ABSTRACT

International Trade and Economic Growth: A Network Perspective

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International trade is a complex network of import and export relationships, which is commonly referred to as the World Trade Network. It displays many topological characteristics that were recently suggested to be tightly related to the Gross Domestic Product of economies. There are four centrality measures commonly used in describing these characteristics, namely closeness centrality, betweenness centrality, eigenvector centrality, and degree centrality. In this paper, I explore the centrality measures of the trading networks of 28 product groups during the 1980-2006 period using the Trade and Production Database of the CEPII. I demonstrate how these measures are related to the economic growth in the long run and which of them performs the best in a wide range of economies.

International Trade and Economic Growth: A Network Perspective

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CHAPTER ONE

Introduction

Over the past three decades, technological advances have triggered a period of remarkable growth in international trade. Decreasing transportation and communication costs, along with various newly established trade agreements, marked rapid international integration and globalization, making our world smaller than ever before.

The theory of comparative advantage first brought up by David Ricardo, described how countries could benefit from trading. It has then become a consensus in the literature that international trade is one of the driving factors of economic growth. Over the past few decades, studies (Acemoglu et al., 2002; Dollar and Kraay, 2001; Liu et al., 2002) utilizing empirical analysis of trade and development have provided new evidence supporting this claim. As a result, international trade has been an important part of the development literature, spanning a wide range of topics including policy-making, institutions, foreign exchange, international finance, etc. However, most of the studies, such as the topics mentioned above, focused on the exogenous factors of international trade, trying to establish a causal relationship from these external factors to international trade and subsequently to economic growth. On the contrary, little work has been done to address the trade relationships directly. To explain further, bilateral international trade is a relation of two countries in essence. These relationships among different countries define a complex network, which is commonly referred to as the World Trade Network. Although network analysis has been routinely applied in many social and natural science subjects, it was not until recently that researchers started to study trade within the network framework (Serrano and Boguna, 2003).

Attempts to address the international trade networks on its structural and topological properties were initialized by several researchers, including Serrano and Boguna (2003), Kali and Reyes (2007), and Fagiolo et al. (2008). While their studies addressed the topological properties of the trade network, they mainly focused on aggregated country-level exports and imports, therefore ignoring heterogeneity among different product groups. On the contrary, Hidalgo et al. (2007) analyzed the disaggregated product-level data to address product specialization and development, which failed to extend to the analysis of trade and development in general.

In this paper, I contribute to the literature of the World Trade Network by associating the evolution of network structures with economic growth. My objective is to extend the understanding of international trade in an evolving network perspective by performing network analysis on disaggregated trade data over a relatively long period. I hypothesize that international trade forms a complex network, which displays many structural characteristics tightly related to Gross Domestic Products of economies. In other words, I argue that the properties of such networks provide an alternative explanation for economic growth. My approach in this paper is related to and motivated by Benedictis et al. (2014) and Baskaran et al. (2010). Specifically, I calculated various centrality and connectedness measures for 28 distinct product groups classified by the International Standard Industrial Classification of All Economic Activities (ISIC) during the 1980-2006 period. These product-level measures were aggregated to the country level by computing the volume-weighted centrality indices. I then compare and contrast the explanatory power of different types of centrality measures using regression analysis to test my hypothesis that closeness centrality performs the best in explaining economic growth.

The remainder of the paper proceeds as follows. Chapter two provides a synopsis of the network theories in social and natural sciences and discusses the network literature in international trade. Chapter three introduces the dataset being used in this paper and outlines the methods for calculating various centrality measures, and the volume-weighted centrality indices I proposed. Moreover, I show descriptive statistics and selected results from the computation in this chapter. Chapter four highlights the regression models I applied. Chapter five entails the results from the regression analysis and elaborates on implications and interpretations. Chapter six concludes the paper.

CHAPTER TWO

Literature Review

Network analysis is built upon its mathematical definition, which defines networks as a set of elements called vertices or nodes. These vertices are connected with each other through links, which are named edges. Baskaran et al. (2010) provided a more formal definition of networks, which states that a network is “a pair $G = (V, E)$ consisting of a set of vertices V and a set of edges $E \subset V \times V$” and that “each edge $(i, j) \in E$ is directed and can be assigned a non-negative real edge weight a_{ij}”. According to their definition, the number of nodes is denoted by n. An $n \times n$ adjacency matrix $A = (a_{ij})$ can be used to represent a network, where the element (i, j) represents the weight a_{ij} of the edge from node i and node j. Missing edges correspond to zeros in the adjacency matrix.

In the international trade perspective, each country is a node of the set V. The trade relationships between countries make up the set of edges E. t denotes the time (year) and p denotes the classification number of products. The weight $a_{ij}(t, p)$ or a_{ijtp} denotes the trade flow (export) of product p from country i to country j in year t. Note that the edges are directed, meaning that the order of i and j matters. Since international trade relationships evolve dynamically over time, the structure of the corresponding network changes continuously. Let n_t or $N(t)$ denote the number of countries involved in the network in year t.

Analyzing international trade in the network perspective provides many benefits that are unattainable from the descriptive statistics used in applied international trade analysis (Benedictis et al., 2014). First, instead of focusing on the individual country i or j , networks emphasize the relation a_{ij} between them. More importantly, such relationship is not analyzed in isolation (Benedictis et al., 2014), but rather with respect to all other relations. Specifically, network analysis explores international trade data in a structural perspective. Second, conventional international trade analysis relies heavily on the assumption that the countries are somehow homogeneous. However, international trade in the real world is a complex network defined by numerous bilateral interactions and negotiations, and not in a perfectly competitive market with exogenous prices (Baskaran et al., 2010). With that in mind, network analysis allows for heterogeneity among countries, making it more straightforward to study the structural interdependence and peer effects. Last but not least, international trade networks can be visualized easily with the help of some software. Such visualization, often in the format of graphs, can be interpreted intuitively. Figure 1 below is an example of such network graphs.

Figure 1 depicts an export network of textiles in 2006. Note that this graph is limited to the two largest trading partners in this product segment (textiles). The color of the nodes denotes the continent in which the respective country the node represents is located. The size of the nodes indicates the volume of export from that country. As shown in the graph, China (CHN) is the center of the network of textile exports with the highest export volume and the most trading links among other countries. Moreover, note that there are some other regional centers and patterns within this trade network. For example, the United States (The USA is a regional center of the American continent, which exports mostly to other Latin American countries. A cluster of Asian countries exports their textiles mainly to African countries. Another interesting pattern is that European countries trade with each other while importing from selected Asian countries. A story here might be that these European countries are importing cheap textiles from Asian countries while exporting luxury textiles to each other.

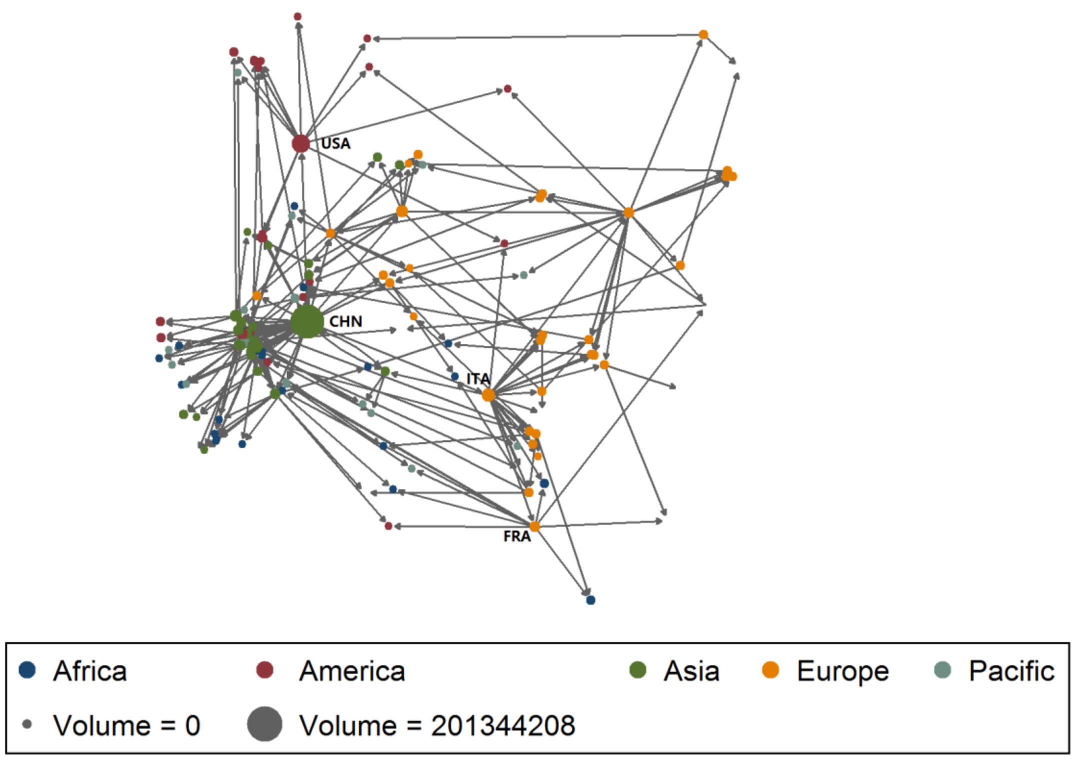

Figure 1. The export network of textiles in 2006.

Serrano and Boguna (2003) were among the researchers that first analyzed international in a network perspective, classifying the World Trade Network as a complex network with scale-free degree distribution and the small-world property. Specifically, the number of edges connected to a node, denoted as k, follows a power-law distribution with $p(k) \sim k^{-\gamma}$. The small-world property is characterized by the preservation of local neighborhood and a logarithmic increase of network diameter with respect to number of nodes $N(t)$ (Amaral et al., 2000). In the perspective of international trade, such properties can be interpreted as follows. First, the number of trade interactions a country has with respect to a specific good follows a power-law distribution. Second, a cluster of trading partners (neighborhood) is likely to be preserved as the World Trade Network evolves. Third, the average trade volume between any two countries grows logarithmically with the size of the World Trade Network (or number of countries $N(t)$ involved in the network).

While trying to analyze international trade in a sophisticated network perspective, some researchers have taken a step further to link these properties to other important economic measures. Recent studies have shown that the topological properties of networks can be used to explain trade shares (Baskaran et al., 2010) and Gross Domestic Products (Garlaschelli and Loffredo, 2005). Baskaran et al. (2010) estimated a network parameter to measure unobservable product characteristics that determined the structure of a product's trade network. They adopted a maximum likelihood estimation method concerning that other standard fitting methods may produce systematically biased estimates (Goldstein et al., 2004). In an attempt to reconcile the data with the model prediction, they incorporated the network parameter into the standard Heckscher-Ohlin model. With network parameters taken into account, regression results favored the Heckscher-Ohlin model prediction. However, it is hard to interpret their estimated network parameters analytically. Specifically, it is clear that this parameter measures some structural properties of the networks, but its meaning remains unknown. Garlaschelli and Loffredo (2005) took a different approach by applying a fitness network model. Their conclusion suggested that the topological properties of the World Trade Network always displays a peculiar dependence on the Gross Domestic Product. However, they did not explicitly interpret the casual relation between network evolution and economic growth.

I was thus motivated to calculate some centrality measures for different product groups over time, interpret how the networks evolve based on these measures and find the relation between these measures and economic growth. There are four types of centrality measures that were commonly used for network analysis (Jackson, 2010), namely the degree centrality, the closeness centrality, the betweenness centrality, and the eigenvector centrality. Each of these four centralities measures the topological property of a network in a different perspective with certain benefits and drawbacks. Therefore, some measures may be more appropriate than others depending on the structure of networks and the questions of interest. I argue that closeness centralities are better predictors of economic growth as we add more controls to the model. More details regarding these centrality measures are in Chapter Four.

CHAPTER THREE

Data and Methods

Data

The Trade and Production Database

The international trade data used in this paper is from the Trade and Production Database of the CEPII (Centre d'Études Prospectives et d'Informations Internationales), which was developed from the BACI database. The BACI database, which was originated from the COMTRADE database, made more data available as compared to the original dataset. It was achieved by adopting a special harmonization procedure that reconciles the declarations of the exporter and the importer. As a result, the exhaustive dataset in this paper contains the bilateral trade flows for 28 product groups, defined at the 3-digit level according to the International Standard Industrial Classification Revision 2, of more than two hundred countries over the period of 1980-2006. A list of the product classifications and their corresponding 3-digit codes can be found in Table 1, along with some descriptive statistics of the centrality measures.

A Stata package called *nwcommands* was adapted to perform network analysis and calculate the centrality measures. The dataset was broken up into a total of 702 subsets by year and by product group. Each subset was then converted into a three-column format called the "edgelist" format, with the first column being the exporting country (node i), the second column being the importing country (node j), and the third column being the trade flow (edge weight a_{ij}). Each of these subsets, A_{pt}, contains an exhaustive list of the edges within the trade network of product group p in year t. The Stata package can read these "edgelists", convert them into matrices, and calculate centrality measures accordingly.

The GeoDist Database

To add more control variables, as well as construct an instrument to deal with the potential endogeneity problem, I incorporated a database called GeoDist from the CEPII into my dataset. This database, developed by CEPII, provides many important geographic variables for 225 countries in the world, including region, continent, Area, the Number of cities, landlock status, etc. These variables were used in my analysis as controls to add more robustness to the results.

In addition to the control variables, a network was constructed from bilateral geographic distances, from which centrality measures were calculated and utilized as an instrument for the international trade network centralities. I will elaborate on the construction, reasoning, and interpretation of this instrument in the next chapter.

The World Development Indicators

The economic measures and other control variables used in this paper, including GDP per capita, oil rent, life expectancy, etc., were retrieved from the World Bank's World Development Indicators (WDI) Database. This database contains an exhaustive list of measures of development for countries around the world. Data regarding the respective countries was collected over the period of 1980-2006 and merged with the dataset containing the calculated centrality measures.

Centrality Measures

There are four types of centrality measures that were commonly used for network analysis (Jackson, 2010). First, degree centrality, C_D, measures how connected a node (country) is with respect to other nodes based on binary edges ($a_{ij} \in \{0,1\}$), which indicates whether a link (trade relation) exists. A weighted version of degree centrality, called strength centrality, can be derived by replacing binary edge with actual weights of the links ($a_{ij} = trade\ flow$, for example). Second, closeness centrality, C_C, measures how accessible a node is by other nodes. Third, betweenness centrality, C_B, measures the importance of a node as an intermediary between other nodes. Last but not least, eigenvector centrality, C_E, measures the importance of a node by calculating how crucial, influential, and clustered the node's neighbors are. Detailed explanations for each of the centrality measures can be found in the following section. Note that in an international trade perspective, a node represents a country and a link represents an interaction or trade relation. "Node" and "country" are used interchangeably in the remainder of the paper.

Degree Centrality

Degree centrality is the simplest measure compared to the others. It uses an unweighted version of the network, in which all the edges are binary ($a_{ij} \in \{0,1\}$). The centrality of a node is calculated by counting the number of edges connected to it.

$$C_i^D = \sum_{j \neq i}^{N} a_{ij} \tag{1}$$

Note that N denotes the total number of nodes (countries) in the network, and a_{ij} denotes the edge connecting node i to j, where i and j correspond to exporting countries and importing countries, respectively. As mentioned above, edges are converted to a binary variable, indicating whether there is a trade relation between country i and j.

One of the drawbacks of simple degree centralities is that the measures are not comparable when networks change in size. Therefore, it is important that we standardize it with the total number of possible edges connected to it, namely $N-1$.

$$C_i^{SD} = \frac{\sum_{j \neq i}^{N} a_{ij}}{N-1} \tag{2}$$

Recall that the maximum number of edges connected to any node is $N-1$, meaning that $C_D^S \in [0,1]$. It follows that the higher the standardized degree centrality is, the more connected a node is with respect to other nodes.

Since the World Trade Network is directed, an interaction between two nodes may contain two edges: one for inflow (imports) and one for outflow (exports). Therefore, there are two measures of degree centrality for each node, which are called in-degree centrality and out-degree centrality. In the context of international trade, in-degree centrality measures the number of countries that a country is importing from, while out-degree centrality measures the number of countries to which a country is exporting.

$$C_i^{SD_{out}} = \frac{\sum_{j \neq i}^{N} a_{ij}}{N-1} \quad C_i^{SD_{in}} = \frac{\sum_{j \neq i}^{N} a_{ji}}{N-1} \tag{3}$$

In-degree centrality and out-degree centrality are defined in equation (3). The out-degree centrality measures of selected countries (China, United States, and Ghana) and product groups (textiles and transport equipment), along with some descriptive statistics, can be found in Table 1. Note that the centralities measures have been standardized with 0 representing the lowest connectedness and 1 representing the highest connectedness.

Table 1. Out-degree centrality of China, United States, and Ghana in textile industry and transport equipment industry.

	China		United States		Ghana	
	Textiles	Transport Equipment	Textiles	Transport Equipment	Textiles	Transport Equipment
Year	Out-Degree	Out-Degree	Out-Degree	Out-Degree	Out-Degree	Out-Degree
1980	0.2920	0.2301	0.6460	0.6460	0.0531	0.0354
1981	0.3142	0.2611	0.6549	0.6504	0.0575	0.0487
1982	0.2832	0.2389	0.6549	0.6504	0.0442	0.0221
1983	0.3407	0.3009	0.6681	0.6726	0.0398	0.0265
1984	0.3009	0.2611	0.6504	0.6504	0.0221	0.0354
1985	0.3186	0.2655	0.6593	0.6681	0.0221	0.0575
1986	0.3496	0.3186	0.6637	0.6726	0.0310	0.0398
1987	0.3407	0.3142	0.6726	0.6593	0.0265	0.0487
1988	0.3540	0.3319	0.7257	0.7478	0.0398	0.0354
1989	0.3673	0.3451	0.7080	0.7257	0.0398	0.0531
1990	0.3761	0.3717	0.6858	0.7301	0.0531	0.0398
1991	0.3850	0.3761	0.6947	0.7080	0.0487	0.0442
1992	0.4071	0.4027	0.7876	0.7965	0.1018	0.2478
1993	0.4248	0.4115	0.8097	0.8274	0.0619	0.0575
1994	0.4558	0.4469	0.8097	0.8407	0.0796	0.0531
1995	0.8274	0.7832	0.8186	0.8673	0.1150	0.1106
1996	0.8186	0.7655	0.8142	0.8761	0.1460	0.1770
1997	0.8451	0.7743	0.8407	0.8805	0.1460	0.1504
1998	0.8319	0.8097	0.8407	0.8850	0.1814	0.1593
1999	0.8451	0.8186	0.8451	0.8938	0.1460	0.1858
2000	0.8584	0.8319	0.8451	0.8982	0.1681	0.1814
2001	0.8628	0.8363	0.8496	0.8938	0.1637	0.2124
2002	0.8717	0.8407	0.8407	0.9027	0.1726	0.1549
2003	0.8717	0.8628	0.8496	0.9071	0.2389	0.1858
2004	0.8584	0.8540	0.8761	0.9027	0.2168	0.1858
2005	0.8717	0.8673	0.8761	0.9115	0.2434	0.2389
2006	0.8805	0.8717	0.8451	0.9115	0.2478	0.2434
Min	0.2832	0.2301	0.6460	0.6460	0.0221	0.0221
Max	0.8805	0.8717	0.8761	0.9115	0.2478	0.2478
Average	0.5760	0.5479	0.7642	0.7917	0.1077	0.1123
Variance	0.0655	0.0674	0.0074	0.0112	0.0057	0.0062

It is obvious from this table that the United States, as a long-time developed country, has been mostly connected to other countries in the trade networks of these two industries since 1980. There has been some improvement in its connectedness over time, but the change is not comparable to that of China, which has been a major driver of world economy recently. China started off with some relatively low centrality measures but experienced a dramatic change in its connectedness over time. Its export degree centrality has surpassed the United States in the textile industry and almost caught up with the United States in the transport equipment industry by the year of 2006. It is consistent with the remarkable economic growth China has experienced in the past couple decades. Ghana, on the other hand, has been showing some really low centrality measures over time. There is not much improvement over time, either, which might explain Ghana's poverty level and slow economic growth.

Given that degree centrality only cares about the existence of connections, but not the weights of the edges, people who are concerned may choose to adopt a strength centrality measure. However, strength centrality measures are not particularly useful in the context of international trade. Equation (4) and (5) below describe two ways of standardizing strength centrality measures. Equation (4) uses the total number of possible connections, $N-1$, as a standardization factor, while Equation (5) uses the total strength of all the edges within the network as a standardization factor.

$$C_i^{SS_{out}} = \frac{\sum_{j\neq i}^{N} a_{ij}}{N-1} \quad C_i^{SS_{in}} = \frac{\sum_{j\neq i}^{N} a_{ji}}{N-1} \tag{4}$$

$$C_i^{PS_{out}} = \frac{\sum_{j\neq i}^{N} a_{ij}}{\sum_{i,j} a_{ij}} \quad C_i^{PS_{in}} = \frac{\sum_{j\neq i}^{N} a_{ji}}{\sum_{i,j} a_{ij}} \tag{5}$$

Note that a_{ij} is now the weight of the edge (trade flow) between country i and j. Equation (4) measures a standardized trade flow, while Equation (5) provides a measure that is exactly the same as trade share. In this case, strength centrality measures of the network provide no more information than trade statistics. Therefore, degree centrality and strength centrality, naïve in its nature, lack the very important ability to incorporate and analysis the structure of the entire network. In an international trade perspective, my hypothesis is that these two centralities could explain economic growth to some degree, but they won't be the best predictors as I add more controls.

Closeness Centrality

Another commonly used centrality measure is closeness centrality. Rather than focusing on the direct connections a node has to other nodes, closeness centrality takes into consideration the structure of the entire network. It measures the topological distance between a node and all other nodes within the network. Specifically, topological distance in network analysis is commonly referred to as the number of steps needed for a node to reach to another node in the network (Baskaran et al., 2010). The smallest number of steps between node i and j, denoted as D_{ij}, is called the geodesic distance between node i and j. The sum of the geodesic distance between a node i and all the other nodes in the network, $\sum_{j \neq i}^{N} Dij$, can be considered as a measure of "farness" from node i to the rest of the network. Take the inverse of the "farness" measure and multiply it by the minimum possible total geodesic distance $N - 1$ (i.e. the node is directly connected to all other nodes), and we get a standardized centrality measure of the "closeness" a node is with respect to the rest of the network.

$$C_i^{SC_{out}} = \frac{N-1}{\sum_{j \neq i}^{N} D_{ij}} \quad C_i^{SC_{in}} = \frac{N-1}{\sum_{j \neq i}^{N} D_{ji})} \tag{6}$$

Standardized closeness centrality measures are defined above in Equation (6). $\forall i, C_i^{SC} \in [0,1]$. The shorter the topological distance between a node i and the rest of the network, the closer C_i^{SC} is to one. In other words, when a country i is directly connected with all other countries (i.e. has trade relations with all other countries), $C_i^{SC} = 1$. On the contrary, when a country i is isolated from all other countries, $C_i^{SC} = 0$. Recall that international trade is a directed network. Just like what we did for degree centrality measures, we should also consider the direction of flow for closeness centrality measures. Out-flow closeness centrality measures how far in terms of topological distance a node has to go in order to send out connections to the rest of the network, while in-flow closeness centrality measures how far in terms of topological distance the rest of the network have to go to send connections to a single node. To put it another way, out-flow closeness centrality measures how difficult it is for a country to export its products to all the other countries, while in-flow closeness centrality measures how difficult it is for all the other countries to import their products to a single country.

Closeness centrality measures for selected countries (China, United States, and Ghana) and product groups (textiles and transport equipment), along with some descriptive statistics, can be found in Table 2.

Table 2. Out-closeness centrality of China, United States, and Ghana in textile industry and transport equipment industry.

	China		United States		Ghana	
	Textiles	Transport Equipment	Textiles	Transport Equipment	Textiles	Transport Equipment
Year	Out-Closeness	Out-Closeness	Out-Closeness	Out-Closeness	Out-Closeness	Out-Closeness
1980	0.6020	0.5815	0.8170	0.8311	0.5041	0.5056
1981	0.6182	0.5948	0.8356	0.8349	0.5069	0.5056
1982	0.5897	0.5791	0.8106	0.8206	0.4920	0.4906
1983	0.6174	0.6120	0.8214	0.8512	0.4881	0.4959
1984	0.6007	0.5948	0.8125	0.8349	0.4764	0.5028
1985	0.6020	0.5916	0.8062	0.8440	0.4766	0.5069
1986	0.6280	0.6071	0.8288	0.8238	0.4792	0.4921
1987	0.6120	0.6154	0.8170	0.8364	0.4867	0.5083
1988	0.6339	0.6164	0.8863	0.8910	0.5040	0.5040
1989	0.6258	0.6104	0.8400	0.8468	0.4935	0.5013
1990	0.6382	0.6416	0.8386	0.8868	0.5054	0.5054
1991	0.6416	0.6382	0.8430	0.8578	0.5027	0.5054
1992	0.6269	0.6314	0.8434	0.8636	0.5134	0.5710
1993	0.6386	0.6320	0.8653	0.8765	0.5084	0.5012
1994	0.6554	0.6416	0.8730	0.8765	0.5182	0.5024
1995	0.7576	0.7329	0.7525	0.7813	0.4881	0.4881
1996	0.7450	0.7500	0.7426	0.8182	0.4945	0.5196
1997	0.7525	0.7143	0.7500	0.7732	0.4923	0.4945
1998	0.7377	0.7329	0.7426	0.7759	0.4978	0.4956
1999	0.7525	0.7525	0.7525	0.7979	0.4934	0.5102
2000	0.7923	0.7840	0.7840	0.8272	0.5056	0.5161
2001	0.8123	0.7951	0.8036	0.8333	0.5102	0.5294
2002	0.8182	0.7895	0.7979	0.8303	0.5184	0.5079
2003	0.8396	0.8123	0.8242	0.8427	0.5474	0.5196
2004	0.8242	0.8242	0.8364	0.8588	0.5396	0.5294
2005	0.8459	0.8242	0.8491	0.8555	0.5501	0.5422
2006	0.8621	0.8555	0.8364	0.8858	0.5556	0.5542
Min	0.5897	0.5791	0.7426	0.7732	0.4764	0.4881
Max	0.8621	0.8555	0.8863	0.8910	0.5556	0.5710
Average	0.6989	0.6872	0.8152	0.8391	0.5055	0.5113
Variance	0.0087	0.0083	0.0016	0.0010	0.0005	0.0004

As shown in the table above, the story here with the closeness centrality is similar to that of the out-degree centrality. The United States had established its trade network with the world long ago and had since been able to distribute its products to the other parts of the world easily. China had a relatively low closeness centrality at the beginning, meaning that it was difficult for China to distribute its products to the rest of the world. However, China experienced a dramatic improvement in the closeness centrality as it gradually established more and more trade partnerships. As of 2006, China had come close to the United States regarding the closeness centrality. Meanwhile, Ghana represents the other half of the story. Like many African countries, Ghana experienced almost zero improvements in the closeness centrality. Troubled by its deeply-rooted poverty, Ghana was not capable of producing products that can penetrate more markets, nor could Ghana afford to build the infrastructure to facilitate trade.

The fact that closeness centrality measures incorporate the structure of the entire network makes it stand out as a good predictor of economic growth. In an international trade context, this feature allows closeness centralities to measure how difficult it is for a country to access the world market compared to other countries. However, closeness centrality does not take the strength of links into the calculation. That said, it provides a bigger picture of the entire network structure, making it a better predictor than degree centralities.

Betweenness Centrality

Betweenness centrality is another measure of the importance of a node in a network. First introduced by Freeman (1977), it captures the importance of a node as an intermediary that connects other nodes through paths. Betweenness centrality of a node is defined as the number of shortest paths among all other nodes in which the node serves as an intermediary. Nodes with high betweenness centrality scores play an important role in connecting other nodes.

$$C_i^B = \frac{P_{xy}(i)}{P_{xy}} \tag{7}$$

Equation (7) defines betweenness centrality measure, in which P_{xy} is the total number of shortest paths from node x to node y. $P_{xy}(i)$, a function of i, represents the number of shortest paths between node x and node y that go through node i. Having a high betweenness centrality measure means that a country is playing an important role in connecting other countries, probably as an intermediary who consumes raw materials and produces finished goods. In theory, this centrality measure is well-suited for explaining the economic growth of many economies, such as Japan and South Korea. However, our dataset is restrained to aggregated product-level data, meaning that we might not be able to distinguish raw materials from final products. People may argue that raw materials and finished goods make up a major part of the trade flows of such intermediaries. Therefore, country-level weighted centrality might be able to capture the economic growth of value-adding intermediaries. However, without proper identification, it is hard to interpret the results from my empirical analysis. An alternative theory supporting betweenness centrality is that high betweenness centralities may suggest an important role in the trading network as a pure trade hub, which could potentially explain the growth stories of Hong Kong and Singapore. That said, pure trade hubs make up only a small portion of all the countries around the world, so the effectiveness of this alternative explanation remains doubtable when applied to a broader range of economies.

Since I am not able to distinguish raw materials from final products, it makes no sense to show descriptive statistics of betweenness centrality measures based on individual product groups. I will report the country-level weighted betweenness centrality in later sections.

Eigenvector Centrality

Eigenvector centrality measures the influence of a node in a very different approach. While many of the other centrality measures analyze the links that are connected to a node, eigenvector emphasizes the nodes that a node is connected. Specifically, it measures the connectedness and influence of a node by measuring the connectedness and influence of the nodes connected to it. In other words, a node within a sub-network of well-connected nodes is considered as well-connected. In the context of international trade, a country which trades closely with other well-connected and developed countries has higher eigenvector centrality than a country which does the opposite.

Eigenvector centrality also uses an unweighted version of the network, in which all the edges are binary ($a_{ij} \in \{0,1\}$). A country i's eigenvector can be calculated as following:

$$C_i^E = \sum_{j \neq i}^{N} a_{ij} C_j^E \quad (8)$$

We can solve this equation by mathematically computing the eigenvalues of the matrix. There can be multiple solutions to this equation, but there is always a unique solution with the highest eigenvalues, to which the corresponding eigenvector has all positive coefficients. Due to the nature of eigenvector centrality, it is highly correlated with degree centralities.

Eigenvector centrality measures for selected countries (China, United States, and Ghana) and product groups (textiles and transport equipment), along with some descriptive statistics, can be found in Table 3.

It is clear that the United States has maintained a relatively high eigenvector centrality over the entire period in both products. However, depending on the product classification, eigenvector centrality shows drastically different patterns. For example, China caught up with the United States in the textile industry in less than five years and kept growing throughout this period. By the year of 2006, China has an eigenvector centrality twice as large as that of the United States in the textile industry. Meanwhile, the eigenvector centrality of transport equipment tells a different story. The United States has been having a high eigenvector centrality in this industry consistently while China has not been able to improve very much. It is likely because textile industry is a typical low technology industry that does not require much innovation nor human capital, whereas transport equipment is a high technology industry that does the opposite. In the 1980s, China quickly became the leading exporter in the textile industry, resulting in a very high eigenvector centrality score. However, without enough human capital and the establishment of supporting industries, China remained low in eigenvector centrality in this field.

Table 3. Eigenvector centrality of China, United States, and Ghana in textile industry and transport equipment industry.

	China		United States		Ghana	
	Textiles	Transport Equipment	Textiles	Transport Equipment	Textiles	Transport Equipment
Year	Eigenvector	Eigenvector	Eigenvector	Eigenvector	Eigenvector	Eigenvector
1980	0.0941	0.0904	0.1353	0.6602	0.0006	0.0009
1981	0.1714	0.0934	0.2445	0.6679	0.0009	0.0007
1982	0.1773	0.0933	0.2470	0.6694	0.0005	0.0003
1983	0.2553	0.1012	0.3342	0.6082	0.0006	0.0008
1984	0.3819	0.0961	0.4285	0.6915	0.0004	0.0001
1985	0.3346	0.0927	0.3931	0.6915	0.0005	0.0004
1986	0.3838	0.1027	0.3534	0.6976	0.0005	0.0002
1987	0.3985	0.1003	0.3073	0.6875	0.0008	0.0002
1988	0.4638	0.0994	0.2816	0.6834	0.0007	0.0002
1989	0.5487	0.1022	0.3163	0.6716	0.0004	0.0002
1990	0.4254	0.1038	0.2712	0.6455	0.0007	0.0003
1991	0.5860	0.1048	0.3412	0.6489	0.0004	0.0002
1992	0.5241	0.1030	0.3795	0.6380	0.0010	0.0004
1993	0.6354	0.1005	0.3424	0.6836	0.0004	0.0002
1994	0.6519	0.1004	0.3038	0.6826	0.0002	0.0002
1995	0.6513	0.1324	0.2916	0.6821	0.0006	0.0002
1996	0.6532	0.1261	0.2911	0.6810	0.0007	0.0006
1997	0.6466	0.1244	0.3335	0.6851	0.0008	0.0004
1998	0.6270	0.1247	0.3764	0.6824	0.0013	0.0004
1999	0.6262	0.1228	0.3908	0.6884	0.0013	0.0004
2000	0.6376	0.1209	0.3661	0.6898	0.0012	0.0002
2001	0.6441	0.1199	0.3587	0.6847	0.0014	0.0002
2002	0.6432	0.1192	0.3781	0.6823	0.0014	0.0002
2003	0.6544	0.1189	0.3708	0.6700	0.0031	0.0003
2004	0.6555	0.1168	0.3763	0.6642	0.0063	0.0006
2005	0.6575	0.1136	0.4329	0.6654	0.0036	0.0005
2006	0.6639	0.1124	0.4449	0.6653	0.0034	0.0004
Min	0.0941	0.0904	0.1353	0.6082	0.0002	0.0001
Max	0.6639	0.1324	0.4449	0.6976	0.0063	0.0009
Average	0.5108	0.1087	0.3367	0.6729	0.0013	0.0004
Variance	0.0314	0.0001	0.0045	0.0004	0.0000	0.0000

Centrality Index

Volume-Weighted Centrality Index

As explained in the previous section, my data consists of bilateral trade flows for 28 industrial product groups, defined at the 3-digit level according to the International Standard Industrial Classification Revision 2, of more than two hundred countries over the period of 1980-2006. Instead of turning this data into a country-level aggregated dataset before computing the centralities, I want to illustrate how influential one product group may be within a country and thus computed export-volume-weighted centrality measures. Specifically, I regarded the trade flows for every single product group in every single year as an individual network. By doing that, I generated a total of 756 networks and computed the centrality measures for every country in every product group during 1980-2006. I then calculated a weighted average for each country based on the export share of different product groups within that country. Equation (8) below shows the formula of such calculation:

$$C_{ti} = \sum_{j=1}^{28} W_{tij} C_{tij} \tag{8}$$

As shown in equation (8), C_{ti} represents the weighted centrality measure of country i in year t. W_{tij} represents the export share of product group j in country i in year t, while C_{tij} represents the centrality measure of country i in year t within the trade network of product group j.

My logic behind this was that countries improve their products gradually from the least sophisticated to the most. It is very unlikely that a country can improve in all the industries at the same time since it must learn and establish the fundamentals before it proceeds to the more advanced industries. It is particularly true in a development context where countries exercise learning-by-doing. Suppose we have two countries with the same volumes of total export: country A specializes in some fundamental industries and experiences dramatic improvements in these industries while country B is doing ok in every industry. These two countries would probably have the same level of centrality if we were to compute it based on country-level aggregated exports. However, country A obviously has more potentials to carry its development in the fundamental industries to more sophisticated industries and experience economic growth. In this case, a volume-weighted centrality is a much better indicator of economic growth since such measures would surely capture the improvement country A is experiencing in certain industries and assign country A higher centrality measures than that of country B.

Table 4 below shows the volume-weighted centrality indices computed based on the above method. For the purpose of this paper, I am only showing the results of 2006 for selected countries, including OECD, BRICS, and the "Next Eleven," which were referred to by Benedictis et al. (2014) as the "most prominent countries in international trade."

Table 4. Volume-weighted average centrality measures of selected countries.

iso3	country name	Degree	Betweenness	Closeness	Eigenvector
AUS	Australia	0.7000	542.9474	0.7408	0.1066
AUT	Austria	0.7295	234.4477	0.7610	0.1085
BEL	Belgium	0.0000	0.0000	0.0000	0.0000
BGD	Bangladesh	0.6210	150.0585	0.7063	0.0952
BRA	Brazil	0.7238	233.1901	0.7546	0.1077
CAN	Canada	0.8027	544.5771	0.8054	0.1152
CHE	Switzerland	0.8144	320.4445	0.8179	0.1114
CHL	Chile	0.4153	41.8964	0.6076	0.0835
CHN	China	0.8506	482.7530	0.8316	0.1149
CZE	Czech Republic	0.6617	216.4608	0.7246	0.1037
DEU	Germany	0.9061	692.0637	0.8776	0.1163
DNK	Denmark	0.7788	330.2656	0.7935	0.1087

Table 4. Volume-weighted average centrality measures of selected countries—continued.

iso3	country name	Degree	Betweenness	Closeness	Eigenvector
EGY	Egypt, Arab Rep.	0.4957	72.4593	0.6378	0.0964
ESP	Spain	0.7843	316.8334	0.7862	0.1136
EST	Estonia	0.3685	81.9335	0.5906	0.0817
FIN	Finland	0.6713	151.9533	0.7316	0.1030
FRA	France	0.8510	509.9633	0.8328	0.1154
GBR	United Kingdom	0.8849	574.4672	0.8647	0.1146
GRC	Greece	0.5685	135.1009	0.6700	0.1006
HUN	Hungary	0.5916	78.3812	0.6935	0.0926
IDN	Indonesia	0.7262	337.1928	0.7600	0.1074
IND	India	0.8020	490.9173	0.8039	0.1154
IRL	Ireland	0.7158	228.1593	0.7541	0.1035
IRN	Iran, Islamic Rep.	0.4494	82.2055	0.6187	0.0895
ISL	Iceland	0.3358	25.2424	0.5815	0.0749
ISR	Israel	0.5975	86.1650	0.6953	0.0907
ITA	Italy	0.8428	514.6710	0.8272	0.1148
JPN	Japan	0.8598	403.1509	0.8531	0.1101
KOR	Korea, Rep.	0.7924	377.0269	0.8017	0.1101
LUX	Luxembourg	0.0000	0.0000	0.0000	0.0000
LVA	Latvia	0.3578	34.8116	0.5839	0.0756
MEX	Mexico	0.5980	247.7607	0.6903	0.1020
NGA	Nigeria	0.1697	103.9033	0.5153	0.0827
NLD	Netherlands	0.8283	422.9655	0.8197	0.1148
NOR	Norway	0.6058	110.8175	0.6962	0.0992
NZL	New Zealand	0.6939	366.1015	0.7460	0.0999
PAK	Pakistan	0.6147	216.4614	0.7082	0.0972
PHL	Philippines	0.6487	138.3542	0.7278	0.0915
POL	Poland	0.6543	277.7887	0.7164	0.1064
PRT	Portugal	0.6526	189.0988	0.7165	0.1021
RUS	Russian Federation	0.5619	136.4729	0.6638	0.1027
SVK	Slovak Republic	0.5130	141.2245	0.6555	0.0926
SVN	Slovenia	0.5298	118.5200	0.6614	0.0864
SWE	Sweden	0.7595	244.1565	0.7796	0.1093
TUR	Turkey	0.7309	269.9661	0.7561	0.1087
USA	United States	0.8741	676.8734	0.8488	0.1168
VNM	Vietnam	0.6071	188.7477	0.6923	0.0985
ZAF	South Africa	0.7546	487.8321	0.7693	0.1119

CHAPTER FOUR

Model

Panel

Naïve OLS

My first attempt to address the relationship between economic growth and the centrality measures of international trade network was established in the panel data structure. I ran a naïve OLS regression with year fixed effects and various control variables. The dependable variable that I used in this model is the yearly percentage growth in GDP per capita. However, due to the fact that international trade is strongly correlated with economic growth, one of the major problems of my analysis is endogeneity. Centrality measures, which were computed based on international trade flows, are highly likely to be endogenous variables, making it difficult to interpret the causal relationship between them and economic growth. Moreover, since the regressors are correlated with the residual, naïve OLS estimates are biased and inconsistent. To mitigate this issue, I implemented three strategies as shown below.

Fixed-Effect Estimation

Fixed-effect estimation controls for the average differences across countries in both observable and unobservable regressors, which offers a solution to the endogeneity problem without resorting to instrumental variables. As a result, all time-invariant regressors were absorbed by the fixed effects and thus omitted. The treatment in this analysis would be the year-to-year difference in centrality measures, which is my question of interest. However, it would be difficult to sell the idea that the change in GDP per capita of a particular year was caused by the change in centrality the year before. Economic growth is a slow and prolonged process, but regression results based on yearly panel data could only suggest some short-term effects. To cope with this new issue, I must turn my analysis into a long-run story.

10-Year Moving Average

The easiest way of turning annual data into a long-run analysis is to take averages of the variables. Instead of analyzing the effect of improvement in centrality on economic growth on a yearly basis, I investigated this effect through long-term averages. One of the techniques I adopted was the 10-year moving average, in which case my treatment became the difference between the 10-year average centrality measures, effectively turning this into a long-run analysis. Now my hypothesis is that improvement in centralities over a long period of time can explain long-term economic growth and the level of GDP per capita. My dependent variables, in this case, would be the average growth in GDP per capita in the 10-year period and the level of GDP per capita after the 10-year period. Since I am adopting the moving average, the difference in average centrality that I am investigating is essentially the difference between centrality measures in year 1 and year 11. In addition to that, this technique helped me smooth out changes in centralities and GDP per capita by filtering out the outliers.

5-Year Block Average

Another averaging technique I adopted was the 5-year block average. My treatment is still the change in average centrality, and this technique also worked in terms smoothing out changes and filtering out outliner. However, the smoothing process is not as powerful as that of the 10-year moving average. Instead of analyzing the point-to-point changes from year 1 to year 11, I am now investigating the difference between the two five-year periods.

System Generalized Method of Moments

As is often the case, I suspected that economic growth and level of GDP per capita are highly correlated with their lagged values. My regression, to which I added the lagged variables, turned into a dynamic panel data model. As a result, error terms are correlated with regressors even when the number of units in my panel approaches infinity, in which case fixed-effect estimators will not consistently estimate the coefficients. This issue is often referred to as the dynamic panel bias or the Nickell bias (Nickell, 1981). A solution to this problem is System Generalized Method of Moments, in which the model is specified as a system of equations. For each period in the panel, an equation was generated with applicable instruments. These instruments are not necessarily the same as those of other equations. Given that it is often difficult to find instruments for macroeconomic data and that macroeconomic measures are often correlated with their lagged values, this method is popular in macro analysis.

Instrumental Variable

An alternative solution to the endogeneity problem and dynamic panel bias is a cross-sectional model with instrumental variables. To achieve this, I have to turn my panel dataset into a cross-sectional dataset first. Since I was more interested in the long-run aspect of centrality measures and economic growth, I computed the average value of these variables over the entire period, after which I have a cross-section of countries. By doing that, I eliminated the dynamic panel bias from my analysis. Moreover, the treatment I had in my new model is the difference in average centralities between two countries, making this a typical long-run analysis.

To deal with the endogeneity problem, I generated an instrumental variable based on the geographies of countries. Specifically, I computed a strength centrality measure for all the countries based on the actual geographic distance from the respective country to all the other countries. I hypothesize that a country's trade network is strongly correlated with its location and the geographies around that country. For example, Landlocked countries cannot take the advantages of low-cost ship transport since they don't have access to the sea; countries surrounded by mountains cannot take the advantages of fast cargo airplanes since they have limited access to the sky. More generally speaking, I hypothesize that a country who has a low strength centrality in the network of actual geographic distances (e.g. a country which is geographically far from all the other countries) is going to suffer from increased logistic costs and thus have a lower centrality in the trade network. Moreover, I argue that the location of a country could only affect GDP per capita through the channel of trade network, which fulfills the exclusion restriction.

CHAPTER FIVE

Results and Discussions

Panel

Table 5 reports the results of a fixed-effect estimation using the yearly panel, which I refer to as regression Panel-Annual. While fixed effects should be able to take away the endogeneity problem, it would be hard to justify that the change in centrality from one year to another is going to affect the economic growth of a country. With that being said, I am reporting these results for the purpose of comparison with those of more sophisticated models.

Table 5. Results of regression Panel-Annual.

VARIABLES	(1) Growth	(2) Growth	(3) Growth	(4) Growth
Oil rents	0.00130***	0.00139***	0.00131***	0.00142***
	(0.000493)	(0.000522)	(0.000491)	(0.000504)
Closeness	0.179***			
	(0.0361)			
Betweenness		3.72e-05***		
		(1.23e-05)		
Eigenvector			0.860***	
			(0.183)	
Degree				0.0904***
				(0.0165)
Constant	-0.0844***	0.00864***	-0.0538***	-0.0123**
	(0.0202)	(0.00289)	(0.0152)	(0.00553)
Observations	2,941	2,941	2,941	2,941
R-squared	0.046	0.011	0.041	0.033
Number of countries	134	134	134	134

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Since fixed-effect estimators absorbed all time-invariant variables, I omitted the time-invariant variables from the results. A quick glance at the table shows that all four centrality measures have positive coefficients at 1% significance level, providing some support for the hypothesis that centrality in the international trade network could explain economic growth.

Table 6-9 entail the results of fixed-effect estimation using average GDP per capita, average growth, and average centrality measures. The treatment in these models is the difference in average centrality measures over long periods of time. Table 6 shows the results of the fixed-effect regression with GDP per capita as the dependent variable and 10-year moving averages of centralities as independent variables. I denote this regression as Panel-GDPPC-10year.

Table 6. Results of regression Panel-GDPPC-10year.

VARIABLES	(1) GDP per capita	(2) GDP per capita	(3) GDP per capita	(4) GDP per capita
Oil rents	-0.00166	-0.00149	-0.00209	0.00113
	(0.00260)	(0.00259)	(0.00282)	(0.00221)
Closeness	1.662**			
	(0.782)			
Betweenness		0.000580*		
		(0.000297)		
Eigenvector			-0.323	
			(1.974)	
Degree				1.342***
				(0.135)
Constant	7.722***	8.597***	8.718***	8.259***
	(0.454)	(0.0480)	(0.166)	(0.0434)
Observations	1,729	1,729	1,729	1,729
R-squared	0.054	0.055	0.003	0.497
Number of countries	105	105	105	105

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In this model, closeness centrality has a coefficient of 1.662, suggesting that every 1% decrease in the total number of steps needed to connect to all other countries leads to a 1.662% increase in GDP per capita. Meanwhile, degree centrality has a coefficient of 1.34, suggesting that having an additional 2.2 direct trade connections leads to a 1.34% increase in GDP per capita.

Table 7 shows the results of the fixed-effect regression with the average growth of GDP per capita as the dependent variable and 10-year moving averages of centralities as independent variables. I denote this regression as Panel-Growth-10year.

Table 7. Results of regression Panel-Growth-10year.

	(1)	(2)	(3)	(4)
VARIABLES	Avg_Growth	Avg_Growth	Avg_Growth	Avg_Growth
Oil rents	-0.000604	-0.000599	-0.000640	-0.000527
	(0.000393)	(0.000392)	(0.000391)	(0.000387)
Closeness	0.0124			
	(0.0429)			
Betweenness		7.94e-06		
		(1.61e-05)		
Eigenvector			0.354***	
			(0.128)	
Degree				0.0311**
				(0.0143)
Constant	0.0124	0.0184***	-0.0107	0.00958*
	(0.0253)	(0.00318)	(0.0109)	(0.00493)
Observations	1,700	1,700	1,700	1,700
R-squared	0.018	0.019	0.042	0.041
Number of countries	103	103	103	103

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As shown above, eigenvector centrality has a coefficient of 0.354. However, it is difficult to interpret the results of eigenvector centrality numerically. Meanwhile, degree centrality has a coefficient of 0.0311, suggesting that having an additional 2.2 direct trade connections leads to a 0.0311% increase in average growth rate.

Table 8 presents the results of the fixed-effect regression with GDP per capita as the dependent variable and 5-year block averages of centralities as independent variables. I refer to this regression as Panel-GDPPC-5year.

Table 8: Results of regression Panel-GDPPC-5year.

VARIABLES	(1) GDP per capita	(2) GDP per capita	(3) GDP per capita	(4) GDP per capita
Oil rents	0.00202	0.00276	0.00229	0.00581*
	(0.00353)	(0.00357)	(0.00379)	(0.00304)
Closeness	1.858***			
	(0.586)			
Betweenness		0.000483		
		(0.000291)		
Eigenvector			0.162	
			(1.763)	
Degree				1.343***
				(0.145)
Constant	7.509***	8.510***	8.573***	8.159***
	(0.338)	(0.0489)	(0.146)	(0.0488)
Observations	483	483	483	483
R-squared	0.097	0.045	0.003	0.499
Number of countries	105	105	105	105

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In this model, closeness centrality has a coefficient of 1.858, suggesting that every 1% decrease in the total number of steps needed to connect to all other countries leads to a 1.858% increase in GDP per capita. Meanwhile, degree centrality has a coefficient of 1.343, suggesting that having an additional 2.2 direct trade connections leads to a 1.343% increase in GDP per capita.

Table 9 presents the results of the fixed-effect regression with the average growth of GDP per capita as the dependent variable and 5-year block averages of centralities as independent variables. I refer to this regression as Panel-Growth-5year.

Table 9. Results of regression Panel-Growth-5year.

VARIABLES	(1) Avg_Growth	(2) Avg_Growth	(3) Avg_Growth	(4) Avg_Growth
Oil rents	-0.00102	-0.00100	-0.00107	-0.000923
	(0.000763)	(0.000766)	(0.000750)	(0.000785)
Closeness	0.0385			
	(0.0318)			
Betweenness		8.35e-06		
		(1.11e-05)		
Eigenvector			0.515***	
			(0.150)	
Degree				0.0336**
				(0.0150)
Constant	-0.00105	0.0199***	-0.0224	0.0106
	(0.0199)	(0.00508)	(0.0138)	(0.00738)
Observations	481	481	481	481
R-squared	0.029	0.028	0.057	0.041
Number of countries	105	105	105	105

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As shown above, eigenvector centrality has a coefficient of 0.515. However, it is difficult to interpret the results of eigenvector centrality numerically. Meanwhile, degree centrality has a coefficient of 0.0336, suggesting that having an additional 2.2 direct trade connections leads to a 0.0336% increase in average growth rate.

To conclude the results, the coefficient of export degree centrality remains positive and statistically significant in all four models. It is surprising that such a simple measure of trade (e.g. how many trading partners a country has) could explain economic growth and level of GDP per capita very well, not to mention that it does not incorporate the structure of the trade network at all. On the contrary, closeness and eigenvector centralities both have their limitations. Specifically, export closeness centrality did well in explaining the level of GDP per capita while eigenvector centrality did well in explaining the average growth. Closeness centrality measures how hard it is for a country to export its products to the other countries. In this case, developed countries, who are likely to have much higher closeness centralities, grow relatively slow in percentage points. As a result, closeness centrality failed to explain the average growth rate of economies. Eigenvector centralities, on the other hand, focuses on the sub-network in which a country trades. A possible explanation is that being in a sub-network of industrialized countries may suggest learning-by-doing, which boosts economic growth dramatically. Betweenness centrality is the worst performing measure in these models. I only see it statistically significant in one of the regressions, and the significance level is relatively low at 10%. This result is likely due to the data limitation we have. As discussed previously, there are some development theories that are supported by the betweenness centrality. However, certain limits of my data prevent me from analyzing this further.

System Generalized Method of Moments

Table 10 reports the regression results of the system GMM model. Instrumental variables were generated using lagged dependable variable and centrality measures. The dependent variable in this model is year-to-year growth in GDP per capita. I refer to this model as regression GMM-Growth-Annual in the rest of the paper.

Table 10. Results of regression GMM- Growth-Annual.

VARIABLES	(1) Growth	(2) Growth	(3) Growth	(4) Growth
Lag. Growth	0.310***	0.308***	0.317***	0.315***
	(0.0745)	(0.0741)	(0.0737)	(0.0734)
America	-0.0165	-0.0151	-0.000660	-0.0173
	(0.0244)	(0.0186)	(0.0118)	(0.0185)
Asia	-0.0110	-0.0134	-0.000816	-0.0149
	(0.0244)	(0.0180)	(0.0122)	(0.0178)
Europe	-0.00318	-0.0126	0.0115	-0.00386
	(0.0235)	(0.0171)	(0.0156)	(0.0126)
Pacific	-0.0310	-0.0322	-0.0536	-0.0416*
	(0.0254)	(0.0229)	(0.0346)	(0.0244)
Area	1.45e-09	-1.34e-09	-4.49e-10	-9.80e-10
	(1.18e-09)	(2.62e-09)	(2.00e-09)	(1.43e-09)
Landlocked	-0.0235	-0.0186	-0.0191	-0.0153
	(0.0228)	(0.0197)	(0.0177)	(0.0170)
Number of cities	-0.000651	-0.000560	-0.00124	-0.000720
	(0.000689)	(0.000613)	(0.000839)	(0.000724)
Betweenness	-1.29e-05			
	(2.19e-05)			
Lag. Betweenness	1.20e-05			
	(2.15e-05)			
Closeness		-0.0771		
		(0.0723)		
Lag. Closeness		0.133**		
		(0.0598)		
Eigenvector			-0.576	
			(0.714)	
Lag. Eigenvector			0.247	
			(0.531)	
Degree				0.0274
				(0.0724)
Lag. Degree				0.00797
				(0.0729)
Constant	0.0401	0.0131	0.0680*	0.0358
	(0.0310)	(0.0255)	(0.0358)	(0.0249)
Observations	4,082	4,082	4,082	4,082
Number of ID	184	184	184	184

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Regression results from the system GMM model show that lagged growth is the single most important explanatory variable in this model. It took away the explanatory power of almost all other variables except the closeness centrality. The results seem acceptable since the system GMM solved the dynamic panel bias and the endogeneity problem. However, a closer look at the results raised some concerns. First, this model was running on 649 instruments, which is more than the number of countries I have in this dataset. As a result, I may have an over-identification problem in this regression. Second, lagged centralities were used to generate instruments, meaning that two coefficients of the centrality measures (centrality and lagged centrality) were estimated by this model. Browsing through the results of all GMM regressions, I realized that these two coefficients often show the opposite signs, which made it difficult to interpret the coefficients in this model. With the over-identification problem and ambiguity in interpreting coefficients, none of the four centrality measures could consistently explain economic growth under this model.

Instrumental Variable

GDP per capita

Table 11 and 12 report the results of my first cross-sectional regression with an instrumental variable. Since the dependent variable in this regression is the level of GDP per capita in 2006, the regression is denoted as regression IV-GDPPC for the rest of the paper.

Table 11. First-stage results of regression IV-GDPPC.

VARIABLES	(1) Betweenness	(2) Closeness	(3) Eigenvector	(4) Degree
Europe & Central Asia	-46.49	-0.172***	-0.00633	-0.0302
	(80.73)	(0.0539)	(0.0168)	(0.0979)
Latin America & Caribbean	-180.8***	-0.113***	-0.0302**	-0.217***
	(66.13)	(0.0393)	(0.0126)	(0.0752)
Middle East & North Africa	-81.09	0.0213	0.0298*	0.0522
	(77.55)	(0.0471)	(0.0160)	(0.0931)
North America	309.4	0.0762	0.0190	0.124
	(223.0)	(0.0626)	(0.0159)	(0.113)
South Asia	-36.19	0.0406	0.0179	0.0533
	(75.18)	(0.0416)	(0.0142)	(0.0892)
Sub-Saharan Africa	-106.3	-0.0652	-0.00859	-0.102
	(69.67)	(0.0435)	(0.0147)	(0.0872)
Asia	-18.93	-0.0341	-0.0120	-0.0479
	(24.66)	(0.0265)	(0.00776)	(0.0446)
Europe	182.3***	0.226***	0.0465***	0.265***
	(63.45)	(0.0635)	(0.0164)	(0.0827)
Pacific	-23.61	-0.194***	-0.0646***	-0.341**
	(168.7)	(0.0678)	(0.0210)	(0.134)
Area	1.07e-05	7.39e-09*	3.21e-09**	2.06e-08***
	(6.90e-06)	(4.12e-09)	(1.28e-09)	(7.57e-09)
Landlocked	-70.69*	-0.0578	-0.0170**	-0.0751*
	(36.15)	(0.0371)	(0.00803)	(0.0427)
Number of cities	0.630	0.00129	0.000483	0.00230
	(2.578)	(0.00188)	(0.000649)	(0.00364)
Oil rents	-0.774*	-0.000401	-0.000257**	-0.00191***
	(0.406)	(0.000403)	(0.000120)	(0.000613)
IV	0.0327	4.33e-05***	1.50e-05***	7.71e-05***
	(0.0214)	(1.31e-05)	(4.01e-06)	(2.43e-05)
Constant	-116.6	0.194	-0.0599	-0.394*
	(195.6)	(0.132)	(0.0401)	(0.227)
Observations	130	130	130	130
R-squared	0.337	0.376	0.419	0.476
F-statistic	4.28	20.28	15.20	13.48

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12. Second-stage results of regression IV-GDPPC.

VARIABLES	(1) GDP per capita	(2) GDP per capita	(3) GDP per capita	(4) GDP per capita
Europe & Central Asia	1.973	3.422***	1.407**	1.390*
	(1.501)	(1.216)	(0.660)	(0.720)
Latin America & Caribbean	3.842**	2.192***	1.853***	2.303***
	(1.723)	(0.576)	(0.510)	(0.636)
Middle East & North Africa	3.305*	1.624***	0.777**	1.519***
	(1.691)	(0.522)	(0.394)	(0.522)
North America	-2.319	2.039***	2.318***	2.126***
	(4.555)	(0.758)	(0.573)	(0.743)
South Asia	0.278	-0.879**	-1.023**	-0.739
	(1.267)	(0.405)	(0.398)	(0.510)
Sub-Saharan Africa	2.388	1.401*	0.873	1.298*
	(1.699)	(0.719)	(0.611)	(0.742)
Asia	0.765*	0.883**	0.890**	0.789**
	(0.457)	(0.371)	(0.354)	(0.351)
Europe	-0.182	0.0177	1.217*	1.030
	(1.968)	(1.111)	(0.709)	(0.777)
Pacific	0.306	2.432***	2.339***	2.398***
	(1.774)	(0.620)	(0.609)	(0.566)
Area	-1.05e-07	-1.64e-08	-4.08e-08	-7.09e-08
	(1.49e-07)	(5.71e-08)	(5.67e-08)	(6.95e-08)
Landlocked	0.855	0.387	0.275	0.183
	(0.797)	(0.428)	(0.257)	(0.243)
Number of cities	-0.105***	-0.111***	-0.112***	-0.111***
	(0.0382)	(0.0220)	(0.0219)	(0.0242)
Oil rents	0.0361***	0.0280***	0.0324***	0.0368***
	(0.0114)	(0.00576)	(0.00648)	(0.00705)
Betweenness	0.0173*			
	(0.00965)			
Closeness		13.08***		
		(3.967)		
Eigenvector			37.76***	
			(11.00)	
Degree				7.340***
				(2.272)
Constant	6.393***	1.842	6.636***	7.264***
	(1.943)	(2.454)	(1.093)	(1.013)
Observations	130	130	130	130
R-squared		0.321	0.714	0.653

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note that with F-statistics of 20.28, 15.20, and 13.38, the first-stage regression suggests my instrument is strong for closeness, eigenvector, and degree centrality, respectively. Moreover, the coefficients of my instrumental variable are significant at 1% for the three centrality measures mentioned above. On the contrary, betweenness centrality failed the first stage, which is consistent with my hypothesis that betweenness centrality is limited by, and not applicable to, my data.

These results suggest that closeness, degree, and eigenvector centralities are all good predictors of the level of GDP per capita. The coefficients of these measures have a positive sign at a significance level of 1% across the board, which provides evidence suggesting that higher average closeness, eigenvector, and degree centrality over a period leads to a higher GDP per capita at the end. Specifically speaking, closeness centrality has a coefficient of 13.08, suggesting that every 1% decrease in the total number of steps needed to connect to all other countries leads to a 13.08% increase in GDP per capita. Moreover, degree centrality has a coefficient of 7.34, suggesting that having an additional 2.2 direct trade connections leads to a 7.34% increase in GDP per capita. As discussed previously, it is hard to interpret the coefficient of eigenvector centrality numerically. Betweenness centrality does seem to be significant at 10% level. However, since my instrument is weak for betweenness centrality, the coefficients I got in the second-stage may be biased.

Average Growth

Table 13 and 14 reports the results of my second cross-sectional regression with an instrumental variable. The dependent variable in this regression is the average growth of GDP per capita during 1980-2006. Let us call it regression IV-Growth for the rest of the paper.

Table 13. First-stage results of regression IV-Growth.

VARIABLES	(1) Betweenness	(2) Closeness	(3) Eigenvector	(4) Degree
America	-104.3**	-0.0870***	-0.0171**	-0.118**
	(50.78)	(0.0315)	(0.00849)	(0.0481)
Asia	-6.858	-0.0393	-0.00264	0.0151
	(20.98)	(0.0251)	(0.00548)	(0.0277)
Europe	144.0**	0.0319	0.0171*	0.190***
	(58.49)	(0.0459)	(0.0102)	(0.0556)
Pacific	-88.61	-0.252***	-0.0508***	-0.295***
	(119.2)	(0.0652)	(0.0178)	(0.104)
Area	1.98e-05*	5.12e-09	2.64e-09*	2.24e-08**
	(1.11e-05)	(6.70e-09)	(1.54e-09)	(9.10e-09)
Landlocked	-65.00***	-0.109***	-0.0260***	-0.0984***
	(22.12)	(0.0289)	(0.00535)	(0.0264)
Number of cities	8.474*	0.00746**	0.00222**	0.0112*
	(4.963)	(0.00367)	(0.00109)	(0.00595)
Oil rents	-2.292***	-0.00122**	-0.000438***	-0.00317***
	(0.740)	(0.000591)	(0.000132)	(0.000723)
Initial GDPPC	0.00508**	4.20e-06***	1.12e-06***	5.60e-06***
	(0.00205)	(1.32e-06)	(3.01e-07)	(1.76e-06)
IV	0.0416**	4.81e-05***	8.64e-06**	6.05e-05***
	(0.0190)	(1.29e-05)	(3.46e-06)	(1.93e-05)
Constant	-470.4***	-0.0278	-0.0541*	-0.550***
	(171.6)	(0.115)	(0.0287)	(0.150)
Observations	130	130	130	130
R-squared	0.364	0.387	0.490	0.539
F-statistic	6.67	21.31	17.97	16.41

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Similarly, the F-statistics are well above 10 for closeness, eigenvector, and degree centrally, with values of 21.31, 17.97, and 16.41 respectively. They suggest that I have a strong instrument for the endogenous variables I specified. Furthermore, the instrument is also statistically significant in the first stage regression. Again, my instrument is weak when explaining betweenness centrality, suggesting that my second-stage results for betweenness centrality may be biased.

Table 14. Second-stage results of regression IV-Growth.

VARIABLES	(1) Avg_Growth	(2) Avg_Growth	(3) Avg_Growth	(4) Avg_Growth
America	0.00257	-0.00196	-0.000839	-0.00107
	(0.00502)	(0.00510)	(0.00540)	(0.00470)
Asia	0.00765	0.0119**	0.00857	0.00496
	(0.00617)	(0.00585)	(0.00683)	(0.00642)
Europe	0.0175	0.0357***	0.0272**	0.0196
	(0.0150)	(0.0107)	(0.0119)	(0.0119)
Pacific	-0.0118	0.00846	0.0126	0.00610
	(0.0126)	(0.00985)	(0.00822)	(0.00775)
Area	-1.72e-09	6.83e-10	-6.15e-10	-1.04e-09
	(1.88e-09)	(6.82e-10)	(9.72e-10)	(9.80e-10)
Landlocked	0.000848	0.00548	0.0103	0.00127
	(0.00699)	(0.00779)	(0.0107)	(0.00608)
Number of cities	-0.00232**	-0.00201**	-0.00267*	-0.00220**
	(0.00115)	(0.000896)	(0.00140)	(0.00105)
Oil rents	0.000610**	0.000416*	0.000581*	0.000593**
	(0.000309)	(0.000242)	(0.000313)	(0.000274)
Initial GDPPC	-1.48e-06**	-1.25e-06***	-1.52e-06***	-1.29e-06***
	(6.00e-07)	(3.74e-07)	(5.53e-07)	(4.09e-07)
Betweenness	0.000157**			
	(7.80e-05)			
Closeness		0.136***		
		(0.0503)		
Eigenvector			0.754**	
			(0.339)	
Degree				0.108**
				(0.0420)
Constant	0.0604**	-0.00941	0.0276	0.0461**
	(0.0265)	(0.0254)	(0.0258)	(0.0227)
Observations	130	130	130	130

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Similar to the results of IV-GDPPC, closeness, degree, and eigenvector centralities are good predictors of average growth during 1980-2006. The coefficient of closeness centrality is positive at a significance level of 1% while the coefficients of eigenvector and degree centrality are positive at a significance level of 5%. These results suggest that countries with higher average closeness, eigenvector, and degree centrality over a period experience faster economic growth during the same time. Specifically speaking, closeness centrality has a coefficient of 0.136, suggesting that every 1% decrease in the total number of steps needed to connect to all other countries leads to a 0.136% increase in average growth rate. Moreover, degree centrality has a coefficient of 0.108, suggesting that having an additional 2.2 direct trade connections leads to a 0.108% increase in GDP per capita. The coefficient of betweenness centrality is also positive at a significance level of 5%. However, with a first-stage F-statistic of 6.67, I may have a weak instrument problem, invalidating the results on betweenness centrality.

Conclusion

This paper analyzes the relationship between the structure of international trade network and economic growth. By computing various centrality measures for different products in different countries during 1980-2006, I could generate weighted centralities to represent the structure and properties of a country's position in the international trade network. These centrality measures were put into some relevant models to test their explanatory power on economic growth and the level of GDP per capita. In particular, I implemented regressions such as naïve OLS with the panel, fixed-effect estimation, system GMM, and cross-section with instrumental variables. My regression results suggest that these centrality measures, except the betweenness centrality, are good predictors of GDP per capita and economic growth. To be more precise, improvement in these centrality measures leads to higher GDP per capita and faster economic growth. Surprisingly, degree centrality is not an inferior estimator as I once believed, even though the concept of it was rather simple. Judging from the results, I would argue that closeness centrality is still slightly better than other measures since its results tend to be more statistically significant. Having said that, I believe the advantage of closeness centrality is marginal. Moreover, I showed that betweenness centrality was a particularly bad predictor of GDP per capita and growth, possibly due to the limitation in my data.

The real-world implication of my findings is that having more trade connections, either directly or indirectly, leads to higher GDP per capita and faster growth. In particular, the positive coefficient of degree centrality suggests that having more direct trade connections results in faster economic growth, while the positive coefficient of closeness centrality suggests that having more indirect trade connections also leads to faster economic growth. Regarding the indirect trade connections, I argue that economies benefit from having well-connected trade partners, which helps them connect to other economies with whom they don't have direct connections. In this case, well-connected countries create a spillover effect that benefits their less-connected trade partners, which is captured by the closeness centrality.

Moving forward, researchers can conduct similar analysis using the latest data instead of this relatively outdated dataset. One of the biggest problems I had with my analysis was missing data. There are more than two hundred countries around the world, but I only have sufficient data for about 130 of them, not to mention that these missing countries are mostly developing countries. Adding them into the regression may or may not improve the results, but it improves the robustness of such analysis. Another interesting topic would be to develop a different algorithm for computing the weighted average centrality. For example, instead of using export shares as the weight, one could generate a price or sophistication level indicator as the weight when computing the averages. I hypothesize that centrality measures of different product groups tend to have different magnitudes of effect on economic growth, with higher income products being more influential on development. Researchers can test this hypothesis by developing a new averaging algorithm mentioned above.

Development of an economy is undoubtedly multifaceted. While my thesis only covers a small aspect of the story, it is my sincere hope that my work can inspire and encourage future research.

APPENDIX

APPENDIX

Additional Table

Table A.1. Volume-weighted average centrality measures of all countries in 2006.

iso3	country name	Degree	Betweenness	Closeness	Eigenvector
ABW	Aruba	0.0970	1.5585	0.4830	0.0342
AFG	Afghanistan	0.1768	3.0085	0.5305	0.0476
AGO	Angola	0.0571	5.2441	0.4769	0.0498
ALB	Albania	0.1484	6.1080	0.5133	0.0564
AND	Andorra	0.1898	3.4887	0.5361	0.0394
ARE	United Arab Emirates	0.4619	81.4188	0.6241	0.0957
ARG	Argentina	0.5790	87.5086	0.6851	0.0955
ARM	Armenia	0.1571	6.4611	0.5186	0.0596
ASM	American Samoa	0.0945	1.4036	0.5074	0.0233
ATG	Antigua and Barbuda	0.1611	9.1687	0.5278	0.0494
AUS	Australia	0.7000	542.9474	0.7408	0.1066
AUT	Austria	0.7295	234.4477	0.7610	0.1085
AZE	Azerbaijan	0.1794	13.7515	0.5200	0.0639
BDI	Burundi	0.0808	4.0501	0.4942	0.0335
BEN	Benin	0.0460	0.9023	0.4212	0.0310
BFA	Burkina Faso	0.0748	0.5048	0.4890	0.0322
BGD	Bangladesh	0.6210	150.0585	0.7063	0.0952
BGR	Bulgaria	0.5311	103.8796	0.6552	0.0955
BHR	Bahrain	0.2745	25.9980	0.5528	0.0780
BHS	Bahamas, The	0.1883	12.6210	0.5340	0.0568
BIH	Bosnia and Herzegovina	0.2597	32.8568	0.5564	0.0711
BLR	Belarus	0.3265	20.9457	0.5717	0.0733
BLZ	Belize	0.1889	5.2498	0.5349	0.0495
BMU	Bermuda	0.1075	1.0547	0.5132	0.0367
BOL	Bolivia	0.1834	5.3855	0.5297	0.0536
BRA	Brazil	0.7238	233.1901	0.7546	0.1077
BRB	Barbados	0.2756	48.7019	0.5608	0.0659
BRN	Brunei Darussalam	0.1919	2.9847	0.5387	0.0523
BTN	Bhutan	0.0223	0.0015	0.4661	0.0097
CAF	Central African Republic	0.0765	0.3650	0.4917	0.0312
CAN	Canada	0.8027	544.5771	0.8054	0.1152

Table A.1. Volume-weighted average centrality measures of all countries in 2006—continued.

iso3	country name	Degree	Betweenness	Closeness	Eigenvector
CHE	Switzerland	0.8144	320.4445	0.8179	0.1114
CHL	Chile	0.4153	41.8964	0.6076	0.0835
CHN	China	0.8506	482.7530	0.8316	0.1149
CIV	Cote d'Ivoire	0.3062	76.8020	0.5654	0.0779
CMR	Cameroon	0.2392	31.5161	0.5411	0.0704
COG	Congo, Rep.	0.0899	2.4786	0.4872	0.0422
COL	Colombia	0.3847	67.6862	0.5983	0.0818
COM	Comoros	0.0887	6.6023	0.5095	0.0549
CPV	Cabo Verde	0.1000	1.5264	0.5009	0.0362
CRI	Costa Rica	0.4530	83.0374	0.6341	0.0807
CUB	Cuba	0.2456	52.2659	0.5460	0.0723
CYM	Cayman Islands	0.1066	0.9749	0.5129	0.0385
CYP	Cyprus	0.4278	38.0420	0.6179	0.0813
CZE	Czech Republic	0.6617	216.4608	0.7246	0.1037
DEU	Germany	0.9061	692.0637	0.8776	0.1163
DJI	Djibouti	0.0721	0.7947	0.4971	0.0385
DMA	Dominica	0.1769	12.8630	0.5286	0.0484
DNK	Denmark	0.7788	330.2656	0.7935	0.1087
DOM	Dominican Republic	0.3239	20.1636	0.5770	0.0674
DZA	Algeria	0.2565	33.5170	0.5422	0.0835
ECU	Ecuador	0.3952	30.1355	0.6049	0.0755
EGY	Egypt, Arab Rep.	0.4957	72.4593	0.6378	0.0964
ERI	Eritrea	0.0501	0.2236	0.4746	0.0222
ESP	Spain	0.7843	316.8334	0.7862	0.1136
EST	Estonia	0.3685	81.9335	0.5906	0.0817
ETH	Ethiopia	0.1960	25.2793	0.5317	0.0656
FIN	Finland	0.6713	151.9533	0.7316	0.1030
FJI	Fiji	0.2083	62.2824	0.5361	0.0479
FRA	France	0.8510	509.9633	0.8328	0.1154
FSM	Micronesia, Fed. Sts.	0.0342	0.0134	0.4880	0.0131
GAB	Gabon	0.2237	23.0918	0.5318	0.0641
GBR	United Kingdom	0.8849	574.4672	0.8647	0.1146
GEO	Georgia	0.2317	13.9602	0.5410	0.0655
GHA	Ghana	0.2443	37.3174	0.5493	0.0761
GIB	Gibraltar	0.1607	3.1639	0.5171	0.0419
GIN	Guinea	0.0820	1.6714	0.4921	0.0402
GMB	Gambia, The	0.1077	3.7418	0.5091	0.0467

Table A.1. Volume-weighted average centrality measures of all countries in 2006—continued.

iso3	country name	Degree	Betweenness	Closeness	Eigenvector
GNB	Guinea-Bissau	0.0367	0.1672	0.4796	0.0253
GNQ	Equatorial Guinea	0.0502	0.4706	0.4805	0.0262
GRC	Greece	0.5685	135.1009	0.6700	0.1006
GRD	Grenada	0.0949	6.7296	0.5035	0.0446
GRL	Greenland	0.1653	10.8672	0.5271	0.0608
GTM	Guatemala	0.3174	14.6435	0.5758	0.0669
GUM	Guam	0.0336	0.0388	0.4639	0.0207
GUY	Guyana	0.1916	41.6178	0.5319	0.0480
HKG	Hong Kong SAR, China	0.7828	243.5526	0.8012	0.1058
HND	Honduras	0.3352	14.4382	0.5840	0.0680
HRV	Croatia	0.4033	64.3179	0.6075	0.0847
HTI	Haiti	0.2347	3.0637	0.5518	0.0500
HUN	Hungary	0.5916	78.3812	0.6935	0.0926
IDN	Indonesia	0.7262	337.1928	0.7600	0.1074
IND	India	0.8020	490.9173	0.8039	0.1154
IRL	Ireland	0.7158	228.1593	0.7541	0.1035
IRN	Iran, Islamic Rep.	0.4494	82.2055	0.6187	0.0895
IRQ	Iraq	0.0537	1.2036	0.4737	0.0407
ISL	Iceland	0.3358	25.2424	0.5815	0.0749
ISR	Israel	0.5975	86.1650	0.6953	0.0907
ITA	Italy	0.8428	514.6710	0.8272	0.1148
JAM	Jamaica	0.2013	23.4618	0.5317	0.0607
JOR	Jordan	0.2857	15.4655	0.5548	0.0713
JPN	Japan	0.8598	403.1509	0.8531	0.1101
KAZ	Kazakhstan	0.2407	20.3625	0.5431	0.0745
KEN	Kenya	0.3963	59.8878	0.6010	0.0787
KGZ	Kyrgyz Republic	0.1128	3.5759	0.5009	0.0472
KHM	Cambodia	0.3669	8.0785	0.5945	0.0677
KIR	Kiribati	0.0334	0.1003	0.4880	0.0155
KNA	St. Kitts and Nevis	0.1514	9.5708	0.5318	0.0442
KOR	Korea, Rep.	0.7924	377.0269	0.8017	0.1101
KWT	Kuwait	0.2143	10.0509	0.5313	0.0688
LAO	Lao PDR	0.1180	0.7640	0.5016	0.0312
LBN	Lebanon	0.3476	16.9403	0.5850	0.0723
LBR	Liberia	0.1632	3.1281	0.5300	0.0480
LBY	Libya	0.1258	3.4215	0.4999	0.0566
LCA	St. Lucia	0.1047	8.2801	0.4992	0.0401

Table A.1. Volume-weighted average centrality measures of all countries in 2006—continued.

iso3	country name	Degree	Betweenness	Closeness	Eigenvector
LKA	Sri Lanka	0.3918	17.9468	0.5994	0.0721
LTU	Lithuania	0.3892	33.4807	0.5965	0.0785
LVA	Latvia	0.3578	34.8116	0.5839	0.0756
MAC	Macao SAR, China	0.3302	8.5198	0.5827	0.0671
MAR	Morocco	0.4520	55.0623	0.6241	0.0860
MDA	Moldova	0.2241	13.9664	0.5396	0.0674
MDG	Madagascar	0.2838	20.7570	0.5639	0.0665
MDV	Maldives	0.1783	0.2604	0.5325	0.0417
MEX	Mexico	0.5980	247.7607	0.6903	0.1020
MHL	Marshall Islands	0.0784	0.5533	0.5063	0.0308
MKD	Macedonia, FYR	0.1969	12.9696	0.5288	0.0612
MLI	Mali	0.1079	5.1930	0.5062	0.0482
MLT	Malta	0.3983	26.7941	0.6120	0.0731
MMR	Myanmar	0.2082	1.3983	0.5377	0.0458
MNE	Montenegro	0.0358	0.0002	0.4780	0.0228
MNG	Mongolia	0.1165	1.4562	0.5084	0.0466
MNP	Northern Mariana Islands	0.1070	0.0450	0.5079	0.0248
MOZ	Mozambique	0.1148	10.6539	0.5022	0.0485
MRT	Mauritania	0.2224	5.6901	0.5468	0.0604
MUS	Mauritius	0.3692	46.2489	0.5948	0.0766
MWI	Malawi	0.2494	17.4377	0.5465	0.0623
MYS	Malaysia	0.7412	270.6927	0.7743	0.1048
NCL	New Caledonia	0.1048	14.2012	0.5038	0.0527
NER	Niger	0.1689	19.4173	0.5217	0.0536
NGA	Nigeria	0.1697	103.9033	0.5153	0.0827
NIC	Nicaragua	0.2075	12.1943	0.5380	0.0617
NLD	Netherlands	0.8283	422.9655	0.8197	0.1148
NOR	Norway	0.6058	110.8175	0.6962	0.0992
NPL	Nepal	0.2402	2.3180	0.5512	0.0505
NRU	Nauru	0.0521	0.0774	0.4791	0.0137
NZL	New Zealand	0.6939	366.1015	0.7460	0.0999
OMN	Oman	0.2443	20.4892	0.5429	0.0695
PAK	Pakistan	0.6147	216.4614	0.7082	0.0972
PAN	Panama	0.3130	17.5215	0.5752	0.0684
PER	Peru	0.4404	66.7030	0.6211	0.0844
PHL	Philippines	0.6487	138.3542	0.7278	0.0915
PLW	Palau	0.0138	0.0048	0.4604	0.0111

Table A.1. Volume-weighted average centrality measures of all countries in 2006—continued.

iso3	country name	Degree	Betweenness	Closeness	Eigenvector
PNG	Papua New Guinea	0.0827	0.6819	0.4968	0.0300
POL	Poland	0.6543	277.7887	0.7164	0.1064
PRK	Korea, Dem. People's Rep.	0.3541	19.0666	0.5922	0.0612
PRT	Portugal	0.6526	189.0988	0.7165	0.1021
PRY	Paraguay	0.3275	15.3549	0.5777	0.0619
PYF	French Polynesia	0.1310	25.5002	0.5191	0.0613
QAT	Qatar	0.2627	29.0286	0.5541	0.0782
RUS	Russian Federation	0.5619	136.4729	0.6638	0.1027
RWA	Rwanda	0.1055	13.2927	0.5074	0.0434
SAU	Saudi Arabia	0.5064	127.3290	0.6412	0.0999
SDN	Sudan	0.0708	15.7878	0.4784	0.0665
SEN	Senegal	0.2878	42.0610	0.5622	0.0714
SGP	Singapore	0.6798	200.2483	0.7358	0.1014
SLB	Solomon Islands	0.0857	0.4198	0.4999	0.0243
SLE	Sierra Leone	0.1713	2.1935	0.5259	0.0465
SLV	El Salvador	0.2543	12.1877	0.5541	0.0617
SMR	San Marino	0.0422	0.0189	0.4801	0.0078
SOM	Somalia	0.0633	0.1640	0.4858	0.0217
SRB	Serbia	0.3722	49.8573	0.5949	0.0816
STP	Sao Tome and Principe	0.0760	9.6619	0.5044	0.0283
SUR	Suriname	0.0774	2.9993	0.4925	0.0357
SVK	Slovak Republic	0.5130	141.2245	0.6555	0.0926
SVN	Slovenia	0.5298	118.5200	0.6614	0.0864
SWE	Sweden	0.7595	244.1565	0.7796	0.1093
SYC	Seychelles	0.1976	5.0665	0.5317	0.0532
SYR	Syrian Arab Republic	0.4456	40.8366	0.6248	0.0803
TCA	Turks and Caicos Islands	0.0663	0.5852	0.4954	0.0205
TCD	Chad	0.0181	0.3058	0.4526	0.0233
TGO	Togo	0.0655	1.7022	0.4743	0.0387
THA	Thailand	0.8019	396.0309	0.8087	0.1086
TJK	Tajikistan	0.1267	0.6885	0.5087	0.0393
TKM	Turkmenistan	0.1137	0.6816	0.5053	0.0411
TON	Tonga	0.0390	0.9039	0.4815	0.0197
TTO	Trinidad and Tobago	0.2362	81.1574	0.5303	0.0670
TUN	Tunisia	0.4708	51.2303	0.6353	0.0853
TUR	Turkey	0.7309	269.9661	0.7561	0.1087
TUV	Tuvalu	0.0277	0.0967	0.4844	0.0131

Table A.1. Volume-weighted average centrality measures of all countries in 2006—continued.

iso3	country name	Degree	Betweenness	Closeness	Eigenvector
TZA	Tanzania	0.2722	24.8143	0.5537	0.0685
UGA	Uganda	0.2472	26.2735	0.5526	0.0614
UKR	Ukraine	0.5915	150.1454	0.6820	0.1031
URY	Uruguay	0.4422	50.3250	0.6265	0.0788
USA	United States	0.8741	676.8734	0.8488	0.1168
UZB	Uzbekistan	0.1352	0.5893	0.5155	0.0423
VCT	St. Vincent and the Grenadines	0.1390	4.3537	0.5223	0.0460
VEN	Venezuela, RB	0.2737	29.8872	0.5488	0.0728
VGB	British Virgin Islands	0.1538	4.9150	0.5238	0.0406
VNM	Vietnam	0.6071	188.7477	0.6923	0.0985
VUT	Vanuatu	0.1243	6.1898	0.5138	0.0290
WSM	Samoa	0.1051	3.4127	0.5143	0.0260
YEM	Yemen, Rep.	0.2220	19.7086	0.5353	0.0603
ZAF	South Africa	0.7546	487.8321	0.7693	0.1119
ZMB	Zambia	0.1795	6.9395	0.5256	0.0546
ZWE	Zimbabwe	0.1894	11.5334	0.5310	0.0560

BIBLIOGRAPHY

Acemoglu, Daron, Simon Johnson, and James Robinson. "The Rise of Europe: Atlantic Trade, Institutional Change and Economic Growth." The American Economic Review, 2002. doi:10.3386/w9378.

Amaral, L. A. N., A. Scala, M. Barthelemy, and H. E. Stanley. "Classes of small-world networks." *Proceedings of the National Academy of Sciences* 97, no. 21 (2000): 11149-1152. doi:10.1073/pnas.200327197.

Baskaran, Thushyanthan, Florian Blöchl, Tilman Brück, and Fabian J. Theis. "The Heckscher–Ohlin model and the network structure of international trade." International Review of Economics & Finance 20, no. 2 (2011): 135-45. doi:10.1016/j.iref.2010.11.003.

Benedictis, Luca De, Silvia Nenci, Gianluca Santoni, Lucia Tajoli, and Claudio Vicarelli. "Network Analysis of World Trade using the BACI-CEPII Dataset." Global Economy Journal 14, no. 3-4 (2014). doi:10.1515/gej-2014-0032.

Dollar, David, and Aart Kraay. *Trade, growth, and poverty*. Washington, DC: World Bank, Development Research Group, Macroeconomics and Growth, 2001.

Fagiolo, Giorgio, Javier Reyes, and Stefano Schiavo. "On the topological properties of the world trade web: A weighted network analysis." *Physica A: Statistical Mechanics and its Applications* 387, no. 15 (2008): 3868-873. doi:10.1016/j.physa.2008.01.050.

Freeman, Linton C. "A Set of Measures of Centrality Based on Betweenness." *Sociometry* 40, no. 1 (1977): 35. doi:10.2307/3033543.

Garlaschelli, Diego, and Maria I. Loffredo. "Structure and evolution of the world trade network." *Physica A: Statistical Mechanics and its Applications* 355, no. 1 (2005): 138-44. doi:10.1016/j.physa.2005.02.075.

Goldstein, M. L., S. A. Morris, and G. G. Yen. "Problems with fitting to the power-law distribution." *The European Physical Journal B* 41, no. 2 (2004): 255-58. doi:10.1140/epjb/e2004-00316-5.

Hausmann, Ricardo, Jason Hwang, and Dani Rodrik. "What you export matters." *Journal of Economic Growth* 12, no. 1 (2006): 1-25. doi:10.1007/s10887-006-9009-4.

Hidalgo, C. A., B. Klinger, A.-L. Barabasi, and R. Hausmann. "The Product Space Conditions the Development of Nations." *Science* 317, no. 5837 (2007): 482-87. doi:10.1126/science.1144581.

Jackson M. (2010) Social and Economic Networks, Princeton University Press, Princeton University Press.

Kali, Raja, and Javier Reyes. "The architecture of globalization: a network approach to international economic integration." *Journal of International Business Studies* 38, no. 4 (2007): 595-620. doi:10.1057/palgrave.jibs.8400286.

Liu, Xiaohui, Peter Burridge, and P. J. N. Sinclair. "Relationships between economic growth, foreign direct investment, and trade: evidence from China." Applied Economics 34, no. 11 (2002): 1433-440. doi:10.1080/00036840110100835.

Nickell, Stephen. "Biases in Dynamic Models with Fixed Effects." Econometrica 49, no. 6 (1981): 1417. doi:10.2307/1911408.

Serrano, Ma Ángeles, and Marián Boguñá. "Topology of the world trade web." *Physical Review E* 68, no. 1 (2003). doi:10.1103/physreve.68.015101.