceania tend to trade globally rather than within their regions (Figure 6).

Africa did not form a stable regional cluster during the 1995–2019 period as the intensity of intraregional trade in Africa is low and countries in the region tend to trade more globally. In fact, African countries appear to have had a high rate of entries into and exits from other clusters (Figure 6). The identification of clear trade patterns could be confounded by the fact that the trade intensity of African countries is generally low, their trade relationships are often less stable, and trade of African countries also tends to be underreported (Besedeš and Prusa, 2011; Bouët, Tadesse and Zaki, 2021).

The modularity index, which is calculated based on the identified clusters, shows that these clusters became indeed more pronounced (Table 3), with the trade intensity among countries within clusters increasing relatively stronger than the trade intensity among countries in different clusters. However, in terms of trade links, the cluster structure is not very significant and countries link to many countries inside and outside their own clusters.

Overall, clusters shaped by regional proximity and trade agreements are clearly evident.[24] There also appears to be a trend towards a rise in regionalization with trade intensity increasing faster within than between regions (also indicated by Table 3).

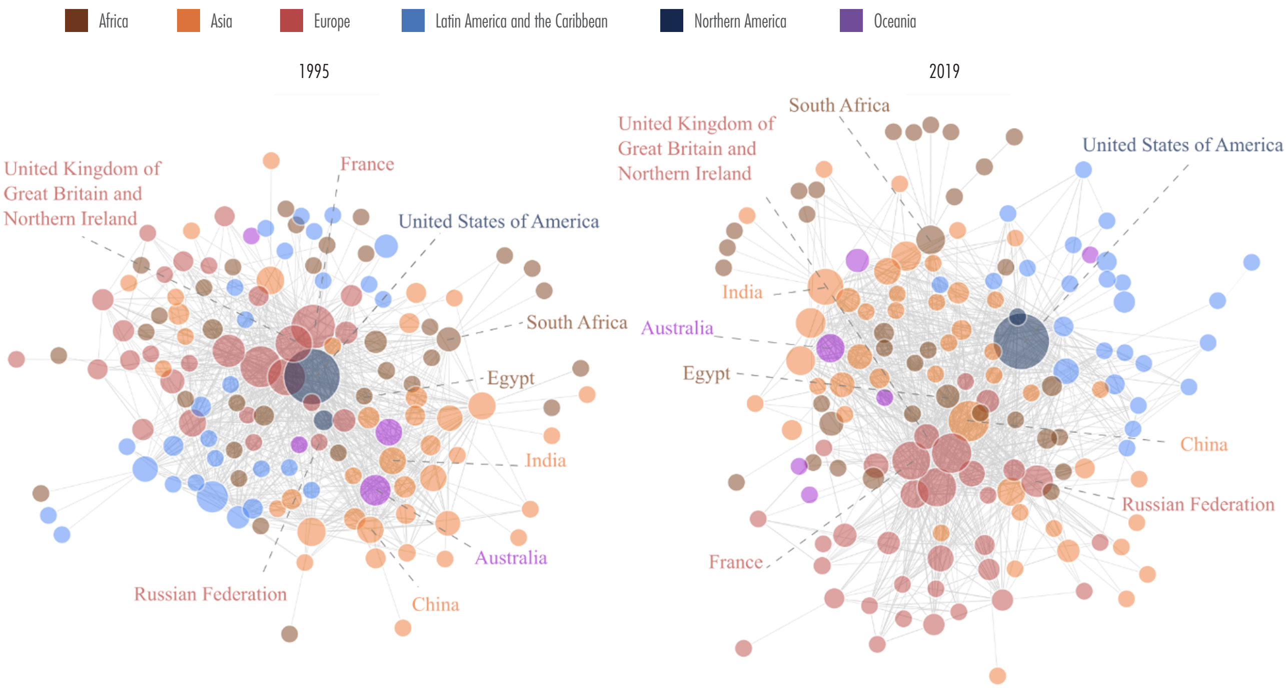
Figure 3. Distribution of betweenness connectivity across countries



Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

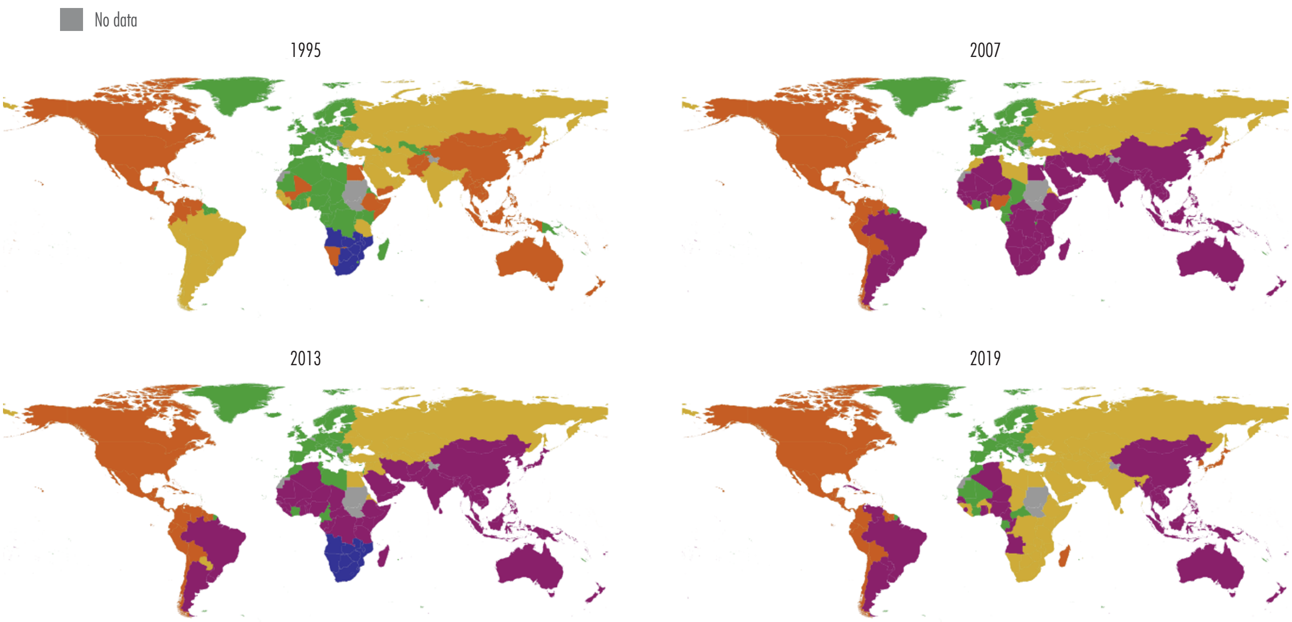
[24] Clusters formed on the basis of regional proximity and regional trade agreements have also been identified in an analysis of global meat trade networks by Chung *et al.* (2020); and for several food and agricultural products independently by Torreggiani *et al.* (2018).

Figure 4. The food and agricultural trade network and trade hubs, 1995 and 2019



Note: Based on trade intensity.
Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

Figure 5. Regional food and agricultural trade clusters, 1995–2019



Note: Based on trade intensity. Trade communities have been identified based on total food and agricultural trade defined as (exports + imports)/2.
Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

Table 3. Assortativity and modularity in the food and agricultural trade network

	Trade links				Trade intensity			
	1995	2007	2013	2019	1995	2007	2013	2019
Assortativity by degree/strength	-0.46	-0.32	-0.33	-0.35	-0.14	-0.1	-0.1	-0.1
Assortativity by country income group	-0.05	-0.02	-0.02	-0.02	0.08	0.04	0.04	0.03
Assortativity by regions	0.03	0.03	0.03	0.02	0.01	0.01	0.02	0.02
Modularity	0.08	0.08	0.07	0.07	0.30	0.32	0.33	0.34

Note: Income classification according to World Bank (2019); regional classification distinguishes Africa, Asia, Europe, Latin America and the Caribbean, Northern America, and Oceania; modularity index refers to trade communities as identified in Figure 5.

Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

4.3 Implications for the resilience of the food and agricultural trade network

Network analysis can shed light on the extent to which the global food and agricultural trade network is vulnerable to shocks by assessing the connectivity of countries and the distribution of connectivity across the world.

Considering both connectivity and its distribution, one can distinguish between the following pathways the trade network could move to: (I) higher connectivity and a more even distribution of connectivity across countries, (II) higher connectivity overall, but a more heterogeneous distribution of connectivity across countries, (III) lower connectivity overall, but a more even distribution of connectivity across countries, and (IV) lower connectivity and more heterogeneous distribution of connectivity across countries (Arriola *et al.*, 2020; Korniyenko, Pinat and Dew, 2017). The first pathway would be ideal to improve resilience of the network, while the fourth pathway represents the worst case scenario. There are trade-offs between the two intermediate pathways.

We analyse both countries' direct connectivity with trade partners and their indirect connectivity. Indirect connectivity is assessed based on second-order and eigenvector connectivity. The distribution of different direct and indirect connectivity measures provides insights on the short- and medium-term impact of shocks originating from network cores. The distribution of countries' direct connectivity can give an indication on the spillover effects of shocks in the short term, as direct trading partners would be immediately affected. Higher order connectivity measures can provide an indication on the impacts over a relatively longer time period and on more countries. If countries are connected with countries that themselves are connected with more trading partners, shocks from network cores can more easily transmit through the network, especially if global value chains are affected that span across several countries. However, the spread across the network would take longer than the immediate effects experienced by direct trade partners. At the same time, both higher direct and higher indirect connectivity would also mean that alternative suppliers could more easily substitute missing imports if only specific countries were affected by the shock, as respective trade relationships would already exist.

The number of direct trade links per country increased from an average of 60 in 1995 to 90 in 2019, indicating an enhanced connectivity among countries (see Figure A 4 in Appendix A and Table B 1 in Appendix B). At the same time, the distribution of trade links across countries became more even, with the majority of changes having occurred between 1995 and 2007. In

1995, the distribution of direct trade links by countries was strongly right-skewed as shown in Figure 3 (panel A). In this year, only a few countries were highly connected to the global trade network (10 percent of the countries had more than 121 import links). Most countries were not well-integrated into global markets and remained in the periphery of the network (50 percent had below/above 48 import links and 10 percent had less than 19 import links) (Table B 1 in the appendix). Over time, the distribution became more symmetric. Skewness and kurtosis decreased (Table 4) and the distribution shifted to the right, showing that the number of countries with which the average country is connected increased over time. In 2019, 10 percent of the countries had more than 148 import links, 50 percent had below/above 86 import links and 10 percent had below 36 import links (Table B 1 in the appendix). The value of the obesity index was always below the theoretical value of an exponential distribution (0.75) and generally decreased over time (Table 4). Similarly, the percentage of observations outside the interval of mean ± standard deviation decreased, indicating a lower number of countries with both very high and low connectivity, which results in a thinner tail of the distribution. Overall, the network moved from a core-periphery structure to a more symmetric structure with more but less dominant cores. This is related to Pathway I: higher connectivity and a more even contribution of countries to the overall connectivity. The result is also consistent with the findings of Sartori and Schiavo (2015) and Konar *et al.* (2011). Both studies observed that the distribution of first-order degree connectivity shifted rightward and that the tails of the distribution became thinner over time.

At the aggregate level of trade links for all food and agricultural products, resilience to disruptions in a major exporter can be better balanced through increased imports from other countries than at the individual product level. For a single product, such as wheat, only a few countries have a comparative advantage and are main exporters, which may imply a high dependency of other countries in the network on these key exporters (d'Amour *et al.*, 2016; Gutiérrez-Moya, Adenso-Díaz and Lozano, 2021; Karakoc and Konar, 2021; Puma *et al.*, 2015; Soffiantini, 2020). The distribution of trade links weighted by the number of products imported (Figure 7) is much more imbalanced than the distribution of trade links at the aggregate level (Figure 6). Although significant imbalances still exist in 2019, indicating that many countries import a narrow range of products from a small number of trade partners (see also Figure A 4 and A 5 in Appendix A), the distribution of connectivity by country and product became less concentrated since 1995, with the largest change having occurred between 1995 and 2007. During the whole period 1995 to 2019, the number of trade links by country and product more than doubled and the share of actual trade links over the number of total possible trade links increased from 1.4 percent in 1995 to 3.2 percent in 2019. Similar to the distribution of trade links per country and product, also the distribution of trade intensity, measured as trade links weighted by trade values is strongly right-skewed. Still, the connectivity of countries in terms of trade intensity increased and the distribution became more symmetric.

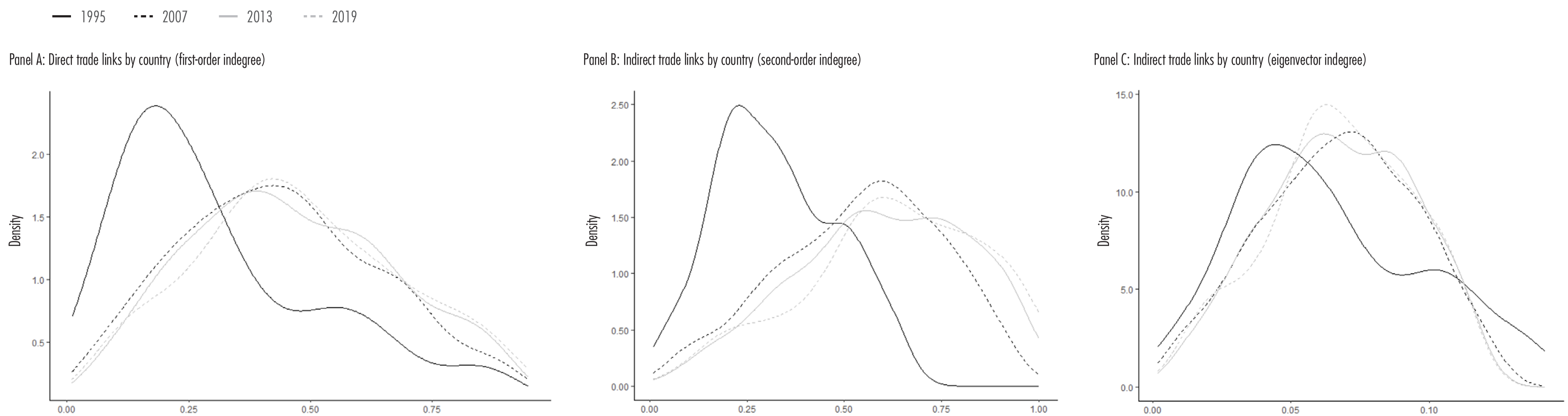
The distribution of connectivity at detailed product level and the distribution of trade intensity indicate increasing connectivity overall and a more even distribution of connectivity across countries, a process that evolved mainly between 1995 and 2007 (Table 4). While the average connectivity still increased between 2007 and 2019, though at a slower pace, the tail-heaviness of the distributions showed an increasing trend between 2013 and 2019. Both kurtosis and skewness decreased between 1995 and 2007, but increased thereafter. This would suggest a development reflecting Pathway II: higher connectivity, but a more uneven distribution of connectivity across countries, indicating that the resilience of the network increased between 1995 and 2007, with little progress since then.

Similar patterns as for the direct connectivity are found for indirect connectivity measured as second-order and eigenvector connectivity. With the rising number of trade links among countries, also the indirect connectivity of countries as indicated by the second-order and the eigenvector connectivity increased. The body of the distributions generally shifted rightwards (Figure 6, Figure 7, and Figure 8, panels B and C), indicating an increase in the average connectivity, particularly between 1995 and 2007. The measures of tail-heaviness for second-order connectivity (Table 4) suggest a slight reversal of the trend towards a more evenly distributed trade integration between 2013 and 2019. Since 2007, the distribution of trade links by country at second and higher orders of connectivity has tended to be left-skewed (Figure 6, panel B and C): the network moved from a state in which a small fraction of highly connected countries coexist alongside a large number of countries with few connections to a state in which only a small fraction of countries has a low level of indirect connectivity, implying that still some counties lag behind in terms of connectivity. The distribution of the second-order indegree and the eigenvector connectivity of trade links by country and product and trade intensity (Figure 7 and Figure 8, panels B and C) is less skewed than their first-order connectivity, suggesting that the indirect connectivity of marginal countries could be conducive to reducing their vulnerability to shocks in the system.

As shown by Figure 9, the connectivity of countries is distributed unevenly across the world. Northern American, Eastern Asian, Oceanian and European Union countries, and partly South Africa and countries in Northern Africa, were already well-connected in 1995. By 2019, the connectivity of most countries had improved, especially the connectivity of countries of the former Soviet Union. Connectivity of countries in Africa remained low and, in general, African countries are least connected in the world.

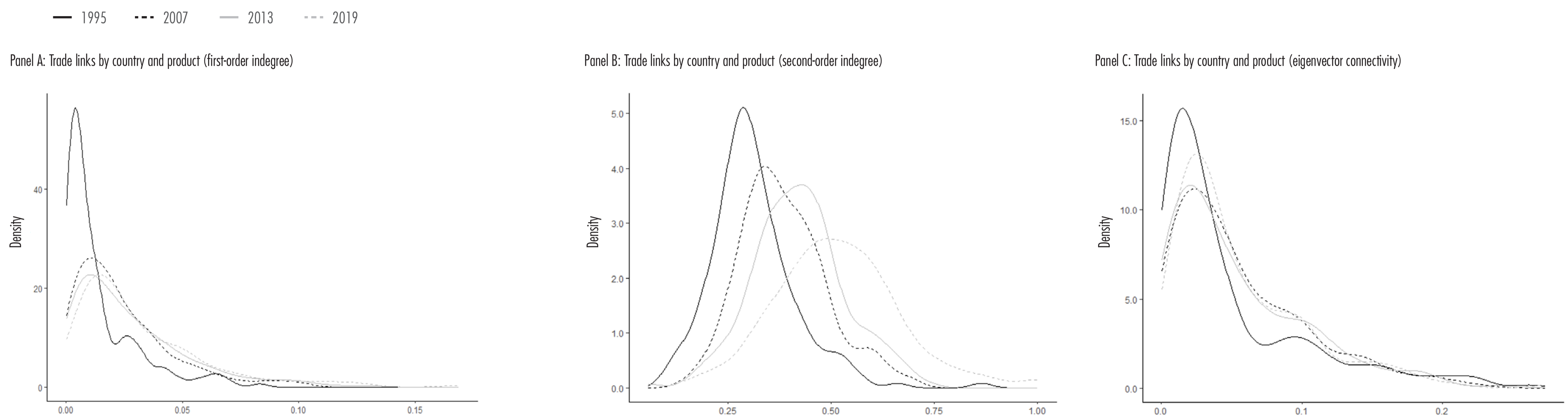
Beyond the global distribution of connectivity, also trade clusters are important (see section 4.2), as they affect how a shock in one country could spread within the global network of trade. For example, if the epicentre of a shock is within a regional cluster, countries in that cluster would be more directly affected than outside countries as they would face reduced supply from their trading partners and higher prices. Countries outside the epicentre cluster would be indirectly affected through increasing international prices and possible trade interventions by their own trading partners (Torreggiani *et al*., 2018).

Figure 6. Distribution of connectivity of trade links by country



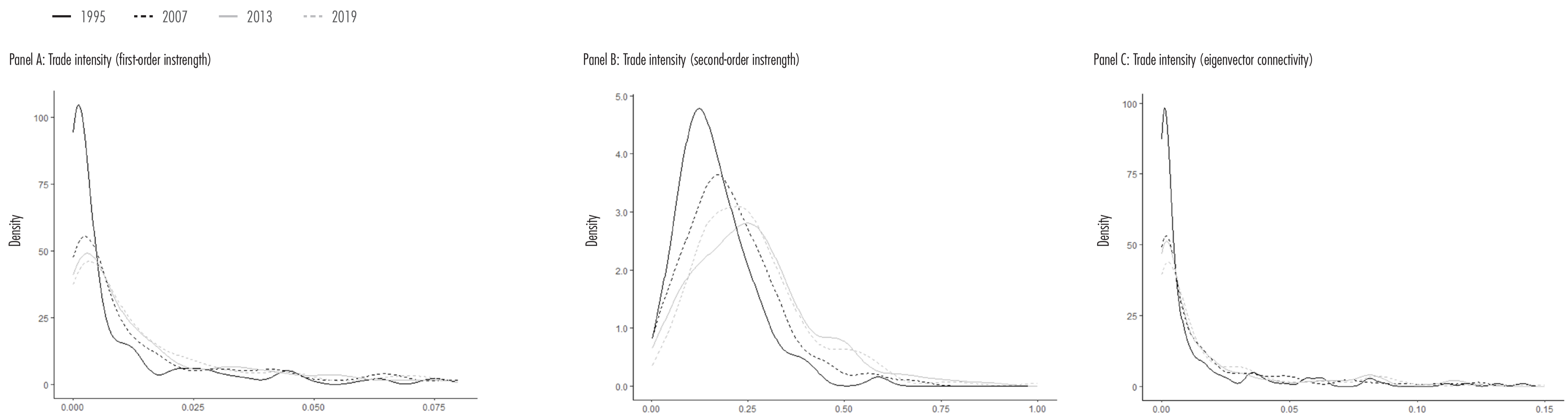
Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

Figure 7. Distribution of connectivity of trade links by country and product



Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

Figure 8. Distribution of connectivity of trade intensity



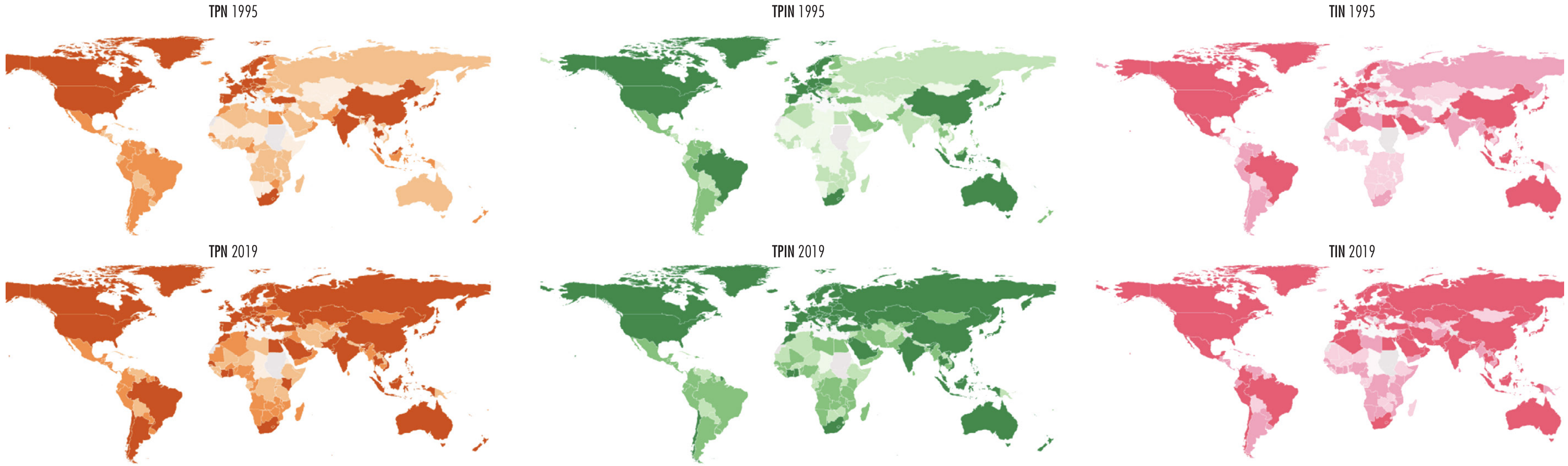
Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

Table 4. Measures of tail-heaviness

	Trade links by country				Trade links by country and product				Trade intensity by country			
	1995	2007	2013	2019	1995	2007	2013	2019	1995	2007	2013	2019
First order connections												
First order indegree connectivity	0.32	0.44	0.46	0.47	0.67	0.75	0.76	0.79	0.67	0.72	0.74	0.75
Percentage of observations out of interval	6.32	4.02	1.72	2.87	5.79	5.79	5.79	5.26	3.68	4.74	4.74	3.68
Obesity index	0.71	0.54	0.54	0.55	0.82	0.73	0.74	0.77	0.91	0.89	0.9	0.89
Kurtosis	2.78	2.33	2.2	2.31	6.51	5.22	5.27	7	26.92	24.28	26.05	33.91
Skewness	0.87	0.19	0.13	0.15	1.91	1.49	1.48	1.83	4.7	4.34	4.48	5.09
Second order connections												
Second order indegree connectivity	0.87	0.93	0.94	0.94	0.87	0.89	0.9	0.93	0.89	0.9	0.91	0.92
Percentage of obs out of interval	1.72	2.87	2.87	3.45	4.74	6.32	5.26	5.26	4.74	4.21	4.21	4.21
Obesity index	0.57	0.45	0.45	0.48	0.59	0.58	0.53	0.55	0.64	0.61	0.61	0.64
Kurtosis	2.18	2.46	2.37	2.57	7.12	3.26	3.29	3.79	5.62	4.74	4.37	6.24
Skewness	0.23	-0.31	-0.3	-0.31	1.25	0.56	0.1	0.49	1.25	1.09	0.99	1.39

Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

Figure 9. Connectivity to the global food and agricultural network by country



Note: The darker colours indicate countries with high connectivity. A lighter shade indicates countries with lower connectivity. TPN: trade links by country; TPIN: trade links by country and product; TIN: trade intensity. Conforms to Map No. 4170 Rev. 19 United Nations (October 2020).
Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

CHAPTER 5

Conclusions

5 Conclusions

Based on network analysis, this paper explored the evolution of connectivity within the network of food and agricultural trade since 1995, its structure and implications for resilience to trade shocks. Food and agricultural trade evolved rapidly and countries worldwide became better connected to global markets in the period 1995-2007, but progress has since been limited. Between 1995 and 2007, countries formed closer ties among each other both at the micro-level and from a global perspective. Emerging economies became important players and link smaller and less-connected countries to the global market. The connectivity of countries increased globally and the network of food and agricultural trade became more balanced and resilient, although vulnerabilities and dependencies remain in the trade of specific products. Also, despite the emergence of new players and a more even distribution of connectivity across the world, still not many countries account for most of the value traded.

Since the 2008 financial crisis, the process of further trade integration has largely stalled, but evidence suggests that countries have continued deepening their trade intensity with partners in dedicated trade clusters, which are often shaped by regional proximity and trade agreements. The distributions of connectivity among trade partners and with partners of trade partners indicate a reversal of the trend towards a more even and balanced trade network between 2013 and 2019, which may imply a loss in resilience in the future, were this trend to continue.

Developments in recent years give rise to concerns over a fragmentation of global food and agricultural trade and reduced resilience of the network to shocks, which may pose a risk to countries' food security and dietary diversity. A fragmentation of the global market into regional trading blocs could prevent countries from fully leveraging the gains from trade and may imply less efficient outcomes in terms of production allocation and resource use.

Further research could deepen the discussion on the contribution of regional trade agreements and regional trade integration to these processes, for example, by exploring the features of regional trade clusters and modelling their interaction within the multi-layered system. This could shed light on the impact of geopolitical shifts on the global network of food and agricultural trade and help explain the impact of deep trade agreements on global trade integration and the risk of excluding countries from the integration process more specifically.

REFERENCES

References

Acemoglu, D., Akcigit, U. & Kerr, W. 2016. Networks and the macroeconomy: An empirical exploration. *NBER Macroeconomics Annual*, 30: 273–335.

Acemoglu *et al.*, 2012. The network origins of aggregate fluctuations. *Econometrica*, 80(5): 1977–2016.

Acemoglu, D., Ozdaglar, A. & Tahbaz-Salehi, A. 2015. *Networks, shocks, and systemic risk*. Working Paper. Working Paper Series 20931. National Bureau of Economic Research.

Aguiar *et al.*, 2020. Global changes in crop diversity: Trade rather than production enriches supply. *Global Food Security*, 26: 100385.

Ahcar, J. & Siroën, J.-M. 2017. Deep integration: Considering the heterogeneity of free trade agreements. *Journal of Economic Integration*, 32(3): 615–659.

Allouche, J. 2011. The sustainability and resilience of global water and food systems: Political analysis of the interplay between security, resource scarcity, political systems and global trade. *Food Policy*, 36: S3–S8.

d'Amour *et al.*, 2016. Teleconnected food supply shocks. *Environmental Research Letters*, 11(3): 035007.

Anderson, J.E. 2011. The gravity model. *Annual Review of Economics*, 3(1): 133–160.

Anderson, J.E. & van Wincoop, E. 2003. Gravity with gravitas: A solution to the border puzzle. *American Economic Review*, 93(1): 170–192.

Anderson, J.E. & van Wincoop, E. 2004. Trade costs. *Journal of Economic Literature*, 42(3): 691–751.

Arita *et al.*, 2022. Has global agricultural trade been resilient under coronavirus (COVID-19)? Findings from an econometric assessment of 2020. *Food Policy*, 107: 102204.

Arriola *et al.*, 2020. *Efficiency and risks in global value chains in the context of COVID-19*. Paris, OECD.

Baldwin, R. 2008. *Big-think regionalism: a critical survey. Working Paper 14056*. National Bureau of Economic Research.

Baldwin, R. 2016. The World Trade Organization and the future of multilateralism. *Journal of Economic Perspectives*, 30(1): 95–116.

Barrat *et al.*, 2004. The architecture of complex weighted networks. *Proceedings of the National Academy of Sciences*, 101(11): 3747–3752.

Bartesaghi, P., Clemente, G.P. & Grassi, R. 2022. Community structure in the world trade network based on communicability distances. *Journal of Economic Interaction and Coordination*, 17(2): 405–441.

Beghin, J. & O'Donnell, J. 2021. Trade agreements in the last 20 years: Retrospect and prospect for agriculture. *EuroChoices*, 20(3): 63–68.

Bergstrand, J.H. 1989. The generalized gravity equation, monopolistic competition, and the factor-proportions theory in international trade. *The Review of Economics and Statistics*, 71(1): 143–153.

Bernard, A.B. & Moxnes, A. 2018. Networks and trade. *Annual Review of Economics*, 10(1): 65–85.

Besedeš, T. & Prusa, T.J. 2011. The role of extensive and intensive margins and export growth. *Journal of Development Economics*, 96(2): 371–379.

Bhagwati, J. 1991. *The world trading system at risk*. Princeton, Princeton University Press.

Bhagwati, J. 1993. Regionalism and multilateralism: An overview. In: J. de Melo & A. Panagariya, eds. *New dimensions in regional integration*. pp. 22–51. Cambridge University Press.

Bhagwati, J.N. 1995. US trade policy: The infatuation with FTAs.

Bhattacharya *et al.*, 2008. The international trade network: Weighted network analysis and modelling. *Journal of Statistical Mechanics: Theory and Experiment*, 2008(02): P02002.

Blondel *et al.*, 2008. Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008(10): P10008.

Bouët, A., Tadesse, G. & Zaki, C., eds. 2021. *Africa agriculture trade monitor 2021*. AKADEMIYA2063.

Campi, M., Dueñas, M. & Fagiolo, G. 2021. Specialization in food production affects global food security and food systems sustainability. *World Development*, 141: 105411.

Cepeda-Lópe *et al.*, 2019. The evolution of world trade from 1995 to 2014: A network approach. *The Journal of International Trade & Economic Development*, 28(4): 452–485.

Chen, L. & De Lombaerde, P. 2014. Testing the relationships between globalization, regionalization and the regional hubness of the BRICs. *Journal of Policy Modeling*, 36: S111–S131.

Chiesi, A.M. 2001. Network analysis. In: N.J. Smelser & P.B. Baltes, eds. *International Encyclopedia of the Social & Behavioral Sciences*. pp. 10499–10502. Oxford, Pergamon.

Chung *et al.*, 2020. The spatial and temporal dynamics of global meat trade networks. *Scientific Reports*, 10(1): 16657.

Cooke, R.M., Nieboer, D. & Misiewicz, J. 2014. *Fat-tailed distributions: Data, diagnostics and dependence*, Volume 1. John Wiley & Sons.

Cottrell *et al.*, 2019. Food production shocks across land and sea. *Nature Sustainability*, 2(2): 130–137.

Crawford, J.-A. & Laird, S. 2001. Regional trade agreements and the WTO. *The North American Journal of Economics and Finance*, 12(2): 193–211.

Daugbjerg, C. & Swinbank, A. 2008. Curbing Agricultural Exceptionalism: The EU's Response to External Challenge. *The World Economy*, 31(5): 631–652.

De Benedictis, L. & Tajoli, L. 2011. The World Trade Network. *The World Economy*, 34(8): 1417–1454.

Dellink, R., Dervisholli, E. & Nenci, S. 2020. *A quantitative analysis of trends in agricultural and food global value chains (GVCs): Background paper for The State of Agricultural Commodity Markets (SOCO) 2020*. Rome, Italy, FAO.

Distefano *et al.*, 2018. Shock transmission in the international food trade network. *PLOS ONE*, 13(8): e0200639.

Dixit, A.K. & Stiglitz, J.E. 1977. Monopolistic competition and optimum product diversity. *The American Economic Review*, 67(3): 297–308.

Dupas, M.-C., Halloy, J. & Chatzimpiros, P. 2019. Time dynamics and invariant subnetwork structures in the world cereals trade network. *PLOS ONE*, 14(5): e0216318.

Engemann, H. & Jafari, Y. 2022. COVID-19 and changes in global agri-food trade. *Q Open*, 2(1): qoac013.

Ercsey-Ravasz *et al.*, 2012. Complexity of the International Agro-Food Trade Network and Its Impact on Food Safety. *PLOS ONE*, 7(5): e37810.

Fagiolo, G. 2010. The international-trade network: gravity equations and topological properties. *Journal of Economic Interaction and Coordination*, 5(1): 1–25.

Fagiolo, G., Reyes, J. & Schiavo, S. 2009. World-trade web: Topological properties, dynamics, and evolution. *Physical Review E*, 79(3): 036115.

Fagiolo, G., Reyes, J. & Schiavo, S. 2010. The evolution of the world trade web: a weighted-network analysis. *Journal of Evolutionary Economics*, 20(4): 479–514.

Fair, K.R., Bauch, C.T. & Anand, M. 2017. Dynamics of the Global Wheat Trade Network and Resilience to Shocks. *Scientific Reports*, 7(1): 7177.

FAO. 2018. *The State of Agricultural Commodity Markets 2018. Agricultural trade, climate change and food security*. Rome, FAO.

FAO. 2020. *The State of Agricultural Commodity Markets 2020. Agricultural markets and sustainable development: Global value chains, smallholder farmers and digital innovations*. Rome, FAO.

FAO. 2021. *Agricultural trade and policy responses during the first wave of the COVID-10 pandemic in 2020*. Rome, FAO.

FAO. 2022. *Agricultural trade in the Global South: An overview of trends in performance, vulnerabilities, and policy frameworks*. Rome, Italy, FAO.

FAO *et al.*, 2011. *Price volatility in food and agricultural markets: Policy responses*. Working Paper. Washington, DC, World Bank.

Feenstra, R.C. 2015. *Advanced International Trade: Theory and Evidence - Second Edition*. 2 edition edition. Princeton, Princeton University Press.

Freeman, L.C. 1978. Centrality in social networks: Conceptual clarification. *Social Networks*, 1:

215–239.

Garlaschelli, D. & Loffredo, M.I. 2005. Structure and evolution of the world trade network. *Physica A: Statistical Mechanics and its Applications*, 355(1): 138–144.

Geyik *et al.*, 2021. Does global food trade close the dietary nutrient gap for the world's poorest nations? *Global Food Security*, 28: 100490.

Grant, J.H. & Boys, K.A. 2012. Agricultural trade and the GATT/WTO: Does membership make a difference? American Journal of Agricultural Economics, 94(1): 1–24.

Grant, J.H. & Lambert, D.M. 2008. Do regional trade agreements increase members' agricultural trade? *American Journal of Agricultural Economics*, 90(3): 765–782.

Gutiérrez-Moya, E., Adenso-Díaz, B. & Lozano, S. 2021. Analysis and vulnerability of the international wheat trade network. *Food Security*, 13(1): 113–128.

Gutiérrez-Moya, E., Lozano, S. & Adenso-Díaz, B. 2020. Analysing the structure of the global wheat trade network: An ERGM approach. *Agronomy*, 10(12): 1967.

Hallak, J.C. 2006. Product quality and the direction of trade. *Journal of International Economics*, 68(1): 238–265.

Hofmann, C., Osnago, A. & Ruta, M. 2019. The content of preferential trade agreements. *World Trade Review*, 18(3): 365–398.

Iapadre, P.L. & Tajoli, L. 2014. Emerging countries and trade regionalization. A network analysis. *Journal of Policy Modeling*, 36: S89–S110.

Jackson, M.O. 2010. *Social and Economic Networks*. Princeton University Press.

Janssens *et al.*, 2020. Global hunger and climate change adaptation through international trade. *Nature Climate Change*, 10(9): 829–835.

Kali, R. & Reyes, J. 2007. The architecture of globalization: a network approach to international economic integration. *Journal of International Business Studies*, 38(4): 595–620.

Karakoc, D.B. & Konar, M. 2021. A complex network framework for the efficiency and resilience trade-off in global food trade. *Environmental Research Letters*, 16(10): 105003.

Kerr, W.A. 2021. Agriculture after a year with COVID-19: Any long-term implications for international trade policy? *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, 69(2): 261–267.

Kim, S. & Shin, E.-H. 2002. A longitudinal analysis of globalization and regionalization in international trade: a social network approach*. *Social Forces*, 81(2): 445–468.

Kohl, T., Brakman, S. & Garretsen, H. 2016. Do trade agreements stimulate international trade differently? Evidence from 296 trade agreements. *The World Economy*, 39(1): 97–131.

Konar *et al.*, 2011. Water for food: The global virtual water trade network. *Water Resources Research*, 47(5).

Korniyenko, M.Y., Pinat, M. & Dew, B. 2017. *Assessing the fragility of global trade: the impact of localized supply shocks using network analysis*. International Monetary Fund.

Krugman, P. 1980. Scale economies, product differentiation, and the pattern of trade. *The*

American Economic Review, 70(5): 950–959.

Krugman, P. 1989. *Is bilateralism bad? Working Paper 2972*. National Bureau of Economic Research.

Krugman, P.R. 1987. Is free trade passe? *Journal of Economic Perspectives*, 1(2): 131–144.

Kummu *et al.*, 2020. Interplay of trade and food system resilience: Gains on supply diversity over time at the cost of trade independency. *Global Food Security*, 24: 100360.

Lucas, R.E. 1977. Understanding business cycles. *Carnegie-Rochester Conference Series on Public Policy*, 5: 7–29.

Marsden, P.V. 2015. Network centrality, measures of. In: J.D. Wright, ed. *International Encyclopedia of the Social & Behavioral Sciences (Second Edition)*. pp. 532–539. Oxford, Elsevier.

Mattoo, A., Mulabdic, A. & Ruta, M. 2017. *Trade creation and trade diversion in deep agreements*. SSRN Scholarly Paper. ID 3044150. Rochester, NY, Social Science Research Network.

Mujahid, I. & Kalkuhl, M. 2016. Do trade agreements increase food trade? *The World Economy*, 39(11): 1812–1833.

Nemeth, R.J. & Smith, D.A. 1985. International Trade and World-System Structure: A Multiple Network Analysis. *Review (Fernand Braudel Center)*, 8(4): 517–560.

Newman, M.E.J. 2003. The structure and function of complex networks. *SIAM Review*, 45(2): 167–256.

Opsahl, T., Agneessens, F. & Skvoretz, J. 2010. Node centrality in weighted networks: Generalizing degree and shortest paths. *Social Networks*, 32(3): 245–251.

Pomfret, R. 2021. 'Regionalism' and the global trade system. *The World Economy*, 44(9): 2496–2514.

Pomfret, R. & Sourdin, P. 2010. Why do trade costs vary? *Review of World Economics*, 146(4): 709–730.

Puma *et al.*, 2015. Assessing the evolving fragility of the global food system. *Environmental Research Letters*, 10(2): 024007.

Remans *et al.*, 2014. Measuring nutritional diversity of national food supplies. *Global Food Security*, 3(3): 174–182.

Rose, A.K. 2004. Do We Really Know That the WTO Increases Trade? *American Economic Review*, 94(1): 98–114.

Sacks, M.A., Ventresca, M.J. & Uzzi, B. 2001. Global Institutions and Networks: Contingent Change in the Structure of World Trade Advantage, 1965-1980. *American Behavioral Scientist*, 44(10): 1579–1601.

Sarker, R. & Jayasinghe, S. 2007. Regional trade agreements and trade in agri-food products: evidence for the European Union from gravity modeling using disaggregated data. *Agricultural Economics*, 37(1): 93–104.

Sartori, M. & Schiavo, S. 2015. Connected we stand: A network perspective on trade and global food security. *Food Policy*, 57: 114–127.

Schmidhuber, J. & Qiao, B. 2021. *Surging trade, record import bills and rising food prices: how the international food system kept a lid on a global health crisis. Food Outlook - Biannual Report on Global Food Markets. June 2021*. Rome, FAO.

Scott, J. 2017. *Social Network Analysis*. London, SAGE Publications Ltd.

Serrano, M.Á. & Boguñá, M. 2003. Topology of the world trade web. *Physical Review E*, 68(1): 015101.

Shutters, S.T. & Muneepeerakul, R. 2012. Agricultural Trade Networks and Patterns of Economic Development. *PLOS ONE*, 7(7): e39756.

Smith, D.A. & White, D.R. 1992. Structure and Dynamics of the Global Economy: Network Analysis of International Trade 1965–1980*. *Social Forces*, 70(4): 857–893.

Snyder, D. & Kick, E.L. 1979. Structural Position in the World System and Economic Growth, 1955-1970: A Multiple-Network Analysis of Transnational Interactions. *American Journal of Sociology*, 84(5): 1096–1126.

Soffiantini, G. 2020. Food insecurity and political instability during the Arab Spring. *Global Food Security*, 26: 100400.

Staiger, R.W. 2021. *A world trading system for the twenty-first century*. Working Paper. Working Paper Series 28947. National Bureau of Economic Research.

Summers, L.H. 1991. Regionalism and the World Trading System. *Economic Review, Federal Reserve Bank of Kansas City*: 295–302.

Thompson-Lipponen, C. & Greenville, J. 2019. *The evolution of the treatment of agriculture in preferential trade agreement*s. Paris, OECD.

Tinbergen, J. 1962. *Shaping the world economy: Suggestions for an international economic policy*. New York, The Twentieth Century Fund.

Tombe, T. & Zhu, X. 2019. Trade, migration, and productivity: A quantitative analysis of China. *American Economic Review*, 109(5): 1843–1872.

Torreggiani *et al.*, 2018. Identifying the community structure of the food-trade international multi-network. *Environmental Research Letters*, 13(5): 054026.

UNCTAD. 2019. *Trade and vulnerability. Note by the UNCTAD Secretariat*. TD/B/C.I/48.

Vandermarliere, B., Standaert, S. & Ronsse, S. 2018. Structure and evolution of the world's historical trade patterns. In: S. Gorgoni, A. Amighini & M. Smith, eds. *Networks of International Trade and Investment: Understanding globalisation through the lens of network analysi*s. Vernon Press.

Vidya, C.T., Prabheesh, K.P. & Sirowa, S. 2020. Is trade integration leading to regionalization? Evidence from cross-country network analysis. *Journal of Economic Integration*, 35(1): 10–38.

Wasserman, S. & Faust, K. 1994. *Social Network Analysis: Methods and Applications*. Structural Analysis in the Social Sciences. Cambridge, Cambridge University Press.

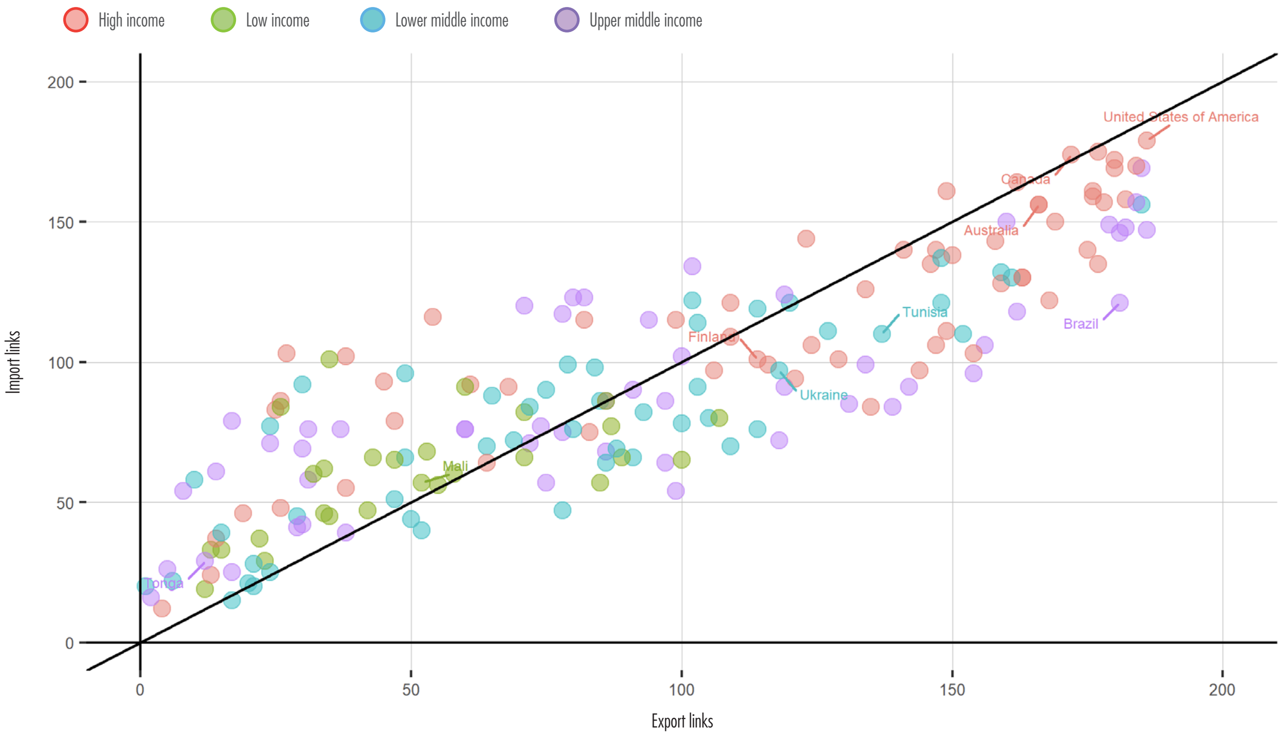
Wood *et al.*, 2018. Trade and the equitability of global food nutrient distribution. *Nature Sustainability*, 1(1): 34–37.

WTO. 2022. Regional trade agreements database. https://rtais.wto.org/UI/PublicMaintainRTAHome.aspx

APPENDIX

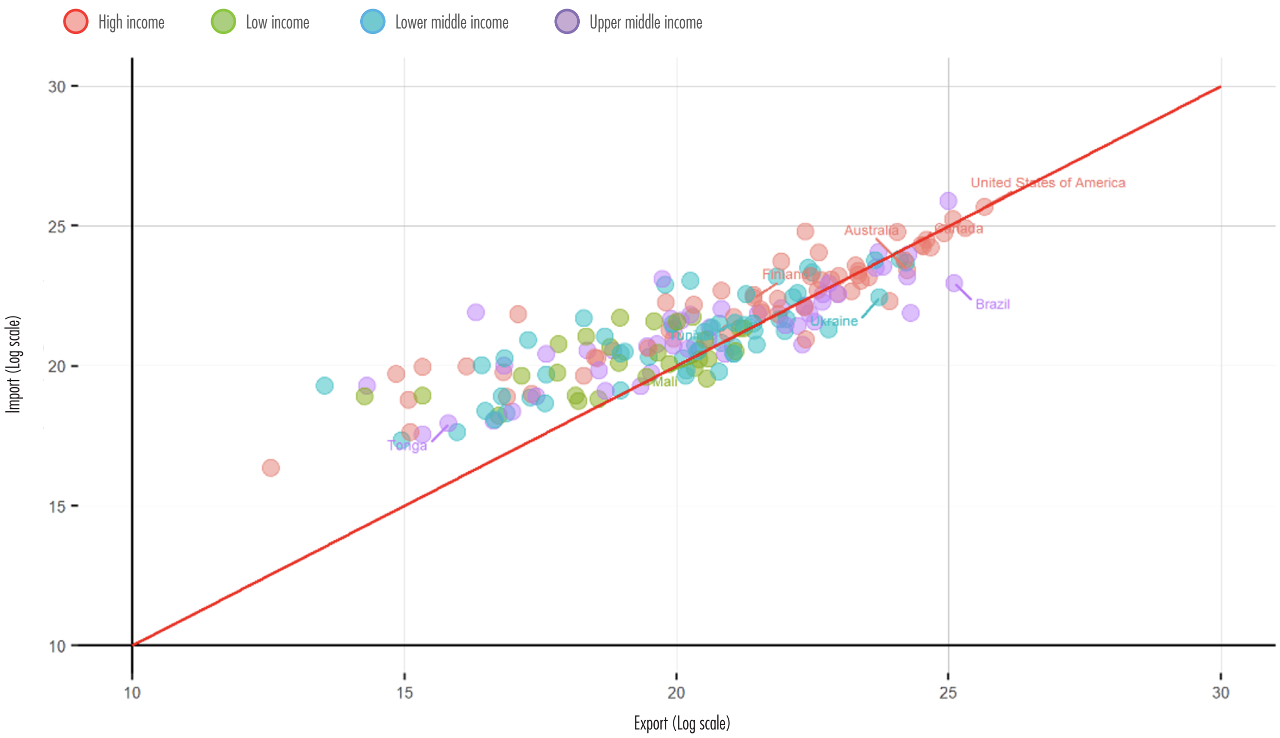
Appendix A – Background information

Figure A1. Correlation between import and export links, 2019



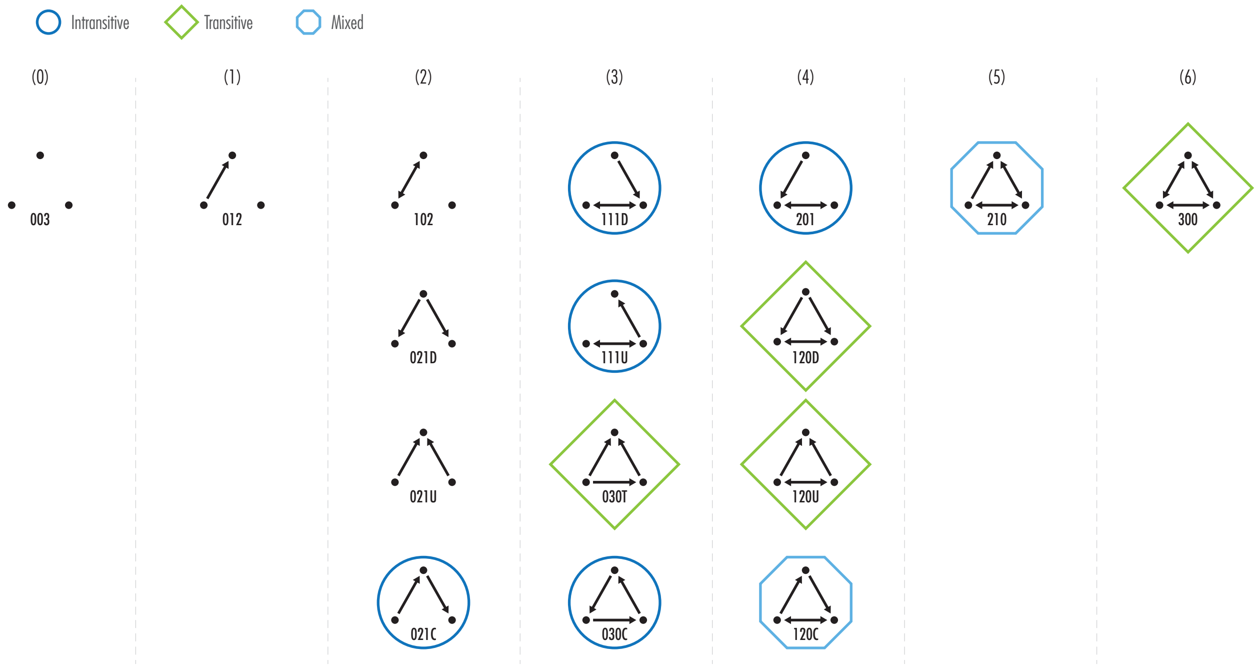
Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

Figure A2. Correlation between import and export values, 2019



Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

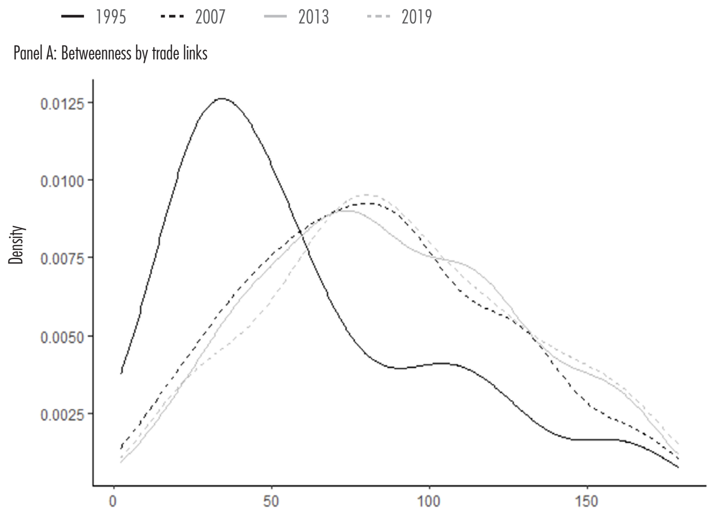
Figure A3. Triad isomorphism classes (following James Moody)



Note: In a triad, countries can be related in sixteen different types. Thirteen types of triads indicate some form of connection among the three actors, which means 13 different motifs are observed. Each type is labelled according to the three digits MAN scheme. The first digit shows the number of observed mutual (M) trade relationships, the second digit shows the number of observed symmetric (A) trade relationships and the third one shows the number of null (N) trade relationships. If two triad types have an equivalent number of dyads, the fourth digit is used to distinguish the triads further based on edge directions (U: up and D: down), cyclicity (C: cyclic), and transitivity (T: transitive).[25]

Source: Moody, J. *Introduction to networks: Methods and measures.* Duke Network Analysis Center, Department of Sociology.

Figure A4. Distribution of the number of trade partners per country

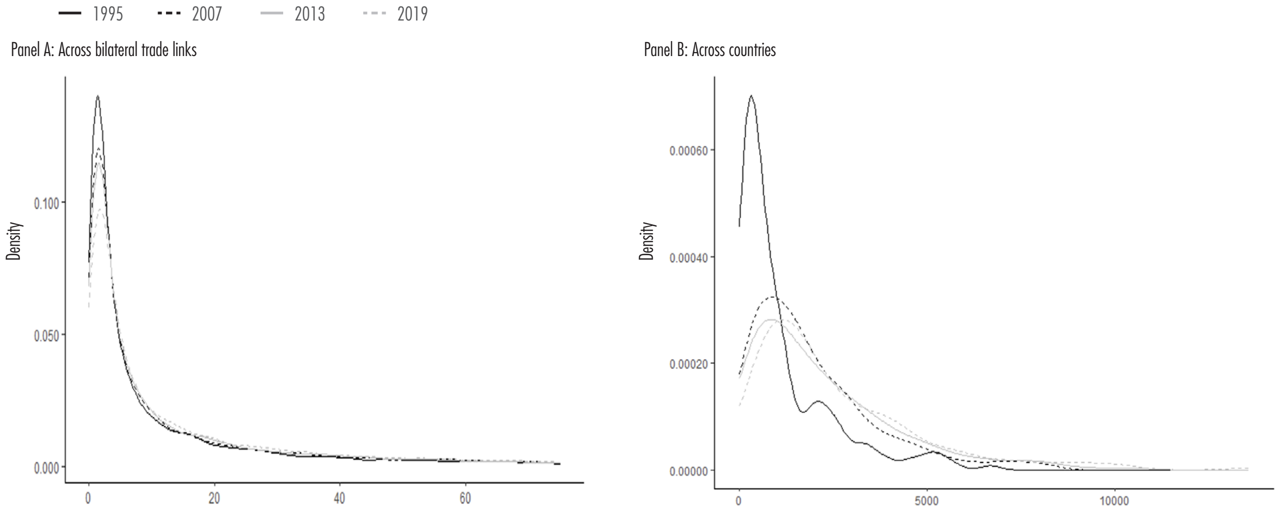


Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

---

[25] A triple of nodes *i,j,k* is cyclic if *i*→*j*, *j*→*k*, →*i* ; it is transitive if *i*→*j* and *j*→*k* implies *i*→*k* ; and intransitive if *i*→*j* and *j*→*k* but *i*↛*k*.

Figure A5. Distribution of the number of traded products



Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

Appendix B – Sensitivity analysis of the distribution of trade links

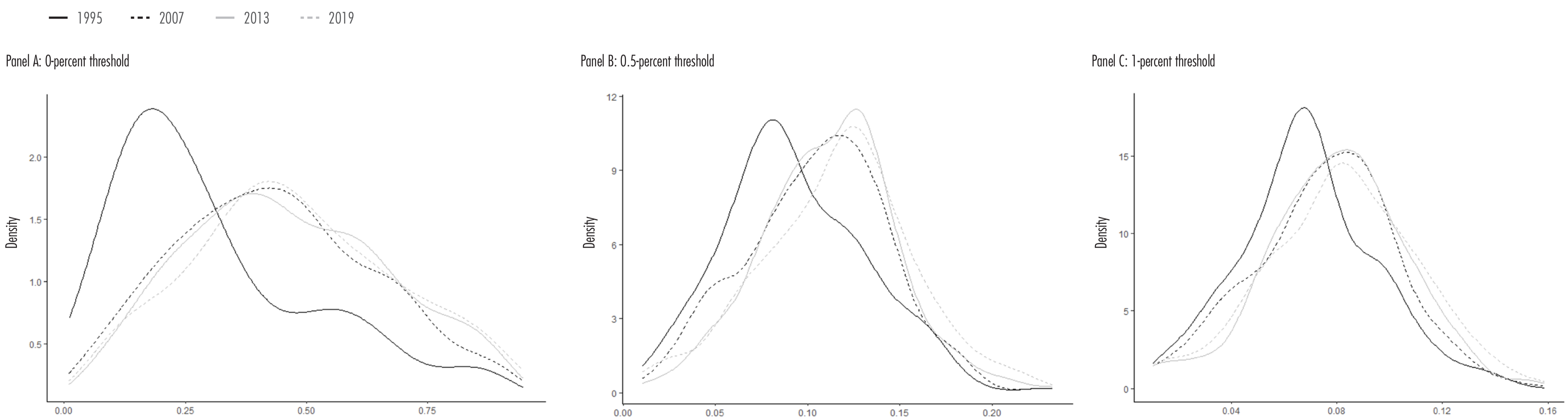
Many trade relationships occur with very small trade values. Once links with small trade values are excluded, the analysis can deviate significantly (Kali and Reyes, 2007). For this reason, some studies consider only trade links with values above a certain threshold as non-zero trade flows. There is no consensus on the value of this threshold. For example, Kim and Shin (2002) use cut-off values of USD 1 million and USD 10 million and thus remove the trade of many small countries from the sample. Kali and Reyes (2007) use different thresholds defined as shares of a country's bilateral exports over the country’s total exports. If the share is below a certain level (0.5 percent, 1 percent and 2 percent) the observed trade relationship is ignored. In our analysis, once taking out import links with values below 0.5 percent and 1 percent of the overall import value of each importing country, the number of active trade links declines to almost a third compared to the case when all data reported by the countries are considered (Table B 1). While absolute values differ significantly when applying different cut-off thresholds, the patterns of change over time remain the same, with distributions shifting rightward between 1995 and 2007, suggesting higher direct and indirect connectivity overall and a more even distribution of connectivity across countries (Figure B 1 and B 2).

Table B1. Sensitivity analysis of the distribution of trade links considering different cut-off thresholds

	0-percent threshold				0.5-percent threshold				1-percent threshold			
	1995	2007	2013	2019	1995	2007	2013	2019	1995	2007	2013	2019
Number of active links	11 395	15 768	16 635	17 016	3 356	3 792	4 026	4 157	2 480	2 709	2 867	2 924
Average number of links per country	60	83	88	90	18	20	21	22	13	14	15	15
10th percentile of links	19	32	38	36	8	10	13	12	7	7	9	9
Median links	48	80	83	86	16	21	22	23	13	15	15	15
90th percentile of links	122	136	147	148	28	28	29	31	19	20	21	22

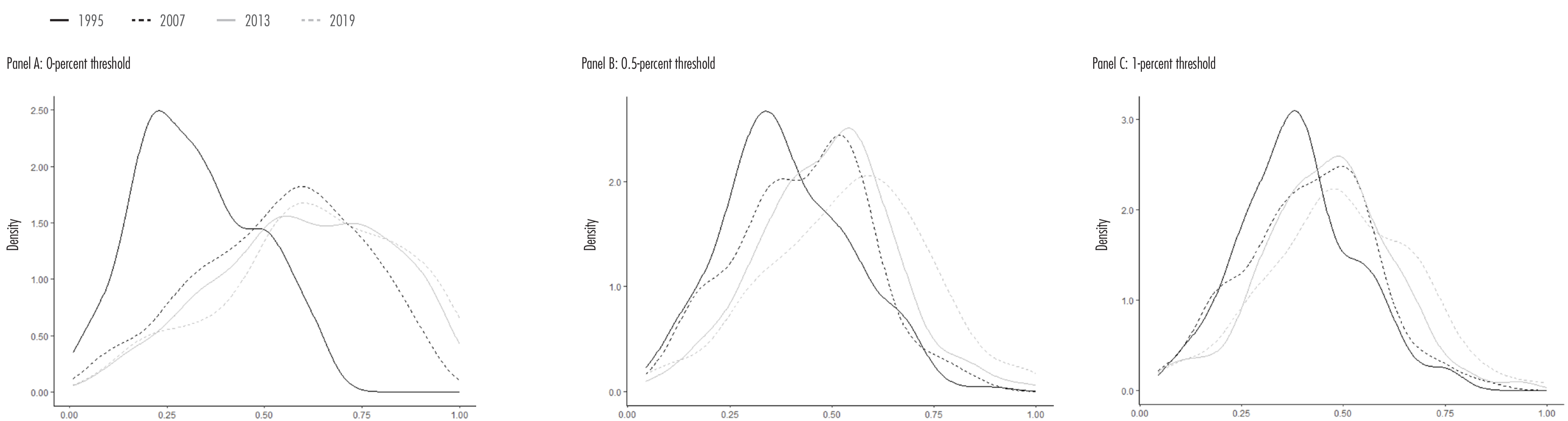
Note: In the sensitivity analysis, all observed trade relationships (links) are considered (0-percent threshold); or trade relationships are excluded if import values are below 0.5 percent (0.5-percent threshold) or below 1 percent (1-percent threshold) of the overall import value of each importing country.
Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

Figure B1. Sensitivity analysis of the normalized first-order indegree distribution by cut-off threshold



Note: In the sensitivity analysis, all observed trade relationships (links) are considered (0-percent threshold); or trade relationships are excluded if import values are below 0.5 percent (0.5-percent threshold) or below 1 percent (1-percent threshold) of the overall import value of each importing country.
Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

Figure B2. Sensitivity analysis of the normalized second-order indegree distribution by cut-off threshold



Source: Jafari, Y., Engemann, H. & Zimmermann, A. 2022. *The evolution of the global structure of food and agricultural trade: Evidence from network analysis.* Background paper for The State of Agricultural Commodity Markets (SOCO) 2022. Rome, FAO. https://doi.org/10.4060/cc4145en

Appendix C – Network definition, its mathematical representation, and basic network measures

Network definition

Network analysis is one of the main approaches to analysing the structure and changes of trade networks represented by straight lines showing trade flows between countries. In network terminology, countries are called nodes or vertices, the straight lines are called links, arcs, or edges, and the strength of a trade flow, i.e. the value associated with the trade flow, is called weight. If the trade flows are represented only with nodes and lines and the direction of the trade flows is given, the network is called an unweighted or binary directed trade network. Adding weights (e.g. value or number of products traded) to each link gives a weighted directed trade network. In binary/weighted undirected trade networks, the direction of the trade flows is ignored.

Mathematical representation of the network

A network (N) can be represented by $\mathrm{i} = (1,2, \ldots, \mathrm{n})$ number of vertices $(\mathrm{V_i})$ where each pair of vertices (i, j) can potentially be linked with a line $(\mathrm{L_{ij}})$ resulting in $\mathrm{L} = (1,2, \ldots \mathrm{m})$ number of links. Each vertex has its properties $(\mathrm{P_i})$ and each line connecting two vertices can have a weight $(\mathrm{W_{ij}})$. Abstracting from the subscripts the network can be represented as $\mathrm{N} = \mathrm{f}(\mathrm{V}, \mathrm{L}, \mathrm{W}, \mathrm{P})$.

If there are no multiple edges between each pair of vertices and there are no loops for any vertex then it is called a simple graph. Simple graphs can be directed or undirected graphs. In simple graphs, $\mathrm{L_{ij}}$ is a variable representing trade flows. It can be a binary variable taking the value of 0 or 1 reflecting the absence or presence of a link between two vertices i and j. If the lines carry pair-specific characteristics then the network is called a weighted network. The following parts show the mathematical notations related to the structure of directed and undirected networks and the related measures applied in this study.

Summary statistics of the network

The density of an unweighted network is the number of lines (m) in the network over the total number of possible lines $(\mathrm{m_{max}})$ and it is expressed as $\frac{\mathrm{m}}{\mathrm{m_{max}}}$. The total number of possible links is $(\mathrm{n}-1) * \mathrm{n} * 2$.[26] The density in the network weighted by product is calculated in a similar way as the unweighted network. The difference is that multiple lines can connect the two vertices so that if the network is directed the total possible density is $(\mathrm{n}-1) * \mathrm{n} * 2$ times the number of products (h). In the trade intensity network (the network weighted by trade value), we calculate the arithmetic average of trade per possible link: [Trade values/ $(\mathrm{n}-1) * \mathrm{n} * 2$].

The shortest path (geodesic distance) in the unweighted network is defined by the minimum number of steps required to move from one node to another $(\mathrm{d_{ij}})$. In the weighted network, the shortest path is defined by the minimum cost/distance between two nodes $(\mathrm{V_{ij}})$. Given the interpretation of the shortest path, the cost/distance representing weight in the network is defined as the inverse of trade values (see Newman, 2003; Opsahl, Agneessens and Skvoretz,

[26] In the undirected network, the total number of possible links is $(n-1) * n$.

2010). In addition, for technical reasons, we scale up each value by a maximum edge value so that each cell in the normalized trade value matrix reads as $V_{ij} = \frac{Max\,(Tij)}{Tij}$. Given the above definition, one can construct distance matrices d_{ij} and V_{ij} representing the shortest distance between every two nodes in unweighted and weighted networks, respectively. Considering these distance matrices, the diameter of each network is the maximum element of each matrix. The average shortest distance associated with these matrices is also the average of the elements of distance matrices d_{ij} and V_{ij} ,$\frac{\sum_{j=}^{n}\sum_{i=1}^{n} dij}{(n*n)-n}$ and $\frac{\sum_{j=1}^{n}\sum_{i=1}^{n} Vij}{(n*n)-n}$, respectively.

Local connectivity measures

The position of every node in the network is shown by different measures of connectivity. The degree connectivity is the degree of the network (d) over the maximum possible degree $2(n-1)$: $\mathscr{b}_i^d = \frac{d}{2(n-1)}$. The closeness connectivity of a node $\mathscr{b}_i^c$ is based on the geodesic distances of node i from all nodes j in the network, δ_{ij}. It is the ratio of the total number of other vertices $(n-1)$ over the sum of all geodesic distances: $\mathscr{b}_i^c = \frac{n-1}{\sum_{i\neq j}^{n-1}\delta_{ij}}$. Generally, the closeness connectivity is below one but it can exceed one if there exist some relatively isolated countries in the network, i.e. a given country does not have many trade links. The betweenness connectivity of node i is the proportion of the geodesic distances between any pairs of nodes in the network that pass through this node over the total geodesic distances. The higher the betweenness connectivity of the node, the more important the node is in the network. In the unweighted network, it is defined as the ratio of the number of shortest paths that go through the node $({\delta_{jk}}^i)$ over the number of shortest path in the network (δ_{jk}): $\mathscr{b}_i^b = \sum_{j\neq k}\frac{{\delta_{jk}}^i}{\delta_{jk}}$. In the weighted network, the betweenness index is the proportion of the geodesic distance between any pairs, V_{ij}, that pass through this node over the total geodesic distances: $\mathscr{b}_i^b = \sum_{j\neq k}\frac{V({\delta_{jk}}^i)}{V(\delta_{jk})}$.

The connectivity measures such as degree, betweenness, and closeness consider the topological position of nodes in the network but not the importance of the neighbouring nodes (Barrat et al., 2004). That is, these measures are not able to accurately describe the power of collaboration between nodes. Second-order degree measures consider this by taking the importance of the second-order neighbour, that is, a trade partner of a trade partner, into account. In the unweighted network, the second-order degree is calculated by squaring the adjacency matrix, where the row sum elements of the resulting matrix show the second-order degree connections. In the weighted network, we multiply the second-order degree distribution with the transpose of the first-order strength. We then normalize these measures by dividing them over the maximum of the natural logarithm of the values across years to be able to compare across years.

We also consider higher orders of integration, that is, the level of connectivity of a node to every other node in the network, by calculating the eigenvector connectivity. This measure defines the connectivity of a node based on the connectivity of the neighbours, which, in turn, define their connectivity by the connectivity of their neighbours and so on. The eigenvector connectivity defines the connectivity of a node proportional to the sum of connectivity indices of the neighbours. The more important the neighbours in the network, the higher the connectivity of a given node.

Mathematically, the eigenvector connectivity of each node i is calculated as

$\lambda C_i^{(eig)} = \sum_{j=1}^{n} a_{ji} * C_j^{(eig)}$, where λ is a proportionality constant. a_{ji} implies that node i receives the contribution to the connectivity from its neighbours through incoming links. The above formula in matrix form is $A^T C^{eigen} = \lambda C^{eigen}$, which means the vector of connectivities C^{eigen} is an eigenvector of A^T with eigenvalue λ.

The weighted eigenvector connectivity measure is straightforward, in this case a_{ji} refers to the weights (e.g. trade values).

We calculate the connectivity measures at network level by taking the arithmetic average of the individual connectivity measures.

Appendix D – Overview of the literature on network analysis of food and agricultural trade

Table D1. Relevant literature on the analysis of agrifood trade networks

Reference	Objectives and methodology	Data and scope	Main results
Chung *et al.* (2020)	Applying a community detection algorithm to identify clusters in the weighted directed network of agrifood products.	Yearly export quantity matrix from FAOSTAT; 14 red meat and six processed meat sectors; 134 countries; period: 1995-2015.	In 1995, there are eight significant clusters mainly driven by geographic location (four main clusters in which all high-income countries are included, four minor clusters with only low- and middle-income countries that are less engaged in global trade). In 2015, there are only four significant clusters.
Dupas, Halloy and Chatzimpiros (2019)	Measuring the global integration of trade networks of cereal commodities based on several connectivity measures applied on the weighted directed network.	Trade quantities from FAOSTAT, 61 cereal commodities; 200-221 countries; period: 1986-2013.	The cereal network evolves from a scale-free network to an exponential degree distribution network. The network density increased. A decrease in the dominance of hubs led to a lower vulnerability to local crises.
Ercsey-Ravasz *et al.* (2012)	Understanding the evolution of the trade network of some agri-food commodities based on several network connectivity measures.	Trade values from UN Comtrade; HS-2-digit (01-24) commodities; 207 countries; period: 1998-2008	Trade networks became highly heterogeneous. Seven countries are the network core (hubs) as they trade with more than three-quarters of all countries in 2008.
Fair, Bauch and Anand (2017)	Investigating the structural changes in terms of vulnerability and assortativity of the wheat trade network based on connectivity and assortativity measures applied on an unweighted directed trade network.	Trade data from FAOSTAT; wheat; period: 1986-2011.	Over time, the network becomes less vulnerable to shocks; the assortativity and symmetry of the trade network increased; short-term shocks diversified the network, thereby leading to long-term structural changes in favour of more stability of the trade network to shocks.
Gutiérrez-Moya, Lozano and Adenso-Díaz (2020)	Understanding the topographical characteristics of the trade network and identification of the drivers of network connectivity. This is based on several connectivity measures applied on the weighted directed network of wheat; The exponential Random Graph Model (ERGM) is applied to identify the determinants of network connectivity measures.	Trade data from FAOSTAT; wheat; period: 2009-2018.	The trade network shows "small world" properties with moderate reciprocity and a scale-free structure. Trade connectivity is mainly driven by country openness, reciprocity, having the United States of America or Canada as trade partners and the geographical location of trading partners, the economic size of the importer, and the land area of the exporter.

Reference	Objectives and methodology	Data and scope	Main results
Gutiérrez-Moya, Adenso-Díaz and Lozano (2021)	Identifying the characteristics of the wheat trade network and patterns of trade among countries, and simulating the vulnerability of the wheat trade network against shocks with different intensities. The analysis is based on the calculation of several individual, local, and global connectivity measures applied to the weighted directed network of wheat products.	Trade data from FAOSTAT; wheat; period: 2009-2013.	The wheat trade network shows a high degree of reciprocity and clustering. First-order degree and -strength show a power law distribution. There exists only a small number of recurrent motifs, particularly, transitive motifs. The wheat trade network is disassortative based on the regional dimension. The network in 2013 is generally more resilient than in 2009; however, some developing countries become more vulnerable over time. Countries with low dependency on imports are more resilient towards shocks. Geographically, countries in Asia, Southern America, and Europe are better positioned with regards to their immediate ability to respond to shocks.
Konar *et al.* (2011)	Identification of the characteristics of the global virtual water network based on directed and weighted water trade data.	Virtual water associated with trade data from FAOSTAT; 58 commodities; 233 countries; year: 2000.	The weighted network follows a stretched exponential distribution. Countries with more trade partners and/or higher trade values trade more virtual water content.
Puma *et al.* (2015)	Investigating the connectivity and resilience of the trade network. Several connectivity measures are calculated based on the weighted directed network. The network response to supply shocks is simulated to test its vulnerability.	Trade and food supply data from FAOSTAT; wheat (191-233 countries) and rice (173-218 countries), period: 1992-2009	The global food system is rather homogenous and no significant changes are observed across years although the global connectivity has increased. The vulnerability to supply-side shocks in exporting countries has increased for least developed countries in 2005-2009 compared to 1992-1996; this is driven by the increased dependence on imports of staple foods.
Sartori & Schiavo (2015)	Analysing the connectivity and vulnerability of the network of virtual water trade, and the vulnerability of the food production system. First and second-order degree connectivity of the weighted directed network, and distributions of countries' connectivity measures are used to achieve the objectives.	Production and trade data from FAOSTAT; 309 crops and animal products; 253 countries; 1986–2010.	Globalization has increased over time. The vulnerability of the food production system has decreased as evident from reduced network asymmetry measures. Central players are gradually reducing their importance as dominant hubs, however, the high concentration of trade flows with a few very strong relations makes some of the nodes still critically important. The vulnerability of the virtual water network has also decreased.

Reference	Objectives and methodology	Data and scope	Main results
Shutters and Muneepeerakul (2012)	Identification of major triads in the network of some agrifood products. This is based on the triadic analysis performed on both directed and undirected unweighted networks of several commodities.	Trade statistics from FAOSTAT, several agricultural commodities; year 2000.	The most frequent triads are 13 followed by 7, 9, 10 (see Figure A 3 for the details of the type of triads). Import degrees are normally distributed. Triad 6 ("unbalanced triad") is the least occurring motif. 166 countries fall into one class (mainly triad 1 and 5) while 18 that are all highly isolated with respect to international agricultural trade fall into the other classes (mainly triad 2, 3, and 4; triad 1 and 5 are nearly non-existent).
Torreggiani *et al.* (2018)	Analyse the evolution of trade networks for different commodities. This is based on connectivity, vulnerability, and community detection measures applied on a weighted directed network. A comparison of the networks across different commodities is also performed. Econometric analysis of the impact of some explanatory variables (distance, common border, GDP, colonial relation, trade agreements, etc.) on the probability of countries belonging to the same cluster.	Trade data from FAOSTAT; 16 food commodities; 178 countries; 1992-2011.	The trade network is highly connected but there exist different levels of connectivity across commodities. Connectivity varies only slightly over the years. Countries are more connected in terms of imports than in terms of exports. Significant clusters are observed, distance negatively affects the probability that countries belong to the same cluster (with the exception of milk products). Most of the clusters of countries across commodities are similar.

Appendix E – Evolution of the international trade network

Referring to variants of "dependency" and "world system" theories of economic development[26], many sociological papers have shown the position of countries in international trade networks in relation to their development status (Fagiolo, Reyes and Schiavo, 2010). The dependency theory distinguishes between core countries (countries that export their production surplus) and peripheral countries (countries that receive the production surplus from core countries), thus analysing international relationships from a core-periphery perspective. The world system theory builds on the dependency theory but views international relationships as a system. In this system, bilateral relationships are influenced by the overall network. The theory thus views international trade relationships from a core, semi-core, and periphery perspective. An important finding of this literature is that international trade relationships are based on the economic characteristics of individual countries. For example, Snyder and Kick (1979) investigate trade relationships among 118 countries in 1965 and show that positions of countries, i.e. their grouping into the core, semi-core, and periphery classification of countries, is related to the GDP growth of countries.[27] More recently, Sacks, Ventresca and Uzzi (2001) constructed a measure of network position for each country based on the concept of "structural autonomy" and showed the positive effect of this measure on countries' per capita GDP. The existence of a core-periphery setup was also confirmed in later studies (e.g. Kim and Shin, 2002) with core countries being mainly exporters and peripheral countries being mainly importers.

With increasing globalization and the emergence of new players who became more dominant centres, the structure of the international trade network became more decentralised (Kim and Shin, 2002).[28] Over time, the number of core countries has increased and there is a progressive marginalization of very peripheral countries. The first paper that effectively investigated the dynamics of trade networks over time (considering the years 1965, 1970, and 1980) dates back to Smith and White (1992). The authors report a core-periphery structure, where countries form a continuum from the core to the periphery. Over time, the cores expand due to the appearance of more competitive centres. This is also evident from the study of Kim and Shin, 2002), who study three snapshots of directed trade participation (1959, 1975, and 1996) for a large set of commodities and 105 countries. They also found an increase in the number of trade linkages in the network over time. Similarly, Kastelle, Steen and Liesch (2006) study the evolution of the network of countries' participation in international trade between 1938 and 2003. They found an enhanced connectivity among countries and the emergence of new dominant centres that resulted in more but weaker cores. Despite this movement, the authors saw potential for higher integration and pointed out that the international trade network had not reached a fully globalized structure. Kali and Reyes (2007) reiterated this finding by evaluating the evolution of the trade network over the 1990s. Their results pointed towards a more globalized, i.e. connected/decentralized network that coexists with many core-periphery structures, i.e. regionalized networks that are determined by spatial proximity. The findings of Fagiolo, Reyes and Schiavo (2009) and De Benedictis and Tajoli (2011), who investigated the trade network over 1981–2000 and 1950-2000, respectively, also show that the trade network is not fully integrated. More recently, Cepeda-López *et al.* (2019) described the evolution of the world trade network between the mid-1990s and 2014.

[26] Dependency and world system theories are two related theories of economic development. Both theories partly emerged as a critique of the modernization theory of economic development. The former emphasizes the role of nations as unit of analysis in the development process, while the latter emphasizes the role of the system as unit of analysis in the development process.

[27] The relationship of countries' network position and countries' economic growth and development path is also stressed by Nemeth and Smith (1985).

[28] See also Vandermarliere, Standaert and Ronsse (2018) for an explanation of different trade structures referring to core-periphery, regionalization, and globalization.

Using network analysis, the authors find that the trade network became more decentralized both locally and globally during this time period.

Nonetheless, countries' integration in the global trade network is unevenly distributed. A large number of studies find that trade networks are scale-free (e.g. De Benedictis and Tajoli, 2011; Cepeda-López *et al*., 2019), that is, they are shaped by a large number of countries with a low level of connectivity and a small number of countries having a high level of connectivity to the network.[29] This has also been shown for the network of the international trade of food and agricultural products (Gutiérrez-Moya, Lozano and Adenso-Díaz, 2020). Kim and Shin (2002) showed that the distribution of countries' connectivity in the overall network became more uneven between 1959, 1975 and 1996. Similar patterns have been found by De Benedictis and Tajoli (2011) for the time period 1981-2000 and by Cepeda-López *et al*. (2019) for the time period mid-1990s to 2014.

[29] Power laws mathematically formulate the fact that, in many networks, the majority of nodes have only a few links, and that these nodes coexist with a few big hubs – nodes with an anomalously high number of links. In contrast, in a random network, the peak of the distribution implies that the majority of nodes has the same number of links. Therefore, a random network has a characteristic scale in its node connectivity, embodied in the average node and fixed by the peak of the degree distribution. The absence of a peak in a power-law distribution implies that there is no characteristic node. In other words, there is no intrinsic scale in a power-law network. Such networks are therefore referred to as being scale-free. The international trade network is thus scale-free at higher levels of trade, implying that there is no 'typical' country in terms of the number of trading partners.

ISBN 978-92-5-137589-1

9 789251 375891

CC4145EN/1/02.23