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Is Geography 'Dead' or 'Destiny' in a Globalizing World? A Network Analysis and Latent Space Modeling Approach of the World Trade Network

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Abstract

Drawing on advancements made in network analysis, statistical modeling and computer science, this paper employs latent space modeling techniques to explore the role of geography in the global trade economy. Latent space models postulate that the probability of a link between pairs of actors depends on the distance between them in unobserved Euclidean social space and on observed covariates. Using probabilistic models, I investigate the effect that distance has on influencing trade ties in social space, while also controlling for several covariates, including region-based homophily (a proxy for regionalization), transitivity and country wealth. The findings are posited within the 'Geography is Dead' thesis and reveal that the distance-destroying result attributed to globalization may be over-estimated in the global trade economy.

Keywords: *network analysis, latent space model, world trade network, geography, regionalization, globalization.*

1. Introduction

Since Toffler (1970) first argued that place is no longer an important determinant due to the evolution of transport and communication systems, numerous scholars have speculated the 'death of geography', giving rise to a heated debate (Ohmae 1990, 1995; Friedmann 1995). O'Brien (1992) proclaimed that the globalization era equates to 'the end of geography', because geographical location no longer matters for economic development due to the increasing rate of globalization. In this context, globalization is defined as 'the deepening integration of global economic activity facilitated by the rapid development of information and communications technology and the underlying trend towards liberalization in trade and investment' (Staples 2007: 99).

Despite the 'geography is dead' claims, many notable (economic) geographers emphasize the critical role of geography in trade, as well as in innovation, knowledge and development (Krugman 1993; Yeung 1998; Massey 1984, 1999; Morgan 2004). It is well known that the effects of globalization are not distributed uniformly throughout the global economy, and 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 trade and economic development. Regionalization is defined here as a process, 'whereby economic interaction, such as flows of goods and capital, increase faster among countries within a particular geographical area than between those countries and others outside the area' (Moore 2007: 36).

In the present paper, I apply latent space modeling – developed by Hoff *et al.* (2002) – to test the 'geography is dead' thesis. Hoff *et al.* (2002) postulate that the probability of a link between pairs of actors depends on the distance between them in unobserved Euclidean social space and on observed covariates. Using the latent space modeling approach, I investigate the effect that distance has on trade ties in latent space, while also controlling for several covariates, including region-based homophily (a proxy for regionalization), transitivity and country wealth.

Stochastic models can be used to identify the specific processes that have led the network to its particular configuration. Both the gravity model and the exponential random graph model (ERGM) are possible approaches to test the relationship between geography and trade. Aside from weak theoretical backing, another main shortcoming with these approaches is that they assume independence among all trade linkages between country pairs. In reality, it is very likely that there is inherent dependency between ties (Shortreed *et al.* 2006). For example, if South Africa and Brazil are trade partners, and China and Brazil are trade partners, then it is more likely that South Africa and China are trade partners then it is if these previous trade relationships did not exist.

By implementing proxies to take into account second- and third-order dependences in the network, the latent space model is one method to deal with this dependency.

This paper attempts to add to the growing literature on the World Trade Network (WTN), as well as to test the 'death of geography' thesis, by statistically analyzing the role of geography and trade integration using latent space stochastic models. To carry out these objectives, I estimate several simple latent space models to capture the relationship between distance and the likelihood of two countries establishing a trade partnership in the WTN, while also taking into account higher order dependencies in the network. Results from the analysis support regionalization, in favor of the 'geography is destiny' thesis (Dieter 2007), implying that proponents of the 'geography is dead' overestimate the distance-destroying effects of globalization on the global trade economy.

The outline of this paper is as follows. In the subsequent section, I provide a brief background on relevant network analysis studies. In Section 3, I discuss issues related to building, specifying and representing the trade network. In Section 4, I provide an overview of the main network statistics and network properties commonly used to infer patterns in the trade network. Specifically, I consider connectivity, centrality, clustering and hierarchy, as well as homophily and transitivity. In Section 5, I specify several latent space models and test the principles of propinquity, homophily and transitivity. Lastly, Section 6 concludes with some final remarks.

2. Background

Due to advancements in physics and computer science, network analysis is increasingly relied upon to study the world trade network and is a powerful tool that can be used to reveal topological properties, as well as the underlying structure of the trade network (Fagiolo *et al*. 2009; Reyes *et al*. 2007, 2010). For instance, network analysis applications of the world trade network (WTN) have most notably addressed two major questions: (1) does the trade network follow a core-periphery structure (Clark 2008, 2010; Kali and Reyes 2007); and (2) 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).

Although comparatively underdeveloped, network analysis has also been employed to investigate the role of geography in the global trade economy. Kim and Shin (2002) argue that network analysis can naturally be extended from dependency/world-systems theory to test the globalization *vs.* regionalization thesis that indirectly tests the role of geography by determining whether countries in the network are globalizing or regionalizing (Aggarwal and Koo 2005; Kim and Shin 2002; He and Deem 2010).

Findings from network analysis contribute to the debate over whether regionalization is a stepping stone or stumbling block to globalization (Bhagwati *et al*. 1999). On the one hand, some scholars believe that regionalization is a transitory step that some countries pursue to become more competitive on the global market, eventually promoting globalization and rendering geography unimportant. On the other hand, other scholars 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.

For instance, Kastelle *et al*. (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'. The authors' finding is significant because it highlights the power of geography to influence trade outcomes; even in an ever-increasing global-

ized world, countries still pursue regional trade integration policies with nearby countries.

Conversely, Kim and Shin (2002) argue that globalization and regionalization are not necessarily competitive, but complementary processes. From 1959–1996, the authors show that the WTN became globalized (overall network density increased significantly), while it also became regionalized (intraregional density also significantly increased). Based on their findings, the authors suggest that regionalization does not jeopardize globalization; rather the two processes are complimentary and can coincide with one another.

While the authors' findings have far reaching implications into the effects of regionalization and globalization on the global economy, the findings are predicated merely on descriptive statistics, in this case, a network statistic called node degree. 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.[11] The problem with this network statistic, like any other descriptive statistic, is that no statistical model is used to control for other potential intermediating variables that may influence the outcome of a trade tie being established.

Most of the literature on the WTN only examines the network's summary statistics to track topological changes, and few attempts are made to statistically analyze the trade network using stochastic models (notable exceptions are Garlaschelli and Loffredo 2005; Garlaschelli *et al.* 2007). Fitting statistical models to networks, in general, is still in its infancy stages due to the complexity of modeling networks and the high level of computation that is required (Hunter and Handcock 2005). It is not surprising, therefore, that the WTN literature has only recently begun to be modeled; despite the complicated nature of the WTN, pertinent topological properties of the global trade system can and should be extracted through modeling the system as a network (Serrano 2008).

3. The Network Data: Specification and Representation

Bilateral trade data are extracted from the United Nations COMTRADE database. Data for GDP per capita and the trade/GDP share are extracted from Penn World Table 6.2 (for a country listing, see Appendix). In the trade network, countries represent nodes and the links between two countries are their shared imports and exports. 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 2002).

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[1] Node degree is discussed in greater detail in Section 4.

A network can be set up as some combination of binary/weighted, directed/undirected and static/longitudinal. For the purposes of this research, I build a binary, undirected and static network. These specifications are chosen for the following reasons: (1) Squartini *et al*. (2011) specify various combinations of the network and find that the projections made by the binary matrix are maximally informative and should be the focus of subsequent models of trade; (2) the number of in and out ties are highly correlated, and in accordance with Fagiolo *et al*. (2009) and Serrano and Boguna (2003), the WTN is sufficiently symmetric to use an undirected analysis; and (3) 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). To avoid the complexities of using longitudinal data, it is suffice to select a stochastic model for a single year, 2008, to examine the statistical properties of the WTN.

Network Representation

Graph theory, advanced by Harary and his collaborators (Harary 1959; Harary *et al*. 1965), is used to inform much of what we know about how networks work. A graph is a network model consisting of dichotomous (binary) relations. The network can be represented with the following graph notation:

$$G = (V, E) \qquad \text{(Eq. 1)}$$

where V is a vertex set, $V = \{v_1, \ldots, v_2\}$, and in the undirected graph, $E \subseteq \{(v_i, v_j) : v_i, v_j \in \in V\}$. In the undirected case, if country i exports to country j or country j exports to country i, then $y_{ij} = 1$. 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 WTN literature (Kim and Shin 2002) 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. Y_{ij} is a binary random variable which indicates the state of the i, j edge. The Pr $(Y_{ij} = y_{ij})$ is the probability of the Yij edge state. I can express y_{ij} in terms of the WTN as a dichotomous outcome:

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

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:

$$\Delta = \frac{\Sigma_{i,j} y_{ij}}{g(g-1)} \,. \qquad \text{(Eq. 3)}$$

The density for the WTN in 2008 is .59, which means based on the number of nodes, trade ties represent approximately 59 per cent of the total possible.

There are 7,177 mutual ties in 2008, but 2,799 asymmetric trade ties. Germany, the U.S., and China are the biggest traders averaging around US $8 billion to each of its trading partners. Almost 40 per cent of countries export something to almost every other country, and every country exports to at least 20 other countries, indicating that the trade network is very concentrated.

Table 1. Network statistics for 2008

	2008
Countries Reporting Trade	190
Graph Density	.59
Total number of dyad trade ties	7 177
Total number of asymmetric trade ties	2 799
Countries making up 50 % of exports	9

Source: Author's calculations using COMTRADE database on reported trade 2008.

4. Network Summary Measures: Definitions and Descriptive Statistics

Each network statistic attempts to explore the underlying structure of the network along one of the four major dimensions: connectivity, assortativity, clustering and centrality. Within each dimension, various node level statistics can be employed to quantify individual positions in the network and describe the local neighborhood. For example, node degree (ND) and node strength (NS) are network statistics used to measure node connectivity. ND is used when dealing with a binary network, and is the fractional count of trading partners a country has relative to all possible trade links in the network. NS is used when dealing with weighted networks, and measures the intensity of these trade links.

Both statistics calculate the number of direct ties coming in and going out of a node and represent how connected a country is within a trade network. High degree positions are influential in the network, and at the same time, may be vulnerable to other actors' influence. 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.

The average nearest neighbor degree (ANND) and average nearest neighbor strength (ANNS) are the most common network statistics to test assortativity. They measure 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, ANND/ANNS gives ND/NS statistics for each of country A's trading partners. These two statistics are commonly employed to assess whether certain group-

ings of countries tend to trade with well- or less-connected countries. For example, ANND/ANNS can be used to test whether a 'rich club phenomenon' has emerged in the WTN.

The binary clustering coefficient (BCC) and the core clustering coefficient (CCC) are statistics for clustering. 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. These statistics offer a perspective on the multi-lateralism *vs.* bilateralism debate. Clearly, if the statistics increase over time, the WTN 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. The betweenness (BET) and the random walk betweenness centrality (RWBC) measures are the most commonly employed statistic for the centrality dimension and are based on reach and flow mediation. Both statistics quantify the ability of the ego-node to influence other vertices in the network. The higher is the measure for a country, the higher is the degree of influence that country has on the WTN. Most often, this measure has been found to show a core-periphery hierarchy in the WTN, thus strengthening the position of world-systems perspective.

In addition to network statistics, homophily is an important feature in this 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 than dissimilar people (Louch 2000; 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 (McPherson *et al*. 2001), so it makes intuitive sense to group countries based on geographic proximity (refer back to the Appendix for a country listing by region).

Transitivity is another main feature found within networks. Transitivity is a statistics 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, that is 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' (Krivitsky *et al*. 2009). Balance theory predicts that if ties exist between country A and country B and country B and country C, then country A and country 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).

Descriptive Network Statistics: Connectivity, Centrality and Homophily

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 ties will equal out-degree ones, expressed as

$$\frac{C_i(n_i) = \Sigma_{j=1}^{g} x_{ji}}{(g-1)} . \qquad \text{(Eq. 4)}$$

Histograms of the node degree show that the distribution of trading partners is right-skewed, meaning that most countries in the network have a small number of trading partners but a smaller number of countries, referred to as 'hubs', have a comparatively larger number of trading partners (see Fig. 1).
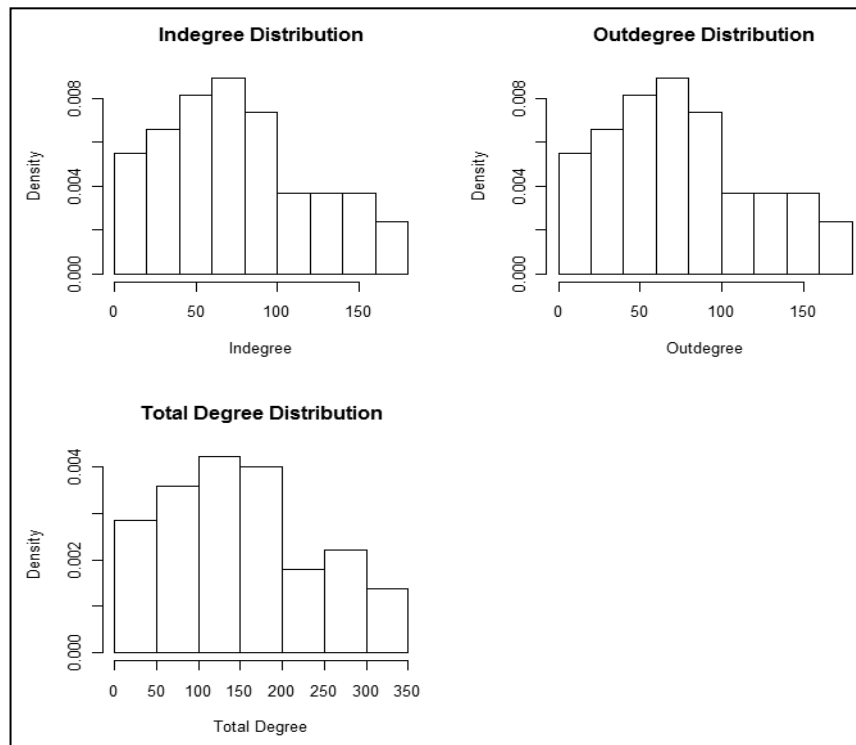

Fig. 1. Node degree distribution for the world trade network

Along the second dimension, centrality measures the quantity of walks that pass through the ego-node, that is betweenness. Betweenness (BET) is the tendency for an ego-node to reside on the shortest paths between third parties, that is, to serve as a bridge between two other nodes.

Betweenness relies on the concept of geodesic distance, which is the shortest path between two nodes, *i* and *j*. Betweenness can be quantified and expressed as:

$$C_b(n_i) = \frac{\sum_{j<k} \frac{g_{ik}(n_i)}{g_{jk}}}{\frac{(g-1)(g-2)}{2}} . \qquad \text{(Eq. 5)}$$

g_{jk} is the number of *j, k* geodesics (the shortest path between *j, k*) and g_{ik} *(n_i)* is the number of *j, k* geodesics that include *i*. High betweenness 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 centrality measure that is less commonly explored in the world trade network 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:

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

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

Table 2 reports the statistics for a selective number of measures, including connectivity (ND) and centrality (BET, EC) by region. The findings reveal the most connected countries within regions, as well as compare the degree of influence across regions. For example, 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.

Table 2. Connectivity and Centrality Measures by Region and Select
Countries

Region	ND	BET	EC
1	2	3	4
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
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**
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

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 the number of its trading partners and becoming better connected with the global economy, its actual influence in the network in terms of trade remains limited relative to Japan. Japan, along with the UK, and the USA 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 (see Fig. 2).

　　To gain a better understanding on whether homophily by region is present in the WTN, I present the mixing matrix for each region (Table 3). 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, then there would be 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.
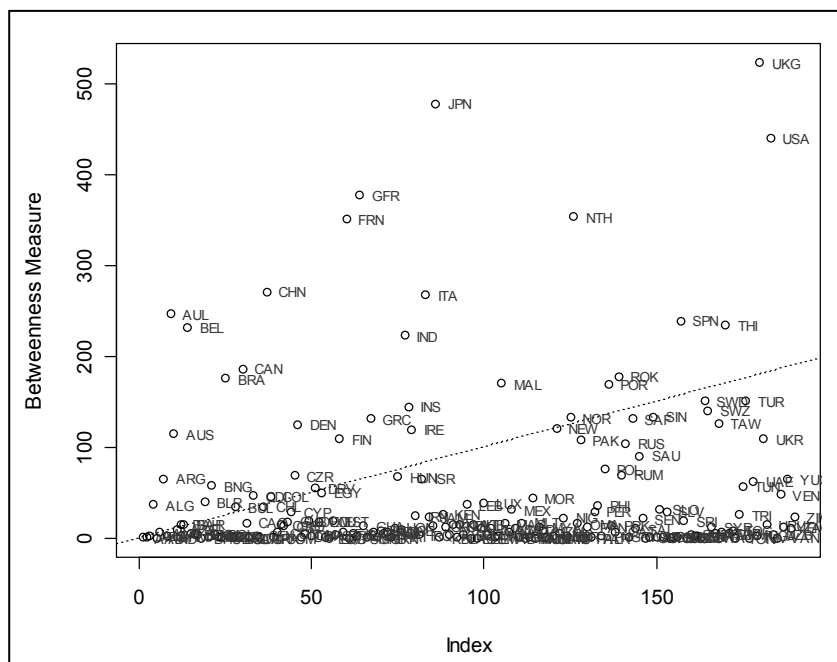

Fig. 2. Centrality score by country

Table 3. 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

There are two 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). The trade network is also 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. Second, there are 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 in certain cases, since its value along the diagonal is 0, and the data only cover international trade. Therefore, it is not possible to see China's intra-trade relationships and how it compares to other countries' international trade within a particular region.

The number of triangles found in the network area is a proxy for measuring the transitivity. Of the 7,177 ties in the network, 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. This is significant because it reveals the dyadic trade dependencies among countries supporting the use of a latent space modeling approach.

5. Latent Space and Latent Position Model: Is Geography Dead?

Latent space models have replaced block-modeling as the primary approach to study issues of propinquity, the tendency of spatially proximate vertices to be tied. In other words, latent space models are used to determine the role of geography in the international trade context, and can help examine whether the trade network is globalizing or regionalizing. If proponents of globalization who suggest 'geography is dead' are correct in their assertion, then the results of the latent space model will 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.

In order to test the role of geography in determining the probability two countries (i, j) form a trade relationship, I specify several latent space models. Based on the presence of homophily indicated by the descriptive statistics, there is evidence that propinquity – the probability of a link between two actors is a function of the distance between them in an unobserved latent space – exists in the trade network.

The latent position model assumes a conditional independence approach to modeling. Let $\{z_i\}$ be the positions of the actors in the social space 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:

$$P(Y|Z, X, \theta) = \prod P(y_{i,j} \mid z_i, z_j, x_i, \theta), \quad \text{(Eq. 7)}$$

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 *et al.* 2002). I use logistic regression to parameterize Eq. 3.

$$\eta_{i,j} = \log\ odds\left(y_{i,j} = 1 \mid z_i, z_j, x_{i,j}, \alpha, \beta\right). \quad \text{(Eq. 8)}$$

$$\eta_{i,j} = \alpha + \beta' x_{i,j} - \left| z_i - z_j \right|, \quad \text{(Eq. 9)}$$

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

$$\log P\left(Y|\eta\right) = \sum_{i \neq j} \left\{ \eta_{i,j} y_{i,j} - \log\left(1 + e^{\eta_{i,j}}\right) \right\}, \quad \text{(Eq. 10)}$$

where η is a function of parameters and unknown positions. As such, I use maximum-likelihood to estimate η. 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 underlying 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). To check for issues of degeneracy, I carry out an MCMC estimation procedure for each model that I estimate. The results show that the model statistics do not diverge from the mean, meaning that the models are not degenerate and the maximum likelihood estimates are reliable.

I specify several simple latent space models to test the role of distance and region-based homophily. Table 4 reports the coefficients generated from the latent space models. 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 estab-

lishing 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 Models 2 and 3, I give additional measures to control for underlying structures within the network that may affect whether a trade tie is established.

Table 4. Latent space models (d = 2)

	Model 1	Model 2	Model 3	Model 4
Edges	2.56***	−5.73***	−6.21***	−6.13***
Latentcov (homoregion)		26.25***	27.20***	27.81***
Triangle			1.84***	2.02***
Nodecov.GDP				1.42***

A good model is the one that accounts for a country's tendency for assortative mixing, which is based on the notion of homophily (Goodreau *et al.* 2008). In the present context, I want to account for assortative mixing that may occur for countries that belong to 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 introduces *Homoregion*, a covariate that accounts for homophily. In this model, I find the sign of the EDGES coefficient switches 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 *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 within their own region than with countries from other regional groupings, in support of the regionalization thesis. Model 3 adds *Triangle* to take into account the transitive nature of the network. The significant, positive coefficient for *Triangle* confirms that if two countries *i, j,* have a mutual trading partner, *m*, then the likelihood that countries *i, j* begin to trade increases.

In addition to controlling for network statistics, Model 4 adds real per capita GDP, *Nodecov.GDP* as an additional covariate to control for the effect of wealth on countries forming a tie. The positive, statistically significant coefficient produced by the wealth covariate reveals the hierarchical structure of the network, meaning that rich countries tend to trade disproportionately among themselves.

6. Conclusion

The findings presented in this paper suggest that regionalization is a particularly important strategy pursued by countries in the global economy. The integration of regional blocs, along with the proliferation of regional trade agreements (RTAs) promote regionalization and have emerged as individual countries attempt to mitigate the new economic and security vulnerabilities (unregulated capital flows, human and drug trafficking, transnational terrorist net-

works, disease, *etc*.) brought about by globalizing forces that undermine individual states' territorial sovereignty. The process of regionalization signals that 'geography is destiny' (Dieter 2007: 11), as opposed to 'geography is dead'.

The results of the descriptive analyses in this report agree with other previous works. The WTN network has a high density, the node degree has a high right-skew, trade partners of well-connected countries are less interconnected relative to those of poorly connected ones, and countries holding many trade partners are on average connected with countries holding relatively few countries. 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 and other covariates, the Euclidean distance – calculated in social space – is returned negative, significant, and large in magnitude. This result supports findings in the gravitas literature on trade and reaffirms that the probability that trade ties are established decreases as distance increases. Lastly, the latent space models add an additional dimension of analysis of the WTN by controlling for network dependencies, and reveals that region-based homophily – the proxy for regionalization – has a large and significant influence on trade outcomes, even more so than a country's wealth.

Despite the complicated nature of the WTN, pertinent topological properties of the global trade system are extracted through modeling the system as a network, and are used to show the significance of geography in influencing trade outcomes. Understanding the structure of the global trade network has implications for research across numerous social science disciplines trying to examine the effects of geography on economic integration and internationalization. Future areas of research can extend the latent space model applied in this paper to examine the evolutionary role of geography over time. Although evidence reported in this paper suggests that geography maintains a crucial role in the trade network, it is indeterminate whether geography's impact on trade ties is increasing or decreasing over time.

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Appendix

190 countries are placed into 11 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 all categorized as one European region based on their geographical proximity. Similarly, UNASUL, Caribbean Community and the Central American Integration System member countries are all categorized as Latin America.

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)
(Also Region 4)
JPN
MON
PRK
ROK
TAW
CHN

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
DRV
MYA
PHI
SIN
THI

South Asia Association
(Region 7)
AFG
BHU
BNG
IND
MAD
NEP
PAK
SOL
SRI

Arab League (Region 8)	COL	ETH
BAH	COS	GAB
EQG	CUB	GAM
IRN	DOM	GHA
IRQ	ECU	GNB
ISR	GRN	KEN
JOR	GUA	LBR
KUW	GUI	LES
LEB	GUY	LIB
MOR	HAI	LIE
OMA	HON	MAG
PAL	JAM	MAS
QAT	MSI	MAW
SAU	NIC	MLI
SUD	PAN	MZM
SYR	RUM	NAM
UAE	SAL	NIG
YEM	SKN	NIR
Pacific Islands	SLU	PAR
(Region 9)	SUR	PER
AAB	SVG	RWA
AUL	TRI	SAF
AUS	URU	SEN
DMA	VEN	SEY
FJI	**African Union**	SIE
FSM	**(Region 11)**	SOM
KBI	ANG	STP
NAU	BEN	SWA
NEW	BFO	TAZ
PNG	BOT	TOG
TON	BUI	TUN
TUV	CAO	UGA
VAN	CAP	ZAM
Latin America (Region 10)	CDI	ZIM
ARG	CEN	
BAR	CHA	
BHM	COM	
BLZ	CON	
BOL	DJI	
BRA	DRC	
BRA	EGY	
CHL	ERI	