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A Network Analysis of Food Flows within the United States of America

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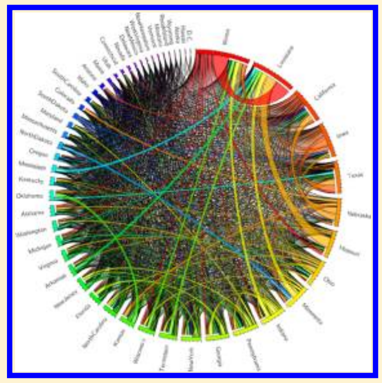
Supporting Information

ABSTRACT: The world food system is globalized and interconnected, in which trade plays an increasingly important role in facilitating food availability. We present a novel application of network analysis to domestic food flows within the USA, a country with global importance as a major agricultural producer and trade power. We find normal node degree distributions and Weibull node strength and betweenness centrality distributions. An unassortative network structure with high clustering coefficients exists. These network properties indicate that the USA food flow network is highly social and well-mixed. However, a power law relationship between node betweenness centrality and node degree indicates potential network vulnerability to the disturbance of key nodes. We perform an equality analysis which serves as a benchmark for global food trade, where the Gini coefficient = 0.579, Lorenz asymmetry coefficient = 0.966, and Hoover index = 0.442. These findings shed insight into trade network scaling and proxy free trade and equitable network architectures.



1. INTRODUCTION

Food security is being placed under increased pressure due to economic development, population growth, and climate change.[1,2] The world food system is increasingly globalized and interconnected,[3] making it imperative to understand the consequences of this increasingly complex food system for a secure food supply. Trade flows are an essential component of the new, globalized food system and are increasingly important for global food availability,[4,5] with repercussions for carbon emissions,[6] nutrients,[7,8] water resources,[9] and povery.[10] Thus, it is increasingly important to understand the structure of food trade. In this paper, we apply tools of network theory to domestic food flows within the USA, a country with global importance as a major agricultural producer and trade power.[11,12]

Network analysis has been increasingly used to understand complex systems. This recent interest in complex networks is largely due to the discovery of organizing principles in networks,[13,14] such as community structure[15] and scale-free properties.[16] Additionally, network analysis has become increasingly popular due to its flexibility and ability to represent many real-world systems,[17] including transporation systems,[18−20] the worldwide web,[16] international tourism,[21] financial transactions,[22,23] and scientific collaborations,[24,25] among others. In this paper we present a novel application of network analysis to data on food flows within the USA.

Global trade has been studied for quite some time,[26,27] more recently using tools of network theory.[28,22,29−31] Recent work has begun to focus on the network characterization of global food trade.[11,3,32] This study advances reseach in this area in three main ways. First, this network analysis of domestic food flows occurs at a different scale to the studies of global trade networks in the literature. In this way, this study help us to understand the impact of scaling on network properties, which is an important question in the literature.[28] Second, food flows within the USA occur without barriers to their movement (i.e., due to the Commerce Clause of the U.S. Constitution), thereby proxying a free trade setting. Studying the network properties of food flows within the USA can thus help us to understand the network properties that may occur under free trade situations. Third, flows of food within the USA serve as a null model for trade equity (i.e., since the USA has a homogeneous population, national agricultural policy, and absence of trade barriers). In this way, studying food flows within the USA enables us to quantify how equitable we can expect global flows to be, which is an important focus of current research.[10,33,34,5]

2. METHODS

2.1. Food Flow Data. We obtain data on the movement of food within the USA from the Commodity Flow Survey (CFS). The CFS was created through a partnership between the Census Bureau and the Bureau of Transportation Statistics. The CFS presents information on the movement of goods in the United States. It provides information about commodities shipped, their value, weight, and mode of transporation for commodities from mining, manufacturing, wholesale, and select retail and services. The CFS is conducted every five years as part of the Economic

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Census.[35] However, bilateral data is currently only available for the year 2007, so this is the year that we focus our analysis on.

We select food commodities for our analysis. There are five categories of food commodities in the CFS. They are "cereal grains", "other agricultural products", "animal feed and products of animal origin, nec", "meat, fish, seafood, and their preparations", and "other prepared foodstuffs and fats and oils". Note that our analysis relies solely on trade data for these food commodities and does not directly incorporate production or consumption data. However, food flows implicitly capture some production and consumption information.

For the USA, data are provided at both the state and "CFS area" level. A CFS area is a geographic area that is drawn from a subset of Combined Statistical Areas (CSAs) and Metropolitan Statistical Areas (MSAs) as defined by the Office of Management and Budget. If a metropolitan area spans multiple states, then the CFS area is defined for each state part with significant transportation related activity. State parts of otherwise included metropolitan areas with little transportation activity are included in the remainder of that state. The CFS defines the "remainder of state" to represent those areas of a state not contained within a separately published metropolitan area. There are a total of 123 CFS areas for the 2007 database. These are listed in the Supporting Information (SI).

2.2. Network Construction. We create bilateral matrices of food trade connections and volume flows within the USA. Here, we focus on food volume flows [tons], because this unit of measurement has important implications for environmental issues, such as carbon emissions per ton-miles transported,[6] nutrient leaching,[7] and embodied water resources per unit food.[11] Note that this approach provides a different, yet complementary, perspective to other weighting schemes (i.e., financial value,[3] embodied water[11]) commonly employed in studies of food trade. Our weighting scheme will bias toward flows with a greater food weight.

The CFS provides 15 512 data entries for food flow in value terms and 12 672 data entries for food flow in volume terms. We utilize the value flow data to obtain more information for volume flows. We do this by determining the average commoditiy price for each food group. We then divide the value flow data by the commodity specific price information to estimate the volume flow for each instance where the volume data are missing but the value data are available.

In this way we obtain commodity-specific weighted and directed matrices of food flows within the USA for 2007. The nodes of the network are the CFS areas of the USA and the links connecting nodes are weighted by the volume of food flow [tons] and directed by the direction of flow. The individual commodity-specific matrices are summed to obtain the aggregate food flow matrix. For the remainder of the paper, we refer to this network as "aggregate". Unless we specifically refer to the network of a certain commodity, we are referring to the aggregate food flow network.

2.3. Network Statistics. From the weighted and directed matrix of food flows (W), we calculate network statistics. Network density (p) quantifies how interconnected the network nodes are and is measured by $p = M/[N(N-1)]$, where M is the number of links and $N(N-1)$ is the number of possible links. Node degree (k) is a fundamental network property that considers node connectivity. Specifically, k measures the number of links of each node, which is an unweighted property, so we refer to the adjacency matrix (A). Since our network is directed, we consider node in- and out-degree, based on whether the import or export relationship is being considered, respectively. The node in-degree counts the number of links incoming to a node and is measured by $k_{\mathrm{in}_i} = \sum_j a_{ji}$, while node out-degree counts the number of links emanating from a node and is measured as $k_{\mathrm{out}_i} = \sum_j a_{ij}$, where a is an element of A.[36]

To consider the weights assigned to links in our network, we quantify node strength (s). Node strength is the weighted corollary to node degree and measures the sum of the weights for nodal links. To take direction into account, we consider node in- and out-degree, as before. Now, node in-strength sums the value of links incoming to a node and is measured by $s_{\mathrm{in}_i} = \sum_j w_{ji}$, while node out-strength sums the value of links emanating from a node and is measured with $s_{\mathrm{out}_i} = \sum_j w_{ij}$, where w is an element of W.[36] Thus, s differentiates between connections with different values or intensities. Here, the volume of food trade [tons] provides the weight for our trade links.

Node degree and strength provide local measures of the importance of a node to the network. To better understand the importance of a node to the overall structure of the network, we consider average nearest neighbor degree, clustering, and betweenness centrality. Average nearest neighbor degree (knn) measures the affinity of a node to connect to high- or low-degree neighbors, or the network correlation structure.[37,38] When direction is taken into account, weighted values of knn can be measured with four directional pairs: in−in (ii), out−out (oo), in−out (io), and out-in (oi). Clustering can be measured both locally and globally for networks. The global clustering measure indicates overall clustering within the network, while local clustering (C) describes the propensity of nodes in the network to form closed triangles.[37] With direction, there are eight possible combinations of C that fall into four categories (see ref 39 for a complete description and representation): C_{in}, C_{out}, C_{cyc}, and C_{mid}. Our equations for knn and C are provided in the SI and follow that in ref 11.

Betweenness centrality (B) quantifies the importance of a node or link in terms of its importance to the overall network architecture.[38] Here, we calculate node B, which counts the fraction of shortest paths going through a given node, defined as $B = \sum_{i,j}(\sigma(i,u,j)/\sigma(i,j))$, where $\sigma(i, u, j)$ is the number of shortest paths between nodes i and j that pass through node u, $\sigma(i, j)$ is the total number of shortest paths between i and j, and the sum is over all pairs i, j of nodes.[14] We normalize B by $(N-1)(N-2)/2$ to maintain $B \in [0, 1]$.[40] Directed paths are used to calculate directed B and undirected paths for undirected B.

Finally, we conduct a triadic analysis of the USA food flow network. Triads are three-node directed subgraphs. A small number of triad patterns are able to describe a wide variety of real-world networks.[41,32] Triad frequencies of empirical networks are compared to frequencies in a random network to arrive at a normalized z-score for each triad type (refer to SI). When the normalized z-score is plotted for all triad types, the triad significance profile (TSP) is obtained, which can be directly compared across networks.

2.4. Measures of Equality. We calculate several measures for the equality of food flows across CFS areas in the USA. First, we calculate the Gini coefficient (G) which measures the inequality among values of a frequency distribution and has thus often been used to quantify trade equality.[33] $G \in [0,1]$, where 0 indicates perfect equality (i.e., all values are identical) and 1 indicates perfect inequality (i.e., one node has all of the value in the network).[42]

Additional statistics can be used to supplement the Gini coefficient in measuring distributional equality. The Lorenz asymmetry coefficient (S) measures the asymmetry of the Lorenz curve, which describe the inequality in the distribution of a quantity.[43,33] S values = 1 indicate that the Lorenz curve is symmetric, values of $S > 1$ indicate a few nodes consuming more resources, and $S < 1$ values indicate inequality due to a large number of nodes with small food flows. The Hoover index (D) measures the maximum vertical distance between the line of equality and the Lorenz curve and can be interpreted as the proportion of food trade by above-average nodes that would need to be redistributed to below-average nodes to achieve trade equality. If the entirety of food trade would need to be redistributed to achieve perfectly equitable trade then $D = 1$ (i.e., 100%). However, if perfectly equitable trade already exists, then trade would not need to be redistributed, so $D = 0$.[44,33]

3. RESULTS AND DISCUSSION

3.1. Summary Statistics. There are 123 nodes (i.e., CFS areas) and 4198 links in the USA food flow network. Thus, the USA food flow network is almost as interconnected ($p = 0.28$) as global food trade ($p = 0.33$; refer to Table 1 for comparisons between the USA and global food flow networks). Network summary data are provided by commodity in SI, Table S2.

We present a map of the USA food flow network in Figure 1, using network visualization software.[45] This image illustrates the flow of food between states in the USA. We construct this map at the state-level to enhance visual understanding, but all other analyses in this paper are performed using the 123 CFS areas as the network nodes. The volume of food flows represented in Figure 1 is 414.7×10^6 tons (refer to Table 1 and note that other studies of the global food trade network use value [$][3] or embodied water[11,33] to weight the food flows).

Midwestern states are shown as major exporters of food to the key ports in Louisiana, California, and Texas. In other words, the movement of food from the Midwest to ports in Louisiana, Texas, and California are key pathways for domestic food flows before international export. This highlights the fact that domestic food flows are part of a larger system and not closed, unlike global food trade: a key difference to consider when comparing the two systems. The largest link in the USA food flow network is from Illinois to Louisiana. The dense web of connections illustrates how interconnected trade between states is, which is what is expected, given the US Constitutional requirement for free trade between states.

3.2. Degree and Strength. A highly skewed degree distribution is a common feature of many real-world networks. Power law degree distributions are a feature of some networks,[16] while deviations from power-laws,[46] exponential degree distributions,[47] and normal degree distributions[32] have also been shown. From Figure 2A,D it is clear that the USA food flow network exhibits a normal distribution (mean $k_{in} = k_{out} = 34.1$), the hallmark of social networks among people.[48] This differs from the scale-free character of the world trade web of all commodities.[28] For global food trade specifically, the import degree distribution is also normal,[32] similar to USA-only food flows, while the global export degree distribution exhibits a fatter tail than the USA food flow network.[11] Note that mean k in the USA is greater than for global trade in Table 1, indicating a more social network. Refer to the SI for the top 10 nodes in terms of degree.

The normal degree distribution of USA food flows likely occurs as the results of complex social interactions in the food production and trade system. Climate suitability and local politics likely encourage positive feedbacks on the food production system, mimicing a preferential-attachment-like pattern. However, domestic subsidies and policies encourage production in many places, such that no "'superhubs'" are formed. Thus, the normal distribution reflects national policies that balance out the preferential attachment.

The distribution of node strength for the USA food flow network is shown in Figure 2B,E. A Weibull distribution is fit to the data, indicating high heterogenity of food movement around the USA, specifically in terms of export volumes. The equation for the Weibull distribution fit to s_{out} is $P(S_{out} > s_{out}) = e^{-(s_{out}/2.64)^{0.7}}$. The Weibull distribution provides the best fit to s_{in} ($P(S_{in} > s_{in} =$

Table 1. Properties of the USA Food Flow Network and the Global Food Trade Network[a]

	USA	Global
	Summary	
no. nodes	123	202[3]
no. links	4198	13 534[3]
density	0.28	0.33[3]
total flow	414.7×10^6 tons	$1060B[3]
	Degree	
mean k	34.1	32.8[11]
k_{in}	[0,86]	[0,97][11]
k_{out}	[1,94]	[0,159][11]
	Triad	
Antimotif 6	−0.667	−0.497[32]
Motif 13	0.596	0.486[32]
	Equality	
Gini (G)	0.579	0.626[33]
Lorenz (S)	0.966	0.70[33]
Hoover (D)	0.442	0.5[33]
	Assortativity	
unweighted	unassortative	disassortative[28]
weighted	assortative	assortative[11]
	Clustering	
C_{out}	0.72	0.51[11]
C_{in}	0.74	0.74[11]
C_{cyc}	0.23	0.09[11]
C_{mid}	0.28	0.13[11]
C^W_{out}	0.78	0.73[11]
C^W_{in}	0.82	0.94[11]
C^W_{cyc}	0.29	0.16[11]
C^W_{mid}	0.32	0.24[11]
	Betweeness	
ranked B_d	Los Angeles	USA[3]
	Chicago	Germany[3]
	Texas	France[3]
	Pennsylvania	Netherlands[3]
	New York	Great Britain[3]

[a]The network properties of USA food flows [tons] are presented here for the first time. Properties of global food trade are taken from the literature. Note that there are no studies of global food trade weighted by food volumes for direct comparison with the USA food network. Specifically, food trade is weighted by value [$] in ref 3 and by embodied water in refs 11 and 33. Global triad values (an unweighted measure) come from ref 32. Note that "Los Angeles" refers to "Los Angeles-Long Beach-Riverside", "Chicago" refers to "Chicago-Naperville-Michigan City", "Texas" refers to "Remainder of Texas", "Pennsylvania" refers to "Remainder of Pennsylvania", and "New York" refers to "New York-Newark-Bridgeport".

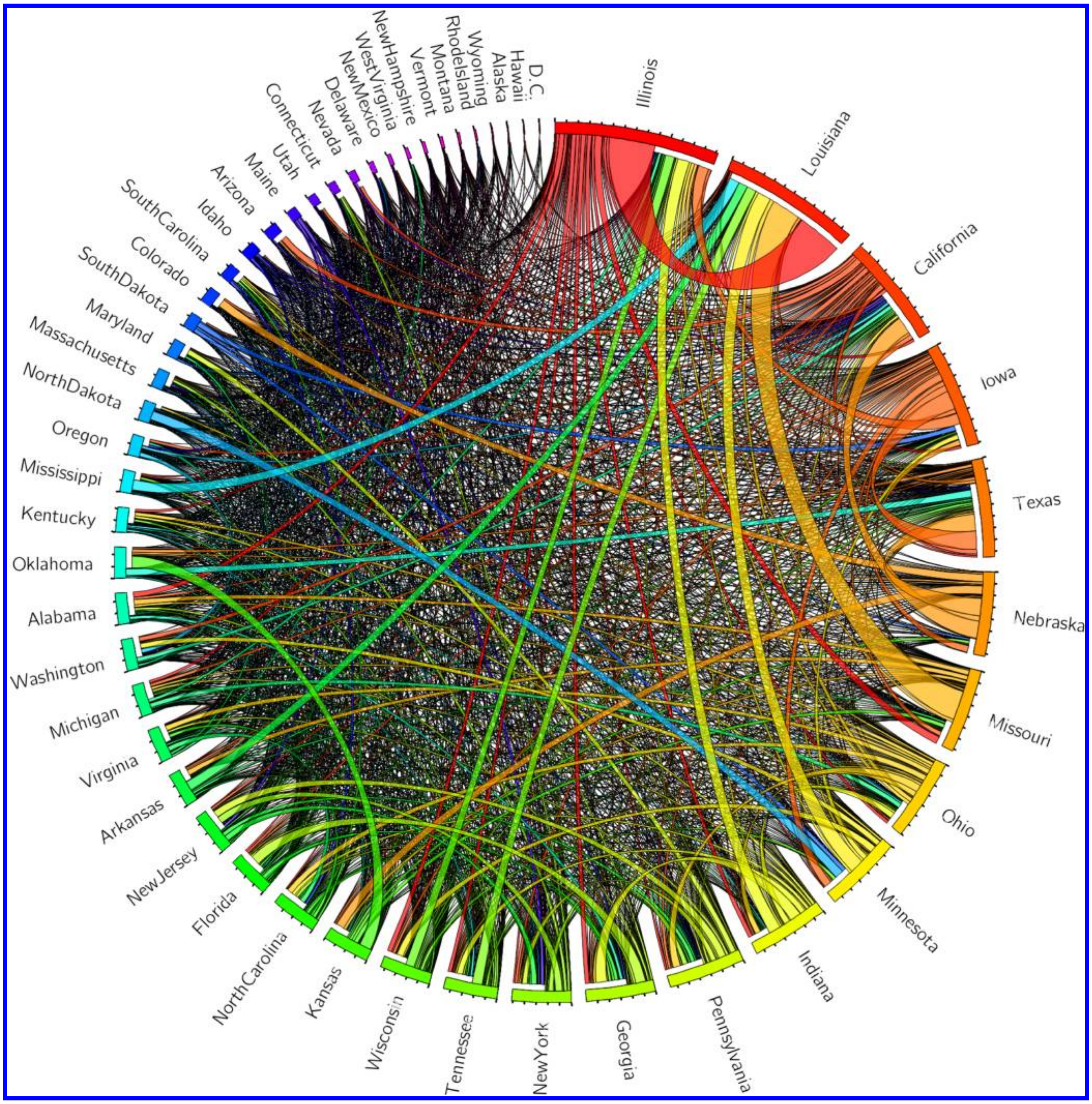

Figure 1. Network representation of food flows between the 50 USA states. The states are ranked according to the total trade volume and plotted clockwise in descending order. The size of the outer bar indicates the total trade volume of each state as a percentage of total USA trade. Export volume is indicated with links emanating from the outer bar of the same color. Import volume is indicated with a white area separating the outer bar from links of a different color. Note that the largest link in the USA food flow network is from Illinois to Louisiana. Midwestern states are shown as major exporters of food to the key ports in Louisiana, California, and Texas. The total trade volume of food represented by this graph is 414.7×10^6 tons.

$e^{-(s_{in}/2.86)^{0.8}}$), although the left tail of the data diverges from the analytical distribution, indicating that more nodes of small import volume exist in the data than expected from the Weibull distribution. The mean node strength in the USA food flow network is 3.4×10^6 tons. Refer to Table 2 for the list of the top 10 nodes in terms of strength. Note that major USA harbors import large volumes of food from the interior of the country for export to the rest of the world.

The relationship between strength and degree is a power law (shown in SI, Figure S1), as in global food trade.[11] This means that as a node increases its connectivity with other nodes, it is much more likely to trade larger volumes of food. Here, the power law relationship between trade connections and volume is essentially independent of direction (i.e., note that the exponent in the power law relationship is very similar for import and export relationships in SI, Table S4), whereas import trade relationships exhibit a larger exponent at the global scale.[11]

The exponent for the power law relationship is very similar across commodities, with the exception of import flows of cereal (refer to SI, Table S4). Increasing import connections leads to

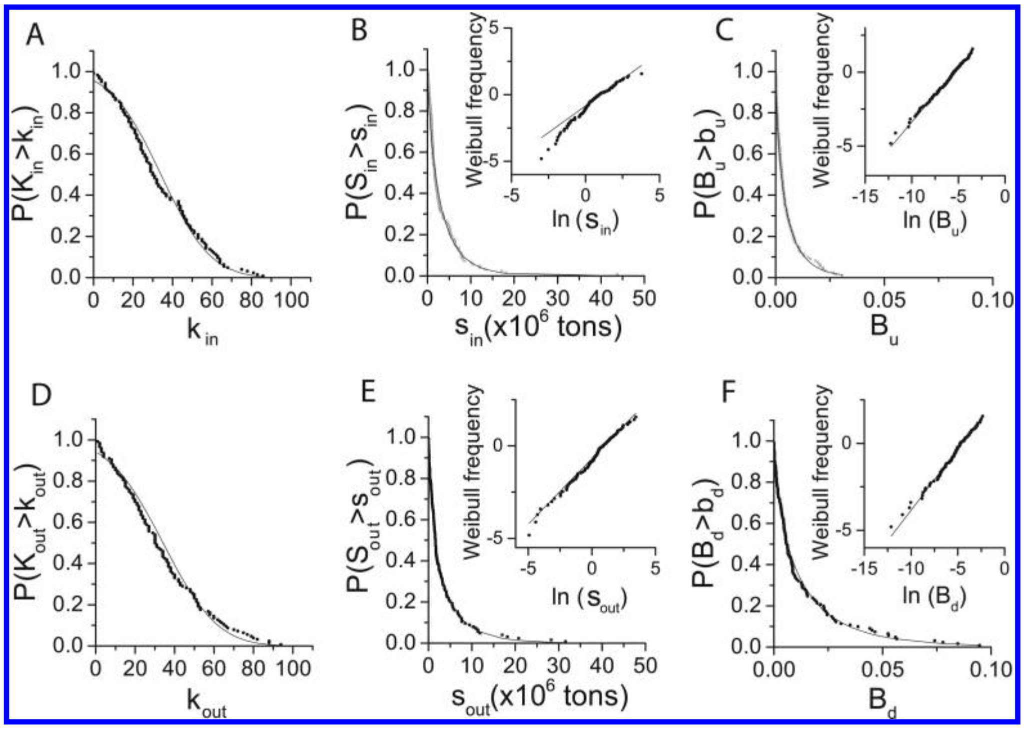

Figure 2. Node degree (k), strength (s), and betweenness centrality (B) distributions. In all plots the gray points indicate data and the black lines indicate analytical distributions. Import (A) and export (D) node degree distributions follow a normal distribution, reminiscent of the small world networks typical in social systems. The Weibull distribution fits export volume (E; $P(S_{out} > s_{out}) = e^{-(s_{out}/2.64)^{0.7}}$), undirected B (C; $P(B_u > b_u) = e^{-(b_u/0.004)^{0.7}}$), and directed B (F; $P(B_d > b_d) = e^{-(b_d/0.01)^{0.7}}$), indicating higher heterogeneity than k with a "fat" tail. Import volume (B; $P(S_{in} > s_{in} = e^{-(s_{in}/2.86)^{0.8}}$) is best fit by the Weibull distribution, but diverges from Weibull for low values of s_{in}, indicating that nodes with small numbers of import partners are more common in the data.

Table 2. Node Strength Rankings in 2007[a]

rank	s_{in}		s_{out}	
1	New Orleans-Metairi-Bogalusa	43.7	Iowa	31.6
2	Remainder of Texas	18.1	Remainder of Illinois	28.3
3	Los Angeles-Long Beach-Riverside	17.1	Remainder of Missouri	20.8
4	Chicago-Naperville-Michigan City	13.4	Nebraska	18.1
5	Remainder of Pennsylvania	12.1	Remainder of California	17.0
6	Remainder of Illinois	12.0	Los Angeles-Long Beach-Riverside	11.9
7	Remainder of California	10.4	Remainder of Pennsylvania	11.4
8	Iowa	10.1	Remainder of Minnesota	11.4
9	Atlanta-Sandy Springs-Gainesville	8.6	Remainder of Wisconsin	10.9
10	Remainder of Louisiana	8.1	Remainder of Indiana	10.4

[a]Top 10 positions according to node in-strength (s_{in}) and out-strength (s_{out}). Note that volume data are provided in 10^6 tons. The maximum node in-strength is 43.7×10^6 tons and the minimum is 0. "New Orleans-Metairi-Bogalusa" exhibits the highest in-strength of 43.7×10^6 tons. The second and third highest in-strength are for the "Remainder of Texas" and "Los Angeles-Long Beach-Riverside", with values of 18.1×10^6 and 17.1×10^6 tons, respectively. The node out-strength ranges from 0.007×10^6 to 31.6×10^6 tons, with a mean value of 3.4×10^6 tons. The largest export volume is for "Iowa" of 31 $\times 10^6$ tons, followed by the "Remainder of Illinois" and "Remainder of Missouri", with volumes of 28.3×10^6 and 20.8×10^6 tons, respectively.

much higher trade volumes of cereal, which is important to note since cereal plays such a dominant role in food security and global trade systems, particularly maize exports from the USA to the rest of the world.[49]

3.3. Assortativity. In the previous section we analyzed node degree and strength, which are first-order network indicators. In other words, statistics on k and s only provide information on a node and its trade partners that are one step away, but do not contain information on the neighbors of that node or on the global network topology. In this section we investigate network assortativity, which is a second-order network indicator, since it includes information on nodes lying two steps away from the one under consideration.[30]

Network assortativity describes how similar connected nodes are in terms of some attribute. Here, we consider how similar the degrees of connected nodes are, that is, assortative mixing by degree. A common method for determing network assorativity is by plotting *knn* vs degree. If this graph exhibits an increasing relationship, the network is referred to as "assortative". However, if a negative relationship is evident, then a "dissassortative" network structure exists. Social networks tend to exhibit assortativity, while technological and biological networks are most often characterized by disassortativity.[50] Interestingly, economic networks exhibit features of both technological and social relationships.[38] For example, the venture capitalist network demonstrates positive degree correlations,[51] while negative degree correlations were shown for bank networks[52] and global trade.[28]

The network topology of domestic food flows (i.e., the unweighted conectivity structure) exhibits the structure of an "unassortative" network, that is, neither assortative nor

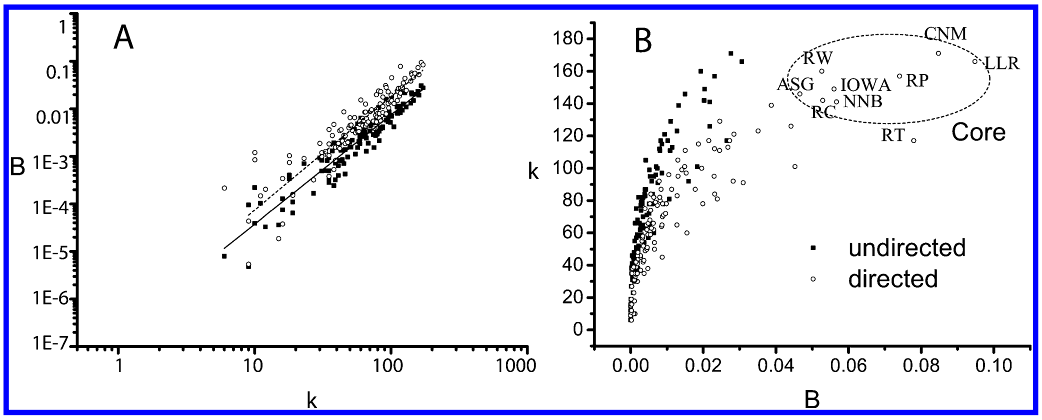

Figure 3. Relationship between node betweenness centrality (B) and node degree (k) for food flows in the USA. (A) Both undirected and directed B display a power law relationship with k. (B) A core group of nodes is evident for directed B. The core nodes are "Los Angeles-Long Beach-Riverside" (LLR), "Chicago-Naperville-Michigan City" (CNM), "Remainder of Texas" (RT), "Remainder of Pennsylvania" (RP), "New York-Newark-Bridgeport" (NNB), "Iowa" (IOWA), "Remainder of California" (RC), "Remainder of Wisconsin" (RW), and "Atlanta-Sandy Springs-Gainesville" (ASG).

disassortative (refer to SI, Figure S2). This differs from the global trade network, whose network topology exhibits disassortativity.[28]

Network assortativity can also be quantified through the Pearson correlation coefficient (τ).[50] Here, we measure τ for degree between pairs of linked nodes, where values $\in (-1, 1)$. Values of $\tau = 1$ indicate perfectly assortative mixing, while values of $\tau = -1$ indicate perfectly disassortative mixing.[53] For an unassortative network $\tau = 0$.

The connectivity structure of the USA food flow network exhibits τ values that are very close to 0, indicating largely unassortative mixing (refer to values of knn_{ii}, $knn_{,io}$, knn_{oo}, and $knn_{,oi}$ in SI, Table S5), particularly in comparison to a τ values for global trade roughly equivalent to -1.[30] Interestingly, knn_{ii} (= -0.128) and knn_{oi} (= -0.177) are both much more strongly disassortative than knn_{io} (= 0.008) and knn_{oo} (= 0.014). This indicates that when you look at the neighbors of a given node, they tend to have lower import trade connections.

The domestic network becomes assortative when food volumes are considered (refer to positive values of knn_{ii}^{W}, knn_{io}^{W}, knn_{oo}^{W}, and knn_{oi}^{W} in SI, Table S5), the difference between the unweighted and weighted relationship is not significant (note the small gap between the "weighted" and "unweighted" lines in SI, Figure S2). In particular, the difference between the unweighted and weighted assortative structure is not as severe as it is for global trade (refer to Table 1). For global trade, the unweighted knn structure is clearly disassortative, but becomes assortative when trade volumes are taken into account.[11] This indicates that certain nodes hoard the majority of the resources among themselves at the global scale. This sharp difference in unweighted and weighted assortativity structure is not evident in USA food flows, although a difference is present. This indicates that the "weighted rich club"[30] feature of global trade is not prominent in domestic food flows. Thus, domestic food flows exhibit assortative sorting, much like social networks,[50] without evidence of a weighted rich club.

3.4. Clustering. Mean values of network clustering are presented in Table 1. Mean C values are higher for USA food flows than for global food trade. This indicates that nodes within the USA are more interconnected than nations participating in international trade (note that even values of C_{cyc} and C_{mid} are higher for USA food trade, which are rare clustering patterns in global trade). However, the exception is for $C_{in}^{W} = 0.82$ for USA and 0.94 for global trade. Mean C values are not significantly different in unweighted and weighted terms for the USA network, providing further evidence for the absence of a weighted rich club. This shows the propensity for certain nations to dominate weighted trade at the global scale.

Node clustering exhibits high heterogenity at the global scale, in which there is a power law relationship between C and k.[28] Here, the directed C and k relationships (refer to SI, Figure S3) are absent of the power law property evident in the global trade network. The relationship between C and k for USA food trade exhibits a much more homogeneous network, with high values of clustering across values of k. The addition of trade volumes to our calculation of local clustering does not change the slope of the graphs significantly, another indication that USA food flows do not exhibit a weighted rich club.[30]

3.5. Betweenness Centrality. Betweenness centrality (B) is a tertiary network measure, as it quantifies the importance of nodes to the entire network structure.[38] The USA exhibits the highest B of all nodes in the global food trade network (refer to Table 1). Thus, in this paper we characterize the network properties of the most central country in the global food trade network.

The distribution of node betweenness for the USA food flow network is provided in Figure 2C,F. B is best fit by a Weibull distribution, indicating a "fat tail" representation of a few key nodes to the network. Directed B is fit by $P(B_d > b_d) = e^{-(b_d/0.01)^{0.7}}$ and undirected B is best fit by $P(B_u > b_u) = e^{-(b_u/0.004)^{0.7}}$. Thus, directed B exhibits a fatter tail than does undirected B. In other words, when direction is taken into account, some nodes increase in importance to the topology of the network (refer to SI, Table S7). The node that exhibits the highest directed B is "Los Angeles-Long Beach-Riverside", with a value of 0.095 (refer to Table 1). The nodes with the second and third highest directed B values are "Chicago-Naperville-Michigan City" and "Remainder of Texas", with values of 0.085 and 0.078, respectively. These are important harbors for the barge transport of food. The USA has the highest B value at the global scale, further highlighting the importance of these harbors for global trade, followed by Germany, France, Netherlands, and Great Britain (refer to Table 1).

Node B vs k exhibits a power law relationship, where connected nodes are much more likely to play a crucial role in the network architecture. This relationship is present for both the undirected and directed network (refer to Figure 3A and SI,

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Table S4). Such a highly nonlinear relationship between B and k suggests the presence of a network "core", much like in the global trade system,[3] making the network particularly vulnerable to failure.[54,55]

To identify the nodes that belong to the network core, we plot k against B in Figure 3B. A core group of nodes is evident only for directed B. In other words, nodes with high directed B also tend to be network hubs, that is, those with the largest degree. The core nodes are "Los Angeles-Long Beach-Riverside", "Chicago-Naperville-Michigan City", "Remainder of Texas", "Remainder of Pennsylvania", "New York-Newark-Bridgeport", "Iowa", "Remainder of California", "Remainder of Wisconsin", and "Atlanta-Sandy Springs-Gainesville". Because of the prominent role that these nodes play in the network architecture, their removal may disturb the movement of food throughout the USA. Thus, the USA food flow network may be vulnerable to the removal of key nodes.

3.6. Triad Analysis. The triad significance profile (TSP) of global food trade recently revealed a unique "superfamily" when compared with existing networks (refer to ref 32 for comparisons of TSPs of many real-word networks). The global food trade TSP revealed properties of both biological and human social networks. The TSP for global food trade indicates an abundance of triad type "13" (i.e., "motif") and lack of triad type "6" (i.e., "antimotif"), the hallmark of human social systems (refer to Figure 4 for triad diagrams). The TSP of global food trade also presented an abundance of triad types "9" and "10", indicators of biological networks.[41,32] Since global food trade exhibits topological characteristics of both biological and human networks, it is not surprising that the TSP of global food trade displays a combination of these network types.[32]

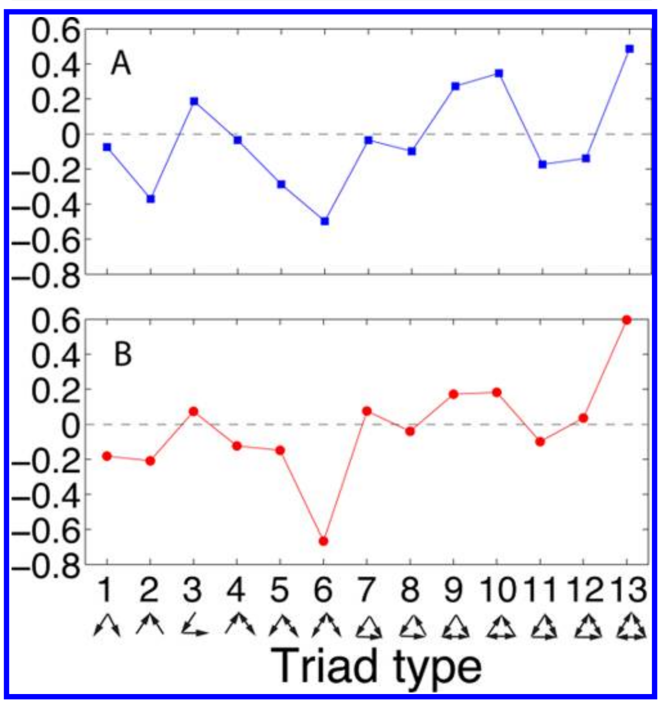

Figure 4. Triad significant profiles (TSPs) for food flows. (A) TSP for global food flows, as presented in ref 32; (B) TSP for food flows within the USA. The general structure of the triad significance profile is retained for domestic food flows. However, the USA food flow network exhibits more characteristics of a social network than does global food trade (i.e., antimotif 6 and motif 13 are more pronounced in panel B; values provided in Table 1) .

We present the triad analysis for domestic food flows in the USA in Figure 4. The overall TSP structure compares well with that for global trade of food. However, the USA food trade network exhibits even stronger signals of a human social network than does global food trade (note that triad type "13" is more prevalent and triad type '6' is less prevalent in Figure 4B and Table 1). Thus, trade connections within the USA are highly social, more so than global trade patterns.

3.7. Equality Analysis. Trade inequality is an important topic in the literature.[33] In this section we compare statistics on global trade inequality with measures within the USA. We assume that food flows within the USA approximate the most equitable distribution that international trade may be expected to achieve. We make this assumption because characteristics important to trade (i.e., wealth, population, resources, politics, etc.) are relatively homogeneous across CFS areas in the USA as compared to the high heterogeneity across countries in the global trade system. Thus, our analysis here serves as a benchmark for comparison for global trade equity.

Conceptually, trade equality refers to the situation in which all trade partners exchange the same volumes of food. Quantitatively, we employ the Gini coefficient (G), Lorenz coefficient (S), and Hoover index (D) to measure trade equality. Table 1 presents the equality coefficients for food flows across the USA and at the global scale, as measured in ref 33. For the USA, G = 0.579, indicating a more equitable distribution of food flows than at the global level (where G = 0.626). The Lorenz curve asymmetry coefficient is essentially symmetric for domestic food flows, since S = 0.97. D for USA food trade is 0.442, indicating that some trade would need to be redistributed to achieve perfect equality, although not as much as at the global level, in which half would need to be redistributed.

The USA cereal trade scores the lowest across equality metrics (i.e., G = 0.908, S = 0.966, and D = 0.442; refer to SI, Table S8) due to high heterogeneity of flows. However, the cereal trade also exhibits the largest exponent in the power law relationship between s and k, indicating that cereal trade may be a key method for improving food security. Thus, these differences in the cereal trade highlight the important trade-off between efficiency and equity in a system. This analysis of domestic food flows raises the question of whether perfect equality is possible or even desirable within a trade system.

The world food system has become increasingly complex and interconnected, particularly due to food trade. The international trade of food commodities has been previously studied using the tools of network analysis.[11,3,32] In this paper, we presented a novel application of network theory to data on food flows within a single country: the USA, a key nation in the global food network, since it is a major agricultural producer, consumer, and trade power. This analysis provides a useful benchmark for network properties across scales of trade, within a free trade setting, and for a relatively equitable case study. As expected, the USA food flow network is more equitable than global food trade. However, even food flows within the USA are not perfectly equitable and present a potential bound for how equitable global food trade can realistically be expected to be.

■ ASSOCIATED CONTENT

Supporting Information

Supplementary methods, eight tables, and three figures as described in the text. This material is available free of charge via the Internet at http://pubs.acs.org.

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Notes

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REFERENCES

(1) Godfray, H. C. J.; et al. Food security: The challenge of feeding 9 billion people. *Science* **2010**, *327*, 812−818.

(2) Kastner, T.; Rivas, M.; Koch, W.; Nonhebel, S. Global changes in diets and the consequences for land requirements for food. *Proc. Nat. Acad. Sci. U.S.A.* **2012**, *109*, 6868−6872.

(3) Ercsey-Ravasz, M.; Toroczkai, Z.; Lakner, Z.; Baranyi, J. Complexity of the international agro-food trade network and its impact on food safety. *PLoS One* **2012**, *7*, e37810.

(4) Burgess, R.; Donaldson, D. Can openness mitigate the effects of weather shocks? Evidence from India's famine era. *Am. Econ. Rev.: Pap. Proc.* **2010**, 449−453.

(5) Porkka, M.; Kummu, M.; Siebert, S.; Varisl, O. From food insufficiency towards trade dependency: A historical analysis of global food availability. *PLoS One* **2013**, *8*, e82714.

(6) Peters, G.; Minx, J.; Weber, C.; Edenhofer, O. Growth in emission transfers via international trade from 1990 to 2008. *Proc. Nat. Acad. Sci. U.S.A.* **2011**, *108*, 8903−8908.

(7) Schipanski, M.; Bennett, E. The influence of agricultural trade and livestock production on the global phosphorus cycle. *Ecosystems* **2012**, *15*, 256−268.

(8) O'Bannon, C.; Carr, J.; Seekell, D.; D'Odorico, P. Globalization of agricultural pollution due to international trade. *Hydrol. Earth Syst. Sci. Discuss.* **2013**, *10*, 11221−11239.

(9) Konar, M.; Dalin, C.; Hanasaki, N.; Rinaldo, A.; Rodriguez-Iturbe, I. Temporal dynamics of blue and green virtual water trade networks. *Water Resour. Res.* **2012**, *48*, DOI: 10.1029/2012WR011959.

(10) Hertel, T.; Burke, M.; Lobell, D. The poverty implications of climate-induced crop yield changes by 2030. *Global Environ. Change* **2010**, *20*, 577−585.

(11) Konar, M.; Dalin, C.; Suweis, S.; Hanasaki, N.; Rinaldo, A.; Rodriguez-Iturbe, I. Water for food: The global virtual water trade network. *Water Resour. Res.* **2011**, *47*, DOI: 10.1029/2010WR010307.

(12) Dalin, C.; Konar, M.; Hanasaki, N.; Rinaldo, A.; Rodriguez-Iturbe, I. Evolution of the global virtual water trade network. *Proc. Nat. Acad. Sci.* **2012**, *109*, 5989−5994.

(13) Newman, M.; Barabasi, A.-L.; Watts, D. J. *The Structure and Dynamics of Networks*, 1st ed.;Princeton University Press: Princeton NJ, 2006.

(14) Costa, L.; Rodrigues, F.; Travieso, G.; Boas, P. V. Characterization of complex networks: A survey of measurements. *Adv. Phys.* **2007**, *56*, 167−242.

(15) Watts, D. J.; Strogatz, S. H. Collective dynamics of small-world networks. *Nature* **1998**, *393*, 440−442.

(16) Barabási, A.-L.; Albert, R. Emergence of scaling in random networks. *Science* **1997**, *286*, 509−512.

(17) Barabasi, A.-L. *Linked: The New Science of Networks*; Perseus Publishing: New York, 2002.

(18) Kalapala, V.; Sanwalani, V.; Clauset, A.; Moore, C. Scale invariance in road networks. *Phys. Rev. E* **2006**, *73*, 026130.

(19) Masucci, A.; Smith, D.; Crooks, A.; Batty, M. Random planar graphs and the london street network. *Eur. Phys. J. B* **2009**, *71*, 259−271.

(20) Kaluza, P.; Kolzsch, A.; Gastner, M. T.; Blasius, B. The complex network of global cargo ship movements. *J. R. Soc., Interface* **2010**, *7*, 1093−1103.

(21) Miguens, J.; Mendes, J. Weighted and directed network on traveling patterns. *Biowire* **2008**, *5151*, 145−154.

(22) Garlaschelli, D.; Loffredo, M. I. Structure and evolution of the world trade network. *Physica A* **2005**, *355*, 491−499.

(23) Kyriakopoulos, F.; Thurner, S.; Puhr, C.; Schmitz, S. W. Network and eigenvalue analysis of financial transaction networks. *Eur. Phys. J. B* **2009**, *71*, 523−531.

(24) Newman, M. Scientific collaboration networks: 1. Network construction and fundamental results. *Phys. Rev. E* **2001**, *64*, 016131.

(25) Barrat, A.; Barthelemy, M.; Pastor-Satorras, R.; Vespignani, A. The architecture of complex weighted networks. *Proc. Natl. Acad. Sci. U.S.A.* **2004**, *101*, 3747−3752.

(26) Smith, A. *The Wealth of Nations*; Strahan and Cadell: London, 1776.

(27) Tinbergen, J. An Analysis of World Trade Flows. In *Shaping the World Economy*; Twentieth Century Fund: New York, 1962.

(28) Serrano, M.; Boguna, M. Topology of the world trade web. *Phys. Rev. E* **2003**, *68*, 015101.

(29) Bhattacharya, K.; Mukherjee, G.; Manna, S. The international trade network. *Econophys. Markets Bus. Networks* **2007**, 139−147.

(30) Fagiolo, G.; Reyes, J.; Schiavo, S. On the topological properties of the world trade web: A weighted network analysis. *Physica A* **2008**, *387*, 3868−3873.

(31) Barigozzi, M.; Fagiolo, G.; Garlaschelli, D. Multinetwork of international trade: A commodity-specific analysis. *Phys. Rev. E* **2010**, *81*, 046104.

(32) Shutters, S. T.; Muneepeerakul, R. Agricultural trade networks and patterns of economic development. *PLoS One* **2012**, *7*, e39756.

(33) Seekell, D.; D'Odorico, P.; Pace, M. Virtual water transfers unlikely to redress inequality in global water use. *Environ. Res. Lett.* **2011**, *6*, 024017.

(34) Konar, M.; Caylor, K. Virtual water trade and development in Africa. *Hydrol. Earth Syst. Sci.* **2013**, *17*, 3969−3982.

(35) CFS. Commodity Flow Survey. http://www.census.gov/econ/cfs/ (accessed 2013).

(36) Wasserman, S.; Faust, K. *Social Network Analysis: Methods and Applications*, 1st ed.; Cambridge University Press: Cambridge, UK, 1994.

(37) Watts, D. *Small Worlds: The Dynamics of Networks between Order and Randomness*, 1st ed.; Princeton University Press: Princeton, NJ, 1999.

(38) Jackson, M. *Social and Economic Networks*; Princeton University Press: Princeton, NJ, 2008.

(39) Fagiolo, G. Clustering in complex directed networks. *Phys. Rev. E* **2007**, *76*, 026107.

(40) Barthelemy, M. Betweenness centrality in large complex networks. *Eur. Phys. J. B* **2004**, *38*, 163−168.

(41) Milo, R.; Itzkovitz, S.; Kashtan, N.; Levitt, R.; Shen-Orr, S.; Ayzenshtat, I.; Sheffer, M.; Alon, U. Superfamilies of evolved and designed networks. *Science* **2004**, *303*, 1538−1542.

(42) Gini, C. Concentration and dependency ratios (in Italian) (English translation). *Riv. Polit. Econ.* **1909**, *87*, 769−789.

(43) Damgaard, C.; Weiner, J. Describing inequality in plant size or fecundity. *Ecology* **2000**, *81*, 1139−1142.

(44) Hoover, E. Interstate redistribution of population, 1850−1941. *J. Econ. Hist.* **1941**, *1*, 199−205.

(45) Krzywinski, M. I.; Schein, J.; Birol, I.; connors, J.; Gascoyne, R.; Horsman, D.; Jones, S.J.; Marra, M. A. Circos: An information aesthetic for comparative genomics. *Genome Res.* **2009**, *19*, 1639−1645.

(46) Newman, M. Coauthorship networks and patterns of scientific collaborations. *Proc. Nat. Acad. Sci.* **2004**, *101*, 5200−5205.

(47) Guimera, R.; Diaz-Guilera, A.; Giralt, F.; Arenas, A. The real communication network behind the formal chart: Community structure in organizations. *J. Econ. Behav. Organ.* **2006**, *61*, 653−667.

(48) Pennock, D. M.; Flake, G. W.; Lawrence, S.; Glover, E. J.; Giles, C. L. Winners don't take all: Characterizing the competition for links on the web. *Proc. Nat. Acad. Sci. U.S.A.* **2002**, *99*, 5207−5211.
(49) Wu, F.; Guclu, H. Global maize trade and food security: Implications from a social network model. *Risk Anal.* **2013**, *33*, 2168−2178.
(50) Newman, M. Assortative mixing in networks. *Phys. Rev. Lett.* **2002**, *89*, 208701.
(51) Mas, D.; Vignes, A.; Weisbuch, G. Networks and syndication strategies: Does a venture capitalist need to be in the center? *ERMES-CNRS Univ. Pantheon Assas Paris II* **2007**, 0714.
(52) May, R.; Levin, S.; Sugihara, G. Ecology for bankers. *Nature* **2008**, *451*, 893−895.
(53) Fricke, D.; Finger, K.; Lux, T. On assortative and disassortative mixing scale-free networks: The case of interbank credit network. *Kiel Work. Pap.* **2013**, 1830.
(54) Motter, A. E.; Lai, Y.-C. Cascade-based attacks on complex networks. *Phys. Rev. E* **2002**, *66*, 065102.
(55) Thai, M. T., Pardalos, P., Eds. *Handbook of Optimization in Complex Networks*; Springer: New York, 2012.