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Virtual water trade and country vulnerability: A network perspective

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Abstract

We analyze the link between virtual water trade, that is, the flow of water embodied in the international trade of agricultural goods, and vulnerability to external shocks from the vantage point of network analysis. While a large body of work has shown that virtual water trade can enhance water saving on a global scale, being especially beneficial to arid countries, there are increasing concerns that more openness makes countries more dependent on foreign food suppliers and especially more susceptible to external shocks. Our evidence reveals that the increased globalization witnessed in the last 30 years is not associated with the increased frequency of adverse shocks (in either precipitation or food production). Furthermore, building on recent advances in network analysis that connect the stability of a complex system to the interaction between the distribution of shocks and the network topology, we find that the world is more interconnected, but not necessarily less stable.

Keywords: virtual water trade, vulnerability, complex network, shocks

JEL codes: F14, F18, Q25, Q56

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1. Introduction

A recent study carried out by the Food and Agricultural Organization of the United Nations (FAO, 2012) deals with the issue of food security under conditions of water scarcity in agriculture. To the extent that water scarcity is a constraint to the achievement of self-sufficiency in food and other agricultural commodities, strategic choices need to be made on national food security policies and the role of trade in agricultural goods. Several nations need to face this urgent and growing problem, particularly those located in the Middle East and North Africa (MENA) region.

International trade may help countries to overcome water scarcity: although importing the water needed to produce agricultural goods is most often impractical, water-scarce countries may import water-intensive products produced elsewhere and thus preserve their domestic resources. In so doing, they import "virtual water" (VW), meaning the amount of water needed to grow the imported product (Hoekstra & Chapagain, 2008). If the flow of this virtual water moves from water-rich to water-scarce countries, then international trade favors a more efficient allocation of food production and contributes to saving water: most existing studies suggest that the net effect of the current VW flows is water saving (e.g. Hoekstra & Chapagain, 2008; Oki & Kanae, 2004).

On the other hand, if the capacity to engage in trade provides water-scarce countries with water and food security (Allan, 2001; Antonelli, Laio, & Tamea, 2014), this poses the problem of water and water-*dependent* food security (Allan, 2001, 2003a, 2003b), as many countries have gradually increased their reliance on intensive water commodity and food imports. An example is Jordan, which imports yearly a virtual water volume, embedded in agricultural products, which is five times higher than its own renewable water resources; while saving its own resources, it amplifies its dependence on other countries and their water resources (Hoekstra & Mekonnen, 2012). For this reason, nations are increasingly concerned about the issue of food "sovereignty" (Burnett & Murphy, 2014). Moreover, the fluctuating prices of basic food staples and their impact on the population, in particular in developing countries, are inducing decision makers to review their food policy in favor of increased self-sufficiency. Of course, in places where water is scarce, this national target of self-sufficiency may, however, be incompatible with the actual stock of water resources available for agricultural production, making the choice of resorting to international trade the only feasible option. This is particularly the case in the Middle East and North African region, which has relied on "trade" in virtual water to secure its food needs to a very large extent (Antonelli et al., 2014).

In addition to political considerations, trade openness is often considered a source of instability and vulnerability to external shocks. One view is that trade openness makes a country more vulnerable to crises, since a country that is highly integrated into the world markets is more exposed to shocks coming from abroad (see, e.g., Aizenman, 2008; Aizenman & Noy, 2004). A second view is that openness allows more rapid dissipation of shocks and, often being associated with better institutions, tends to make countries more stable.

Hence, there seems to be a potential trade-off between the need to import agricultural goods (and the associated potential saving in water resources) and the vulnerability to external shocks. This paper explores this issue from the perspective of network analysis: it investigates whether the topological characteristics of the international *virtual water* network (see Section 2) may favor or enhance countries' vulnerability to external crises. In other words, may trade openness affect a country's vulnerability to crises that originate elsewhere in the world? Does the agricultural world trade network, translated into virtual water trade, have intrinsic topological features that make the countries involved in it prone to instability? To what extent does the network favor the propagation of a crisis situation through the system, thus affecting the socio-economic growth of the nations involved? None of the existing studies address these issues from the perspective of virtual water trade (VWT). In this paper, we will explore the topology of the VWT network and its evolution over time, focusing on the analysis of its potential sources of vulnerability.

Like many other global networks, the global VWT system has the feature of being both interconnected and interdependent. This poses the problem of network vulnerability to exogenous external shocks. On one hand, the growing interconnectivity of global trade increases the robustness of the system to local crises. On the other hand, the increasing interdependency among climatic, demographic and economic networks could make the system prone to catastrophic collapses, since cascading failures may transmit more or less quickly across the interconnected networks. Assessing the vulnerability of the system in crisis situations, like adverse weather events, geo-political crises, and uncontrolled fluctuations in food prices and production volumes, is thus of paramount importance, since one may ask whether the benefits of being part of this network may be cancelled out by its intrinsic vulnerability.

The relationship between network topology and stability has received considerable attention of late, especially since the recent financial crisis has forcefully highlighted the importance of the issue. In this paper, we follow a recent contribution by Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) and consider both the features of shocks and their interaction with first- and second-order network characteristics.

Our work offers several contributions to the existing literature. First of all, we investigate the possible sources of VWT network vulnerability, analyzing their interaction with the network structure. With respect to the existing contributions (e.g. Dalin, Konar, Hanasaki, Rinaldo, & Rodriguez-Iturbe, 2012; Konar, Dalin, Suweis, Hanasaki, Rinaldo, & Rodriguez-Iturbe, 2011), we extend the time frame of the analysis to 2010 and consider virtual water flows associated with a higher number of total commodities (309) and countries/territories (253). We also provide a topological analysis of the VWT network at both a binary and a weighted level.[1] inally, we take into consideration higher-order connectivity, as proposed by Acemoglu et al. (2012).

The paper is structured as follows. The next section provides a brief overview of the literature and explains the methodology followed in this study. Section 3 illustrates the results of the empirical analysis, carried out on potential supply-side shocks and their interaction with the network topology. The final section discusses some policy implications and concludes.

2. Virtual water, network analysis, and methodology

The term "virtual water" was coined and made popular in the early 1990s to draw attention to the global economic processes that ameliorate local water deficits in the MENA region and elsewhere

(Allan, 1993). Thereafter, a flourishing literature on virtual water-related issues has grown, with different applications coming from several fields. As defined by Allan, the VW content of a good is the volume of water that is actually used to produce that good. It depends on several aspects, like the production conditions, including the place and time of production, and water use efficiency.[2] VWT refers, instead, to the implied exchange of water through conventional trade (Chapagain & Hoekstra, 2003). When a good is exported (imported), its VW content is implicitly exported (imported) as well. A trade matrix of value or quantity flows can then be translated in terms of VW-equivalent flows by using country-specific measures of the VW content of each product.[3] This allows the determination of whether one country is a net importer or exporter of VW, which are its trade partners, and the weight of each VW flow. In this sense, the concept of VW not only represents a way to link international trade and water policy, but also provides a novel quantitative framework for the study of water resources used for agriculture and livestock production worldwide and the water exchanges underlying food trade.

VW and derivative concepts have been employed as a descriptive and policy tool in several research areas, ranging from natural to social sciences, encompassing environmental, economic, social, cultural, political, and institutional aspects on a local, regional, and global scale (see, e.g., Hoekstra & Chapagain, 2008; Hoekstra & Mekonnen, 2012). In the last decade, a number of studies have applied complex network analysis to study the features of VWT as a global network. This has led to the unveiling of the main characteristics of the VWT topological structure (Konar et al., 2011; Tamea, Allamano, Carr, Claps, Laio, & Ridolfi, 2013), to highlight clues to small-world behavior (Shutters & Muneepeerakul, 2012), the occurrence of hubs and the rich-club effect (Suweis, Konar, Dalin, Hanasaki, Rinaldo, & Rodriguez-Iturbe, 2011), and the existence of a community structure (D'Odorico, Carr, Laio, & Ridolfi, 2012). In Carr, D'Odorico, Laio, and Ridolfi (2012), Dalin et al. (2012), and D'Odorico et al. (2012), the temporal evolution of the virtual water network is analyzed, showing the progressive intensification of the VW exchanges and the geography of these variations. Notwithstanding these achievements, the VWT issue needs to be investigated further. In fact, the complexity and the possible implications are far from being fully explored, and further efforts are needed to gain a better understanding of the information content of the available data (Tamea et al., 2013).

VWT has been studied on different spatial scales but mostly for a specific time period (see, for instance, Roson & Sartori, 2010, 2013; Velazquez, 2007; Yang & Zehnder, 2002). A temporal analysis of the global VWT network would allow for an assessment of the key impacts of policy, economic, and biophysical factors and thus would greatly contribute to the understanding of the dynamics embedded in the global VWT network. A time evolution can be found in Liu, Zehnder, & Yang (2007) and Oki & Kanae (2004), who analyze the historical trends in China's VWT from 1961 to 2004 and the yearly global VWT volume from 1961 to 2000, respectively. In a more recent study, Dalin et al. (2012) use network theory to characterize the structure of the VWT network over time, from 1986 to 2007.

The methodology that we apply in this paper is the following. A VW flow is obtained by multiplying the estimates of country-specific VW content for various crops by the exchanged agricultural goods registered in the international trade. For a detailed description of the way in which the VW content of the trade flows was computed, we refer to Carr et al. (2012, 2013) and Tamea, Carr, Laio, & Ridolfi (2014).[4] Here we provide only a short explanation.

Food production and international trade data for a total of 309 crops and animal products for the period 1986–2010 were obtained from the FAOSTAT database, while Mekonnen & Hoekstra (2011) provide estimates of the country-specific VW content of various crops. A VWT matrix was then obtained by multiplying the country-specific VW content of various crops by the amount of agricultural goods traded between a country pair. For any product, the VW content was obtained by considering the volume of water needed to produce it in a given country, including both rainfed water (*green water*) and surface water and groundwater (*blue water*).[5] The total number of countries considered is 253; since the number of active countries varies in time due to geo-political changes (e.g. there are 208 in 1986 and 211 in 2010), inactive countries in a given year were simply removed from the analysis. For each single year, the matrix of global VWT flows was obtained by summing the 309 individual crop-specific virtual water trade matrices. The whole database is thus composed of 25 VWT matrices. Without loss of generality, we restricted the analysis to a select group of years, namely 1986, 1990, 1995, 2000, 2005, and 2010.

In the global VWT system, the network is represented by an ($N\times N$) VWT matrix W_N, in which each node represents a country. The rows indicate export flows, whereas the columns stand for import flows. Each cell $w(i,j)$ thus captures the virtual water flow from country i to country j, with $w(i,i)=0$. The sum over row i is the total amount of virtual water exports of country i, while the sum over column j is the total amount of virtual water imports of country j. A link is a connection between two nodes and represents the volume of virtual water flowing between them. The international VWT thus constitutes a weighted and directed network (see, e.g., Wasserman & Faust, 1994), in which the link direction is given by the direction of trade (i.e. from the exporting to the importing country), and the link weights are the volumes of virtual water traded between countries. From the complete network with information on link weights and direction, it is possible to create simpler networks, unweighted and/or undirected, which we perform as part of the analysis.

3. Empirical analysis: Supply shocks and their interaction with network topology

The global VWT system, like many other global networks, is both interconnected and interdependent. These features may result in small, local shocks that have a strong systemic effect, potentially threatening the collapse of the network, due to cascading failures transmitting across the network's ties (see, for instance, Carlson & Doyle, 2002 or Doyle et al., 2005). In the last few years, partly as a consequence of the recent financial crisis, this notion has percolated into economic analysis, and the relationship between network structure and stability has been attracting a large amount of attention, especially in financial economics.[6] Generally speaking, greater connectivity reduces the likelihood of systems failure because shocks are more easily dissipated. However, the relationship between network topology and stability is highly non-linear and marked by the existence of extreme behaviors and tipping points (Haldane & May, 2011). Several studies link the possible emergence of contagion with the degree of heterogeneity in the network, which can refer either to nodes' intrinsic characteristics (such as size, see Iori, Jafarey, & Pailla, 2006) or to nodes' connectivity (Caccioli, Catanach, & Farmer, 2012). Indeed, when the network is not homogeneous, the positive effect of greater density on diversification is counterbalanced by the fragility associated with the presence of very central (and therefore critical) players (Battiston, Puliga, Kaushik, Tasca, & Caldarelli, 2012). In a more recent study, Acemoglu, Ozdaglar, & Tahbaz-Salehi (2013) argue that one should pay attention to the possible interplay between the connectivity distribution of the network and the shape of the distribution of shocks, which are not separable: the same network structure may be more or less vulnerable to shocks' propagation depending on higher-order topological features. Moreover, large systemic effects may occur even in the presence of relatively small-scale disturbances.[7]

The research question at the heart of this paper is whether greater density in the VWT network, due to the globalization of food trade, has made the world and individual countries more vulnerable to shocks and, as a result, whether there is an actual trade-off between stability and openness.

The analysis is performed in two steps. First (Section 3.1), we examine the frequency of supply shocks that might be transmitted across borders via international trade, checking whether extreme events have become more likely over time (because of, for instance, climate change). Second, we investigate the topological properties of the VWT network to determine whether its evolution may give rise to a more fragile world system (Section 3.2).

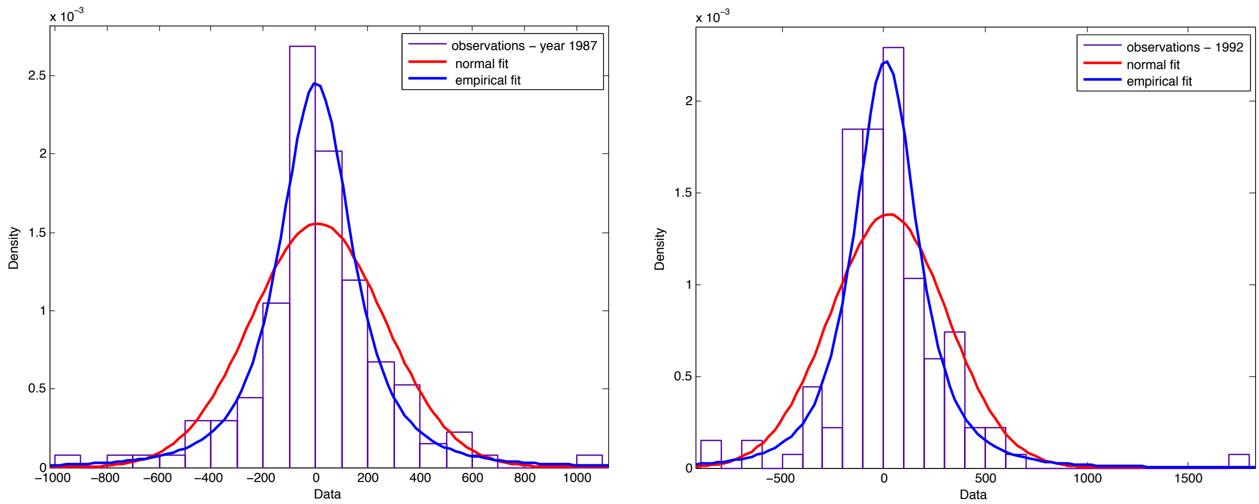
3.1 Supply shocks

As the VWT reflects trade in agricultural goods, we consider, as possible disturbances affecting the countries and the network, (i) extreme events in terms of precipitation levels, like droughts or floods, which may provoke severe output losses, and (ii) considerable fluctuations in agricultural production volumes, which may affect international crop and staple food prices. Our analysis focuses on the probability distribution of shocks, with the aim of determining the presence of fat tails; these imply that the probability of extreme events (e.g. a large output loss or exceptionally heavy rain) is larger than it would be under a normal or another thin-tailed distribution.[8] This in turn has important consequences for the stability of the network and the countries involved in it.

3.1.1 Climate-origin shocks

Fluctuations in precipitation levels may affect crop productivity. Furthermore, variations in crop productivity affect the output volumes and international trade in agricultural goods, which in turn modify the directions and volumes of the water flows exchanged virtually by countries.

Data on precipitation levels are taken from the FAO Aquastat database,[9] which provides the Long-Term Precipitation – LTP – in depth (mm/yr) and the National Rainfall Index – NRI (mm/yr) indicators, with 5-year temporal intervals, for 199 countries. Using the LTP as the yearly observed data and the NRI as an average value, we compute the distribution of deviations from the mean, for which positive (negative) values indicate drier (wetter) years with respect to the average level of precipitation for each country. Figure 1 illustrates the distribution of our sample of data[10] fitted to a normal distribution. A KS normality test performed on the four samples rejects the null hypothesis of normality, with only one exception.[11]



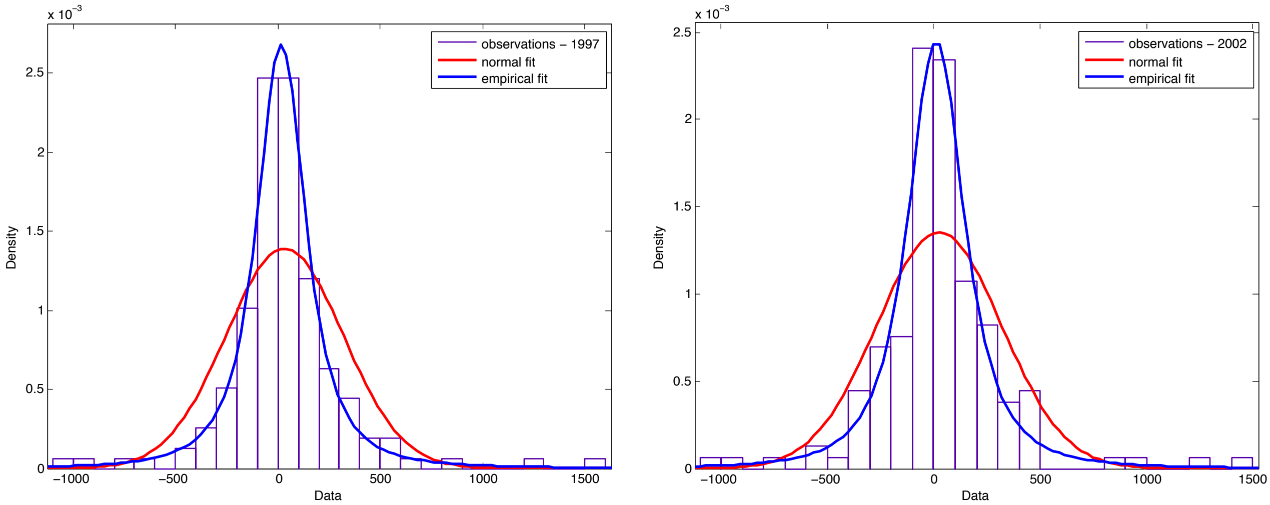


Figure 1. Normal and empirical fitting of precipitation distribution: Deviation from the mean.

We look for the presence of fat tails in the data to figure out the probability of extreme outcomes. We also check the extent to which the tails of the probability distributions have become fatter over time. To this end, a *Clauset test* (Clauset, Shalizi, & Newman, 2009) for power law tail behavior is performed first. As no significant results emerge,[12] we report only the percentage of values above x_{min}[13] (see Table 1, % above Rx_{min} and Dx_{min}). We therefore compute a series of indexes and diagnostics of tail heaviness, commonly used in the literature. Alongside some ordinary descriptive statistics (i.e. kurtosis and skewness), we compute the percentage of observations that stay out of the interval "mean±double standard deviation" and the *Obesity Index* – ObIn (Cooke & Nieboer, 2011).[14] The latter is based on the heuristic that, in the case of heavy-tailed distributions, larger observations lie further apart than smaller observations, and it is computed as follows:

$$Ob(X) = P(X_1 + X_4 > X_2 + X_3 | X_1 \leq X_2 \leq X_3 \leq X_4) \qquad (1)$$

where $\{X_1,\ldots,X_4\}$ are independent and identically distributed values randomly sampled from the data. In our application, the index is based on 1,000 random samples of 4 observations. The results are summarized in Table 1.

Table 1. Indexes of tail heaviness.

Year	Skewness	Kurtosis	St. Dev.	% Out of Interval	Right ObIn	Left ObIn	% above Rx_{min}	% above Lx_{min}
1987	0.06	6.26	256.24	6.7	0.75	0.80	7.6	64.7
1992	1.26	12.70	288.21	4.4	0.75	0.73	22.9	23.4
1997	0.80	10.23	286.93	5.1	0.78	0.78	18.8	47.9
2002	0.74	8.81	294.90	5.7	0.75	0.78	25.3	44.6

The skewness is positive and small, indicating rather symmetric distributions, with a slightly longer right tail. The kurtosis is larger than the reference value for a normal distribution (3), suggesting a higher concentration around the mean and fatter tails relative to a normal distribution. The percentage of values lying more than two standard deviations away from the mean range is between 4.4% (in 1992) and 6.7% (in 1987). The Obesity Index confirms that the tails are not particularly fat: the values range between 0.73 and 0.80 for the left tail (too little rain) and between 0.75 and 0.77 for the right tail (too much rain); these are not far from the theoretical value implied by an exponential distribution (0.75) and far below the value implied by Zipf's law (0.87). Finally, the percentage of values above the right and left tails x_{min} (from the Clauset test) is generally increasing and high, suggesting a very low or even a null probability of fat tails.

A further method to look for fat tails in a distribution is to compare the mean excess plot of the data sample with the mean excess plot of a data set obtained through aggregating the original data set by *k*, as suggested by Cooke & Nieboer (2011). The mean excess function – MEF – of a random variable X gives the expected excess of the random variable over a certain threshold *u*, given that the random variable is larger than the threshold. It is defined as

$$e(u) = E(X - u | X > u) \qquad (2)$$

Following Cooke & Nieboer's procedure, we first divide the data set randomly into groups of size *k* and then we sum each of these *k* values. Indeed, aggregating the sample does not have much effect on the mean excess plot for the data set from the heavy-tailed distribution, while this is no longer valid for the data set from the thin-tailed distribution. That is, in the presence of fat-tailed distribution, the two mean excess plots (of the original and the aggregated samples) are very similar. As an example, Figure 2 plots the MEFs for the distribution for the years 1992 (left panel) and 2002 (right panel).

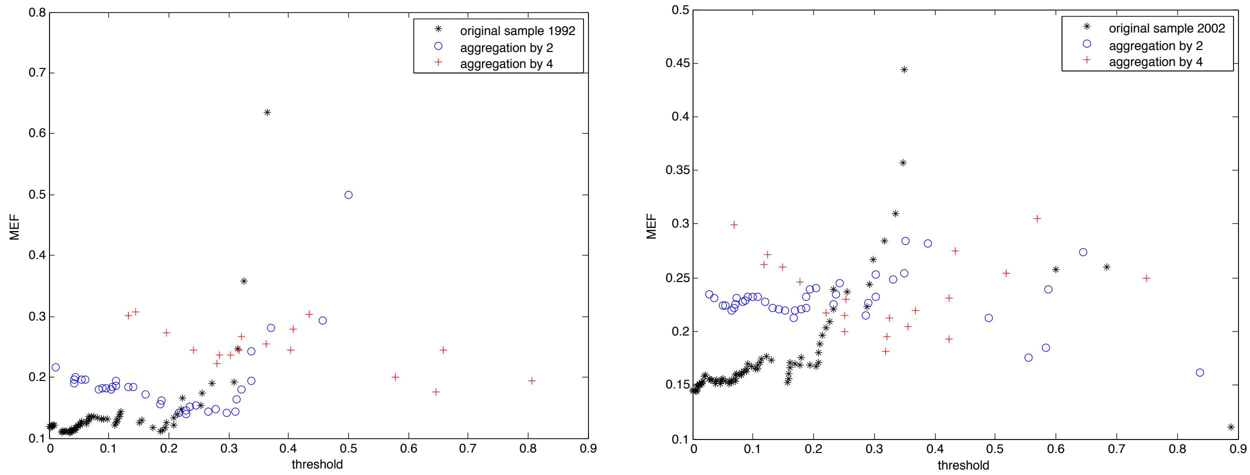


Figure 2. MEF of the original sample and aggregated data set. Years 1992 (left panel) and 2002 (right panel).

The qualitative result displayed in Figure 2 is the same for the four samples analyzed here. First of all, according to Burnecki & Weron (2008) and Ghosh & Resnick (2010), a shape like that of the original sample MEFs plotted in Figure 2 suggests that an exponential law works well for these distributions. Second, by tuning *k*, the MEF plot changes, strengthening the hypothesis of thin tails in all the years. We thus interpret our results in favor of the absence of fat tails in the climate-origin shock distributions, that is, the possibility of incurring an extreme outcome is negligible or absent.

3.1.2 Fluctuations in output volumes

The second potential sources of instability for the countries involved in the VWT network are fluctuations in the agricultural production volumes. Indeed, VWT flows are computed by multiplying the country-specific virtual water content of the various crops produced by the agricultural goods traded. Therefore, they may vary for changes either in the crop-specific water content or in the production volumes. While the variation of the former over time is quite difficult to compute and data are still lacking in the literature, data on past levels of production volumes by country are easily accessible from the FAOSTAT database. Fluctuations in output volumes may have different origins, like staple price volatility, climate change impacts on productivity factors, modified production conditions, technological changes, and the like. These may affect international trade, which in turn modifies the virtual water flows among countries.

Data on agricultural production (ton/yr) are available from 1961 to 2012. By fitting a linear trend to the data, at the country level, we compute the yearly deviation of the empirical data from the simulated values (i.e. the predicted value in a certain year minus the country observation for that year). As a food crisis is only associated with a lack of food, not its over-abundance, we focus only on the positive (right) part of the distributions (Figure 3); this is to say that we only consider cases in which the actual production falls short of its expected value. Instead of taking a long-run average as the benchmark for each country (as for rainfall), the use of a linear trend allows us to take into account variations in productivity or other changes. For the sake of simplicity, we present the results for six selected years.

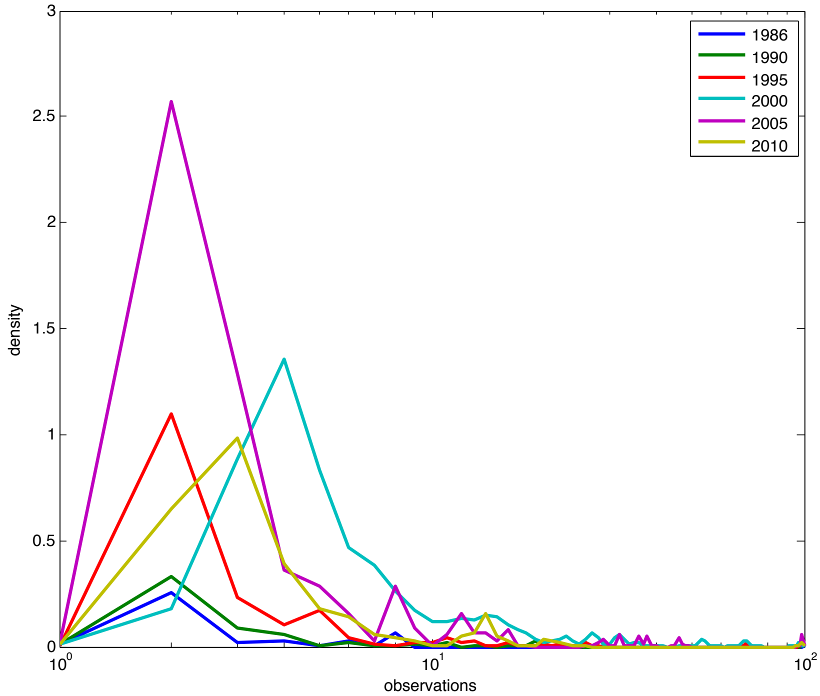


Figure 3. Distribution of positive deviations (output drops) from predicted values. X-axis: log scale.

We carry out the same statistical analysis as described in Section 3.1 to look for the presence of fat tails in the data. In addition, we perform a test for exponential tail behavior (Lilliefors, 1969). The null hypothesis of an exponentially distributed population is always rejected at the 5% significance level. We then compute the same indexes of tail heaviness, the results of which are reported in Table 2, and the MEF plots.

Table 2. Indexes of tail heaviness.

Year	% Out of Interval	ObIn	% above x_{min}
1986	1	0.91	35.5
1990	1	0.91	6.9
1995	2	0.89	10.2
2000	5	0.89	24.8
2005	3	0.90	56.7
2010	2	0.88	51.1

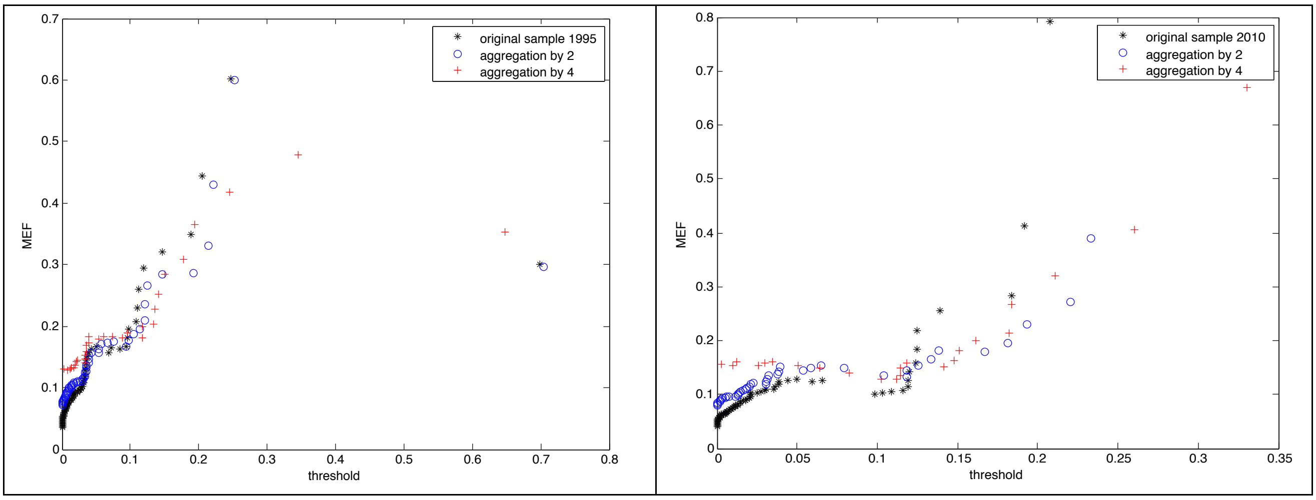


Figure 4. MEF of the original sample and aggregated data set. Years 1995 (left panel) and 2010 (right panel).

The presence of extreme values is quite low. These are mostly associated with some of the largest agricultural producers in the world, namely China, Russia, and India, and they are never lower than -15% of the predicted values, with only one exception (in the year 2010, the observed value is 24% lower than the predicted one).[15] The standard deviation is close to zero in all the samples, as well as the percentage of observations out of the interval "mean±double standard deviation." The Obesity Index is high, between 0.88 and 0.91, but decreasing over time, while the percentage of values above x_{min} is generally increasing. Despite the absence of any significant and clear evidence of power law behavior, the tails of the distributions are likely to be quite fat, but the risk of an extreme outcome diminishes slightly as time passes. This is further confirmed by the MEF plots of Figure 4: the data for 1995 (left panel) are consistent with a heavy-tailed distribution; in fact, the MEF is upward sloping and constant upon aggregation. However, the data for 2010 are much less likely to display heavy tails: over time, the probability of incurring a huge loss of agricultural production decreases.

Summing up, the statistical analysis of historical data on (potential) sources of VWT network shocks, like climate change impacts on rainfed water availability and other shocks affecting the productivity of the agricultural sector, does not reveal notable critical characteristics: during the last 30 years, increased globalization has not been associated with a higher frequency of adverse shocks.

3.2 The topology of the virtual water network

Recently, complex network analysis has been undertaken to investigate the structure and evolution of the global network of VW flows associated with international trade in agricultural goods.

The VWT network represents the VW flows associated with trade in agricultural commodities, where each country is a *node* and the volume of VW flowing between any country pair indicates the strength of the link between them.

The topology of a network is described through several commonly adopted indexes. The most immediate (and first) way to characterize a network is by means of its connectivity, specifically by looking at its *degree* distribution. Node degree (k_i), which measures the number of contacts maintained by each node, here translated as the number of trade partners of a country, is defined as

$$k_i = \sum_j a_{ij} \tag{3}$$

where a_{ij} is the element of the binary adjacency matrix A and may assume a value of one or zero, depending on the presence of a trade connection between node i and node j. This statistic is computed by transforming the network into its *unweighted* form, in which the weight of each trade flow is not considered; only the presence (or the absence) of the link matters.

In the case of *directed* networks, ties have a direction, and two separate measures of degree centrality are usually defined. *Indegree* distribution is a count of the number of edges directed to or caught by a certain node, whereas *outdegree* distribution is the number of ties that the node directs to others. Applied to the VWT network, indegrees are the number of import flows, while outdegrees are the number of export flows. These descriptive measures are summarized in Table 3, alongside other statistics, like the number of active nodes, the number of links, the maximum and the average degree statistics, and the ratio of standard deviation over average degree.

Table 3. Topological features of the *binary* network.

	Active Nodes	Number of Links	Density	Max *Outdegree*	Max *Indegree*	Max Degree (*In+Out-Bil*)	Average Degree[1]	St. Dev./ Mean
1986	208	8,644	20.08%	179	164	184	55.30	0.85
1990	205	8,643	20.67%	181	161	184	54.84	0.86
1995	238[2]	11,605	20.57%	204	178	205	63.60	0.85
2000	213	13,362	29.59%	191	173	195	81.44	0.64
2005	211	14,432	32.57%	198	171	200	90.01	0.58
2010	211	14,669	33.11%	197	169	202	90.63	0.59

We can see that over time the number of active nodes increases. This is associated with a more than proportional increase in the number of links: the network density (defined as the number of active links over the total number of possible connections) moves from 20% to 33%, testifying to rising global trade. The maximum number of trade partners is always smaller than the number of players, meaning that no economic system is connected with everybody else. There is a large difference between the average and the maximum number of partners, while its variability (coefficient of variation) decreases over time. Looking at the distribution of indegree (Figure 5, in which normalization sets the index

[1] Both the "average degree" indicator and the ratio "standard deviation over mean" indicator are computed on the degree distribution (the sum of in- and outdegree net of bilateral links).

[2] This higher value is due to the dissolution of the Soviet Union.

between 0 and 1 for all years to enhance comparability), we can appreciate that the skewness decreases over time and the distribution becomes more symmetric. Still, we can see that alongside a small fraction of highly connected nodes, there is a large group of peripheral countries. Over time, however, the body of the distribution shifts rightward, signaling an increase in the number of trade partners to which the average country is connected.

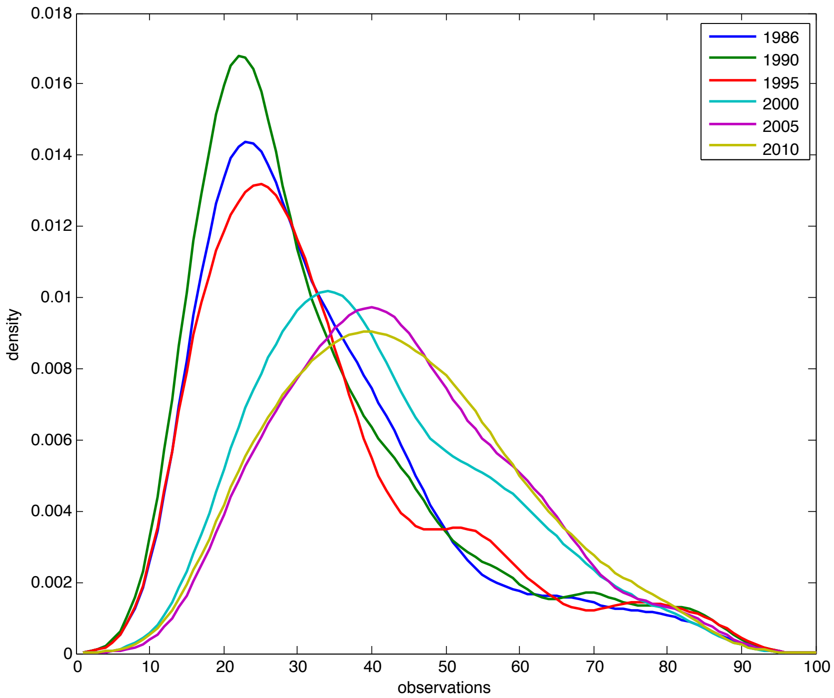


Figure 5. Normalized *indegree* distributions (first order).

Node strength (s_i) is instead the sum of all the link weights w_{ij} of each node (representing the total VW imports or exports):

$$s_i^{in} = \sum_j w_{ji} \qquad\qquad s_i^{out} = \sum_j w_{ij} \qquad (4)$$

of which the maximum and average values are collected in Table 4, together with the global volume of virtual water traded.

Table 4. Descriptive statistics of the virtual water flows.

Network	Global Flow (m^3*10^9)	Max *Out* Strength (m^3*10^9)	Max *In* Strength (m^3*10^9)	Average Strength (m^3*10^9)
1986	1,064.01	176.78	89.98	5.12
1990	1,182.88	198.11	98.49	5.77
1995	1,431.71	239.44	100.10	6.02
2000	1,845.18	243.77	130.01	8.66
2005	2,355.30	243.61	179.10	11.16
2010	2,769.11	298.11	278.09	13.12

The qualitative picture emerging from Tables 3 and 4 is consistent with those obtained by previous studies (Dalin et al., 2012; Konar et al., 2011): the number of trade connections and the volume of water associated with global food trade more than doubles in 25 years, alongside a relatively stable maximum degree. The number of active nodes varies over time due to geo-political changes (mainly the dissolution of the Soviet Union), but remains otherwise stable. This implies that, on average, the number of trade partners of each country increases over time, suggesting that the VWT network has become a more interconnected and more balanced structure, in which the relative importance of the main VW exporters with respect to other minor countries diminishes.

We next consider a measure of the correlation patterns in the degrees of connected nodes, better known as *assortativity*. Through this index, we understand whether relatively high-degree nodes have a higher tendency to be connected to other high-degree nodes. The assortativity index for network G is computed following Newman (2003):

$$r = \frac{\sum_{ij \in G}(k_i - m)(k_j - m)}{\sum_{i \in G}(k_i - m)^2} \tag{6}$$

where k_i is the degree of node i and m is the average degree in the network. The index r ranges between -1 and 1 and can be thought of as a correlation coefficient between the degree of a node and that of its partners.[16] Table 5 shows that the VW network displays negative assortativity, suggesting a hub-and-spoke structure of the network whereby low-connectivity countries establish links mainly with hubs, meaning countries with many partners. Similar results have already been found in the literature, both relative to the overall trade network (Fagiolo, Reyes, & Schiavo, 2010) and, more specifically, for VWT (Konar et al., 2011).

A further element to evaluate the structure of the networks is provided by the clustering coefficient c_i, which represents the tendency of nodes to form tightly connected groups. Formally:

$$c_i = \frac{2e_i}{k_i(k_i-1)} \tag{7}$$

where e_i is the number of links between the neighbors of node i and $k_i(k_i-1)/2$ is the maximum possible number of links existing between the k_i neighbors of i (Boguna & Pastor-Satorras, 2003). In other words, c_i counts the number of closed triangles formed in the neighborhood of node i. This value measures the local cohesiveness of the network and higher values indicate that the neighbors of i are themselves connected. The clustering coefficient reported in Table 5 is an average of each node i's coefficient: the values are decreasing over time, suggesting again that as the number of players increases over time, the relative importance of tightly connected cliques decreases.

Another relevant feature to describe the topology of a network is centrality, which is meant to capture, for each node, its position within the network and its relative importance. The degree, i.e. the number of connections, is the most basic measure of local centrality, as it only looks at the immediate neighborhood of each node. Many other centrality measures exist, each capturing a specific feature of the network and what flows in it. Here we adopt *eigenvector* centrality, which quantifies the influence of a node in the network and is defined recursively as the sum of the centrality of all its neighbors (Bonacich, 1972). It assigns relative scores to each node, based on the concept that connections to high-scoring nodes contribute more to the score of the node in question than links to low-scoring nodes. Eigenvector centrality appears to be more suitable in the case of the VW network, where the role of a country is positively related to its own position and that of the countries it is connected to, in terms of the volume of VW that it exchanges.

Starting from the value of eigenvector centrality of each node, we compute a *centralization* index, which measures how tightly the graph is organized around its most central point. To obtain a single measure of centralization for the entire network, we look at the difference between the centrality of each node relative to the most central player; then, centralization is the ratio of the actual sum of differences to the maximum possible sum of differences, computed on the base of the following formula:

$$Centralization\ Index = \frac{\sum_i |b_{MAX} - b_i|}{\sum_i |\chi_{MAX} - \chi_i|} \quad (5)$$

where b_{MAX} and b_i are the centrality values of the most central node and the i-th node in the observed graph, respectively, whereas χ_{MAX} and χ_i are the centrality values of the most central node and the i-th node in a star graph composed of as many nodes as the observed network, respectively. The index ranges from 0 to 1, where 0 indicates a balanced graph in which all the nodes have the same centrality and 1 implies a star graph with a single node as its center.

Table 5. Topology descriptive indexes of the VWT network.

	Assortativity	Clustering	Centralization
1986	-0.43	0.80	0.16
1990	-0.47	0.72	0.16
1995	-0.45	0.70	0.14
2000	-0.35	0.65	0.11
2005	-0.32	0.65	0.11
2010	-0.33	0.64	0.10

Table 5 shows that the centralization is relatively low and decreasing over time, consistent with the idea that over time the system has become more balanced and homogeneous. Overall, the figures summarized in the table suggest that from 1986 onward, the VWT network has been evolving toward a less centralized and less disassortative network, with a decreasing number of clusters and a greater density. The numbers are mutually consistent and qualitatively similar, suggesting that minor countries have increased their relative importance in terms of their number of trade partners, making the network more interconnected and interdependent, in other words more *balanced*. As shown by Acemoglu et al. (2013), large economic downturns are equally unlikely in balanced economies, irrespective of the distribution of the idiosyncratic shocks. The symmetric structure of balanced economies ensures that, as the number of nodes increases, idiosyncratic shocks average out, without propagating to the rest of the network and preventing the countries involved from suffering sizable economic losses. This first topological analysis suggests that the status of being part of the VWT network does not increase a country's vulnerability to local and global crises, such as those triggered by the shocks analyzed in Section 3.1.

To dig deeper into the possible role of network topology in the propagation of shocks, we consider whether the degree distribution features fat tails, whereby the number of highly connected nodes is larger than one would expect. In fact, Acemoglu et al. (2012) show that when the degree distribution features fat tails, extreme events may result from cascade effects even in the presence of thin-tailed distributions of the original disturbances, as we found in Section 3.1 above. We focus on the indegree distribution because the shocks that we have analyzed so far are supply-side disturbances and, as a result, vulnerability is mainly associated with imports.[17]

Table 6. Indexes of tail heaviness: *Indegree* distributions (first order).

Year	% Out of Interval	% above x_{min}	Obesity Index
1986	7.2	37.0	0.71
1990	7.3	26.8	0.72
1995	6.3	52.9	0.71
2000	4.7	63.4	0.63
2005	3.8	36.5	0.58
2010	4.2	41.7	0.57

Konar et al. (2011) find that the distribution of the number of trade connections held by each country follows an exponential distribution, the tail of which becomes thinner over time. Here we confirm these findings with our data and show that they extend to 2010 as well (see Table 6). A Lilliefors test performed on the indegree distribution cannot reject the null hypothesis that the distribution is exponential and thus not fat tailed. The same conclusion is further confirmed by the values taken by the Obesity Index, which are always lower than the theoretical value under an exponential distribution (0.75) and decrease over time. Similarly, the downward sloping shape of the MEF plots (Figure 6), the high percentages of values above x_{min} as well as the percentage of observations outside the interval "mean±double standard deviation" all point in the same direction.

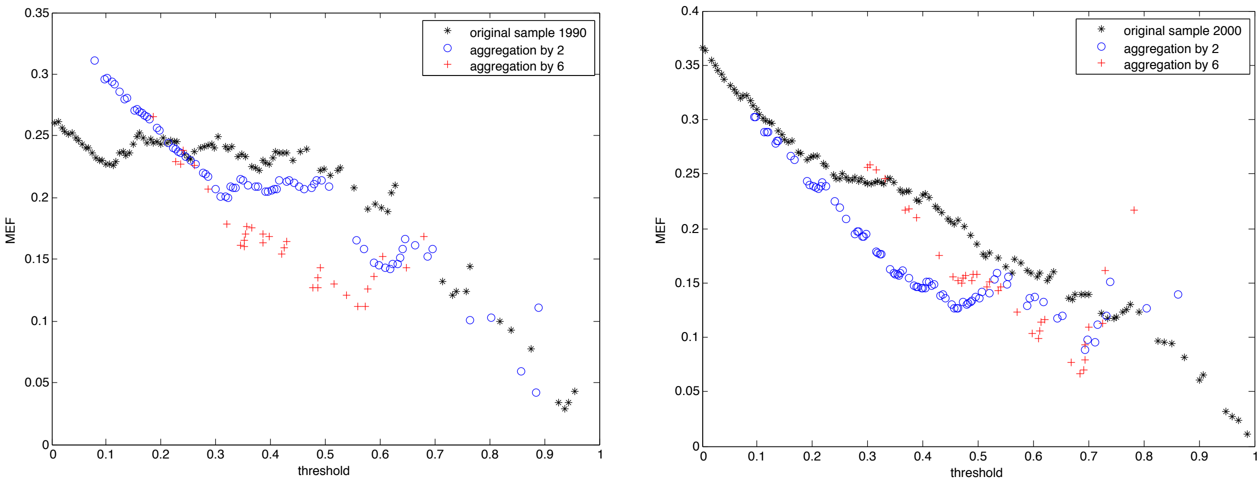


Figure 6. MEF of the original sample and aggregated data set. Years 1990 (left panel) and 2000 (right panel).

Examining the first-order connectivity, however, may not be enough to rule out the possibility of cascade effects. In fact, Acemoglu et al. (2012) stress the notion that the distribution of the node degree only provides partial information about the structure of the network. They show that two networks with identical degree distribution may exhibit considerably different levels of vulnerability, because of the so-called cascade effects. Indeed, a country-specific idiosyncratic shock affects not only those countries immediately connected to it, but also those indirectly connected. As we are interested in discovering possible intrinsic features favoring network instability, we need to explore higher-order connectivity. Following their methodology, we compute the *second-order* (SO) degree vector Q of the virtual water trade network by multiplying the adjacency matrix $A(N\times N)$ of virtual water flows by the degree vector K, according to the following formula:

$$q_i \equiv \sum_{j=1}^{N} a_{ij}\, k_j \qquad (9)$$

where k_j is the degree distribution of node j and a_{ij} is the element of the adjacency matrix $A(N\times N)$, which assumes the value of one if there is a tie linking node i to node j and zero otherwise.

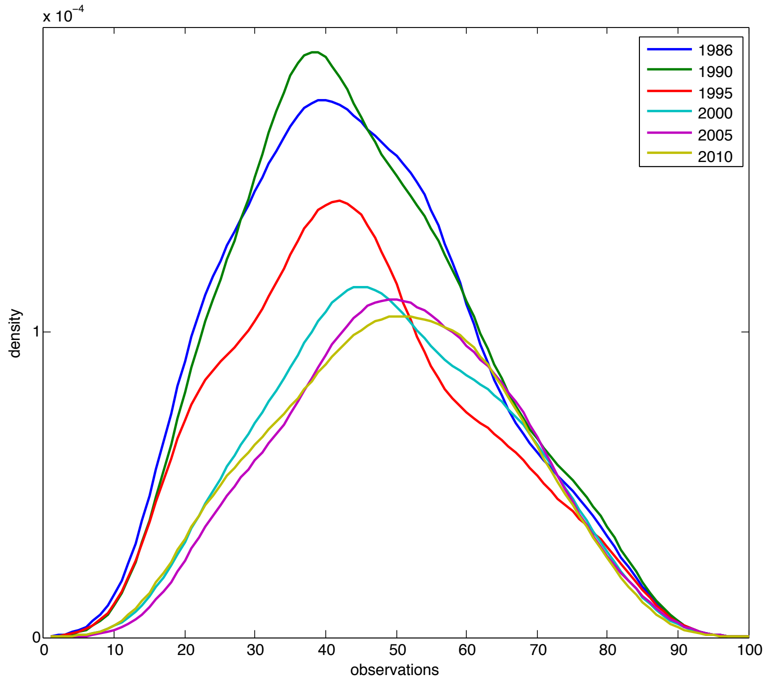


Figure 7. Second-order *indegree* distributions.

Again, the analysis aims to test for the presence of fat tails and to check the extent to which the tails of the distribution have become fatter over time. The distributions, plotted in Figure 7, become less skewed over time: the absence of heavy tails is further confirmed by a decreasing Obesity Index, high and increasing percentages of observations above x_{min} (Table 7), and the decreasing shape of the selected MEF plots (Figure 8).

Table 7. Indexes of tail heaviness: Second-order *indegree* distributions.

Year	% Out of Interval	% above x_{min}	ObInd.
1986	3.8	38.9	0.57
1990	4.4	41.0	0.59
1995	3.4	43.3	0.58
2000	1.9	50.5	0.53
2005	2.4	58.8	0.50
2010	1.0	59.7	0.49

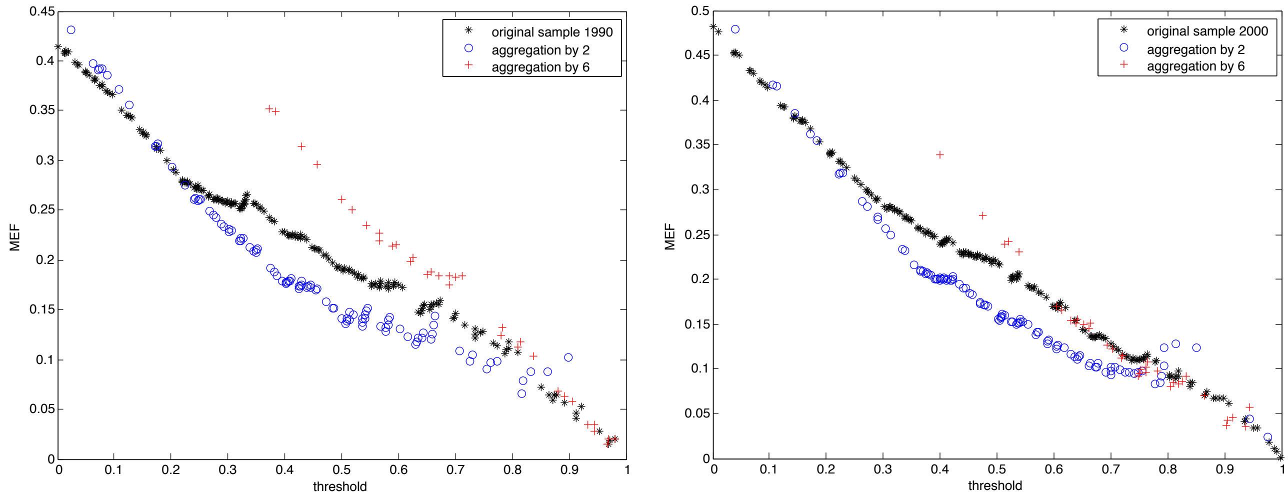


Figure 8. MEF of the original sample and aggregated data set. Years 1995 (left panel) and 2005 (right panel).

To capture the trend of the distribution over time better, we compute the skewness and kurtosis for both node indegree and second-order indegree (Table 8): the decreasing values of both measures confirm once again that the distribution becomes more uniform over time and the possible presence of heavy tails vanishes as time passes. The kurtosis for the second-order indegree distribution is, moreover, always lower than the reference level for a Gaussian distribution, suggesting the presence of *thinner* tails. By interpreting the latter findings together with the qualitative results commented on earlier, that is, the diminishing centrality and the growing density, we can conclude that the network structure is becoming more balanced over time, suggesting a decreasing level of vulnerability for the countries involved in the case of local crises and extreme events. The topological characteristics of the international agricultural trade network, translated into *virtual water*-equivalent flows, suggest that the

VWT network favors neither countries' vulnerability to external crises nor the propagation of a crisis situation through the system, the probability of extreme outcomes being very low.

Table 8. Descriptive statistics. First- and second-order *indegree* distributions.

	Indegree		**Second-Order Indegree**	
	Kurtosis	Skewness	Kurtosis	Skewness
1986	4.37	1.32	2.40	0.35
1990	4.29	1.35	2.42	0.40
1995	3.95	1.24	2.39	0.37
2000	2.75	0.68	2.21	0.12
2005	2.75	0.52	2.29	0.004
2010	2.55	0.44	2.21	-0.04

To make our results comparable with those of Acemoglu et al. (2012), a third type of analysis is carried out. In their seminal work, the authors perform a *weighted* network analysis, which allows them to take into account the existing heterogeneity in the intensity of VWT flows. Until now, our analysis has been performed on the *unweighted* version of the VWT network, as the degree distributions have been computed on the base of the corresponding binary adjacency matrix A. In this way, the weight of each trade flow is not considered: only the presence (or the absence) of the link matters, and some important characteristics might be lost.

In the weighted version of the VWT network, each existing link is assigned a value $z_{ij}>0$, proportional to the weight of that link. Since we are mainly interested in inflows, the weight z_{ij} for each flow is computed as the ratio of a country's in-flow of virtual water over the country's *outdegree*, such that the row sum $\sum_j z_{ij} = 1$. Formally:

$$z_{ij} = \frac{w_{ij}}{\sum_{j=1}^{n} wij} \qquad (10)$$

In this way, the weighted VWT network is fully described by its (NxN) weighted matrix $Z=\{z_{ij}\}$, where $z_{ij}=0$ for all $i=j$.

Figure 9 shows the graphical representation of the weighted first-order (wFO) and the weighted second-order (wSO) degree distributions only for some selected years (1990, 2000, and 2010).

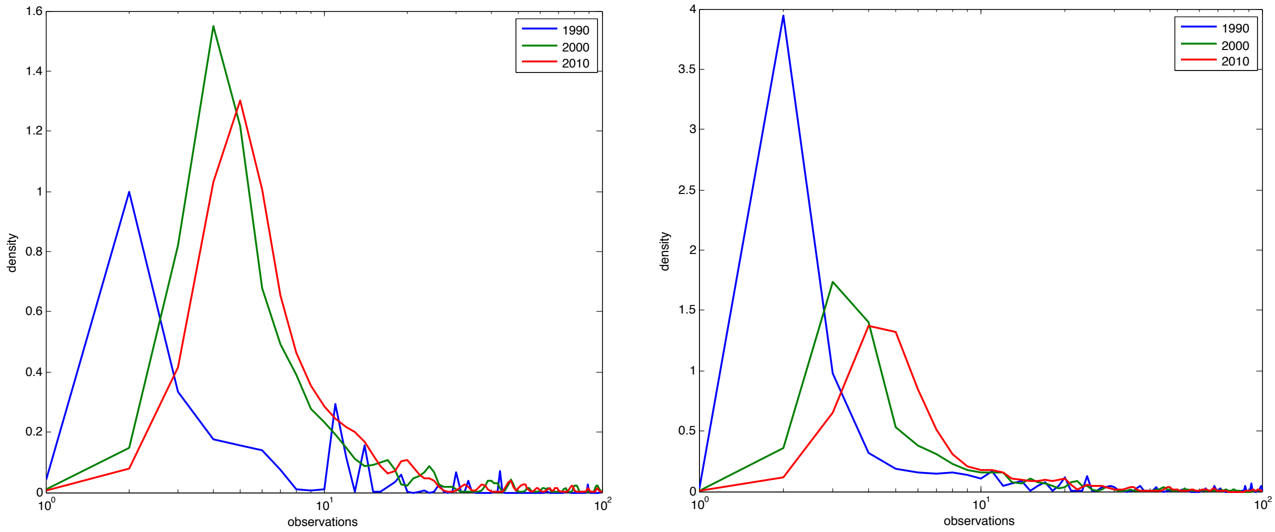


Figure 9. Left panel: *Weighted* first-order indegree distributions for selected years.

Right panel: *Weighted* second-order indegree distributions for some selected years. X-axis: log scale.

The *Clauset test* for power law tail behavior performed on both groups of distributions does not show any significant result, as in the previous cases, while the Lilliefors test always rejects the hypothesis of exponential distribution of the samples. This last result is consistent with the values of the Obesity Index reported in Table 9, which are well above the threshold indicating an exponential distribution, that is, 0.75, and with the shapes of the MEF plots of Figure 10 and Figure 11.

Table 9. Indexes of tail heaviness. *Weighted* first- and second-order indegree.

Year	**Weighted First-Order *Indegree***			**Weighted Second-Order *Indegree***		
	% of Values Out of Interval	ObIn	% above x_{min}	% of Values Out of Interval	ObIn	% above x_{min}
1986	3.4	0.93	12.0	3.8	0.91	19.7
1990	3.4	0.93	17.1	4.9	0.92	23.9
1995	4.2	0.92	18.4	4.6	0.92	19.7
2000	5.2	0.89	40.8	5.2	0.89	21.6
2005	5.7	0.87	46.9	4.7	0.89	19.0
2010	6.2	0.87	32.7	5.1	0.88	21.2

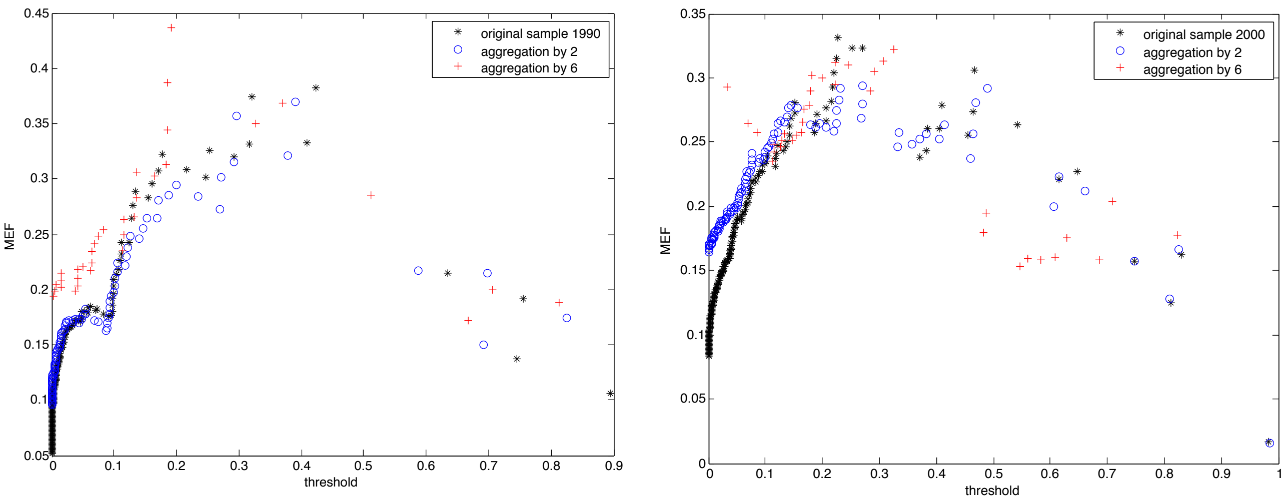


Figure 10. MEF of the original sample (weighted first-order indegree) and aggregated data set.

Year 1990 (left panel) and year 2000 (right panel).

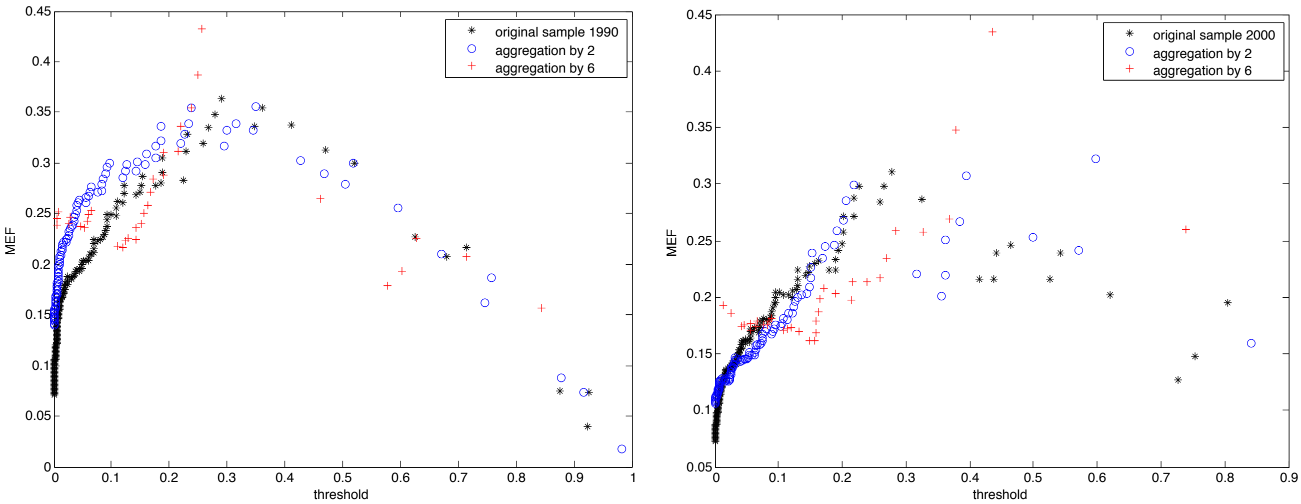


Figure 11. MEF of the original sample (weighted second-order indegree) and aggregated data set.

Year 1990 (left panel) and year 2000 (right panel).

With respect to their *unweighted* counterparts, both first- and second-order *weighted* indegree distributions have fatter tails; therefore, the risk of shock propagation through the network is higher. However, only some of the MEFs are consistent with the presence of power law tails: in other words, the tails of the weighted indegree distribution are likely to be *fatter*, but not fat.[18] Moreover, the Obesity Index for both probability distribution functions slightly decreases over time, suggesting a decrease in the tail heaviness. Finally, even if the percentages of values above x_{min} are on average lower than those of the *unweighted* cases, they are still relatively high and increasing over time, particularly for the first-order degree distributions.

The analysis carried out so far has the merit of shedding light on two facts: first, both the *unweighted* and the *weighted* analysis of the same network are useful, because different characteristics may be highlighted; second, the first-order interconnections provide only partial information about the structure of the VW network. The need to look at higher-order degree distributions, as suggested by Acemoglu et al. (2012), is thus empirically confirmed.

4. Policy implications and concluding remarks

This work investigates the relationship between countries' participation in virtual water trade and their vulnerability to external shocks from a network perspective. In particular, we investigate whether (i) possible sources of local national crises may interact with the system, propagating through the network and affecting the other countries involved; (ii) the topological characteristics of the international agricultural trade network, translated into virtual water-equivalent flows, may favor countries' vulnerability to external crises.

Our work contributes to the debate on the potential merits and risks associated with openness to trade in agricultural and food products. On the one hand, trade helps to ensure that even countries with limited water (and other relevant) resources have access to sufficient food and contribute to the global saving of water. On the other hand, there are fears that openness may increase the vulnerability to external shocks and thus make countries worse off. Here we abstract from political considerations about food sovereignty and independence from imports and focus instead on investigating whether the increased participation in global trade that the world has witnessed in the last 30 years has made the system more susceptible to large shocks.

Our analysis reveals that: (i) the probability of larger supply shocks has not increased over time; (ii) the topological characteristics of the VW network are not such as to favor the systemic risk associated with shock propagation; and (iii) higher-order interconnections may reveal further important information about the structure of a network. Regarding the first result, fluctuations in output volumes, among the sources of shock analyzed here, are more likely to generate some instability. The first implication is that, on one side, past national or regional economic crises were not necessarily brought about or strengthened by global trade. The second, more remarkable, implication is that, on the other side, supporting a national policy of self-sufficiency in food production while progressively reducing the participation in international agricultural trade does not necessarily protect a country from economic instability. Moreover, it is well established in the literature that, over time, international food trade has favored more efficient use of water resources, at the global level (e.g. Aldaya, Allan, & Hoekstra, 2010; Chapagain, Hoekstra, & Savenije, 2006; De Fraiture, Cai, Amarasinghe, Rosegrant, & Molden, 2004; Oki & Kanae, 2004). This fact, together with our conclusions, highlights the important role of international trade in driving the efficient allocation of water resources.

To sum up, our evidence reveals that the increased globalization witnessed in the last 30 years is not associated with an increased frequency of adverse shocks (in either precipitation or food production). Furthermore, building on recent advances in network analysis that connect the stability of a complex system to the interaction between the distribution of shocks and the network topology, we find that the world is more interconnected, but not necessarily less stable.

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[1] See Section 2 for an explanation.

[2] Producing one kilogram of grain in an arid country can require two or three times more water than producing the same amount in a humid country (Hoekstra, 2003).

[3] Throughout the paper, we use the country-specific measures of VW content provided by Mekonnen & Hoekstra (2011). Dalin et al. (2012) and Konar et al. (2011) use instead the H08 global hydrological model developed by Hanasaki et al. (2008a, 2008b) to determine the virtual water content of different goods.

[4] We owe a debt of gratitude to these authors, who shared the data on virtual water trade flows.

[5] For a definition of water resource components, see Falkenmark & Rockström (2006). Freshwater pollution (*grey water*) is excluded from the calculations, due to the strong uncertainties inherent in its determination (see Hoekstra, Chapagain, Aldaya, & Mekonnen, 2011).

[6] For an overview of the literature on financial networks, see Allen & Babus (2009) or Bougheas & Kirman (2014).

[7] Acemoglu et al. (2012) study the likelihood of large economic downturns, showing that it is determined by the interplay between the inter-sectoral input–output linkages and the nature of the idiosyncratic sectoral shocks. Even though some economies exhibit the same deviation properties as balanced structures in the presence of normally distributed shocks, they may experience significantly more frequent downturns in the presence of exponential-tailed shocks.

[8] In the presence of a thin-tailed probability distribution, the upper tail declines to zero exponentially or faster. Such a distribution has a moment generating function, and all moments exist. A normal or a gamma distribution is an example of the thin-tailed probability distribution function, as is any distribution with finite supports, like a uniform distribution or a discrete-point finite distribution. On the contrary, a fat-tailed distribution falls to zero much more slowly. The standard example of a fat-tailed probability distribution function is the power law or Pareto distribution, although a Student-*t* or inverted-gamma distribution is also fat-tailed.

[9] See http://www.fao.org.

[10] Data are available for the years 1987, 1992, 1997, and 2002.

[11] The p-value of the sample for the year 1987 is slightly above the 5% significance level (0.056).

[12] The same result is valid for all the other simulations in the present paper, when performing a Clauset test on the sample distribution.

[13] This test fits the power law form only for the part of the distribution above x_{min}. If x_{min} is large, then only a small fraction of the data set falls above it and thus the larger the value of x_{min}, the larger the total value of n needed to reject the power law. That is, the higher the percentage of values above x_{min}, the lower the probability of a fat-tailed sample of data.

[14] We also compute the *Hill estimator* of the tail index – HI (Hill, 1975), but it does not provide any useful results.

[15] 1986: China, -13%; 1990: China, -11%; 1995: China, -6%; 2000: Russia, -11%; 2005: India, -4%; 2010: Russia, -24%. As a percentage of global agricultural production, these lower output volumes are respectively: -2.7%, -2.5%, -1.5%, -0.3%, -0.4%, and -0.6%.

[16] In the applied literature, one often finds that many social networks display positive assortativity, while the opposite holds true for technological and biological networks (Costa, Rodrigues, Travieso, & Boas, 2007; Newman, 2003).

[17] In fact, the same analysis is also carried out on the distributions of the outdegree and total degree (the sum of the in- and outdegree net of bilateral links). The qualitative picture is unchanged. The interested reader will find a sample of results derived from the analysis of the outdegree in the Appendix.

[18] Embrecht, Klueppelberg, & Mikosch (1997) suggest that a necessary condition for saying that a distribution follows a power law is that its MEF tends to infinity.

Appendix

We present a sample of results derived from the analysis of the *outdegree* probability distribution functions, for the same selected years. A comparison with the *indegree* analysis carried out previously shows that the qualitative picture does not change.

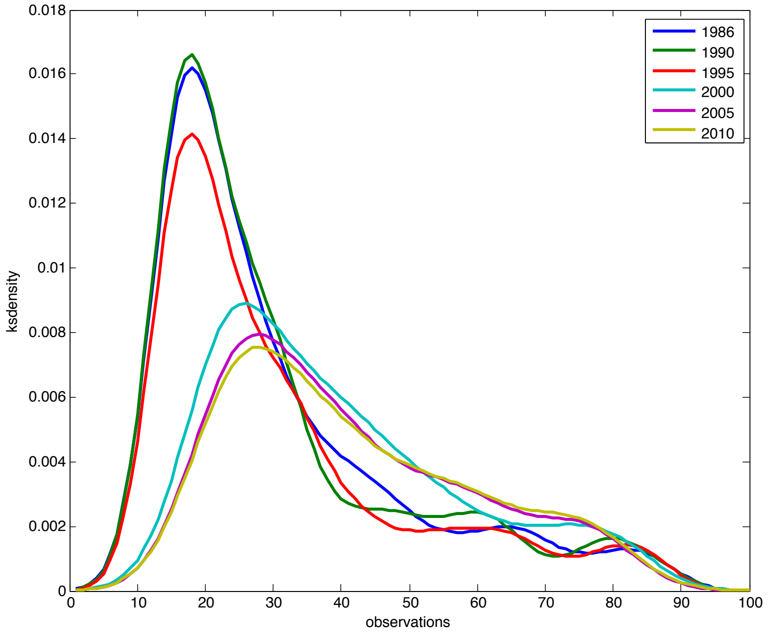


Figure A1. Normalized *outdegree* distributions (first order).

Table A1. Indexes of tail heaviness: *Outdegree* distributions (first order).

Year	% Out of Interval *Outdegree*	% above x_{min} *Outdegree*	ObInd. *Outdegree*
1986	6.7	51.5	0.78
1990	6.3	49.8	0.78
1995	5.9	41.6	0.78
2000	7.0	27.2	0.70
2005	5.2	30.3	0.69
2010	4.3	29.9	0.68

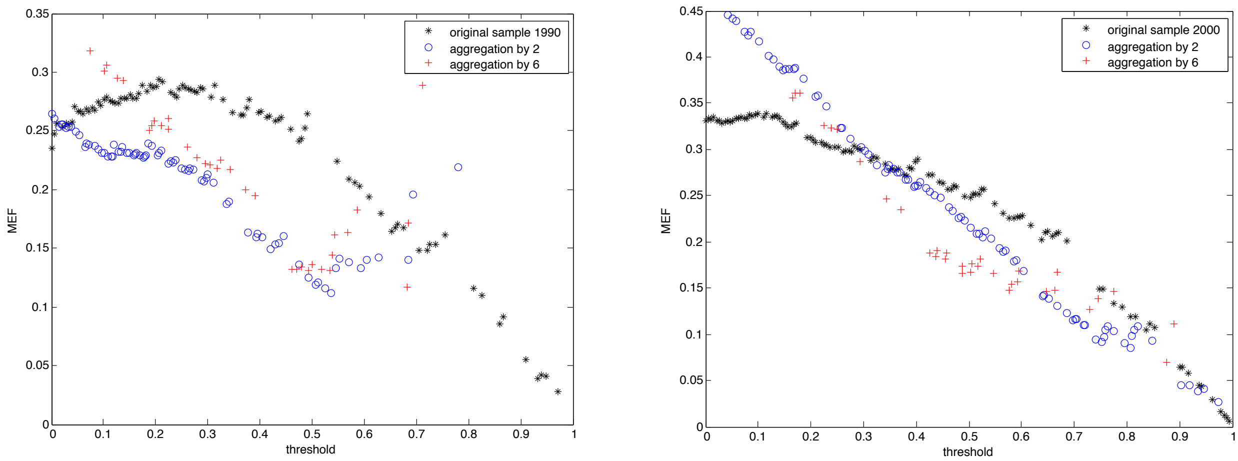


Figure A2. MEF of the original sample and aggregated data set (first-order *outdegree*).

Years 1990 (left panel) and 2000 (right panel).

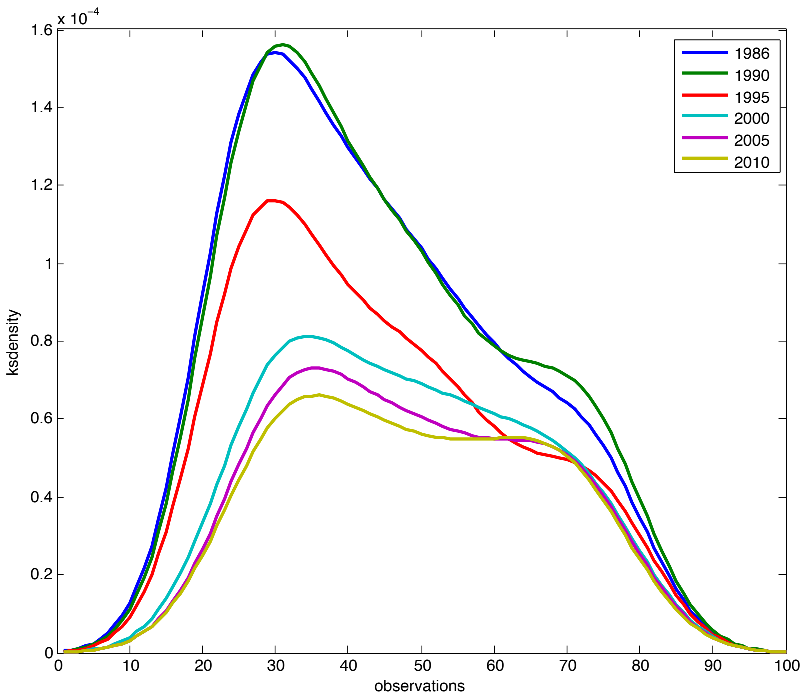


Figure A3. Normalized *outdegree* distributions (second order).

Table A2. Indexes of tail heaviness: *Outdegree* distributions (second order).

Year	% Out of Interval	% above x_{min}	ObInd
1986	2.4	50.0	0.6463
1990	1.5	46.8	0.6361
1995	2.1	40.3	0.6460
2000	0	51.6	0.5737
2005	0	56.4	0.5730
2010	0	50.2	0.5471

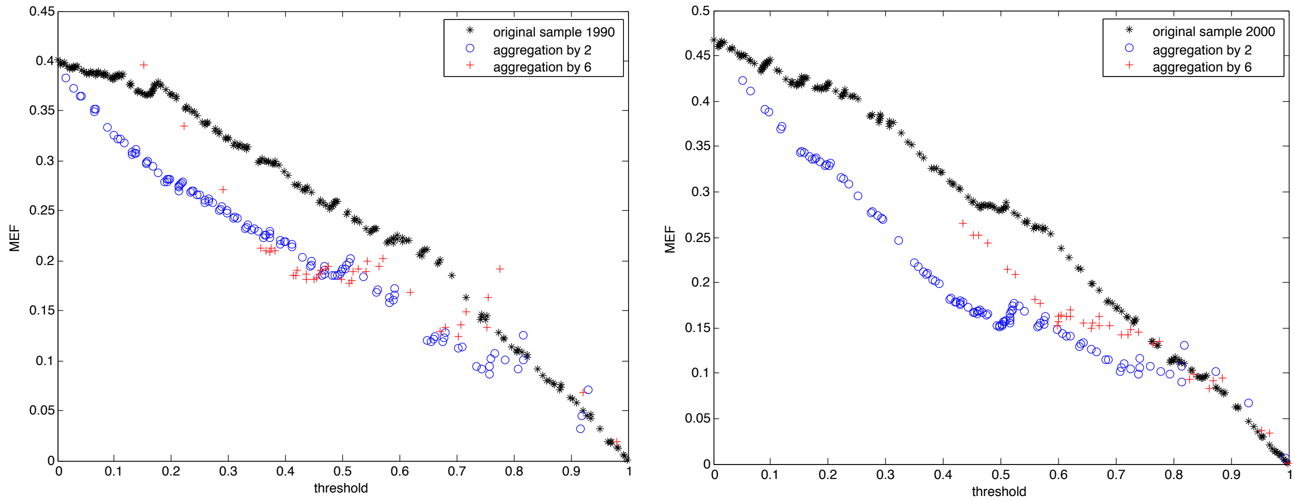


Figure A4. MEF of the original sample and aggregated data set (second-order *outdegree*).

Years 1995 (left panel) and 2005 (right panel).

Table A3. Descriptive statistics. First- and second-order *outdegree* distributions.

	Indegree		**Second-Order Indegree**	
	Kurtosis	Skewness	Kurtosis	Skewness
1986	4.11	1.40	2.09	0.52
1990	4.06	1.41	2.03	0.50
1995	3.97	1.37	2.07	0.52
2000	2.75	0.88	1.80	0.26
2005	2.39	0.73	1.71	0.23
2010	2.27	0.68	1.63	0.15

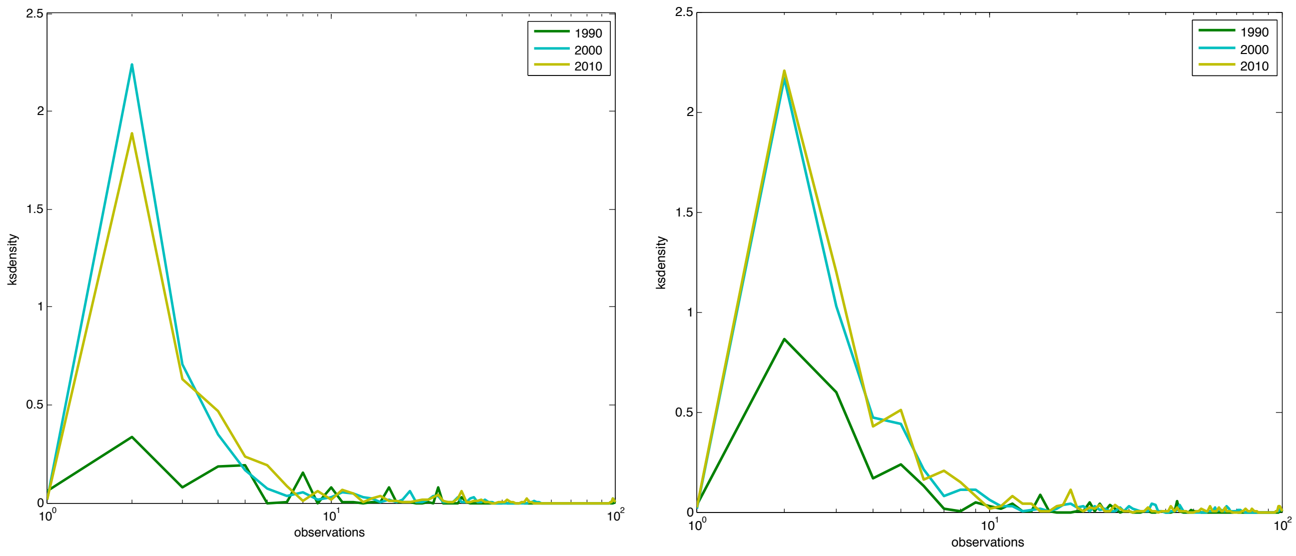


Figure A5. Left panel: *Weighted* first-order outdegree distributions for selected years.

Right panel: *Weighted* second-order outdegree distributions for some selected years. X-axis: log scale.

Table A4. Indexes of tail heaviness. *Weighted* first- and second-order outdegree.

Year	**Weighted First-Order Degree**			**Weighted Second-Order degree**		
	% of Values Out of Interval	ObIn	% above x_{min}	% of Values Out of Interval	ObIn	% above x_{min}
1986	2.5	0.9284	63.2	3.9	0.9220	65.2
1990	2.9	0.9425	6.3	4.4	0.9275	37.6
1995	3.8	0.9348	3.8	5.1	0.9193	34.3
2000	3.8	0.9062	42.7	5.2	0.9040	36.0
2005	4.3	0.9054	42.4	4.8	0.9074	35.2
2010	4.3	0.9032	39.8	4.7	0.9112	34.1

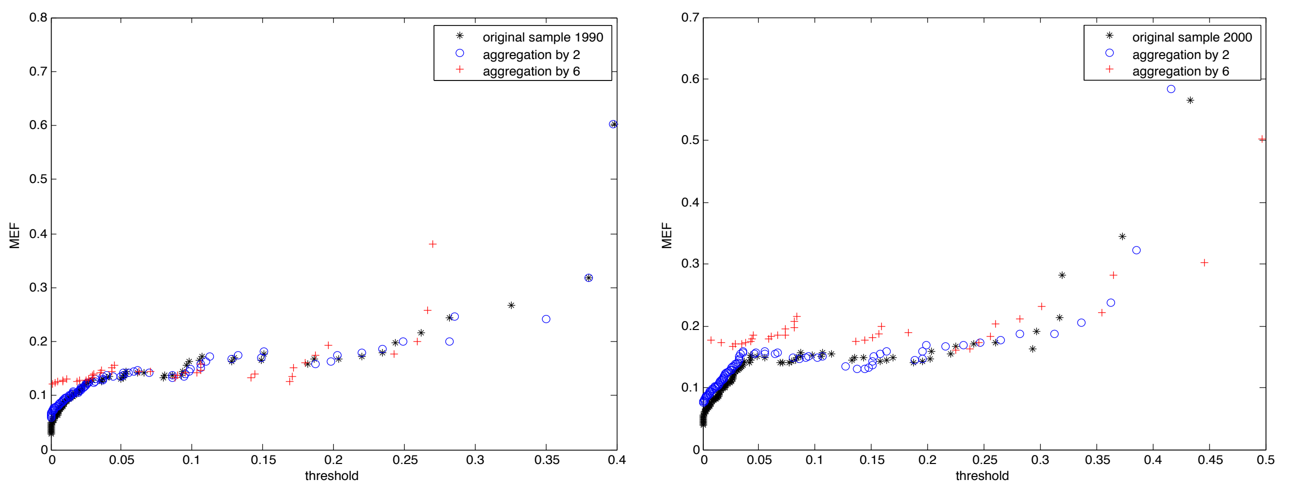
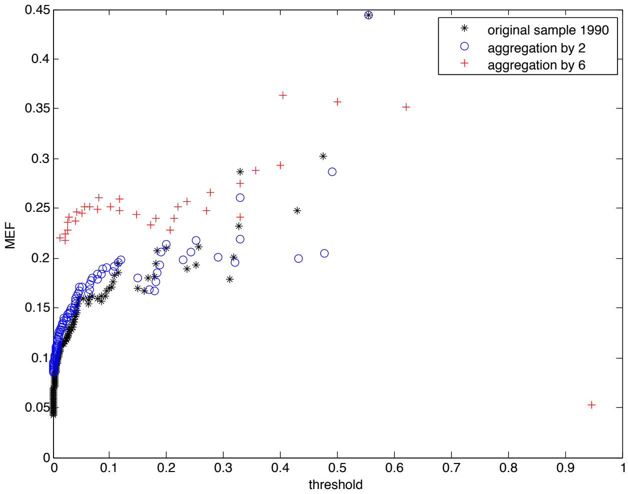


Figure A6. MEF of the original sample (weighted first-order outdegree) and aggregated data set.

Year 1990 (left panel) and year 2000 (right panel).



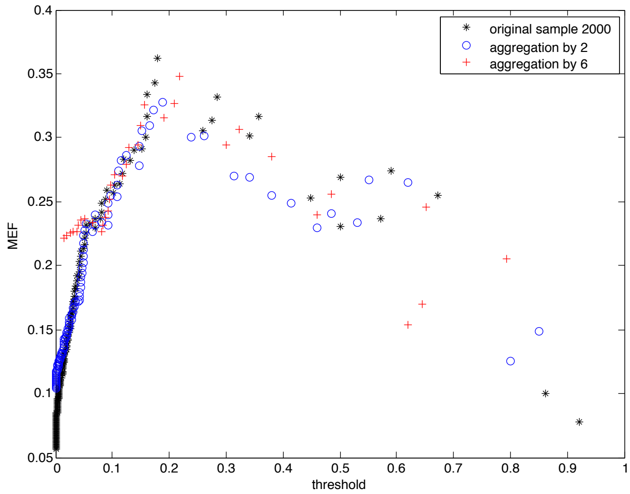


Figure A7. MEF of the original sample (weighted second-order outdegree) and aggregated data set.

Year 1990 (left panel) and year 2000 (right panel).