Homophily or Heterophily?
The Role of Country Logistics in the Global Economy

ABSTRACT

Do countries sharing similar logistics capabilities trade more with each other? How logistics capabilities impact a country's global trade? Collecting various datasets for 163 countries and applying Additive and Multiplicative Effects (AME) modeling in social network analysis, we find that the role of logistics on global trade is heterophilous rather than homophilous, i.e., countries tend to trade more with countries whose logistics capabilities are vastly different from them. Further, despite a country's current level of logistics capabilities, improving logistics capabilities increases both its exports and imports. Finally, different from trade logistics and trade economics literature, we find that shipping efficiency, timeliness, and track and trace capability are not statistically significant with bilateral trade. Only improvement in logistics infrastructure and logistics competence increases trade flows. Our study enriches the understanding of the role of logistics in the global economy by offering fundamentally different findings for country policymakers to invest in the right logistics dimensions to compete. We challenge the classic gravity model used in global trade economics as gravity model shows the worst model fit among a portfolio of models while AME model demonstrates the best model fit. By providing all implementation code in R for all our analysis, we hope to advance the methodological stringency when modeling a complicated network such as the global trade network.

Keywords: logistics, global trade, social network analysis, gravity model

1. INTRODUCTION

Homophily refers to the tendency of people to form relationships with those who are similar to themselves in terms of identity, beliefs, and values (McPherson et al. 2001). Originating in sociology (Byrne 1971), homophily has been studied in finance (Bradley et al. 2020), information systems (Bapna and Umyarov 2015), marketing (Chen et al. 2021), and organization science (Claes and Vissa 2020). Prior research has found that homophily enhanced investment decisions (Hegde and Tumlinson 2014), promoted communication frequency (Reagans 2005), and increased the probability of purchasing (Bapna and Umyarov 2015, Ma et al. 2015). However, the application of homophily in operations management has been largely ignored. In addition, the majority of homophily research examined homophily either at the individual level (Singh et al. 2010, Reza et al. 2021, Mostagir and Siderius 2022) or at the firm level (Autry et al. 2014, Hegde and Tumlinson 2014, Schoenherr and Wagner 2016). Little attention has been paid to homophily at the country level (Zhou 2011, 2013). Given the increasing importance of country level research (Nachum et al. 2008, McKenzie and Woodruff 2017) and country level operations issues (Özer et al. 2014), we find it necessary to fill this gap by extending homophily research to a country level in operations management. More specifically, we focus on one area in operations management – logistics – to investigate how homophily in logistics across different countries impacts global economic outcome. In other words, do countries trade more with each other when they share similar levels of logistics capabilities? This is our first research objective.

Following extant economics and global trade literature, we use country Logistics Performance Index (LPI) to measure homophily in logistics across countries and global trade between countries to proxy global economic outcome. Country LPI is an aggregated measure constructed by the World Bank for 163 countries using six logistics dimensions: customs efficiency, logistics infrastructure, shipping efficiency, logistics competence, timeliness, and track and trace capability. Global trade, measured by a country's exports and imports, has been examined in marketing (Chang et al. 2022), business strategy (Brynjolfsson et al. 2019, Loertscher and Marx 2022), and information systems (Hui 2020). However, research on the impact of logistics on global trade is rare even though logistics has long been hailed as the backbone of global economy (Gropman 1997, Bowersox et al. 2002). Further, the quintessential role of logistics in global trade was accentuated by the recent global Pandemic, where countries with better logistics capabilities recovered faster from the Pandemic. Therefore, our second research objective reviews the role of logistics in the global economy from an individual country's perspective, i.e., among the 163 countries that were measured by the World Bank for LPI, what is the effect of improving LPI on global trade for *any* individual country in the global trade network? Meanwhile, World Bank still acknowledges the vast differences between developed and developing countries and reports that developed countries boast better logistics capabilities than developing countries (World Bank 2023). A natural question follows is: if both a developed country and a developing country improved their LPI by the same level, who would benefit more? Our third research objective, therefore, answers this question by investigating the differentiating effect of improving LPI on global grade between developed and developing countries.

The ultimate purpose of the World Bank to publish LPI and its six logistics dimensions for 163 countries is to provide a benchmark so that different countries can improve their different logistics dimensions to compete in the global trade network. A country policymaker would probably ask: among the six logistics dimensions measured by the World Bank, should a country improve all the six dimensions or some of the six dimensions? In other words, do all the six logistics dimensions positively contribute to global trade? Our fourth research objective addresses this concern.

In delineating the relationships between country LPIs and global trade, we realize that the global trade network is an exceedingly intricate system in which the majority of countries engage in bilateral trade with one another. Researchers have discovered the challenges in modeling such a complex network – each actor (country) is usually part of a multiple, as opposed to, single networks – the data of which is referred to as relational data in the literature. The deficiency in modeling relational data in related literature is that extant studies are designed either at a dyadic level or at a triadic level while ignoring the more complex and systematic networks where dyads and triads are embedded (Zhou 2013, Autry et al. 2014). As the global economy becomes increasingly interdependent, bilateral and multi-lateral economic relationships prevail in global economic organizations (Zhou 2011, 2013). As such, the dominant dyadic design (Reagans 2005, Singh et al. 2010, Hegde and Tumlinson 2014, Bapna and Umyarov 2015, Bradley et al. 2020, Reza et al. 2021, Mostagir and Siderius 2022) or triadic design (Song et al. 2019, Autry et al. 2014) is insufficient to simultaneously capture the bilateral and multilateral dependencies in a complex network such as the global trade network. Despite recent attempts to recover the structure of such complicated networks from relational data (Alidaee et al. 2020), modeling relational data still remains a challenging task due to the complexity and heterogeneity arising from three levels of dependencies in the data: dyadic dependency, triadic dependency, and network level dependency, all of which should be accounted for simultaneously in a model to correctly derive causal inferences (Minhas et al. 2019). In our study, we utilize a new modeling approach which simultaneously captures the dyadic, triadic, and network level dependencies in the global trade network. With the increasing popularity of researchers adopting relational data in network analysis, we hope our new modeling approach can help increase research stringency when modeling relational data for the operations management research community. This is our final research objective.

To find answers to our research objectives, we first collect logistics capability data (i.e., LPI) of 163 countries derived by the World Bank from 2007 to 2018. Then, we use these 163 countries and the time frame of 2007 to 2018 as our baseline to continue collecting all other necessary data from various sources (more in Section 3.1). Constructing a difference matrix to measure homophily in country LPI and using

Additive and Multiplicative Effects (AME) models, we find that the effect of country LPIs on global trade is *heterophilous*, rather than homophilous, i.e., a 1% increase in the gap of LPIs between countries *increases* the corresponding bilateral trade by 0.66%. In other words, countries tend to do more business with those countries whose LPIs are vastly different from them. This corroborates findings in trade economics literature revealing the appalling trade disparity and trade volumes between developed and developing countries (Fujita et al. 2001, Venables 2005), with the former normally boasting advanced logistics capabilities and the latter suffering from poorer logistics capabilities.

Since countries tend to do more business with countries whose LPIs (i.e., logistics capabilities) are different from them, if a country already enjoys excellent logistics capabilities or if a country suffers from poorer logistics capabilities, should this country still improve its logistics capabilities? This leads to the analysis of our second research objective. We continue using AME model to answer this question and we find that despite the heterophilous nature of country LPIs on global trade, for *any* individual country, improving its country LPI is still beneficial: a 1% improvement in LPI increases its exports by 7.77% as well as increasing its imports by 5.46%. This finding reinforces the fundamental fact that logistics is still the backbone of global economy. A natural question follows is that does this effect differ between developed and developing countries? We use WTO's definition of developed and developing countries to continue our analysis and find that developing countries benefit more from improving their LPIs: compared with developed countries, a developing country benefits from 3.81% more *exports* for the same 1% improvement in LPI. However, the relationship between improving LPI and *imports* is not statistically significant for a developing country. Therefore, for a developing country, improving LPI only helps to increase more exports but does not help to attract more imports, echoing the report from the World Bank that the economy of developing countries is still mostly export-driven (Mulabdic and Nayyar 2022).

Given the findings of the positive relationship between a country's LPI and its exports and imports, a country policy maker will most likely ask: among the six logistics-related LPI dimensions measured by the World Bank, should a country improve all the six dimensions? This leads to our analysis at the six dimensional level of LPI. Extant trade logistics literature revealed that all six logistics dimensions positively contribute to global trade (Marti et al. 2014, Gani 2017, Çelebi 2019). However, our AME model results indicate that only customs efficiency, logistics infrastructure, and logistics competence are statistically significant while shipping efficiency, timeliness, and track and trace capability are statistically non-significant. We attribute this to the strenuous efforts made by global logistics service providers and local governments who have continuously improved shipping efficiency, timeliness, and track and trace capability to such a high degree that these three dimensions have become order qualifiers over the years – hence the non-significant findings.

In addressing our research objectives, we make distinct theoretical, methodological, and managerial contributions. Theoretically, combining various datasets from different sources for 163 countries, our study is among the very few research in operations management to apply the theory of homophily at a country level. Our findings of the heterophilous effect of country logistics on global trade partially corroborates the stochastic equivalence structure found in the formation of preferential trade agreements (Manger et al. 2016) in that countries with high LPI levels tend to form trade with countries with middle or low LPI levels. However, the heterophilous nature of country logistics in global trade contradicts other country level homophily research where homophily in geography, culture, and political regime was found to facilitate global trade (Zhou 2011, 2013). To this end, our research enriches the understanding of homophily literature both in operations management and in global trade economics and logistics. Second, in sharp contrast to existing trade logistics research where all six logistics dimensions are found to positively contribute to global trade (Marti et al. 2014, Çelebi 2019), our study, using a different modeling approach, reveals that only logistics infrastructure and logistic competence *positively* contributes to global trade while customs clearance efficiency is *negatively* associated with global trade. The other three dimensions, shipping efficiency, timeliness, and track and trace capability are not statistically significant. Specifically, Hausman et al. (2013), using gravity model, found that bilateral trade is strongly affected by the timeliness of both origin and destination countries. However, using AME model, we find that timeliness is not statistically significant either for origin or for destination countries in bilateral trade. Therefore, our research reveals a fundamentally different story. Lastly, most of the prior network studies focused on examining the effects of network centrality measures (i.e., degree, betweenness, and closeness) on firm operational performance (E-companion E-A1). In this study, we focus on how actual logistics measures impact the global trade network itself. While it is critical to understand the potential benefits and pitfalls of network centrality measures, how actual operations measures impact the network itself is equally important. As such, we call for future research to explore more operations measures, rather than network centrality measures, that may impact the network itself.

Methodologically, our study challenges the dominant role of using gravity model (Silva and Tenreyro 2006, Head and Mayer 2014) in trade economics literature. We employ a recent social network analysis advancement (i.e., AME model) to capture dyadic, triadic, and network level dependencies to study the role of logistics in the global economy and our study yields fundamentally different results compared with research using gravity model in global trade. There are two major deficiencies of using gravity model to examine the global trade network. First, the common practice of using exports and imports as two separate dependent variables (Marti et al. 2014, Gani 2017) in gravity model cannot truly capture the cointegrated nature of bilateral trade as both exports and imports happen simultaneously and it has long been established that imports are critical inputs for exports in some countries (Khan and Knight 1988).

Second, gravity model at its core is a log-linear regression model assuming observation independence, which is violated in global trade data where countries have multiple relationships with each other. Indeed, these deficiencies result in the worst model fit of gravity model in our model fit comparison among different models (more in Section 6). Different from gravity model, we adopt a recent advancement in social network analysis – AME model – to solve these two deficiencies. Despite social network analysis has been increasingly popular in operations management for studying relational data (e-companion E-A1), researchers either only focus on dyadic relationships (Carter et al. 2007, Kim et al. 2011, Kim 2014) or only investigate triadic relationships (Peng et al. 2010, Autry et al. 2014). None of the prior research has investigated dyadic and triadic relationships simultaneously, let alone studying dyadic, triadic, and network level relationships simultaneously. AME model, however, enables us to simultaneously account for dyadic, triadic, and network level dependencies in relational data to achieve better research stringency. In comparing AME model with gravity model and other social network models such as ERGM (exponential random graph model) and LSM (latent space model), we find that AME model demonstrates the best model fit and yields the least biased estimates. To this end, our research contributes to advancing the reassessment of gravity model and other social network models in studying relational data. As neither gravity model nor other social network models can correctly reproduce the observed network data, we call for researchers to utilize AME model to derive more accurate statistical inferences, as almost all the network studies in operations management we surveyed in E-A1 utilized relational data.

Managerially, our research provides important insights for global organizations and country policymakers to compete in the global trade market. First, compared with other researchers (Marti et al. 2014, Gani 2017, Çelebi 2019) who found all six logistics dimensions positively contribute to global trade, we only find logistics infrastructure and logistics competence to be statistically significant in promoting bilateral trade. Therefore, country policymakers should focus on improving the quality of logistics infrastructure and logistics competence to increase competitiveness in the global economy. Timeliness, shipping efficiency, and track and trace capability are not statistically significant. Accordingly, further investment in these three logistics dimensions is not encouraged as further improvement in these three dimensions will not increase exports or imports. Second, in sharp contrast to extant literature, we find customs clearance efficiency is *negatively* associated with global trade with statistical significance in all our models. We attribute this to the rising trade sanctions over the past decades which hinders global trade. We call for country policymakers and trade organizations to reduce trade barriers and protectionism. Third, in all our models, developing countries, compared with developed countries, are disadvantaged in the global trade network in that developing countries witness 0.83% less exports and 0.69% less imports. However, compared with developed countries, developing countries do benefit from more exports, although not from more imports, by improving their LPI, corroborating the long established export-led growth theory for developing countries in macroeconomics literature (Tyler 1981, Balassa 1985). To this end, we call for policymakers in developing countries to continue improving their LPIs. Fourth, various trade organizations have been formed to facilitate global trade and many countries strive to become a member in the hope of benefiting from increased trade flows. Our results, however, show that only being a member of the World Trade Organization (WTO) and regional trade agreements (RTA) positively contribute to increased trade flows. Being a member of EU does not have any statistical significance with bilateral trade flows, which, in hindsight, reinforces the decision of Brexit as UK probably will not benefit at all by staying in the EU.

2. HOMOHPILY AND LOGISTICS PERFORMANCE INDEX

The concept of homophily roots in sociology (Byrne 1971) and has been extended to various disciplines, including operations management (Wagner 2012, Autry et al. 2014, Schoenherr and Wagner 2016) and international trade (Zhou 2011, 2013). The key idea of homophily is that people, organizations, and states tend to cluster together with their counterparts who share similar attributes. Originally analyzed at person level (McPherson et al. 2001), homophily has also been applied to both firm level and country level. At the firm level, Autry et al. (2014) found that triadic homophily improved supply chain performance in the U.S. restaurant industry. Wagner (2012) revealed that higher supplier-customer homophily leads to better effectiveness and efficiency in new product development for customer firms. Schoenherr and Wagner (2016) further found that a higher level of supplier-customer homophily also results in higher engagement of suppliers during the new product development cycle. At the country level, Zhou (2011, 2013) found that homophily in geography, culture, and political regime increases global trade. Maoz (2012) also found that countries tend to form more active trade links with countries that are similar to each other.

Although homophily has been studied from different perspectives in global trade (Zhou 2011, 2013), homophily has not been investigated in the space of logistics in global trade. Therefore, the current study aims to fill this gap as trade is facilitated by logistics – this is exactly why the World Bank complies and measures trade Logistics Performance Index (LPI) for 163 countries. The World bank defines LPI as "an interactive benchmarking tool created to help countries identify the challenges and opportunities they face in their performance on trade logistics and what they can do to improve their performance" (World Bank 2023). The World Bank collects data and develops LPI measures to rank all countries on a biannual basis since 2007 (more details in data section). LPI is the weighted average for an individual country scoring on six dimensions: customs efficiency, logistics infrastructure, shipping efficiency, logistics competence, timeliness, and track and trace capability. LPI indicates "the relative ease and efficiency with which products can be moved into and inside a country" (World Bank 2023).

3. DATA AND METHODOLOGY

3.1. Variables and Measurements

3.1.1. Dependent Variable

We use bilateral trade between countries to proxy economic outcome. Bilateral trade is compiled from International Monetary Fund (IMF 2023). At the time of writing, IMF provides global trade data up to December 2022. LPI, however, has been compiled by the World Bank only for the years of 2007, 2010, 2012, 2014, 2016, 2018, and 2023. To avoid the exogenous shock of Covid-19, we use LPI data up to 2018. Accordingly, we set the timeframe of bilateral trade data from 2007 to 2018 to align with LPI data. Following trade economics literature (Zhou 2011, 2013), we take the average trade flows between 2007 and 2018 to conduct a cross-sectional analysis. In addition, we also conduct a longitudinal analysis for the years of 2007, 2010, 2012, 2014, 2016, and 2018 when LPI data are available (more in Section 5). After data cleaning, we have 163 countries in our data.

The operationalization of our dependent variable bilateral trade (i.e., exports and imports) is fundamentally different from how bilateral trade was operationalized as a dependent variable in related literature. When modeling bilateral trade flows, a common practice in related literature using gravity model is to 1) use exports + imports or just exports as the dependent variable; 2) split export and imports as two separate dependent variables in two separate models (Table 1). There are two deficiencies in the current gravity model approach. First, when the "bilateral" trade flow is summed up in a single variable as exports + imports (Zhou 2011), the directional nature of trade flows is accordingly lost, therefore, the data is not truly bilateral anymore, failing to capture the true relationships of how countries do business with each other. Second, splitting exports and imports as two separate dependent variables in two separate models (Marti et al 2014, Gani 2017) ignores the cointegrated nature of exports and imports as these two trade flows happen simultaneously and imports are critical inputs for exports (Khan and Knight 1988). To specifically model the directional nature of trade flows and reflect the simultaneous and cointegrated relationships between exports and imports, we construct bilateral trade as an adjacency matrix in Table 2, with rows representing exports from a county to all other countries while columns representing imports from all other countries into this country – a true reflection of "bilateral" trade flow.

Table 1 Comparison of Operationalization of Bilateral Trade

Author	Operationalization of Bilateral Trade	Modeling Approach
Çelebi 2019	Exports from country i to country j	Exports only as dependent variable (DV). DV is a single column of data.
Gani 2017	Exports from country i to country j Imports of country i from country j	Exports and Imports are modeled as two separate dependent variables in two regression models. DV is a single column of data.
Hausman et al. 2013	Total exports/imports between country i and country j	Total exports as DV. DV is a single column of data.
Marti et al. 2014	Exports from country i to country j Imports of country i from country j	Exports and Imports are modeled as two separate dependent variables in two regression models. DV is a single column of data.
Zhou 2011	Bilateral trade volume is created by averaging all of the four possible measures, namely, exports from country i to country j, imports into i from j, exports from j to i, and imports into j from i	Average of imports and exports as one single dependent variable in regression. DV is a single column of data.
Current Study	Exports from country i to country j Imports of country i from country j	Exports and Imports are modeled on the rows and columns simultaneously in a matrix in AME model. DV is a matrix, not a single column of data.

Table 2 Mini Version of Bilateral Trade Adjacency Matrix

	AFG	ALB	ALG	ANG	ARG	ARM	AUL	AUS
AFG	-	0	0	-	0	0	1	0
ALB	0	-	1	-	0	0	0	29
ALG	0	10	-	1	3	0	131	297
ANG	-	-	1	-	0	0	12	0
ARG	1	10	1,398	185	-	7	514	85
ARM	0	0	0	0	0	-	1	3
AUL	13	2	44	11	247	7	-	72
AUS	13	70	331	21	189	77	960	-

Table 2 (untransformed values) is a truncated mini version of our dependent variable to illustrate the concept of adjacency matrix. Take Austria (AUS) for example, each cell on the row of AUS represents Austria's exports to all other countries. For example, during the period of 2007 to 2018, Austria on average exported \$331 million/year to Algeria (ALG). Each cell on the column of AUS represents imports from all other countries to Austria. For example, during the period of 2007 to 2018, Austria on average imported \$297 million/year from Algeria (ALG). In our analysis, our dependent variable bilateral trade is a 163×163 matrix as we have 163 counties in our data. Trade adjacency matrix is log-transformed following standard econometrics practice (Wooldridge 2010) and economic development literature (Frankel and Romer 1999).

3.1.2. Independent Variables

The main independent variable is a country's LPI. We compile LPI data from the World Bank who derives these measures biannually since 2007. World Bank uses a 1 – 5 Likert scale to rank a country's LPI with 5 being the best and 1 being the worst. Hausman et al. (2013) elaborated the process and methodology the World Bank adopted to derive these measures. We averaged the scores of LPI for the six years of 2007, 2010, 2012, 2014, 2016, and 2018 to conduct a cross-sectional analysis. We also did a longitudinal analysis as a robustness test in Section 5 following extant trade literature (Zhou 2011, 2013).

To test the homophilous effect of LPI on global trade, we construct LPI at a dyadic level in a 163×163 difference matrix (in absolute values) following social network analysis literature (Minhas et al. 2019). The order of the 163 countries on the rows and columns in our LPI difference matrix corresponds exactly to the order of the 163 countries on the rows and columns in our bilateral trade matrix. Small difference-score between any two countries represents homophily in LPI while large difference-score between any two countries represents heterophily in LPI. Using a difference-score matrix to measure homophily differs from the practice in the extant literature where homophily is measured by just assigning countries to regions (Bandelj and Mahutga 2012) or by using multiple-item scales (Wagner 2012, Autry et al. 2014, Schoenherr and Wagner 2016). Using actual difference-score is a more accurate reflection of the concept of logistics homophily as LPI score is readily available from the World Bank.

To test how improving LPI impacts exports and imports for an individual country, we construct LPI at a nodal level, meaning the LPI scores for each country were assigned at both rows and columns in a 163×163 adjacency matrix corresponding to the bilateral trade matrix. Rows represent how a country's LPI impacts its exports while columns represent how a country's LPI impacts its imports. To test the differentiating effect of improving LPI between developed and developing countries, we first use WTO's definition of developing country to create a developing country dummy. Then, we create an interaction term between developing country and LPI to test the interaction effect.

To test the effect of the six logistic dimensions on global trade, we construct both dyadic level and nodal level variables for these six dimensions. At the dyadic level, we construct a 163×163 difference matrix for each logistics dimension to control how the difference in the six logistics dimensions among different countries affect their bilateral trade. At the nodal level, the scores of each country on these six logistics dimensions were assigned at both rows and columns in a 163×163 adjacency matrix aligned with our dependent variable – the bilateral trade matrix. Rows represent how a country's logistic dimension impacts its *exports* while columns represent how a country's logistic dimension impacts its *imports*. The operationalization of all our variables, therefore, is fundamentally different from the gravity model used in trade economics literature as summarized in Table 1.

3.1.3. Dyadic and Nodal Control Variables

We identify appropriate control variables following extant trade economics and trade logistics literature. Different from related literature (Hausman et al. 2013, Marti et al. 2014, Gani 2017, Çelebi 2019), we also construct two types of control variable wherever possible depending on the nature of the data: dyadic controls and nodal controls. While dyadic controls models the cointegrated dyadic relationships among countries, nodal controls test how each variable simultaneously affect both exports (row effects) and imports (column effects) with values on the rows representing the impact of the covariates on exports and values on the columns representing the impact of the covariates on imports.

At the dyadic level, we control for regime difference, social connectedness, common language, common religion, common colonial heritage, contiguity of borders, distance, and regional trade agreement (RTA). All these dyadic level controls are constructed in a 163×163 matrix corresponding to the order of our dependent variable. Table 3 uses common language to illustrate the matrix. French is spoken in both Belgium (BEL) and Burkina Faso (BFA). Therefore, 1 is coded for the cell where BEL and BFA crosses each other in the matrix.

At the nodal level, we control for GDP, population, ease of doing business (EOB), land mass, landlocked, GATT member, WTO member, EU member, and developing country. These controls are commonly used in trade economics literature. We want to highlight the variable of EOB, which is a relatively new variable. EOB is a score published by the World Bank to evaluate the relative ease of doing business within a country. It is calculated using 10 different Doing Business Indicators to assess the overall business environment in a country, such as legal and accounting standards, financial openness, enforcing contracts, dealing with business permits, and etc. EOB directly relates to the timeliness of exports and imports in global trade (Qazi et al. 2021). Unfriendly environments, such as different legal and accounting practices, can cause severe delays which in turn affect trade. Hence, we include EOB as a control variable. Table 4 summarized variables used in our analysis and the source of each variable. Replication code of how each variable in this section was constructed is provided in E-companion.

Table 3 Example of Dyadic Level Control – Common Language

	BDI	BEL	BEN	BFA	BGD	BGR	BHR	BHS
BDI	0	1	1	1	0	0	0	0
BEL	1	0	1	1	0	0	0	0
BEN	1	1	0	1	0	0	0	0
BFA	1	1	1	0	0	0	0	0
BGD	0	0	0	0	0	0	0	0
BGR	0	0	0	0	0	0	0	0
BHR	0	0	0	0	0	0	0	0
BHS	0	0	0	0	0	0	0	0

Table 4 Description of Variables

Variable	Formula or Definition	Data Source
Bilateral Trade	Export from country i to county j and import of country i from country j	International Monetary Fund
Logistics Infrastructure	Quality of trade and transport-related infrastructure (e.g., ports, railroads, roads, information technology)	World Bank
Logistics Competence	Competence and quality of logistics services (e.g., transport operators, customs brokers)	World Bank
Political Factor		
Regime Difference	Diplomatic disagreement score	United Nations
Social Factor		
Social connectedness	Social connectedness index 2021	Bailey et al. (2018)
Cultural Factors		
Common language	1 if countries share common official or primary language	CEPII
Common religion	Religious proximity index	CEPII
Common colonial heritage	1 if countries share a common colonizer post 1945	CEPII
Trade Organization Member		
Regional Trade Agreement	1 if the pair currently has a RTA	WTO
GATT	1 if country currently is a GATT member	WTO
WTO	1 if country currently is a WTO member	WTO
EU	1 if country currently is an EU member	CEPII
Geographical Factors		
Distance	Centroid distance between countries	*cshapes* R
Contiguity	Dummy equal to 1 if countries are contiguous	CEPII
Landlocked country	Dummy equal to 1 if countries are landlocked	United Nations
Land mass	Country surface area in km	World Bank
Country Economic Factors		
GDP	GDP in 2015 US dollars	World Bank
Population	Country population of each year	World Bank
Ease of Dong Business	Business regulations for local firms in 190 countries	World Bank
Developing Country	Dummy equal to 1 if countries are developing countries	WTO

3.2. AME Model and Global Trade

We elect to adopt additive and multiplicative effects (AME) models in social network analysis to fulfill our research objectives. In this section, we briefly discuss the rationale to adopt this specific model among a portfolio of available models, such as the classic gravity model in global trade and other network models.

"Network" in the current study refers to the global trade network, which is also our outcome variable. Since global trade is a bilateral flow of both exports and imports between and among different countries, the global trade network is relational in its nature and extends beyond monodic country level. Data structure extending beyond monadic/individual level is referred to as relational data. One important characteristic of relational data is the dependency among observations, i.e., the decisions made between one pair of actors also depend on the respective relationships of these two actors with other actors in the network. Actors in our case refer to the different countries involved in the global trade network. For example, if the U.S. decides to sign a new trade agreement with China, it is highly unlikely that the U.S. will not first consider its existing trade relationships with other countries before signing the deal.

The nature of dependency of events, hence the data observed, requires a modeling approach that captures this dependency. However, the widespread approach to handle relational data in operations management is either a pure dyadic approach (Kim et al. 2011, Kim 2014) or a pure triadic approach (Choi and Wu 2009, Autry et al. 2014). In a dyadic approach, each pair of dyads is modeled unconditionally upon the interactions of other pairs in the network (Mansfield et al. 2000), which was proven to be inappropriate to answer the related research questions (Minhas et al. 2019). A dyadic approach ignores a potential important part of relational data, i.e., the network and systematic phenomena (Autry et al. 2014), and fails to capture the dependencies among observations, which will likely lead to biased estimates and misleading inferences (Hoff 2009, Minhas et al. 2019). In the global trade network, such a dyadic design is equivalent to assume that any global trade decisions made between two countries are unimpacted by any other trade activities relating to these two countries, which is unrealistic in today's highly integrated global economy. On the other hand, a triadic approach ignores the bilateral relationships in the data and will also likely yield misleading inferences.

Next, we explain the three different types of dependencies in relational data arising from the interactions within and among the actors in the network: first-order dependency, second-order dependency, and third-order dependency. The first-order dependency is "preferential attachment" (Barabási and Albert 1999, Albert et al. 1999) and is often referred to as nodal level dependency. For example, in our 163×163 bilateral trade matrix (Table 2), each row represents exports from one individual country to all other countries while each column represents imports into one individual country from all other countries. Compared with other countries in terms of exporting (rows in Table 2), China is more active in exporting to almost all other countries. In this case, observations on the rows for China are more similar to each other. Compared with other countries in terms of importing (columns in Table 2), U.S. is more active in receiving imports from almost all other countries, i.e., U.S. is a popular target. In this case, observations on the columns of U.S. are more similar to each other. Therefore, heterogeneity in both row means and column means exists in the global trade network. In addition, U.S. not only imports a lot but also exports a lot, i.e., the row and column means for U.S. may also be correlated to each other. In sum, the different forms of heterogeneities presented in the global trade network lead to the violation of the conditional independence assumption in the classic gravity model as well in standard network model toolkit. A different modeling approach is required.

Second-order dependency is a dyadic dependency only related to directed data, such as in the global trade network. Reciprocity is the common network terminology to describe this dependency. Reciprocity is a notion that actors learn to "respond in kind" to one another (Bolton et al. 1998, Cox et al. 2007). For example, U.S. sanctioned certain Chinese companies in 2020 and China responded by sanctioning certain U.S. companies in return. It is also common to see that bilateral trade increased following mutual state visits by respective state leaders. The prevalence of these interactions/reciprocities in the global trade network also leads to violations of the conditional independence assumption in the typical dyadic network modeling approach adopted in extant network studies (Lu and Shang 2017, Lan et al. 2020, Potter and Wilhelm 2020). Our second research objective (i.e., how a country's LPI impacts exports and imports) tests the first-order and second-order dependencies by constructing country LPI at the nodal level as both sender effect and receiver effect, where the scores of LPI for each country were assigned at both rows and columns in an adjacency matrix. Rows represent sender effect, i.e., how LPI impacts exports while columns represent receiver effect, i.e., how LPI impacts imports.

Third order dependency arises when shared attributes among actors affect their probability to interact with each other. A consistent finding from gravity model in trade economics is that neighboring countries tend to trade more with each other. This is an example of third-order dependency with geographic proximity as the shared attribute. Recent research (Manger 2016) reveals that the greatest probability of forming a preferential trade agreement is between high-high, high-middle, and middle-middle income countries. Low-income countries are very unlikely to form preferential trade agreements with any of the high, middle, or low-income countries. Economic status is the shared attribute driving third-order dependency here. Third order dependency was captured by the various dyadic controls we constructed.

Since the conditional independence assumption in both first-order and second-order dependencies is violated, the classic gravity model is not able to correctly model the relationships in the data. Other social network models, such as social relational model (SRM, Warner et al. 1979) can capture both first-order and second-order dependencies but fails to capture the third order dependency. Without correctly capturing all the three dependencies in the data, a model is prone to be a poor model fit and statistical inference also becomes questionable (more in Section 6). Given these, we elect to use AME model that can correctly capture the three dependencies simultaneously. AME model decomposes the variance of actors (countries in our case) in the adjacency matrix into 1) heterogeneity across row means (out-degree); 2) heterogeneity along column means (in-degree); 3) correlation between row and column means; and 4) correlations within dyads (Minhas et al. 2019). The first three components capture the first-order dependencies and the last component captures second-order dependencies. In addition, AME model also assumes that relationships between and among different nodes (countries in our case) are mediated by a small amount of unobserved latent factors specific to each node – the multiplicative effect that accounts for third order dependency. AME model takes the following forms (Minhas et al. 2019):

$$\mathcal{Y}_{ij} = g(\theta_{ij})$$

$$\theta_{ij} = \beta^{T}\mathbf{X}_{ij} + e_{ij}$$

$$e_{ij} = a_i + b_j + \epsilon_{ij} + \alpha(\mathbf{u}_i, \mathbf{v}_j), \text{where}$$

$$\alpha(\mathbf{u}_i, \mathbf{v}_j) = \mathbf{u}_i^{T}\mathbf{D}\mathbf{v}_j = \sum_{k \in K} d_k u_{ik} v_{jk} \qquad \text{Equation 1}$$

$\mathcal{Y}_{ij}$ is the outcome variable of bilateral trade which is modelled to be conditionally independent given θ, whereas θ depends on both $\mathbf{X}_{ij}$ and the residual e_{ij}. $\mathbf{X}_{ij}$ is the vector accommodating dyadic, sender (rows), and receiver (columns) covariates. e_{ij} is further decomposed into three different components: a_i represents sender effect (row effect), b_j represents receiver effect (column effect), and ε_{ij} represent correlation within dyads. a_i and b_j are modeled simultaneously to account for how active a country is in both exporting and importing, accounting for first-order dependency. ε_{ij}, the dyad effect, accounts for second order dependency. Lastly, $\alpha(\mathbf{u}_i, \mathbf{v}_j)$ accounts for third-order dependencies left over in θ after controlling for covariates $\mathbf{X}_{ij}$. In other words, later factor k accounts for third-order dependencies which have not been explained by the nodal and dyadic covariates in the model. Existing network models either only capture the first-order and second-order dependency, such as social relation model (SRM), or face notable problems like model degeneracy when capturing all three dependencies, such as exponential random graph model (ERGM) (Minhas et al. 2019). AME model not only captures all three dependencies simultaneously but also performs better than similar models like ERGM and latent space model (LSM) (more in Section 6). To this end, AME provides better statistical inferences in facilitating knowledge accumulation.

3.3. Descriptive Statistics

We provide two different descriptive statistics in this section. First, we present typical network centrality measures for the global trade network among the 163 countries. Second, to detect the holistic picture of bilateral trade and logistics more clearly, we provide visualization of bilateral trade and LPI using averaged values for the period from 2007 to 2018.

Degree, betweenness, closeness, and eigenvector are the most frequently used nodal level centrality measures in network analysis (c.f. e-companion E-A1). We calculate these measures for the top 10 countries and report them in E-companion table E-T1. Eigenvector measures the absolute power of players in the network. As was expected, we see that being the top exporters and importers, U.S. and China are the dominant players who hold absolute power in the global trade network in terms of Eigenvector. One interesting phenomenon to notice is that in other dimensions of centrality measures, U.S. and China are not among the top players in the global trade network. For example, Australia (AUL) is the top player in terms of degree centrality, which measures how many trade partners a country has. Zimbabwe (ZIM) is the top player of betweenness centrality measuring the extent to which a country serves as a bridge in the global trade network. Bosnia and Herzegovina (BOS) is the top player in closeness centrality measuring how close a country is to all the other countries in the global trade network.

The correlation matrix for the four nodal level centrality measures of the 163 countries is reported in E-T2. The correlation matrix, to a certain extent, explains the differences in rankings in the four network measures among countries shown in E-T1. All degree measures are weakly and negatively correlated with betweenness and closeness, explaining the very different ranking of countries in these measures. Eigenvector shows a weak positive correlation with all three degree measures and a negative correlation with closeness and betweenness, indicating that power in global trade does not necessarily depend on how many trade partners a country has or how close a country is to all of the others.

We next visualize bilateral trade and LPI to show the overall picture in E-companion E-F1, E-F2, and E-F3. The average annual exports and imports in million U.S. dollars from 2007 to 2018 was used for the visualization of bilateral trade. E-F1 and E-F2 plot exports and imports heat maps for the 163 countries in our data. Darker shades represent higher volumes of exports and imports. We see that both exports and imports are extremely polarized. China, Germany, and the U.S. are the three distinctive top players in the global trade network with these three countries representing 28% of global exports and 30% of global imports between 2007 and 2018. All other countries show a much lower magnitude of trade volumes compared with these three countries. E-F3 plots the heatmap of LPI measured by the World Bank. Compared with exports and imports, we see that countries are less polarized in LPI but still share a similar story: U.S., Canada, West Europe, Australia, New Zealand, and Japan are the first-tier countries with the best quality in LPI, followed by China, East Europe, South Africa, Turkey, Saudi Arabia, and India as the second and third tier countries. The remaining countries are still lacking in terms of logistics capabilities.

4. ANALYSIS AND RESULTS

We run all analyses in *R* (version 4.3.1) to test our hypotheses. Replication code for all analyses in this section is provided in E-companion. Results are reported in Table 5. Model 1 only includes LPI at the dyadic level. Model 2 adds all dyadic level covariates to test the effect of dyad level covariates on bilateral trade. Model 3 further adds the nodal level covariates.

Table 5 AME Model Outputs

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	7.37***(0.36)	11.48***(0.41)	-25.96***(2.37)	-22.92***(2.71)	-22.42***(2.90)
Dyad Level Effects					
LPI	-0.07 (0.11)	0.67***(0.11)	**0.66***(0.12)**	**0.66***(0.13)**	**0.68***(0.13)**
Political Difference		0.40***(0.04)	0.40***(0.04)	0.41***(0.04)	0.41***(0.04)
Social Connectedness		0.23***(0.01)	0.23***(0.01)	0.23***(0.01)	0.23***(0.01)
Common Language		0.72***(0.05)	0.72***(0.05)	0.72***(0.05)	0.73***(0.05)
Common Religion		0.62***(0.07)	0.65***(0.07)	0.65***(0.07)	0.65***(0.08)
Common Colonial		0.65***(0.17)	0.65***(0.17)	0.64***(0.17)	0.64***(0.17)
Contiguity		1.13***(0.11)	1.19***(0.10)	1.19***(0.10)	1.19***(0.11)
Distance		-0.78***(0.02)	-0.73***(0.03)	-0.73***(0.02)	-0.73***(0.02)
RTA		0.73***(0.06)	0.76***(0.06)	0.76***(0.06)	0.76***(0.06)
Sender Effect					
LPI			**7.77***(0.99)**	**6.35***(1.11)**	**6.31***(1.13)**
GDP			0.03 (0.05)	0.03 (0.05)	0.03 (0.05)
Population			0.66***(0.10)	0.62***(0.10)	0.60***(0.11)
Doing Business			-0.08 (0.18)	-0.14 (0.18)	-0.11 (0.18)
Surface			0.09 (0.08)	0.11 (0.08)	0.11 (0.08)
Landlocked			-0.96***(0.25)	-0.82***(0.24)	-0.85***(0.24)
GATT			-0.42 (0.29)	-0.27 (0.28)	-0.14 (0.27)
WTO			1.29***(0.37)	1.18***(0.35)	1.03***(0.35)
EU			-0.05 (0.33)	0.09 (0.33)	0.09 (0.33)
Developing Country			-0.83* (0.34)	-4.68** (1.61)	-4.17* (1.65)
Developing Country*LPI				**3.81* (1.59)**	**3.19* (1.59)**
CN					**2.84* (1.20)**
US					**-0.55 (1.25)**
Receiver Effect					
LPI			**5.46***(0.88)**	**4.99***(1.07)**	**4.87***(1.07)**
GDP			0.02 (0.04)	0.02 (0.04)	0.01 (0.04)
Population			0.68***(0.09)	0.66***(0.09)	0.65***(0.10)
Doing Business			-0.08 (0.16)	-0.11 (0.17)	-0.07 (0.17)
Surface			0.006 (0.07)	0.02 (0.07)	0.01 (0.07)
Landlocked			-0.99***(0.22)	-0.93***(0.23)	-0.96***(0.23)
GATT			-0.26 (0.26)	-0.21 (0.26)	-0.09 (0.26)
WTO			1.15***(0.33)	1.13***(0.31)	0.98***(0.32)
EU			-0.51† (0.30)	-0.47 (0.31)	-0.43 (0.32)
Developing Country			-0.69* (0.32)	-1.99 (1.53)	-1.49 (1.58)
Developing Country*LPI				**1.27 (1.52)**	0.66 (1.56)
CN					**2.90** (1.01)**
US					**0.05 (1.20)**

Notes: Standard errors are given in parenthesis. $^{\dagger}p < .1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

4.1. Testing the Effect of Homophily in Logistics on Global Trade

Our first research objective studies the homophilous effect of LPI on global trade, which was tested by the coefficient of "LPI" under Dyad Level Effects in Model 3 in Table 5. The coefficient for "LPI" is statistically significant (0.66, $p=0.000$). However, because we construct this variable as the differences in LPIs between pairs of countries, the positive coefficient indicates that a 1% increase in the differences of LPIs between countries will *increase* bilateral trade by 0.66%. In other words, the effect of LPI on global trade is actually heterophilous, rather than homophilous.

4.2. The Role of LPI for Individual Countries

Our second research objective aims to explore the effect of LPI on exports and imports for an individual country, which was tested by the nodal level effect, i.e., the coefficients for "LPI" under both Sender Effect and Receiver Effect in Model 3. In network analysis terms, these are the row and column effects in our dependent variable matrix which are modeled jointly by AME to account for row and column correlations to investigate the effect of a country's LPI on exporting and importing. The coefficient for sender effect is 7.77 (*p=0.000*) while that for receiver effect is 5.46 (*p=0.000*), indicating that for any individual country in our sample, a 1% increase in the score of LPI (as measured by the World Bank) will likely increase exports by 7.77% as well as attract more imports by 5.46%. We see that the role of LPI is slightly more pronounced in promoting exports.

4.3. Differentiating Effect of LPI on Global Trade Between Developed and Developing Countries

As the World Bank reports, the world is still categorized by developed and developing countries. If both developed and developing countries improve their LPI by a similar level, will the impact on global trade be different? This is our third research objective and we analyze this by creating an interaction term between developing country and LPI, which was tested in Model 4 in Table 5. We see that under the sender effect, the three terms of LPI (6.35, *p=0.000*), developing country (–4.68, *p=0.004*), and developing country×LPI (3.81, *p=0.02*) are all statistically significant, indicating that compared with developed countries, a developing country benefits from a 3.81% more exports if both developed and developing countries improved their LPI by the same 1% level. However, under the receiver effect, the interaction term developing country×LPI (1.27, *p=0.405*) is not statistically significant, indicating that compared with developed countries, a developing country, even improving its LPI, will not attract more imports, echoing the neoclassic export-led growth theory for developing countries (Tyler 1981, Balassa 1985).

U.S. and China are considered two significant outliers in international trade (Monken et al. 2021). Therefore, we create two separate dummy variables for U.S. and China and add these two dummy variables to Model 5 and re-run our analysis. Despite a slight change in effect size, all findings still remain the same. An interesting phenomena to note is that compared with other countries, China exports more than any other countries (2.84, *p=0.02*) while also importing more than others (2.90, *p=0.004*) while US does not.

4.4. The Six Dimensions of Logistics Performance

The World Bank measures a country's logistics performance on six dimensions. We, accordingly, conducting another analysis using these six dimensions in our fourth research objective and report the results in e-companion E-T3. In contrast to trade economic research using gravity model, our AME model reveals fundamentally different results. The majority of related literature (Marti et al. 2014, Gani 2017, Çelebi 2019) concluded that all the six logistics dimensions positively contribute to both exports and imports. However, in our AME model results, only three dimensions are found to be statistically significant: logistics infrastructure *positively* contributes to both exports and imports; customs clearance *negatively* contributes to both exports and imports; and logistic competence only *positively* contributes to exports but not to imports. Custom efficiency is with the wrong "expected" sign. We attribute this to the prevailing trade sanctions and trade protection policies implemented by various countries and regional trade organizations. As a result, customs efficiency and border management becomes a barrier to global trade. The other three logistics dimensions, i.e., shipping efficiency, timeliness, and track and trace capability are statistically non-significant. We attribute this to the fact that improvement in shipping efficiency, timeliness, and track and trace capability has reached to such a higher level that these three dimensions have become order qualifiers to compete in global trade.

As our findings are fundamentally different from findings in the prevalent gravity model literature, one critical question needs to be addressed: which model to trust? This is a crucial question as it matters the most for country policymakers to make the right decisions. Therefore, we conduct model fit test and model fit comparison in the next two sections.

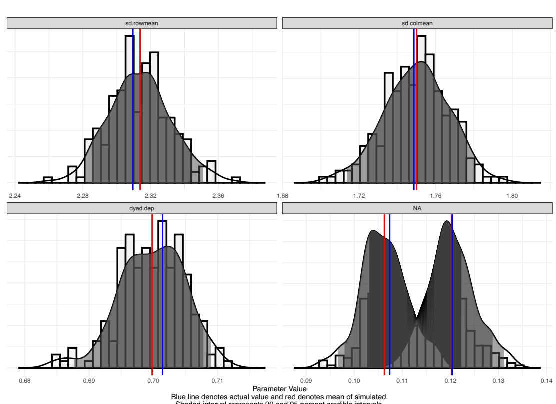
5. AME MODEL FIT TEST

For AME model, we conduct three model fit tests. First, we extract model fit statistics for our AME model using Model 3 in Table 5. Second, we test model specification of AME itself using different latent factors (*k* in Equation 1). Lastly, we conduct a longitudinal analysis to re-assess our findings.

5.1. Model Fit Statistics

In Model 3 of Table 5, the first-order and second-order dependencies were accounted for by classic social relational model while the third order dependencies were accounted for by using the latent factor approach with k=1 (Equation 1). To test our model fit, we extract the goodness of fit statistics generated by AME for Model 3 and plot them in Figure 1. In Figure 1, the blue line denotes actual values observed in our data while the red line denotes the simulated means from AME model. From the four graphs, we see that AME model well captures variation across row means (out-degrees) in the top left graph and variation across column means (in-degrees) in the top right graph. AME model also well captures correlation within dyads (reciprocity) in the bottom left graph and correlation among triads (third order dependencies) in the bottom right graph. We also check the trace plots for Model 3 in Table 5 and report the result in e-companion Figure E-F4, where all parameter estimates are approximately normal, indicating a decent model fit.

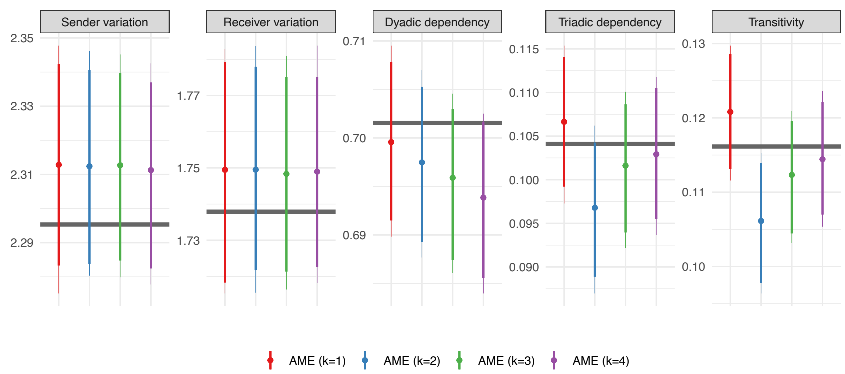
Figure 1 AME GoF for Model 3 in Table 5



5.2. AME with Different Latent Factors

Equation 1 indicates that the latent factor *k* in AME model accounts for third order network dependencies. Minhas et al. (2019) noted that a max *k* value of 2 or 3 is sufficient to capture higher order dependencies in the network. *k*=1 was used for Model 3 in Table 5. Therefore, we accordingly change *k* to 2, 3, and 4 to test if the change in latent factors impacts our findings and the model fit. E-companion E-T4 reports the results of different *k* values and Figure 2 plots the model fit using different *k* values. We see from E-T4 that all findings still remain the same (i.e., same statistical significance for the coefficients of LPI across different *k* values). We also use different *k* values to re-test Model 4 and Model 5 in Table 5 and the findings remain the same (tables omitted).

Figure 2 Model Fit of Different Latent Factors k in AME Model



In Figure 2, the gray horizontal bar represents values from the observed network. Red, blue, green, and purple dots represent estimated values by AME model under *k* = 1, 2, 3, and 4 respectively. The thick and thin shaded lines around each dot represent 95% and 90% intervals of the estimates, respectively. Figure 2 shows that AME model fit changes slightly with the change of latent factor *k*. All AME models (*k* = 1, 2, 3, 4) perform well in two network parameters: 1) standard deviation of row means (sender variation). This is the first-order dependency representing heterogeneity in *exports* across countries; 2) standard deviation of columns means (receiver variation). This is the first-order dependency representing heterogeneity in *imports* across countries. Only AME models with *k* = 1 and 2 perform well in within-dyad correlation (Dyadic Dependency) with *k* = 1 performing better. This is the second-order dependency measuring the reciprocity in the global trade network. AME models with *k* = 1, 3, 4 perform well in triadic dependency and transitivity, with *k* = 4 performing the best. Triadic dependency is the third-order dependency that is left over after accounting for first-order and second-order dependencies. Transitivity is the mutual connections that exist between three countries in the global trade network. Combined, we see that overall the model with *k* = 1 performs the best by capturing all the first-order, second-order, and third-order dependencies (*k* = 1 was used for our main analysis in Table 5).

5.3. Longitudinal Analysis

As our dependent variable and independent variables are all matrices, the methodological way to conduct a longitudinal analysis is fundamentally different from what a longitudinal analysis was done in a panel data where all variables are single columns, rather than matrices, of data. We follow the extant practice (Zhou 2011) and run AME model on each year of data to conduct a matrix longitudinal analysis and report our results in e-companion E-T5. From E-T5, we see that our findings regarding the homophilous role of LPI on global trade still remain the same across all years. Our findings regarding the role of LPI on exports and imports for an individual country also remain the same across all years. We also re-test the differentiating effect of developed and developing countries and the role of six logistics dimensions. All the findings still remain the same (13 models in total and tables were omitted to avoid clutter in reporting).

6. ALTERNATIVE ESTIMATORS: GRAVITY MODEL, EGRM, AND LSM

In this section, we compare AME model with gravity model as well as other popular network models such as exponential random graph model (ERGM) and latent space models (LSM) to see how AME model performs compared to these models.

6.1. Gravity Model

Gravity model is the workhorse in trade economics to model trade flows between countries (Silva and Tenreyro 2006, Head and Mayer 2014). The basic form of the gravity model is shown in Equation 2.

$$T_{ij} = K\,\frac{M_i^{\beta 1} M_j^{\beta 2}}{d_{ij}^{\beta 3}} \qquad \text{Equation 2}$$

where T_{ij} is the total trade flows between country i and country j, K a proportionality constant, Mi the economic mass of origin country i, Mj the economic mass of destination country j, and d_{ij} the physical distance between the two countries. β_1, β_2, and β_3 are the parameters of interest. β_1 estimates origin country i's ability to generate exports, β_2 estimates destination country j's ability to attract imports, and β_3 captures the rate of decrease in bilateral trade with the increase of physical distances between countries pairs ij. The gravity model is a conceptual model rather than a statistical method (Broekel et al. 2014). Therefore, the gravity model is normally estimated in Equation 3 using OLS by taking logarithms of both sides of Equation 2. In addition, researchers can add additional vectors of control variables Xit into Equation 3 to control for other macroeconomic and cultural factors (Zhou 2011, Hausman et al. 2013).

$$\ln I_{ij} = \ln \mathrm{K} + \beta_1 \mathrm{M_i} + \beta_2 \mathrm{M_j} - \beta_3 \mathrm{d_{ij}} + \boldsymbol{Z} X_{it} + \varepsilon_{it} \qquad \text{Equation 3}$$

Popular as it is, gravity model shows some serious issues when used to estimate a global trade network data (Broekel et al. 2014). At its core, gravity model uses OLS estimator which relies on the assumption of observation independence, which is violated in a global trade network as one single country normally appears in multiple dyadic relationships (Stouffer 1940), resulting in biased estimates of coefficients and biased standard deviation of coefficients (Broekel et al. 2014). In other words, OLS does not account for dependencies presented in a global trade network nor it is able to model the global trade network dependencies. To address this issue, Multivariate Regression Quadratic Assignment Procedure (MRQAP) has been combined with gravity model to address the dependencies across observations in relational or network data (Gulati and Gargiulo 1999). MRQAP is a statistical procedure that does not require an assumption of independent observations (Gulati and Gargiulo 1999, Dekker et al., 2007). Therefore, MRQAP is robust against dyadic autocorrelation presented in network data (Gulati and Gargiulo 1999, Dekker et al., 2007). MRQAP, in sum, is a network level gravity model that incorporates the relational nature of variables to specifically account for the interdependencies among these relational variables when assessing their statistical relevance. MRQAP has been accordingly utilized to model global trade flows (Zhou 2011, 2013).

6.2. EGRM and LSM

Two other popular approaches to account for network dependencies are exponential random graph model – ERGM (Frank and Strauss 1986, Wasserman and Pattison 1996) and latent space models – LSM (Hoff et al. 2002). EGRM is based on the assumption that network structure is generated by a set of latent stochastic processes, such as homophily and reciprocity. These processes are represented as a set of parameters, such as ties between nodes and strength of ties, that can be estimated using maximum likelihood estimation. In addition to the possibility of including exogenous, temporal and special variables, EGRM can also incorporate these different types of ties and the strength of those ties (Frank and Strauss 1986, Wasserman and Pattison 1996). Therefore, EGRM can also capture the complexity of real-world networks. However, EGRM is not only computationally intensive requiring large datasets to produce accurate estimates but is also sensitive to small changes in data, resulting in overfitting. When approximating the maximum likelihood estimation using Markov Chain Monte Carlo techniques, ERGM also faces serious model degeneracy issues (Bhamidi et al. 2008, Chatterjee and Diaconis 2013).

LSM aims to create a multi-dimensional latent space to represent real-world data (Hoff et al. 2002). As such, LSM can also capture the complexity of real-world networks to a certain degree. However, LSM struggles to represent the complicated network when there are many ties among nodes (Minhas et al. 2019), which is often the case in relational data.

6.3. Model Fit Comparison

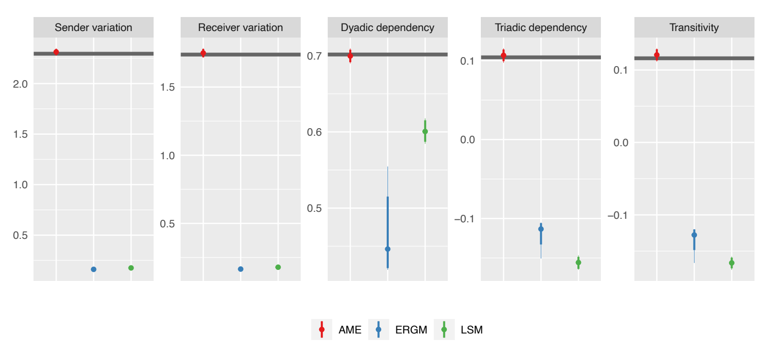
Since Gravity model, ERGM, and LSM are popular choices in modeling global trade (Zhou 2011, 2013, Ward et al. 2013), we accordingly specify our Model 3 in Table 5 using MRQAP (gravity model), ERGM, and LSM by constructing both dyadic and nodal level variables for these three models. Model outputs are reported in e-companion E-T6. We see that LPI is still statistically significant in MRQAP, ERGM, and LSM models in generating more exports (sender effect) and attracting more imports (receiver effect). ERGM and LSM both estimated a similar effect size as AME model but the gravity model estimated a much smaller effect size compared with all the other models. So, the question is: which model to trust, i.e., which model produces the most accurate estimates for the relationship between LPI and bilateral trade?

We, therefore, compare the model fit among these four models. The fundamental criteria to assess a model fit is to check a model's ability to reproduce the observed data (Wooldridge 2010). If the model fits the data poorly, researchers cannot expect the model to have any bearings on the data-generating process and the subsequent coefficients estimates are also questionable. The better a model's ability to reproduce the relationships in the observed data, the more the researchers can trust the model results. Due to the different estimating procedures in different R packages for these four models, we are able to compare MRQAP, ERGM, and LSM as one group while manually generating network simulations to compare ERGM, LSM, and AME in another group (MRQAP model outputs cannot be used to generate simulations).

E-companion Figures E-F5, E-F6, and E-F7 report the goodness of fit test for MRQAP, ERGM, and LSM respectively in different parameters. In each parameter, the black line represents the actual values in the data while the light grey line represents model generated distributions for that parameter. If a model fits the data well, the model generated distribution (the light grey line) should overlap with the observed values in the data (the black line), i.e., model fits the data well. Looking at Figures E-F5, E-F6, and E-F7, we see that MRQAP-generated distributions (the grey line) significantly deviate from actual values in the data (the black line) in all parameters while both ERGM and LSM show a good fit as both ERGM and LSM-generated distributions (the light grey line) overlap with the actual values in the data (the black line). The conclusion we can draw from this group of comparison is that MRQAP, i.e., the gravity model, has the worst model fit.

Turning to the model fit between ERGM and LSM, we see from the graphs that both models fit the data well. It is challenging to identify the winner between ERGM and LSM by just looking at the graphs. Therefore, we further use simulation to test a models' ability to reproduce the five network measures previously discussed in Section 5.2, such as standard deviation of row means and column means. Figure 3 compares how well the simulated networks generated from the models align with the observed values in the data between AME, ERGM, and LSM.

Figure 3 Comparison of Model Fit between AME, ERGM, and LSM



The gray horizontal bar in Figure 3 represents actual values from the global trade network. Red, blue, and green dots represent simulation-generated values from AME, ERGM, and LSM models. The thick and thin shaded lines around each dot represent 95% and 90% intervals from the simulations, respectively. We see that the simulated values from AME models (red dots) are more closely aligned to the actual observed values in the data than the simulated values from ERGM and LSM in all the five network measures. By measuring ERGM and LSM on these five network parameters, we see that despite ERGM and LSM show better model fit than gravity model from the previous group of comparisons, ERGM and LSM still cannot accurately reproduce the global trade network as the simulated values of ERGM and LSM deviate from the actual observed values to a very large extent, reinforcing the fact that when there are many ties in a network such as in the global trade network, ERGM faces model degeneracy issues while LSM struggles to capture all the ties. The conclusion we can draw from this group of comparison is that AME performs better than ERGM and LSM.

Combined, the model fit comparison between Gravity model (MRQAP), ERGM, LSM, and AME reveals that the gravity model (combined with MRQAP) has the worst model fit while AME model has the best model fit. Despite the prevalent role of gravity model in trade economics literature, we demonstrate that it suffers from serious model fitting issues. We call for researchers to carefully implement gravity model to draw more accurate statistical inferences.

7. CONTRIBUTIONS AND IMPLICATIONS

Our research makes theoretical, methodological, and managerial contributions to operations management. Theoretically, our work contributes to both operations management discipline and other disciplines in the following ways. First, our research is one of the few studies in operations management field to investigate the fundamental role of logistics in economic development on a global scale by utilizing data from 163 countries. Our findings reinforce the fact that logistics is still the backbone of the global economy by positively contributing to both exports and imports. Our research calls for future research to focus on operations issues on a global scale to further knowledge accumulation. Second, our findings enrich the understanding of trade logistics literature in both operations management and beyond. Different from extant trade logistics literature where all six logistics dimensions are found to positively contribute to bilateral trade, we only find positive significant statistical relationships between logistics infrastructure, logistics competence, and bilateral trade. In addition, in sharp contrast with extant findings, customs efficiency is found to be *negatively* contributing to bilateral trade. The other three logistics dimensions (i.e., shipping efficiency, timeliness, and track and trace capability) are not statistically significant with bilateral trade. We attribute the different findings to two factors: 1) different modeling approach as all extant literature rely on gravity model, which has serious model fitting issues (Section 6.3); and 2) changing logistics landscapes in the past decades. For example, Hausman et al. (2013) used a single year data of 2005 to study the relationship between timeliness and global trade and concluded that timeliness matters for both exporters and importers. However, the relationship between timeliness and bilateral trade may have evolved since 2005. Third, by constructing the dependent variable bilateral trade in an adjacency matrix that simultaneously captures both exports and imports, our research contributes to both operations management literature and trade economics literature to better understand the operationalization of bilateral trade. In international trade literature where bilateral trade was modeled as the outcome variable (Table 1), bilateral trade is operationalized as a single column of data by taking the mean of exports and imports (Zhou 2011), the sum of exports and imports (Hausman et al. 2013), export only (Çelebi 2019), or is modeled separately in two separate regressions (Marti et al. 2014, Gani 2017), losing the true bilateral nature of trade flows. Since exports and imports happen simultaneously and imports are critical inputs for exports (Khan and Knight 1988), averaging, summarizing, or splitting these two trade flows are flawed. Our approach in constructing exports and imports in one single adjacency matrix serves as an example for scholars to construct similar operations outcome variables which may help yield more meaningful findings for both researchers and policymakers.

Methodologically, we introduce AME model to operations management discipline where relational data are increasingly utilized to analyze relevant operations issues (Autry et al. 2014, Wichmann et al. 2015). The existing modeling approach to handle relational data in operations management is deficient in two ways. First, relational data consists of first-order, second-order, and third-order dependencies while extant research using relational data only focuses on exploring a single dependency in relational data, such as dyadic dependency (Carter et al. 2007, Kim et al. 2011, Kim 2014) or triadic dependency (Peng et al. 2010, Autry et al. 2014). A modeling approach focusing on one dependency while ignoring other dependencies is insufficient to capture the systematic structure of the whole network and may lead to biased statistical inferences. AME model avoids this deficiency by simultaneously capturing the three different dependencies. Second, current social network analysis in operations management remains very descriptive without producing much statistical inferences (Carter et al. 2007) or only focuses on the network centrality measures (Kim et al. 2011, Wichmann et al. 2015). AME model, on the contrary, provides statistical inferences as well as estimates for different dependencies to address more meaningful research questions. Third, compared with the gravity model (using MRQAP) and other social network models (ERGM and LSM) that account for dependencies in the data, AME model provides the best model fit by more accurately reproducing the observed values in the data. Thus, AME model provides more accurate and less biased estimates for researchers to explore similar operations issues. In addition, AME model can be easily implemented in R and we provide all R implementation code along with this study. To this end, our introduction of AME model contributes to knowledge advancement not only in operations management but also in many other fields. Specifically, we want to highlight that the prevalent approach of modeling global trade – the gravity model – has proven to be the worst model fit, failing to capture any of the observed values in the data. We call for researchers to implement gravity model with caution.

For policy makers, our research yields the following managerial insights. First, for an individual country, a 1% improvement in LPI increases exports by 7.77 % and imports by 5.46 %. This informs country policymakers that continuous investment to improve LPI will help boost both exports and imports. Second, developing countries and developed countries benefit differently from improving LPI. The same 1% improvement in the quality of LPI enables developing countries to enjoy 3.81% more exports, although there is no impact on imports. Our findings corroborate the long established export-led growth theory in developing countries in macroeconomics (Tyler 1981, Balassa 1985). We call for global policymakers in developing countries to strengthen their efforts in improving LPI to compete in global economy. Since World Bank measures country logistics in six dimensions, should country policymakers improve all of the six dimensions? This leads to our third contribution. Different from other trade logistics literature (Marti et al. 2014, Gani 2017), we did not find shipping efficiency, timeliness, and track and trace capability have statistical significance with trade flows. We attribute this to the excellent logistics capabilities and logistics technologies achieved by international logistics companies and local governments in the past decade. Due to enhanced and improved logistics capabilities, global firms nowadays enjoy high-level logistics services in shipping, one-time delivery, and track and trace capability, the dimensions of which have subsequently become order qualifiers in global trade and hence the non-significant findings. For country policymakers, this implies that investment efforts to improve logistics capabilities should not be prioritized on shipping, timeliness, and track and trace. However, we call for country policymakers and international logistics companies to at least sustain their current service level in these areas to continue provide excellent services. Fourth, in sharp contrast to extant literature, we find customs clearance efficiency is statistically significant but *negatively* associated with bilateral trade. We attribute this to the prevailing trade sanctions and trade protection policies implemented by various countries and regional trade organizations. We call for country policymakers and global organizations to reduce trade sanctions and trade protectionism to facilitate trade activities. Fifth, despite the increasingly integrated global e-commerce activities which have bridged the geographic challenges in international trade, being landlocked still remains a barrier in international trade: being landlocked means exporting 0.96% less and importing 0.99% less, compared with non-landlocked countries. Policy makers in landlocked countries should seek strategic alliances to increase trade flows, such as collaboration, investment, and co-ownership in other countries' seaports. China's "one belt one road" policy and its tremendous investment in seaports in Middle East and Africa is an excellent example of strategic alliances to promote trade activities globally through landlocked countries.

8. LIMITATIONS AND FUTURE RESEARCH

We review the limitations of our research and propose future research paths in this section. First, our study only focuses on the aggregated measure of LPI and its six logistics dimensions measured by the World Bank. Minute measures like different modes of logistics infrastructure (i.e., rail, road, airports, and etc.) are not considered, which, however, opens up a potential avenue for future research to explore the relationship between different modes of logistics infrastructure and bilateral trade, such as how the quality of seaports impacts bilateral trade. Understanding the varying effects these different modes may have on global trade could provide deeper insights into the intricate relationships between logistics and global trade.

Next, our research aims to answer the overarching question of how LPI contribute to global trade at a country level, so, we did not consider other minute characteristics. However, future research could continue investigating the dynamics between different characteristics of logistics and bilateral trade in different countries. For instance, countries with outdated customs procedures could be assessed for potential benefits gained from improvements in customs efficiency, while countries facing shipping inefficiencies could be analyzed for advantages achieved through enhancements in shipping efficiency. Moreover, product characteristics could also play a role in shaping the relationships between logistics and bilateral trade. For instance, the logistics of exporting oil through pipelines greatly differ from those of exporting perishable items such as vaccines or fresh produce via a cold chain. Therefore, instead of examining total export/import volumes, considering the unique product portfolio of each country may also yield other meaningful operational insights for policymakers.

Lastly, buyer-supplier relationships attract wide attention from researchers in recent years in operations management (Autry and Golicic 2010, Narayanan et al. 2015). A buyer-supplier network is a typical relational data network where one buyer can have many suppliers and one supplier can have many buyers. First-order dependency, second-order dependency, and third-order dependency are prevalent in buyer-supplier networks. However, among the limited research utilizing network analysis to explore buyer-supplier networks (Carter et al. 2007, Choi and Wu 2009, Autry et al. 2014), none of the research accounted for the three dependencies simultaneously in the data. As such, we call for researchers to account for the three dependencies in future buyer-supplier research to yield more nuanced findings. In addition, we also call for researchers in the buyer-supplier research domain to test differences in model fit between different models (AME, ERGM, and LSM) to debunk the differences in model performances in buyer-supplier research as well as to contribute to knowledge accumulation in social network analysis.

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