Title
Network Statistics and Modeling the Global Trade Economy: Exponential Random Graph Models and Latent Space Models: Is Geography Dead?

Author
Howell, Anthony

Publication Date
2012

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

LOS ANGELES

Network Statistics and Modeling the World Trade Network: Exponential Random Graph Models and Latent Space Models

A thesis submitted in partial satisfaction

of the requirements for the degree Master of Science

in Statistics

by

Anthony James Howell

2012

ABSTRACT OF THE THESIS

Network Statistics and Modeling the Global Trade Economy: Exponential Random Graph Models and Latent Space Models: Is Geography Dead?

by

Anthony James Howell

Master of Science in Statistics

University of California, Los Angeles, 2012

Professor David Rigby, Chair

Due to advancements in physics and computer science, networks have becoming increasingly applied to study a diverse set of interactions, including P2P, neural mapping, transportation, migration and global trade. Recent literature on the world trade network relies only on descriptive network statistics, and few attempts are made to statistically analyze the trade network using stochastic models. To fill this gap, I specify several models using international trade data and apply network statistics to determine the likelihood that a trade tie between two countries is established. I also use latent space models to test the 'geography is dead' thesis. There are two main findings of the paper. First, the "rich club phenomenon" identified in previous works using descriptive statistics no longer holds true when controlling for homophily and transitivity. Second, results from the latent space model refute the 'geography is dead' thesis.

The thesis of Anthony James Howell is approved.

Nicolas Christou

Mark Handcock

David Rigby, Committee Chair

University of California, Los Angeles

2012

DEDICATION

This work is dedicated to my loving family who has been instrumental in the completion of this thesis through their unconditional love and support. You are loved and appreciated.

Table of Contents

List of Figures

List of Tables

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my thesis advisor, Dr. David Rigby, as well as my thesis committee members, Dr. Mark Handcock and Dr. Nicolas Christou, for their thoughtful and constructive comments on this thesis and for all their combined help and support over the past three years. I would also like to thank the UCLA Senate for funding support during the AY2010-2011 and the UCLA Asia Institute for funding support during the AY2009-2010 and AY2011-2012.

Introduction

Over the past half century, countries have become increasingly integrated into the global economy, leading to a large, diverse network of country nodes and trade flows. This global network is both more cohesive and more unstable than at any other previous point in history (Kim and Shin, 2003). The East Asian financial crisis in 1997 is a prime example of how the global economy can be conceptualized as a network, whereby a crisis that originated in one country, Thailand, spread through the global 'network' like a disease to other Asian countries and beyond (Li et al., 2003). Similarly, the 2009 global financial crisis, leading to the depression in the Silicon Valley, plummeting housing market in the U.S. and the Eurozone crisis, also exposes the extent to which the global network is integrated. Recently, many scholars rely on network analysis to examine how network statistics can be used to explore the volatility within an increasingly connected and complex global network (Schweitzer et al., 2009).

Due to advancements in physics and computer science, networks analysis has increasingly been applied to the study of various social phenomena, including P2P, neural mapping, transportation, and most recently migration and global trade. In regards to the world trade web (WTW), network analysis has most notably been used to address several major questions: does the trade network follow a core-periphery structure (Clark, 2008; Clark, 2010; Kali and Reyes, 2007); what is the role of geography in forming trade ties (i.e. globalization versus regionalization) (Aggarwal and Koo, 2005; Kim and Shin, 2002; He and Deem, 2010); do global elites tend to trade among themselves; and what are the effects of international trade on economic growth (Bhattacharya et al., 2008; Serrano, 2008; Fagiolo et al., 2009).

Findings from the network literature have produced a wealth of knowledge to better understand answers to these questions that have arisen over the past 30 years, although the results are sometimes mixed. In general, scholars have concluded that a country's position in the global network does influence its economic performance (Fagiolo et al., 2010); the network structure is hierarchical (evidence of a core-periphery relationship) (Nemeth and Smith, 1985; Smith and White, 1992); regionalization and globalization are complimentary and have intensified with time (Kim and Shin, 2002); and lastly, countries that have higher trade intensities tend to trade among themselves (termed as the "rich club phenomenon") (Serrano and Boguna, 2003).

Despite the complicated nature of the WTW, pertinent topological properties of the global trade system can be extracted through modeling the system as a network (Serrano et al., 2008). Understanding the structure of the global trade network has implications for research across numerous social science disciplines trying to examine the effects of economic integration and internationalization. Network analysis is a powerful tool for studying networks and is increasingly applied to the WTW. Proper applications of network analysis can reveal topological properties of the trade network and uncover features of the underlying structure of the network (Fagiolo et al., 2009; Reyes et al., 2010).

Much of the recent literature on the WTW applies network analysis using longitudinal data that spans a decade or more usually at some time period between 1950 and 2010 (Kali and Reyes, 2007; Beckfield, 2010). Longitudinal approaches are ideal to examining structural changes in the network over time; however, most scholarly articles rely only on the network's summary statistics to track changes without ever fitting a statistical model to the network. Opting to not fit a model is a major shortcoming in the WTW literature. It is analogous to non-relational analyses that only report descriptive statistics in cross-sectional analysis; something is missing. Fitting statistical models for network data, in general, is still in its infancy stages

(Hunter and Handcock, 2006), and therefore it is not surprising that the WTW literature has not yet adequately addressed the topic. Moreover, because most scholars that examine dynamic network structures are primarily interested in seeing how topological properties of the WTW change over time, they forego a deeper analysis for any given year (notable exceptions are Garlaschelli and Loffredo, 2005; Garlaschelli et al., 2007). Similar to non-network data, however, relational data can be analyzed at three different levels of analysis: descriptive, hypothesis tests and stochastic modeling.

Descriptive analyses are the most prevalent in the WTW literature and reveal the topological properties of the trade network. Null hypothesis tests compare the network of study with random networks of the same size and basic structure in order to reveal underlying processes that are operating on the network. Lastly, stochastic models are used to identify the specific processes that have led the network to its particular configuration. While the descriptive statistics may change as new countries are incorporated into the network and trade relationships are established and/or strengthened, it is likely that the underlying processes that generate the network are likely to be stable over time (Schiavo et al., 2010). Therefore, to avoid the complexities of using longitudinal data, it is suffice to select a stochastic model for a single year to examine the statistical properties of the WTW.

The network can be set up as some combination of binary/weighted and directed/ undirected. I build a binary, undirected network for the year 2007 using bilateral trade data extracted from the United Nations' COMTRADE database and GDP per capita and the trade/GDP share data extracted from Penn World Table 6.2. For the purposes of my paper, using a binary network is sufficient to examine the variables that influence the likelihood that a trade tie is established between two countries. In support of selecting a binary matrix, Squartini et al.

(2011) specify various combinations of the network and find that the projections made by the binary matrix is maximally informative and should be the focus of subsequent models of trade.

In the network, countries represent nodes and the links between two countries are their shared imports and exports. The number of in and out ties are highly correlated, r=.91, and 61% of the trade relationships are reciprocal. In accordance with Fagiolo et al. (2009) and Serrano (2003), the WTW is sufficiently symmetric to use an undirected analysis. In the undirected case, if country i exports to country j or country j exports to country i, then $y_{ij} = 1$. If a trade tie is not present, then $y_{ij} = 0$. The data offer information on both exports and imports, however, I use only import data because previous scholars suggest that these figures are more accurate than export figures (Kim and Shin, 2003).

One of the goals of this paper is to examine the topological properties of the WTW. Specifically, I examine measures of connectivity, centrality, clustering and hierarchy. I also explore correlation patterns between these network statistics and country-specific characteristics, such as real per capita GDP, and I compare network statistics at the regional level. The second goal of this paper is to fit a model to the network to reveal the underlying processes that shape the WTW. I use the results to statistically test which network features influence the probability of a tie being formed between two countries. To help control for exogenous factors, I incorporate two additional covariates to include in the model, per capita Gross Domestic Product (rpcGDP) in real terms and a regional variable based on present day trade blocks and geographical proximity[1].

The third goal of this paper is to introduce a simple latent space model to reveal country positions in the network and test the hypothesis of whether geography matters. Since Toffler

[1] See Appendix A for a complete listing of countries by region.

(1970) first argued that place is no longer an important determinant due to evolution of transport and communication systems, scholars have speculated that geography is dead. O'Brian (1992) proclaimed that the globalization era equates to 'the end of geography,' whereby geographical location no longer matters for economic development. Despite these claims, it is well known that the effects of globalization are not distributed uniformly throughout the global economy; there are place- and region-based variations that require a geographical lens in order to understand issues of unequal development (Warwick, 2005).

Moreover, the growing forms of regionalization shed further evidence that geography does matter for economic development, as different regions have different collective powers and positions in the global economy. Using network analysis to support this view, Kastelle (2006) provides evidence that the "movement of trade, capital and people is a geographically heterogeneous and historically episodic process and can be interpreted to support regionalization rather than globalization." To determine the role of geography in the WTW, I use a latent space model and test the null hypothesis that distance, measured in social space, does not influence the likelihood of a trade tie being established between two countries.

The outline of this paper is as follows. First, I summarize recent work carried out on the WTW using networks and discuss major findings and applications for the trade-growth literatures. In the second part of this thesis, I carry out the analyses sections, consisting of two subsections: descriptive network statistics and stochastic modeling. At the start of each subsection, I briefly provide a theoretical foundation for each level of analysis, as well as define major statistics and models used in the analyses. I conclude by summarizing my key findings about the trade network and note the relationship between geography and trade.

Literature Review

In the 1970s, world-systems theory replaced “modernization theory” as the major paradigm of thought. Network analysis was first used to test whether trade patterns followed a core-periphery framework. A seminal piece published in 1979 was the first attempt to use the network approach to study the world economic system. Snyder and Kick (1979) used blockmodeling analyses of social structure for trade flows in order to help explain differential economic growth among countries using a world-systems and dependency theoretical framework. They helped to advocate the powerful analytical power that stems from emphasizing the “world economy” as the appropriate level of analysis. The results of their blockmodel analysis supported a core-periphery structure in the global economy and encouraged a flood of subsequent research on the topic.

Nemeth and Smith (1985) mapped countries into structural positions in the economic system based on flows of different types of internationally traded commodities. Whereas Snyder and Kick (1979) placed countries into positions based on trade, military interventions, treaty memberships, and diplomatic exchanges, Nemeth and Smith (1985) exclusively focused on networks of trade and unequal exchange to classify countries into core-periphery-semi-periphery groupings. Their blockmodel analysis partitioned the 89 countries into four distinct structural positions that validated a dependency/world-systems framework.

Another path-breaking article in the WTW network analysis is Smith and White (1992). The authors apply network analysis to study the evolution of the WTW using dynamic analysis for three different years. Previous work examined only one point in time. The advantage of using a dynamic modeling approach is it allows changes in the global network structure to be tracked. The authors are able to track changes in specific position of individual countries.

Specifically, they show that the U.S.-aligned core began to erode away to a larger and less U.S.-dominated core in 1970 and 1980. Their general results also support world-system and dependency arguments regarding the asymmetrical flows of raw materials versus processed goods. Whereby the core nations import raw materials from periphery nations and in turn export processed goods back to the periphery. Network analysis applications in the 1980 and 90s made it clear that the trade network is hierarchical and follows a core-periphery structure.

More recently, network analysis has produced mixed results on whether the present trends in the global trade economy still support a core-periphery structure. On the one hand, Kali and Reyes (2007) use network statistics in a growth regression model and conclude that countries with high position in the network have significantly more growth than countries occupying lower position, thus supporting a core-periphery structure. Fagiolo et al. (2010) also take a world-systems approach and confirm that countries with high positions in the WTW leads to higher growth than countries with low positions.

Using a slightly different approach, Fagiolo et al. (2009) examine the correlation patterns between network statistics and country per capita GDP (pcGDP) in order to see whether countries with a higher income are more/less connected, central and clustered. They find that high-income countries tend to hold more trade relationships and occupy a more central position in the network. At the same time, the same countries tend to trade with few and weakly-connected partners. The authors interpret this result as an emerging pattern that suggests the presence of a "rich club phenomenon" that is indicative of core-periphery structure. On the other hand, Kim and Shin (2003) study the global network from 1959-1996 and provide evidence that refutes much of the previous work produced under the world-systems perspective and suggest that increasing trade (globalization) has decentralized the structure of world trade, which supports neoclassical economic theory as opposed to world-systems theory.

Aside from the core-periphery debate, network analysis has also been applied to study another major debate over whether regionalization is a stepping stone or stumbling block to globalization. Some scholars believe that regionalization is a transitory step that some countries pursue to become more competitive on the global market and will eventually promote globalization. Others suggest that regionalization impedes globalization by hurting the welfare of non-member countries and leading to inefficient production strategies that may work at the regional scale but not at the global scale.

Kim and Shin (2003) argue that network analysis can naturally be extended from dependency/world-systems theory to test the globalization/regionalization thesis. The authors show that globalization and regionalization are not necessarily competitive, but complementary processes. During the time period of analysis, the WTW became globalized (overall network density increased significantly), while it also became regionalized (intraregional density also significantly increased). Therefore, regionalization does not jeopardize globalization; rather the two processes are complimentary and can coincide with one another.

The most recent application of network analysis on the global trade economy is to perform network analysis, obtain relevant network statistics and incorporate them into various forms of economic growth models to examine the role that trade/openness has on economic growth. Standard international-trade indicators and openness measures (e.g. trade to GDP ratio) are limited in that they can only measure first-order relationships, or direct bilateral-trade relationships; however, network indicators can account for higher-order relationships. The ensuring debate following Rodrik et al.'s (2001; 2004) seminal work on the main determinants of growth reveals the inadequacy of the trade/GDP ratio; the authors finds that openness, i.e. trade/GDP ratio, does not have a statistically significant effect on growth. Alcala and Murcia (2003), however, use a more robust measure of openness and find that the more robust measure has a large, significant effect on growth. In search of an appropriate measure for openness, practitioners have now turned to network analysis to obtain a more suitable proxy for openness to incorporate into growth regressions. There are three influential papers that attempt this process, which I will highlight.

First, Kali and Reyes (2007) insert network statistics into a growth regression model. They find that the network statistics offer greater explanatory power on growth compared to traditional volume-based measure (trade/GDP ratio). This finding has large implications in the trade-growth literature and helps to redress the widely influential work of Rodrik and his colleagues who argue that integration has no effect on growth. Reyes et al. (2007) use network analysis to help explain the different growth trajectories of countries in Asia in relation to Latin America. The authors find that over a 20-year time span Asian countries not only expanded the number of trading partners and their volume of trade, but they also experienced higher mobility in the network, whereas Latin America only expanded trade with a small number of trading partners and remained in a constant position or slightly declined in the network. The authors use partial correlations to show that Asia grew faster than Latin America as a result of its higher centrality in the trade network.

Clark (2010) further solidifies the link between network mobility and growth by incorporating network statistics into a neoclassical growth model. He specifies output (Y) as a function of capital (K) and labor (L), where capital refers to both physical and human capital. His findings show that the mobility statistic is the second most influential variable in explaining productivity, behind human capital. This is a major finding produced by network analysis and will have future implications on the way in which network analysis and growth regressions can be used in combination. Although, one author mentions that a drawback of this approach is that there is no specific economic theory for including network statistics in growth models and therefore should not be done. However, I feel that network measures are an extension of the trade/GDP measures that offers far more explanatory power. If trade/GDP ratios can be used in regressions, so too can network statistics.

Descriptive Network statistics

Graph theory is used to inform much of what we know about how networks work. A graph is a network model consisting of dichotomous (binary) relations. I represent the network with the following graph notation

$$G = (V, E) \qquad (1)$$

Where V is a vertex set, $V = \{v_1, \ldots, v_2\}$, and in the directed graph, $E \subseteq \{(v_i, v_j): v_i, v_j \in V\}$. In the WTW, countries represent vertices, and edges between any two countries (v_i, v_j) exist if at least one million U.S. dollars in trade is transacted during the year in observation. The one million U.S. dollar threshold is common in the WTW literature (Kim and Shin, 2003) and is selected in order to focus on significant trade relationships that shape the network.

I set **Y** to be the adjacency matrix for the random graph G. $\boldsymbol{Y}_{ij}$ is a binary random variable which indicates the state of the i, j edge. The Pr($\boldsymbol{Y}_{ij} = \boldsymbol{y}_{ij}$) is the probability of the $\boldsymbol{Y}_{ij}$ edge state. I can express y_{ij} in terms of the WTW as a dichotomous outcome

$$y_{ij} = \begin{cases} 1\ if\ (v_i, v_j)\ trade\ volume \geq \$1\ million\ U.S. \\ 0\ otherwise \end{cases} \qquad (2)$$

The density for the WTW in the year 2007 is 39.9, which means based on the number of nodes, trade ties represent approximately 40% of the total possible. The density of a network is the proportion of present ties to the maximum possible lines in a graph. A gXg nodal graph can be computed as

$$\Delta = \frac{\sum_{i,j} y_{ij}}{g(g-1)} \qquad (3)$$

I present the plot of the WTW in Figure 1 (Appendix B). The vertices are colored according to a country's respective region. Because the observed graph contains 190 vertices, it is difficult to visually inspect the network linkages and make any speculations about whether certain regions tend to trade amongst themselves or not, i.e. homophily by region. Homophily is an important concept in the study of social networks and helps to explain why we observe a particular type of network. The principle of homophily is predicated on the fact that people with similar characteristics will have a higher rate of contact between them then dissimilar people (McPherson et al., 2001). One can scale this principle up to include, organizations, countries, regions, and so forth. In the present context, I am interested in whether homophily by region exists. That is, do regions, delineated by geographical proximity and historical reference tend to trade more among themselves relative to 'outsiders' in other regions that do not share a similar degree of cultural and historical shared experience. While there are many different ways to delineate regions, the most basic source of homophily is space (*ibid*., 2001), so it makes intuitive sense to group countries based on geographic proximity.

To gain better intuition on whether homophily by region is present in the WTW, I present the mixing matrix for each region (Appendix C). The mixing matrix presents the count of trade relationships cross-tabulated by the region of the two countries involved. If a strong presence of homophily is present, I expect to see large values along the diagonal relative to off-diagonal values. Based on the fact that the diagonal values in the matrix do not tend to be higher than the off-diagonal values, countries do not appear to be overwhelmingly trading within their particular region; homophily by region does not appear to be a major factor.

There are three caveats to this interpretation. First, marginal totals can be misleading and do not statistically test for the presence of homophily (this will be carried out in the modeling section below). Also, the trade network is very complex and strict interpretations of homophily are not always straight forward. For example the largest value in the matrix is between Europe (region 2) and Africa (region 11). Due to the colonization era, African and European countries still maintain a strong, client-like relationship in many cases. Third, there is likely some misleading results due to the way countries are grouped. While there is no 'right' way to group countries into regions, defining China (region 4) as its own region has some drawbacks for cases like this, since its value along the diagonal is 0, since the data only cover international trade. It is not possible to see China's intra-trade relationships and see how it compares to other countries' internationally trade within a particular region.

Another interesting feature in networks is transitivity. Transitivity is a statistic that measures the degree of network integration. Balance theory predicts that people should adjust their relations until the network becomes stabilized around a pattern where all dyadic ties are largely transitive, i.e. triadic. This social phenomenon tends to be explained in terms of triadic relationships and by the adage "a friend of a friend is a friend." Balance theory predicts that if ties exist between A and B and B and C, then A and C have a strong propensity to develop a tie. A triangle is defined to be any set f(i; j); (j; k); (k; i)g of three edges (Morris et al., 2008). The trade network consists of 190 countries and 7,177 ties. The number of triangles is surprisingly large, 157,645. This number is far larger than what would be expected by chance and offers initial evidence that the trade network has a high degree of transitivity. A more detailed analysis of edges and triangle terms will be carried out in the modeling section.

In addition to network statistics, there are also node level statistics that can quantify individual positions in the network and describe the local neighborhood. There are four major dimensions, each dimension with its own set of statistics that can be chosen as necessary by the researcher. The four dimensions, followed by the most commonly used statistics, are presented as follows: Connectivity, Assortativity, Clustering and Centrality. ND and NS are statistics used for connectivity. ND is the fractional count of trading partners a country has relative to all possible trade links in the network. NS measures the intensity of these trade links. These statistical measures are used in the empirical studies to offer evidence for or against increasing globalization. If the statistics increase in value, they show the globe is becoming smaller or more integrated over time.

ANNS is the statistic for assortativity. It measures the number of trading partners and the intensity (volume of trade) of a given country's trading partners. For example, if country A has 20 trading partners and each of those 20 countries trades with 20 other countries, ANNS gives ND/NS statistics for each of country A's trading partners. This statistic is commonly employed to assess whether certain groupings of countries (i.e. rich) tend to trade with well-connected countries or less connected countries. It is important to use in order to determine whether a 'rich club phenomenon' has emerged in the WTW.

BCC and the CCC are statistics for clustering, as well as clustering coefficient and ANND. The BCC is a ratio that counts the number of triangles that exist compared to the total number of triangles that are possible in the network. CCC measures the trade intensity of these triangles. Each of these statistics offers a perspective on the multi-laterlism vs. bilateralism debate. Clearly, if the statistics increase over time, the WTW is strengthening multi-lateral ties, whereas if the statistic is decreasing, it is associated with a rise in bilateralism.

Lastly, the centrality dimension has probably received the most attention in the network analysis because of its explanatory power of describing the hierarchy that exists within the network. RWBC is the most commonly employed statistic for this dimension and it measures the degree of influence a particular country has on the entire network. The higher the measure for a country the higher the degree of influence that country has on the WTW. Most often, this measure has been found to show a core-periphery hierarchy in the WTW, thus strengthening the position of world-systems perspective.

ND and BET are the most prominent centrality measures and are based on reach and flow mediation. The former quantifies the ability of the ego-node to reach other vertices. Centrality measures attempt to capture the influence of a node from its position in the network. ND calculates the number of direct ties coming in and going out of a node and represents how connected a country is within the trade network. High degree positions are influential in the network, and at the same time, may be vulnerable to other actors' influence. Histograms of the node degree show that the distribution of trading partners is right-skewed (Appendix D).

Mathematically, the node degree measures the probability of a randomly chosen vertex to have k connections to other vertices and provides a summary of a node's overall activity. The number of incoming ties is called in-degree, expressed as the sum of incoming ties over the number of actors in the network minus 1. In-degree will equal out-degree ties, expressed as

$$\frac{C_I(n_i) = \sum_{j=1}^{g} x_{ji}}{(g-1)} \tag{4}$$

The second common centrality measure is based on the quantity of walks that pass through the ego-node, i.e. betweenness. Betweenness (BET) is the tendency for an ego-node to reside on shortest paths between third parties, i.e. serves as a bridge between two other nodes. Betweenness relies on the concept of geodesic distance, i.e. the shortest path between two nodes, I and j. Betweenness can be quantified and is expressed as

$$C_b(n_i) = \frac{\sum_{j<k} \frac{g_{ik}(n_i)}{g_{jk}}}{(g-1)(g-2)/2} \tag{5}$$

$g_{jk}$is the number of j,k geodesics (shortest path between j,k) and $g_{ik}(n_i)$ is number of j,k geodesics that include i. High betweeness positions are associated with the term "broker." In the network literature, a “broker” is an actor that mediates between third parties who are not directly tied. Both the node degree and betweenness measures are standardized and are compared to the theoretical maximum number of edges possible for that graph, values ranging from 0 to 1.

Another interesting centrality measure is the eigenvalue centrality (EC). This measure quantifies the position of the actor in terms of the sum of the centralities of its neighbors, attenuated by a scaling constant (λ). Eigenvector centrality can be expressed numerically as,

$$C_D(n_i) = \frac{1}{\lambda}\sum_{j=1}^{g} x_{ij} C_D(n_j) \quad (6)$$

Actors with high eigenvector centrality are those with many central neighbors. This centrality measure is often overlooked by previous articles on the WTW, a major oversight considering this statistic is ideally suited to test core-periphery relations, a major focus point for WTW analyses in the past.

Table 3 reports the statistics for connectivity (ND) and centrality (BET, EC) by region and selects the three countries with the highest rankings for a particular measure (Reported in Appendix E). This allows us to see the most connected countries within regions, as well as compare the degree of influence across regions. NAFTA and East Asian countries are the most connected and central/influential regions in the global economy. Despite the high connectivity and centrality scores for the United Kingdom, Germany and France, the EU consists of many small Eastern European countries not very well connected, thereby lowering overall average scores for the EU. SAA and the Arab league are the least connected and least central regions in the global economy.

Within East Asia, China has only 10 fewer trading partners than Japan (i.e. connectivity), yet its BET centrality score is almost half as big as Japan’s. This distinction between connectivity and centrality is a key feature of network analysis. It reveals that although China is increasing its trading partners and becoming better connected to the global economy, its actual influence in the network in terms of trade remains limited relative to Japan. Figure 3 shows a plot of betweenness scores for each country (Appendix F). Japan, along with the UK, and the U.S. have the highest BET centrality score, representing the brokers in the network; China, on the other hand is plotted much lower than any of these three countries.

A major question posed in the era of globalization is whether countries with a large number of trading partners are wealthier. To test this hypothesis, I carry out simple correlations between network statistics and per capita GDP. I find that there is a positive correlation between the number of trade channels of a country and its wealth (pcGDP). The high correlation, .49, means that most high-connected countries tend to be rich, whereas low connected countries tend to be poor. For example, the U.S., Japan, Germany, UK and France are the highest connected countries and are the wealthiest.

Modeling the WTW with ERGM

To model network data, I use the ergm package for R, which offers advanced tools for modeling networks for a class of models called exponential-family random graph models (ERGMs). The ergm package obtains approximate maximum likelihood estimates, simulates random networks from a specified Ergm and performs graphical goodness-of-fit checks on the observed network (Hunter et al., 2008). The terms fit in the ERGM model are network statistics that are used to represent the probability distribution over all possible networks of that size (Morris et al., 2008).

The process that generates ERGM can be explained in the following way. The observed network is the outcome of some unknown stochastic process, which I attempt to model by allowing network ties to vary and fixing network nodes. Model parameters used in my statistical models are estimated from the data and represent regularities in the network. Once I have obtained the parameters, graphs are drawn at random and their characteristics are compared to the observed trade network. Then I can include network structures into the model to see if they can explain the emergence of the trade network. ERGM will place more/less weight on graphs with certain features, as determined by the size of the network and number of nodes, θ, g.

ERGM model parameters are statistical and represent expectations and covariances of relational measurements that allow inferences to be made about network characteristics (Westfeld and Hoff, 2010). The likelihood that a trade tie exists between two countries is the outcome of social processes, which are the product of both regularities and variability. Because I use a binary graph, I use logistic regression to represent the dependent variable, a trade tie. I model tie variables as:

$$\boldsymbol{Y} = [Y_{ij}]$$

$$Y_{ij} = 1 \; if \text{ i has a tie to j}, 0 \text{ otherwise}$$

I compute parameters using Maximum Likelihood Estimator (MLE). The MLE is obtained from a probability distribution on the set of all possible graphs of size n that maximizes the probability that our model parameters predict our observed network. The probability distribution of the set of possible graphs is

$$P(Y = y) = \frac{exp\{\sum_{k=1}^{K} \theta_k g_k(y)\}}{\boldsymbol{k}(\theta)} \tag{7}$$

Where Y is random network on n nodes, $\theta_{1,2\ldots k}$ are parameters. $g_{1,2\ldots k}$ are statistics on y, and $\mathbf{k}(\theta)$ is a normalizing constant:

$$\boldsymbol{k}(\theta) = \sum_{y \in Y} exp\{\sum_{k=1}^{K} \theta_k g_k(y)\} \tag{8}$$

The probability is proportional to some linear combination of the parameters and graph statistics,

$$P(Y) \propto \theta_1 g_1(y) + \theta_2 g_2(y) + \cdots + \theta_k g_k(y) \tag{9}$$

The model can be re-written in terms of the odds of tie y_{ij} conditional on the rest of the graph

$$\frac{\Pr(Y_{ij}=1|y_{ij}^c}{\Pr(Y_{ij}=0|y_{ij}^c)} = exp\left\{\sum_{k=1}^{K} \theta_k (g_k(y_{ij}^+) - g_k(y_{ij}^-))\right\} \tag{10}$$

Where y_{ij}^+ is the graph with $Y_{ij} = 1$ and y_{ij}^- is the graph with $Y_{ij} = 0$. I obtain the MLE using the log likelihood function, expressed as

$$L(\theta) = -\log c(\theta) = \log \sum_{\substack{all\ possible \\ graphs}} exp\{\theta^t g(y)\} \tag{11}$$

The log-odds depends on the vector of change statistics,

$$\Delta(\mathrm{g(y)})_{ij} = g_k(y_{ij}^+) - g_k(y_{ij}^-) \tag{12}$$

Given the log-odds depends on Δ_{ij}, each unit change in g_k for (i,j) tie present (versus absent) increases the conditional log-odds of (i,j) by θ_k. In effect, when I run the ERGM, the theta coefficients measure the impact of the covariate on the log-odds of a tie occurring between two nodes.

Model Specification

In Table 4, I specify several models that attempt to describe different aspects of the trade network (Appendix G). The first model includes three predictors: edges, triangle and gwesp. All predictors represent a specific configuration of links, i.e. edges or triangles; the term is a function of the number of such configurations in the network. Edges represent the likelihood that a trade relationship exists and the output will tell us how likely the observed network is expected to occur if it were a random graph. Triangle is an indicator of transitivity and is a type of configuration of ties that are hypothesized to occur more often or less often than expected by chance (Morris et al., 2008).

The insertion of Triangle in the model implies dependency between dyads, which quickly leads to degeneracy (Morris et al., 2008). Model degeneracy is a serious problem that frequently occurs when dealing with networks. If a model is degenerate then the terms in the model are grossly unsuitable at describing the underling processes that form the observed network. That is, even under the maximum likelihood coefficients in the model, the observed network is so unlikely to occur that the model cannot even be properly estimated (Goodreau et al., 2008). The statistic geometrically weighted edgewise shared partner (gwesp) is similar to triangles, but it has the major advantage in helping overcome the problems associated with model degeneracy (Goodreau et al., 2008; Hunter et al., 2008). The statistic measures the number of pairs of nodes that are connected by a direct edge and by a two-path through another node (Hunter, 2007). In order to help protect against degeneracy, I include the gwesp term for all the models.

According to Goodreau et al. (2008) a good model is one that accounts for a country's tendency for assortative mixing, which is based on the notion of homophily. In the present context, I want to account for assortative mixing that may occur for countries that belong do a particular region. If assortative mixing is present, then countries within the same region have a greater probability of forming a tie relative to countries in other regions. Model 2 therefore is the same as model 1, but it includes an additional term, nodematch, which accounts for assortative mixing. Nodematch assumes each attribute class is uniform – i.e. there is the same tendency for within-region edges, regardless of the region. Based on the recommendation of (*ibid,* 2008), Model 3 adds another term to account for assortativity, i.e. nodefactor. While nodematch captures the "interaction" or "second-order effects", nodematch captures the "main effects." Model 4 includes all of the network statistics in the previous model, but also adds an additional covariate to control for the effect of wealth on countries forming a tie.

In general, all of the models produce similar coefficients that are highly statistically significant and have the same sign. In terms of the best fit model, Model 4 offers the highest model likelihood relative to the other models. Based on the highest likelihood, I select Model 4 to interpret the coefficients. Following an interpretative analysis of the coefficients, I will run diagnostics to see if the model suffers from degeneracy.

The coefficients in model 4 can be interpreted by using the log-odds for the different types of ties. The coefficient on Edges is -6.96. This is the log-odds of two countries, *I* and *j*, becoming trading partners if they do not have any trading partners in common. The significant, positive coefficient for Triangle and GWESP indicates transitivity in this network. The positive, significant coefficient on Nodematch.region reveals that two countries within the same region are more likely to establish a trade link than two countries in different regions, i.e. homophily is present in the model. The MLE of the log-odds of a tie between two countries of the same region is .835. The probability corresponding to this is then $\frac{e^{.835}}{(1+e^{.835})}$ = .70. Conversely, the MLE of the log-odds of a tie between two countries from different regions is -6.96 + .835 = -6.125. The probability then is $\frac{e^{-6.125}}{(1+e^{-6.125})} = .002$.

Nodefactor.region returns a coefficient for each region, allowing for heterogeneous effects of homophily by region. Region 1 (NAFTA) is the reference group. It is clear from the variety in the returned coefficients that homophily is not homogenous across regions. Coefficients that are negative are less likely to from ties with other countries within their region compared to NAFTA. That is the countries in NAFTA (Canada, Mexico, U.S.) are more likely to establish ties among themselves than countries in the E.U., ECE, ASEAN,SAA, Arab League, Pacific Islands, Latin America, and Africa, respectively. Countries in East Asia (China, South Korea, Japan, and Taiwan) are more likely than the countries in NAFTA to develop trade links amongst themselves. In fact, East Asia has the highest coefficient, which indicates the countries in this region have the strongest preferential trade policies relative to other region-based trading blocs. The last coefficient in the model, rpcGDP, shows a small, positive effect on the probability of two countries to form a trade tie. The interpretation on this coefficient is that wealthier countries are slightly more likely to develop ties amongst themselves, controlling for region-based homophily and the three network statistics included in the model.

I test Model 4 for issues of degeneracy and report the diagnostics in Figure 4 (Appendix H). The diagnostics return trace plots and density plots for each coefficient in the model. The plots tell the user what is happening to the model statistics during the last iteration of the Markov Chain Monte Carlo (MCMC) estimation procedure. The default in R is 3 iterations. The trace plots show the chain as one time series for each model statistic and the density plots summarizes the chain in a histogram. In a converged model, these statistics will vary stochastically around the mean, but will not trend steadily away from the mean (Goodreau et al., 2008). From the results, it is clear that the model statistics do not diverge from the mean. This tells us that our initial estimates for the coefficient values generate networks with approximately the same number of statistics that are actually observed, e.g. edges or triangles, which ensure that the maximum likelihood estimation is reliable. Based on the evidence, the selected model does not suffer from degeneracy.

Latent space and latent position model: Is Geography Dead?

In order to test the role of geography in determining the probability two countries (i,j) form a trade relationship, I can extend the ERGM model and specify a latent space model. The Bernoulli random graph models discussed above assume independence among all trade linkages between country pars. However, in reality it is much more likely that there is inherent dependency between ties (Shortreed et. al, 2004). For example, if S. Africa and Brazil are trade partners, and China and Brazil are trade partners, then it is more likely that S. Africa and China are trade partners then it is if these previous trade relationships did not exist. The latent space model is one method to deal with this dependency.

Recently, latent space models have replaced blockmodelling as the primary approach to study issues of propinquity, the tendency of spatially proximate vertices to be tied. Based on the presence of homophily indicated in our models above, there is evidence that propinquity exists in the trade network. The probability of a link between two actors is a function of the distance between them in an unobserved latent space. Following the principles of propinquity, in general, actors tend to form ties to those that are nearby.

I can use latent space models to capture the relationship between distance and the likelihood of establishing a trade partnership in the WTW. Latent space models can help us examine whether the trade network is globalizing or regionalizing. If proponents of globalization who suggest "geography is dead" are correct in their assertion, then I expect the results of the latent space model to confirm that distance does not play a significant role in influencing the probability that a trade tie is established between country I and country j.

The latent position model assumes a conditional independence approach to modeling. Let $\{z_i\}$ be the positions of the actors in the social space $\boldsymbol{R}^k$ and $\{x_{i,j}\}$ denote the observed characteristics that are dyad-specific. That is the presence or absence of a trade tie between two countries is independent of all other ties in the system, given the unobserved positions in social space of the two individuals,

$$P(Y|Z,X,\theta) = \prod P\left(y_{i,j}\middle|z_i, z_j, x_i, \theta\right), \tag{13}$$

Where X and $x_i$and $x_{i,j}$are observed characteristics that are pair-specific and vector-valued and θ and Z are parameters and positions to be estimated (Hoff and Handcock, 2002). I can use logistic regression to parameterize equation (3).

$$\eta_{i,j} = \log odds(y_{i,j} = 1|z_i, z_j, x_{i,j}, \alpha, \beta) \tag{14}$$

$$= \alpha + \beta' x_{i,j} - |z_i - z_j|. \tag{15}$$

Where the log odds ratio for two actors j and k, equidistant from i, is $B'\left(x_{i,j} - x_{i,k}\right)$. I can estimate $\eta_{i,j}$using the log-likelihood of a conditional independence model, expressed as,

$$logP(Y|\eta) = \sum_{i \neq j}\left\{\eta_{i,j}y_{i,j} - \log(1 + e^{\eta_{i,j}})\right\}, \tag{16}$$

Where η is a function of parameters and unknown positions. As such, I can use maximum-likelihood to estimate η.

In Table 5, I specify two simple latent space models to test the role of distance and region-based homophily (Appendix I). Model 1 only examines the role of distance in establishing a trade partner. The coefficient on Edges is highly significant and positive, indicating that larger distances increase the likelihood of two countries establishing a tie. This finding is bizarre and at odds with predictions made by gravity models that predict trade decreases as a function of distance. In Model 2 I add an additional covariate to account for homophily. In this model, I find the sign of the Edges coefficient switched from negative to positive, confirming the conventional relationship between trade and distance. In other words, the likelihood of two countries forming a tie decreases as distance between countries in latent space increases. The coefficient on the second term (homoregion) is very large and statistically significant. This finding indicates that countries classified into the same regional grouping will be more likely to form a trade tie than with countries from other regional groupings.

I select model 2 to carry out model diagnostics. First, I plot the minimum Kullback-Leibler (KML) likelihood estimates for each country (Shortreed et al., 2006). A simple way to visualize the network is to plot each node as a small pie chart, where each slice of the pie is proportionate to MCMC draws for which that node belonged (Krivitsky and Handcock, 2008). Because of the size of the network, it is difficult to inspect the tightly clustered countries; however, some countries on the peripheral of the network are identified. To check for issues of degeneracy, I report diagnostics for model 2 in Figure 6 (Appendix K). As stated above, the MCMC estimation procedure iterates 3 times and produces trace plots and density plots. The results show that the model statistics do not diverge from the mean, meaning that the model is not degenerate and the maximum likelihood estimates are reliable.

Conclusion

Network analysis offers many interesting approaches to studying the WTW. One of the less explored paths taken in the WTW literature is to fit models to the network. I address this oversight by estimating several ERGM and latent space models for the year 2007. The goals of this research are two-fold: 1) explore the topological properties of the WTW and test how they affect the likelihood of a trade linkage being formed between two countries; and 2) use latent space models to test the relationship between distance and trade in the network space.

The results from the descriptive analyses in this report agree with other previous work. The WTW network has a high density, the node degree has a high right-skew, the clustering coefficient and ANND provide evidence of hierarchy – trade partners of well-connected countries are less interconnected relative to those of poorly connected ones – and is very dissortative – countries holding many trade partners are on average connected with countries holding relatively few countries.

Based on the results from ERGM, the trade network can be characterized as transitive and countries are more likely to establish ties with other countries within their region. The degree of homophily based on region is heterogeneous across regions. NAFTA and East Asian countries have the greatest homophily effect. Lastly, in contrast to previous studies that use descriptive statistics to conclude that a "rich club" phenomenon exists – in the sense that rich countries tend to trade amongst themselves – there is little evidence for that in the ERGM model when controlling for homophily and transitivity. Although the coefficient on pcGDP is positive and significant, the magnitude is very low and has only a marginal influence on the probability of a trade tie being established.

The latent space models add an additional dimension of analysis of the WTW. While the ERGM model fit to the data controls for a region-based homophily, which is in itself defined, in part, by geographical proximity, the latent space model tests directly the role of space in determining the likelihood of whether or not a tie will be established. When controlling for regional homophily, the Euclidean distance -calculated in latent space - is returned negative, significant and large in magnitude. This finding supports findings in the gravity literature on trade and reaffirms that trade decreases as distance increases. Despite strong globalizing processes that have led some scholars to claim “geography is dead”, the significant coefficient on Edges reveals that distance continues to play a strong role in determining a trade relationship.

There are a number of ways that my research can proceed in the future and be used to uncover additional properties of the trade network. One interesting avenue for further research will be to add additional covariates used in the growth literature to the ERGM models, and test the robustness of the network coefficients in the presence of other non-network variables. A second future line of research will fit longitudinal ERGM and latent space models to the trade network to examine, respectively, how trade ties are developed and how space and trade vary over time. Lastly, it might prove useful to carry out separate ERGM equations for a bi-modal network – trade flows and FDI flows, respectively – and incorporate them into a simultaneous equations approach. Taking on these areas of future research will promote a deeper understanding of the global economy and better equip scholars, government leaders and global institutions, with the tools to mitigate increasing cases of external shocks to the network, i.e. crisis, and promote an equitable trade regime for the global economy.

Appendices

Appendix A

190 countries are placed into 10 regions. These regions are based on present-day trading blocs and/or geographical location. Several regions combine two or more economic trading blocks that span a certain geographic region. For example, the EU, EFTA and Central European FTA member countries are collapsed into one region based on their geographical region, Europe. Similarly, UNASUL, Caribbean Community and the Central American Integration System member countries were all collapsed into their geographical region, Latin America.

Table 1: Regional Groupings

NAFTA (Region 1)
CAN
MEX
USA
Europe (Region 2)
ALG
AND
ANG
ARG
ARM
AUL
AUS
AZE
BAH
BAR
BEL
BEN
BFO
BHM
BHU
BLR
BLZ
BNG
BOL
BOS
BOT
BRA
BRU
BUI
BUL
CAM
CAN
CAO
CAP
CDI
CEN
CHA
CHL
CHN
COL
COM
CON
COS
CRO
CUB
East Asia (Region 3)
JPN
MON
PRK
ROK
TAW
CHN (**Also Region 4**)
Eurasian Economic Community (Region 5)
ARM
AZE
BLR
GRG
KYR
KZK
RUS
TAJ
TKM
UKR
UZB
ASEAN (Region 6)
BRU
CAM
DRV
INS
LAO
MAL
MYA
PHI
SIN
THI
South Asia Association (Region 7)
AFG
BHU
BNG
IND
MAD

NEP
PAK
SOL
SRI

Arab League (Region 8)

BAH
EQG
IRN
IRQ
ISR
JOR
KUW
LEB
MOR
OMA
PAL
QAT
SAU
SUD
SYR
UAE
YEM

Pacific Islands (Region 9)

AAB
AUL
AUS
DMA
FJI
FSM
KBI
NAU
NEW
PNG
TON
TUV
VAN

Latin America (Reg. 10)

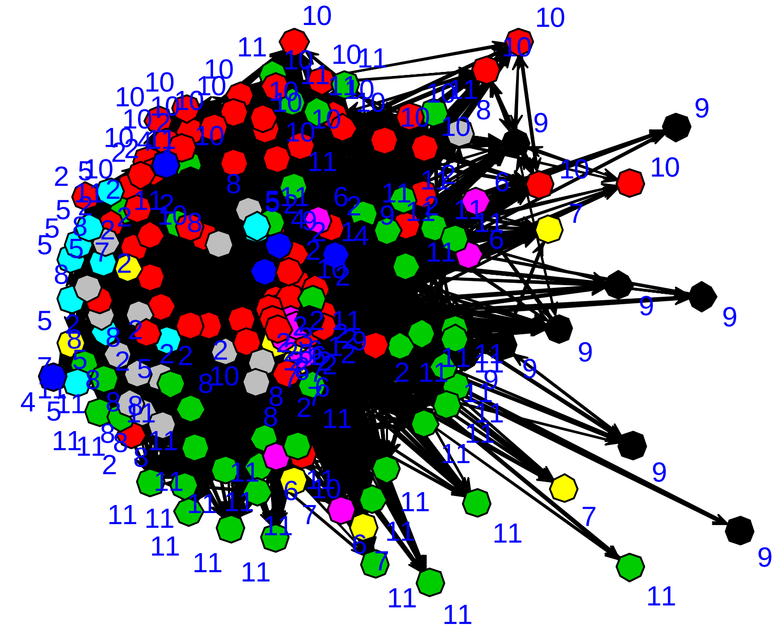
ARG
BAR
BHM
BLZ
BOL
BRA
CHL
COL
COS
CUB
DOM
ECU
GRN
GUA
GUI
GUY
HAI
HON
JAM
MSI
NIC
PAN
RUM
SAL
SKN
SLU
SUR
SVG
TRI
URU
VEN

African Union (Region 11)

ANG
BEN
BFO
BOT
BUI
CAO
CAP
CDI
CEN
CHA
COM
CON
DJI
DRC
EGY
ERI
ETH
GAB
GAM
GHA
GNB
KEN
LBR
LES
LIB
LIE
MAG
MAS
MAW
MLI
MZM
NAM
NIG
NIR
PAR
PER
RWA
SAF
SEN
SEY
SIE
SOM
STP
SWA
TAZ
TOG
TUN
UGA
ZAM
ZIM

Appendix B

Figure 1: World Trade Web (Thresh = $1 million)



Appendix C

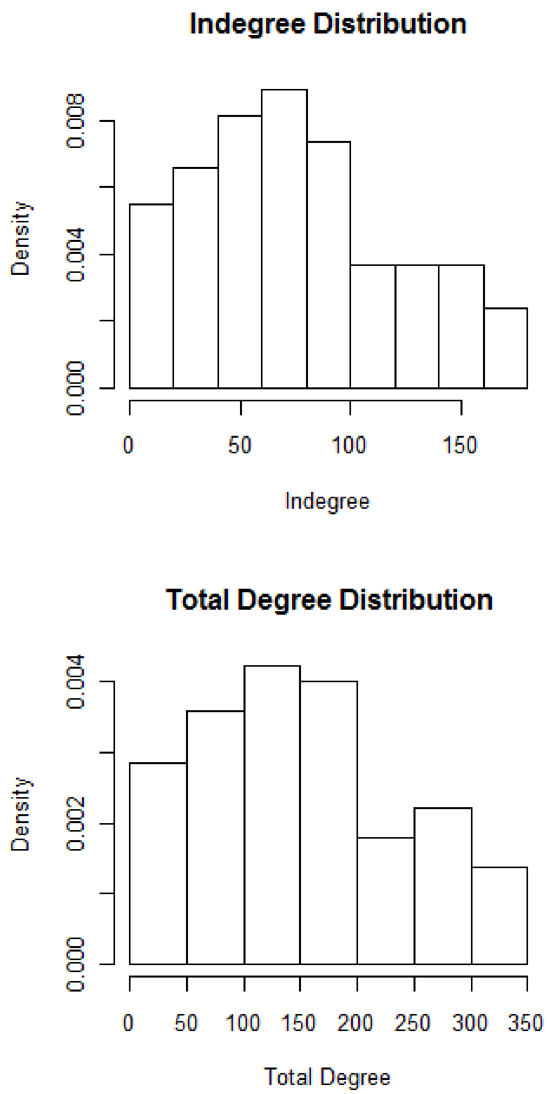
Table 2: Mixing Matrix by Region

	1	2	3	4	5	6	7	8	9	10	11
1	3	104	3	12	21	23	18	40	19	81	92
2	104	590	37	144	302	250	168	388	141	599	893
3	3	37	NA	5	11	10	7	16	7	27	43
4	12	144	5	7	38	37	25	52	23	99	123
5	21	302	11	38	47	48	43	71	27	98	106
6	23	250	10	37	48	40	51	93	43	128	194
7	18	168	7	25	43	51	16	62	29	62	118
8	40	388	16	52	71	93	62	83	44	142	247
9	19	141	7	23	27	43	29	44	13	80	81
10	81	599	27	99	98	128	62	142	80	243	259
11	92	893	43	123	106	194	118	247	81	259	251

* Note: Marginal totals can be misleading for undirected mixing matrices.

Appendix D

Figure 2: ND Distribution for WTW



Appendix E

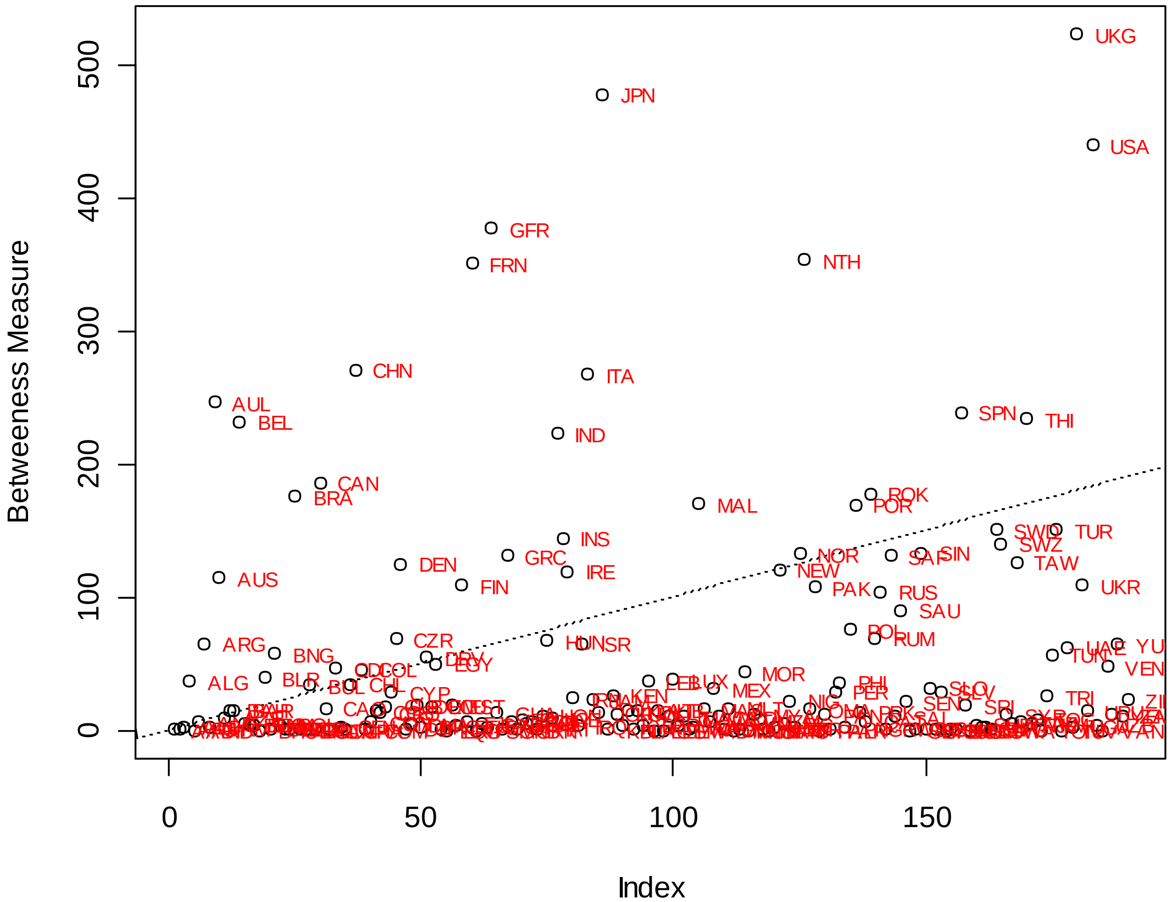
Table 3: Connectivity and Centrality Measures by Region and Select Countries

Region	ND	BET	EC
NAFTA (n=3)	**279.3**	**218.9**	**.107**
USA	346	439.39	.121
CAN	284	186.2	.11
MEX	208	31.2	.09
EU 2 (n=40)	**210.3**	**103.8**	**.084**
UKG	344	522.9	.12
GFR	340	376.9	.121
FRN	338	304.3	.11
East Asia (n=5)	**246**	**177.7**	**.094**
JPN	342	477.7	.12
China	332	270.8	.121
ROK	310	177.21	.11
ECE (n=11)	**156.2**	**27.4**	**.079**
RUS	278	104	.11
UKR	276	109	.12
BLR	194	39.5	.082
ASEAN (n=10)	**191.4**	**78.5**	**.079**
THI	304	233.7	.113
(Table 3 cont.)			
MAL	298	170.4	.113
INS	292	144.4	.112
SAA (n=9)	**136.7**	**45.6**	**.058**
IND	314	222.7	.116
PAK	262	107.6	.102
BNG	196	57.68	.082
Arab League (n=17)	**155.4**	**24.4**	**.068**

Table 3: Continued

SAU	234	90.2	.093
ISR	232	65.3	.095
UAE	218	62.1	.09
Pacific Islands (n=13)	**80**	**38.04**	**.033**
AUL	294	246.7	.11
AUS	266	114.12	.106
NEW	220	120.7	.09
Latin America (31)	**132.9**	**21.2**	**.059**
BRA	294	175.2	.11
ARG	244	65.3	.101
RUM	242	69.4	.1
African Union (50)	**106.3**	**11.2**	**.049**
SAF	280	131.2	.109
EGY	228	49.5	.096

Figure 3: Centrality Score by Country



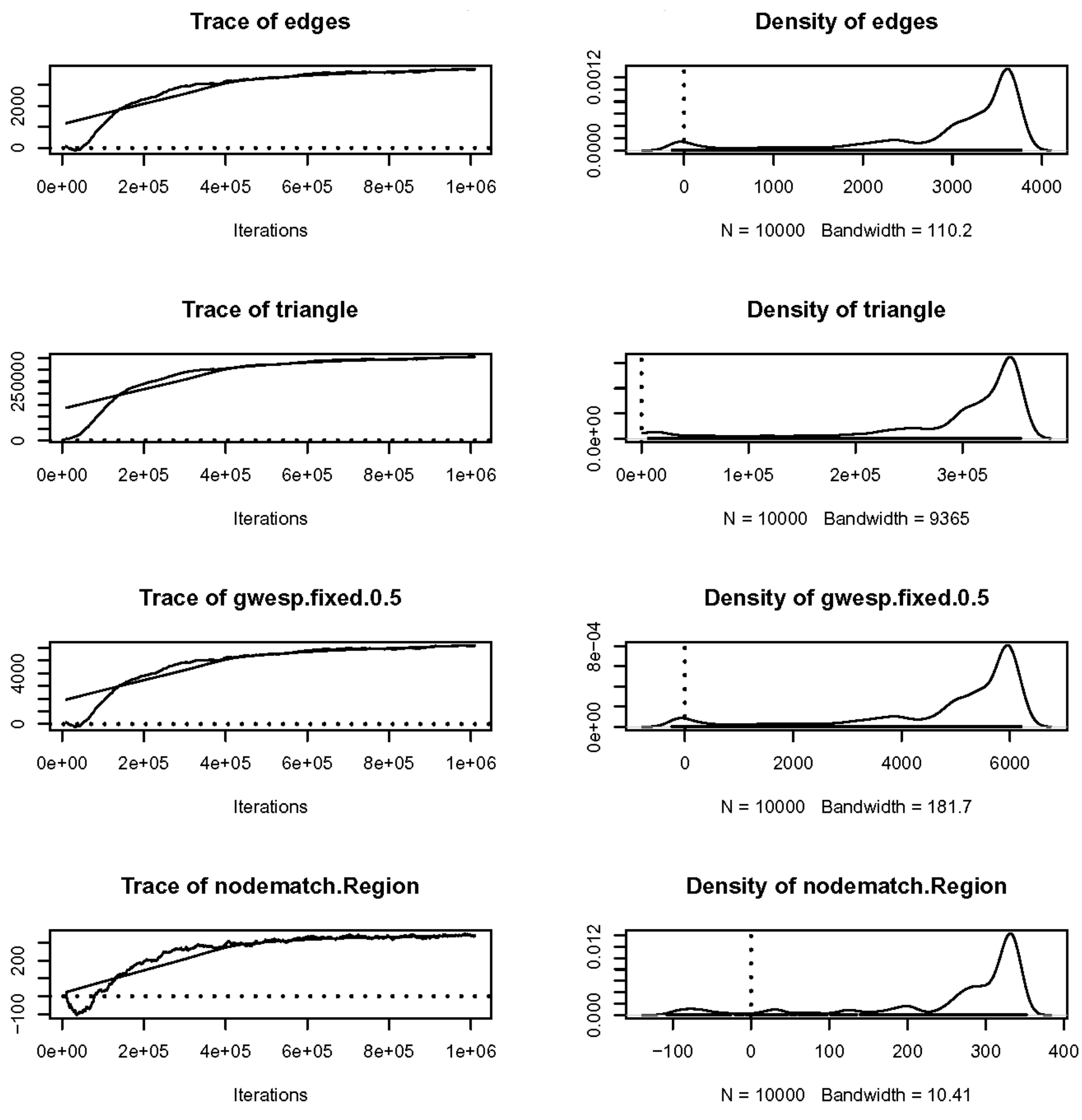
Appendix G

Table 4: ERGM Models

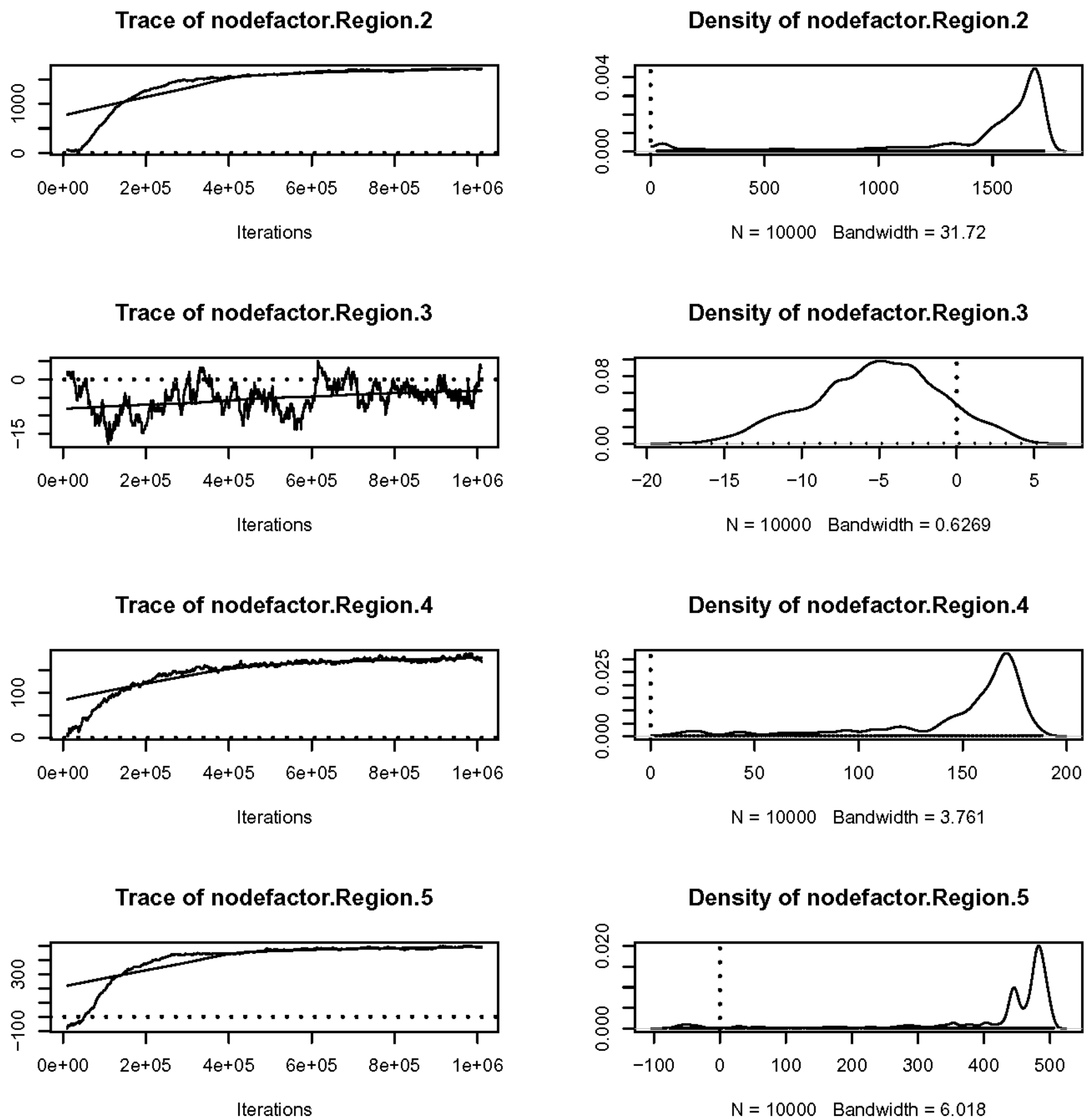
	Model 1	Model 2	Model 3	Model 4
Log Likelihood	-7324.3	-6919.7	-6677.8	-6521.9
Edges	-7.56***	-7.92***	-5.01***	-6.96***
Triangle	.077***	.078***	.081***	.077***
Gwesp.fixed.0.5	2.50	2.62***	1.94***	2.16***
Nodematch.Region	…	.428***	.737***	.835***
Nodefactor.EU	…	…	-.768***	-.483***
Nodefactor.E.ASIA	…	…	1.73 .	3.02**
Nodefactor.ECE	…	…	-.182 *	-4.84*
Nodefactor.ASEAN	…	…	-1.16***	-.119
Nodefactor.SAA	…	…	-.679***	-.0092
Nodefactor.ARAB.L	…	…	-.860***	-.920***
Nodefactor.PAC.ISL	…	…	-1.37***	-.483**
Nodefactor.LAT.AM	…	…	-.734***	-.728***
Nodefactor.AFRICA	…	…	-1.28***	-.565***
Nodecov.pcGDP	…	…	…	.004***

Appendix H

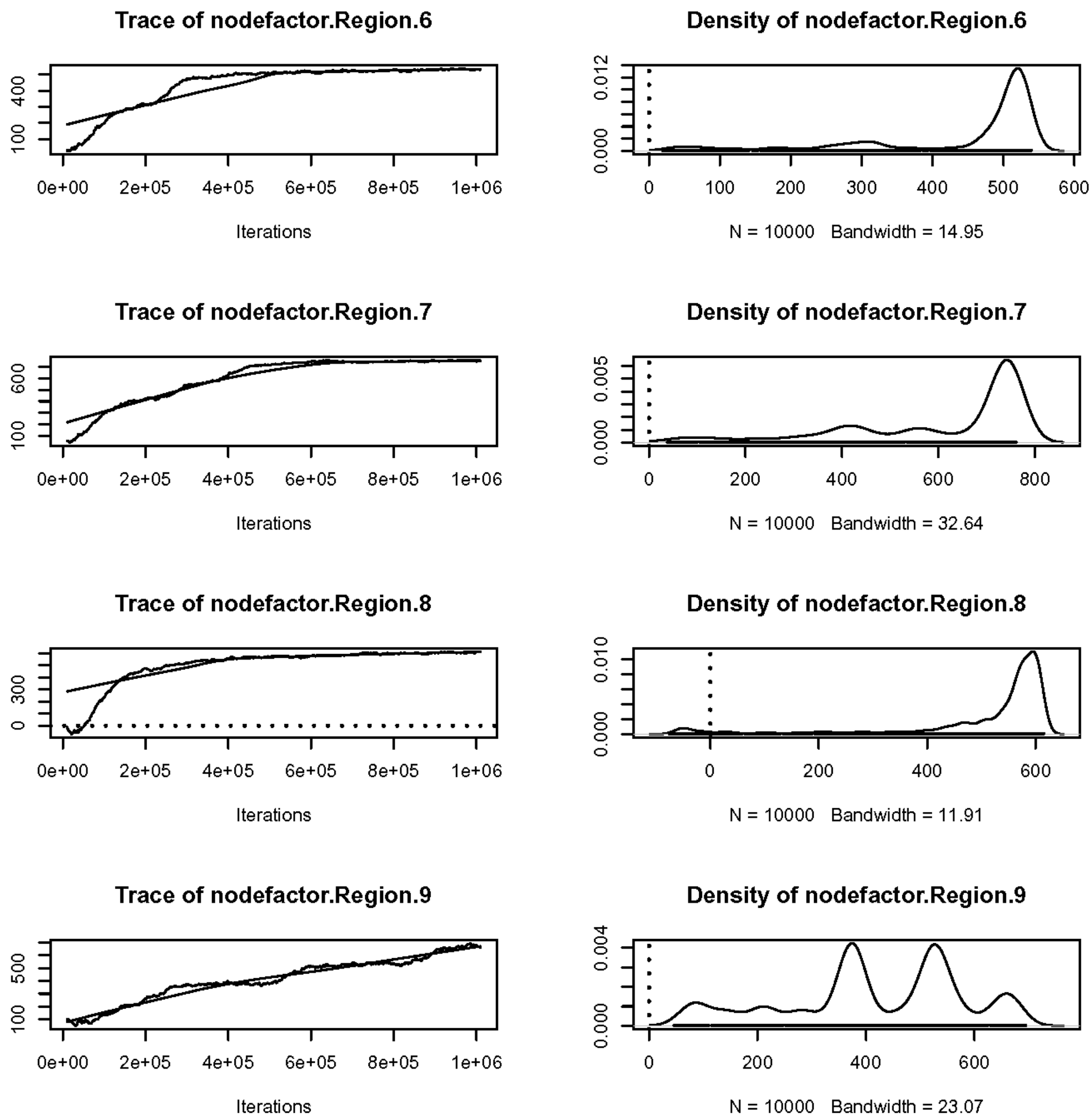
Figure 4: MCMC Degeneracy Plots



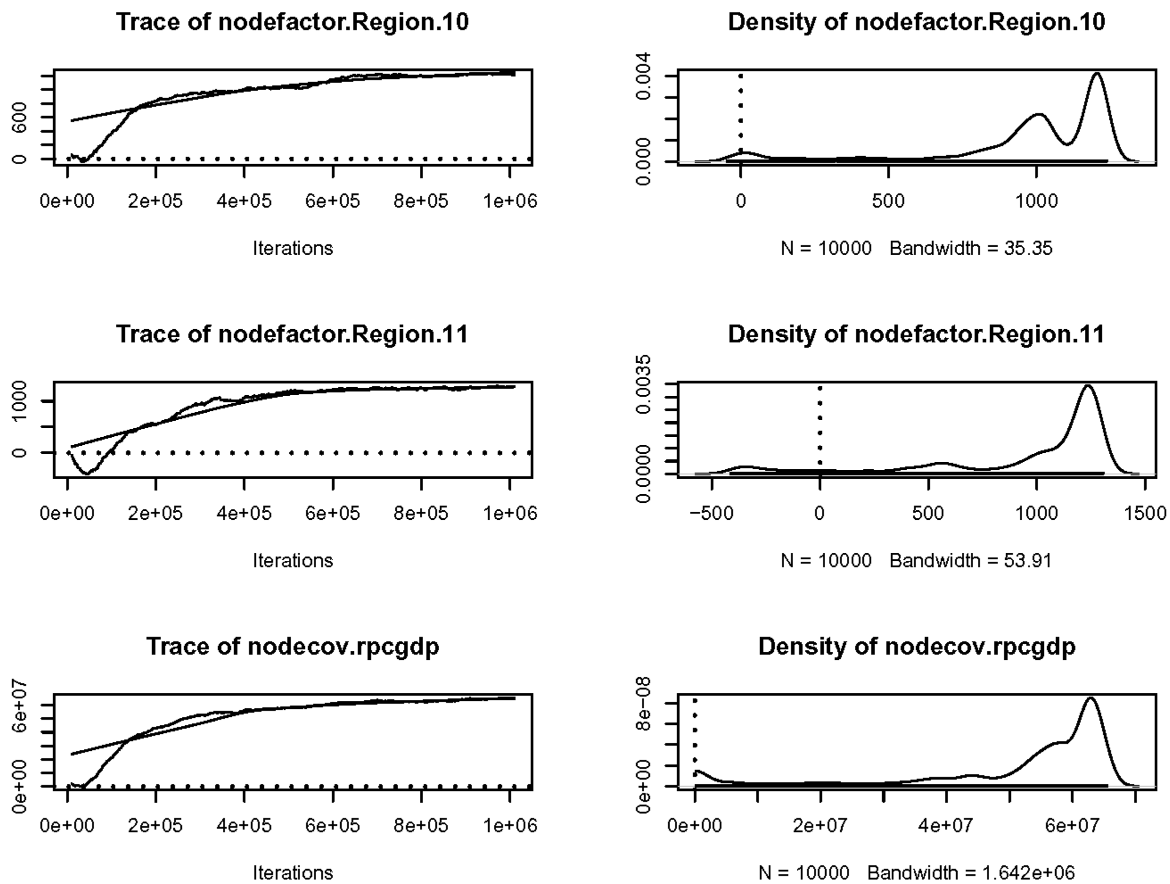
(Figure 4 cont.)



(Figure 4 cont.)



(Figure 4 cont.)



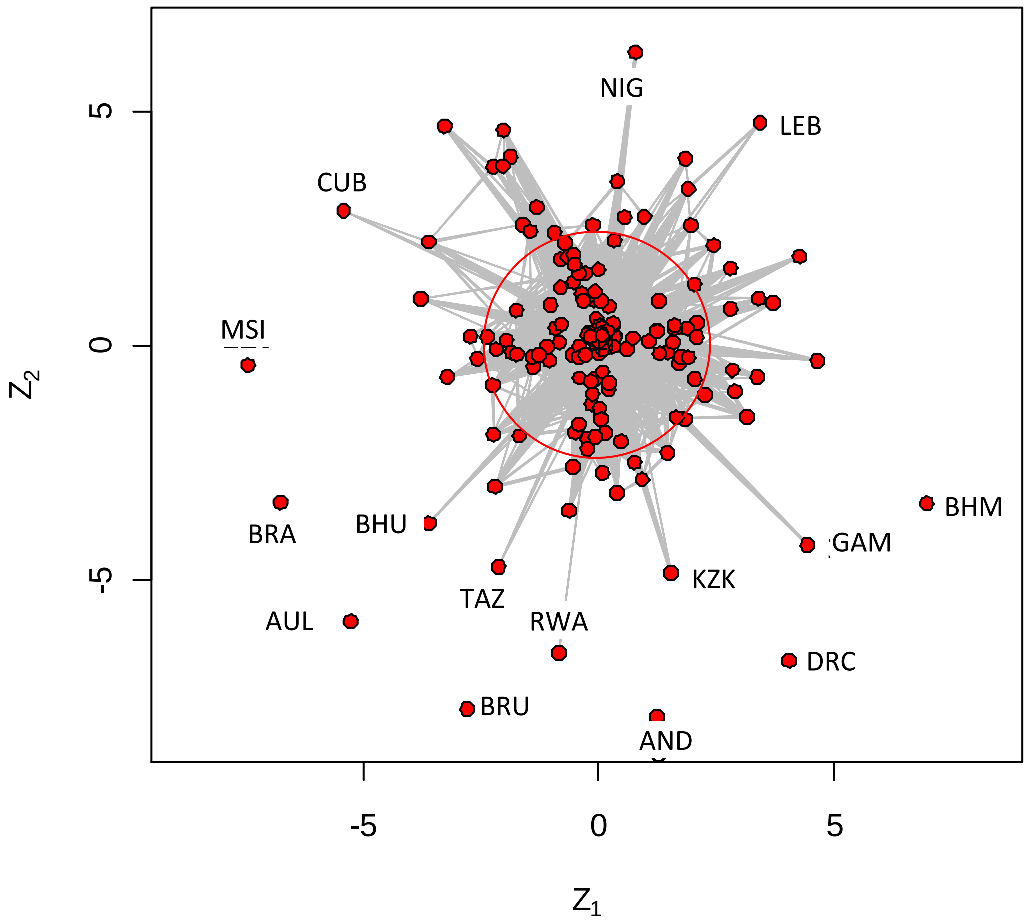
Appendix I

Table 5: Latent Space Models (d=2)

	Model 1	Model 2
Edges	2.56***	-5.73***
Latentcov (homoregion)		26.25***

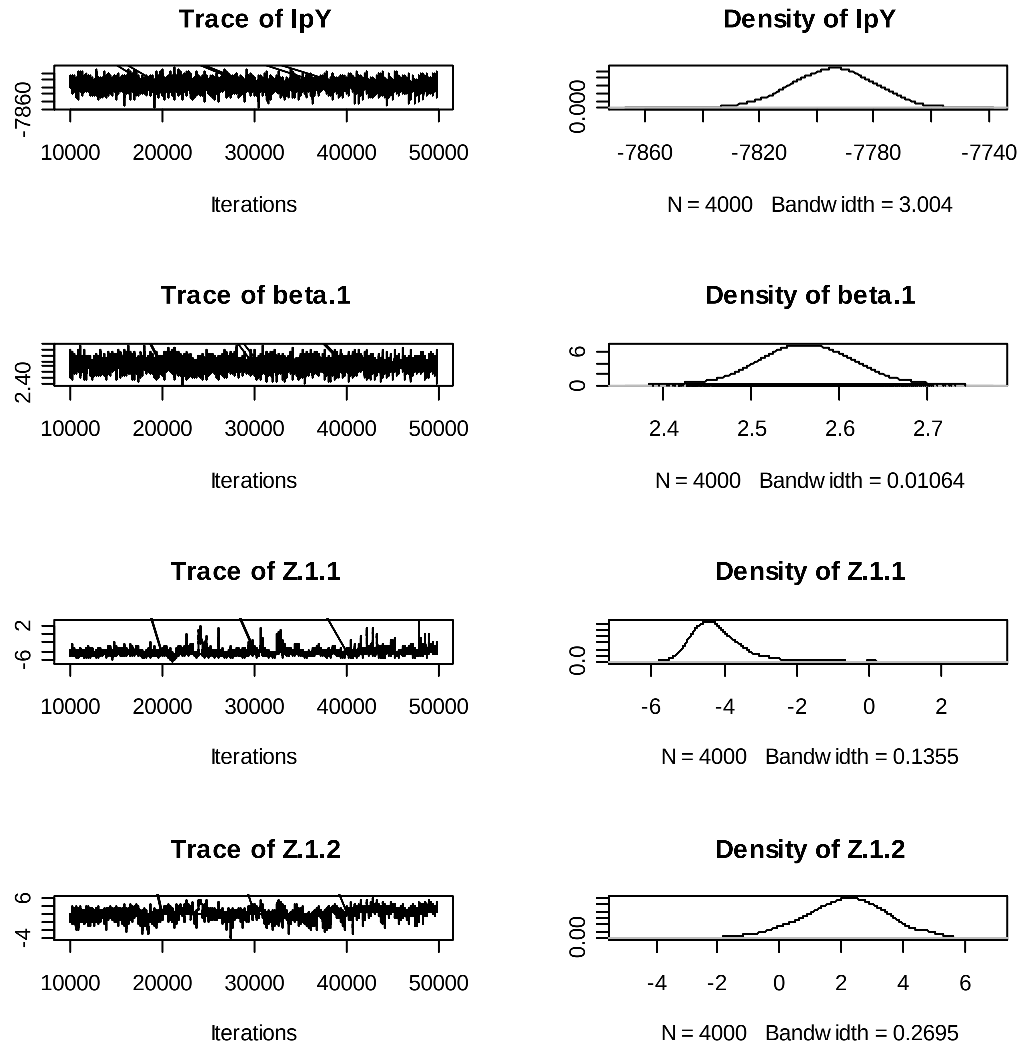
Appendix J

Figure 5: MKL Latent Positions for Model 2



Appendix K

Figure 6: MCMC Diagnostics



Bibliography

Aggarwal, V. K., & Koo, M. G. (2005). Beyond Network Power? The dynamics of formal economic integration in Northeast Asia. *The Pacific Review*, *18*(2), 189-216.

Alcala, F. Ciccone, A. (2004). Trade and Productivity. *The Quarterly Journal of Economics*, *119*(2), 613-646.

Beckfield, J. (2010). The Social Structure of the World Polity. *American Journal of Sociology*, *115*(4),1018-68.

Bhattacharya, K., Mukherjee, G., Saramaki, J., Kaski, K., & Manna, S. (2008). The International Trade Network: weighted network analysis and modeling. *Journal of Statistical Mechanics: Theory and Experiment*, p.02002.

Clark, R. (2010). World-System Mobility and Economic Growth, 1980-2000. *Social Forces*, *88*(3), 1123-1151.

Clark, Rob. (2008). Dependency, Network Integration, and Development. *Sociological Perspectives*, *51*(3), 629-648.

Fagiolo, Giorgio, Reyes, J., & Schiavo, S. (2009). World-trade web: topological properties, dynamics, and evolution, Pt. 2. *Phys. Rev. E*, *79*(3), p.036115.

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

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

Garlaschelli, D., Di Matteo, T., Aste, T., Caldarelli, G., & Loffredo, M. (2007). Interplay Between Topology and Dynamics in the World Trade Web. *The European Physical Journal B*, *57*, 159-164.

Goodreau, Steven M, Handcock, M. S., Hunter, D. R., Butts, C. T., & Morris, M. (2008). A statnet Tutorial. *Journal of statistical software*, *24*(9), 1-27.

He, J., & Deem, M. (2010). Structure and Response in the World Trade Network. *Physical Review Letters*, *105*(19), 1-4.

Hunter, D. R., Handcock, M. S., Butts, C. T., Goodreau, S. M., & Morris, M. (2008). ergm: A Package to Fit, Simulate and Diagnose Exponential-Family Models for Networks. *Journal of Statistical Software*, *24*(3), 1-29.

Hunter, David R. (2007). Curved Exponential Family Models for Social Networks. *Social Networks*, *29*(2), 216-230.

Hunter, D. R., & Handcock, M. S. (2006). Inference in Curved Exponential Family Models for Networks. *Journal of Computational and Graphical Statistics*, *15*(3), 565-583.

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

Kastelle, T., & Liesch, P. (2006). Measuring Globalization : An Evolutionary Economic Approach to Tracking the Evolution of International Trade, *Druid Conference Paper*.

Kim, S., & Shin, E.-H. (2002). A Longitudinal Analysis of Globalization and Regionalization in International Trade: A Social Network Approach. *Social Forces*, *81*(2), 445-468.

Krivitsky, P. N., & Handcock, M. S. (2008). Fitting Position Latent Cluster Models for Networks with latentnet. *Journal Of Statistical Software*, *24*(5), 1-23.

Li, X., Yingjin, Y., & Chen, G. (2003). Complexity and Synchronization of the World trade Web. *Physica A: Statistical Mechanics and its Applications*, *328*(1-2), 287-296.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a Feather: Homophily in Social Networks. *Annual Review of Sociology*, *27*(1), 415-444.

Morris, Martina, Handcock, M. S., & Hunter, D. R. (2008). Specification of Exponential-Family Random Graph Models: Terms and Computational Aspects. *Journal of statistical software*, *24*(4), 1548-7660

Nemeth, R. J., & Smith, D. A. (1985). Trade and International Structure : A Multiple Network Analysis. *Quantitative Studies of the World-System*, *8*(4), 517-560.

O'Brien, R. (1992). *Global Financial Integration: The End of Geography*. *1992*. Foreign Relations Press.

Reyes, J., Schiavo, S., & Fagiolo, G. (2007). Using Complex Network Analysis to Assess the Evolution of International Economic Integration : The cases of East Asia and Latin America. *LEM Working Paper Series*.

Reyes, J., Schiavo, S., & Fagiolo, G. (2010). Using Complex Networks Analysis to Assess the Evolution of International Economic Integration: The cases of East Asia and Latin America. *The Journal of International Trade & Economic Development*, *19*(2), 215-239.

Rodrik, D. (2001). Institutions, Integration, and Geography: In Search of the Deep Determinants of Economic Growth. *Unpublished Working Paper, Cambridge University, MA.*

Rodrik, D., Subramanian, A., & Trebbi, F. (2004). Getting Institutions Right: The Primacy of Institutions Over Geography and Integration in Economic Development. *Journal of Economic Growth*, *9*(2), 131-165.

Schiavo, S., Reyes, J., & Fagiolo, G. (2010). International trade and financial integration: a weighted network analysis. *Quantitative Finance*, *10*(4), 389-399.

Schweitzer, F., Fagiolo, G., Sornette, D., Vega-Redondo, F., & White, D. R. (2009). Economic Networks: What Do We Know and What Do We Need To Know? *Advances in Complex Systems*, *12*(04 & 05), 407-34.

Serrano, M. A., & Boguna, M. (2003). Topology of the World Trade Web. *Phys. Rev.. E,* 68, p.015101.

Serrano, M. (2008). Rich-club vs. rich-multipolarization phenomena in weighted networks. *Phys. Rev. E*, *78*, p.026101.

Shortreed, S., & Handcock, M. (2004). Positional Estimation within the Latent Space Model for Network. *Methodology,* 2, 24-33.

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

Squartini, T., Fagiolo, G., & Garlaschelli, D. (2011). Rewiring World Trade, Part I: A Binary Network Analysis. *LEM Working Paper Series*.

Toffler, A. (1970). *Future Shock*. Bantam Books.

Warwick, M. (2005). *Geographies of Globalization*. London and New York: Routledge.

Westveld, B. A. H., & Hoff, P. D. (2010). A Mixed Effects Model for Longitudinal Relational and Network Data, with Applications to International Trade and Conflict. *Annals of Applied Statistics*, *5*(2), 843-872.