The Role of Logistics in the Global Economy
– A Social Network Analysis

ABSTRACT

We investigate how a country's logistics infrastructure and logistics competence impact a country's exports and imports. Compiling data for 163 countries, we find that logistics infrastructure positively contributes to both exports and imports while logistics competence only positively impacts exports. Different from trade logistics literature, we find that shipping efficiency, timeliness, and track and trace capability are not statistically significant with bilateral trade. In addition, developing countries benefit more from improving their logistics infrastructure and logistics competence. To correctly model the dyadic, triadic, and higher order relationships in a complex global trade network, we adopt a new social network model that simultaneously captures all these dependencies. The new model also performs better than the classic gravity model and other social network models. 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. Our modeling approach also contributes to advancing social network analysis in the operations management community.

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

"We took a monumental step forward as a nation…We did something that's long overdue... a once-in-a-generation investment that's going to create millions of jobs modernizing infrastructure, our roads, our bridges, our broadband, all range of things. I truly believe that 50 years from now, historians are going to look back at this moment and say, that's the moment America began to win the competition of the 21st century."

– *President Joe Biden spoke after signing the $1 trillion infrastructure bill into law on November 15th, 2021*

1. INTRODUCTION

The signing of the $1 trillion infrastructure bill into law by President Biden reminds us of the importance of logistics infrastructure and its fundamental role in business and economic outcome. It has long been established that logistics infrastructure plays a crucial role in improving a country's economic status and achieving a global competitive advantage (Lean et al. 2014, Wang et al. 2021). However, logistics infrastructure is only the "hardware" of logistics. The "software" of logistics, i.e., the competence and quality of logistics services built upon logistics infrastructure, is also essential to enhance economic outcome (Hausman et al. 2013). Despite the widespread research on the impact of either logistics infrastructure or logistics competence on country economic outcome, it is rare to find research examining these two dimensions simultaneously in operations management field. Therefore, the overarching goal of the current study is to simultaneously explore the impact of these two logistics dimensions on country economic outcome. Addressing this question provides vital insights that are not only academically significant, but also practically relevant to country policymakers, offering them meaningful insights to design trade logistics policies on a global scale.

Following extant trade economics literature, we retrieve data compiled by the World Bank to measure a country's logistics infrastructure and logistics competence and use bilateral trade between countries to proxy global economic outcome. Hausman et al. (2013) detailed how the World Bank has painstakingly developed the project to measure each country's logistics performance. We follow Hausman et al. (2013) to continue using the measures derived by the World Bank to proxy the level of a country's logistics infrastructure and logistic performance. Bilateral trade, measured by a country's exports and imports, has been examined in marketing (Chang et al. 2022), business strategy (Loertscher and Marx 2022), and information systems (Hui 2020). However, research on the impact of logistics on bilateral trade is rare in operations management field, 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 Covid-19, where countries with better logistics recovered faster from the global Pandemic. Therefore, we aim to achieve our first research objective by reviewing the fundamental role of logistics in the global economy. Specifically, we investigate how a country's logistics infrastructure and logistics competence affect its exports and imports. Drawing on extant literature, we hypothesize that both logistics infrastructure and logistics competence should positively contribute to a country's exports and imports.

The purpose of the World Bank to publish logistics related measures for each country is to provide a benchmark so that different countries can improve their different logistics dimensions to compete in the global trade. However, trade economics has long established that a country's economic status is positively related to its global trade (Gereffi and Frederick 2010) while the World Bank also reports that developed countries normally boast better logistics infrastructure than developing countries (World Bank 2023). One question naturally follows is: should developed countries and developing countries spend equal efforts to improve their logistics infrastructure and logistics competence? In other words, if both developed countries and developing countries improved their logistics infrastructure and logistics competence by a similar level, who would benefit more? Despite previous research has investigated the relationships between the World Bank logistics measures and global trade (Hausman et al. 2013, Marti et al. 2014, Gani 2017, Çelebi 2019), this question remains unanswered. Therefore, our second research objective is to investigate the differentiating effect of logistics infrastructure and logistics performance on bilateral trade between developed and developing countries. Drawing on the law of diminishing returns (Schmenner and Swink 1998), we hypothesize that developing countries will benefit more from improving their logistics infrastructure and performance.

In delineating the relationships between the two logistics measures 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 each other. 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 the extant 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 popular dyadic design (Bradley et al. 2020, Reza et al. 2021, Mostagir and Siderius 2022) or triadic design (Autry et al. 2014, Song et al. 2019) 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 challenging 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 draw causal inferences (Minhas et al. 2019). In our study, we utilize a new modeling approach that can simultaneously capture 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 rigor in modeling relational data for the operations management community. This is our third research objective.

To examine the impact of the two logistics measures on country economic outcome, we collect data from multiple sources for 163 countries during the period from 2007 to 2018. Specifically, we collect logistics infrastructure and logistics competence measures from the Work Bank and bilateral trade data from International Monetary Fund (IMF). Using Additive and Multiplicative Effects (AME) models, we find that logistics infrastructure positively contributes to country economic outcome: a 1% improvement in logistics infrastructure increases a country's exports by 10.48% as well as increasing its imports by 10.31%. In contrast to findings from extant literature (Marti et al. 2014, Gani 2017, Çelebi 2019), logistics competence only positively contributes to exports but not to imports: a 1% improvement in logistics competence increases a country's exports by 5.64% while the relationship between logistics competence and imports is not statistically significant. We partially contribute the different findings to the nuances in our AME modeling approach which models exports and imports as a single matrix dependent variable, in contrast to the extant literature where exports and imports are modeled separately in two regressions using gravity model. In a model fit comparison, gravity model shows the worst model fit while AME model shows the best model fit (Section 5.3.3). To this end, we call for researchers to implement gravity model with caution when studying a complicated network such as the global trade network as gravity model fails to reproduce the observed values in the data.

Regarding the differentiating effect of logistics infrastructure and logistics performance on global trade between developed and developing countries, we find that developing countries do benefit more from improving these two logistics dimensions. Compared with developed countries, a developing country benefits from 3.9% more exports when improving logistics infrastructure and 3.6% more exports when improving logistics competence. However, this differentiating effect only applies to exports: compared with developed countries, developing countries do not benefit from more *imports* when improving their logistics infrastructure and logistics competence. Therefore, for a developing country, improving logistics infrastructure and competence only helps to increase more exports but does not help to attract more imports, echoing the report from the World Bank that developing countries are still more export-oriented (Mulabdic and Nayyar 2022).

In addressing the three research objectives, we make distinct theoretical, methodological, and managerial contributions. Theoretically, our research is among the very few studies in the past two decades to explore the impact of logistics on economic outcome on a global scale in operations management. Despite the ubiquitous presence and importance of logistics in our daily economy, very few research attempts to test the simple hypothesis that logistics is the backbone of our economy, especially on a global scale. Our research tests this simple yet fundamental hypothesis and our findings reinforce the fact that logistics is unarguably still the backbone of the global economy. We call for more future operations research to continue knowledge accumulation in this domain. In addition, our study contributes to enrich the understanding of the impact of different logistics dimensions on global trade. The World Bank measures a country's overall logistics performance in six different dimensions. In addition to logistics infrastructure and logistics competence, the World Bank also measures a county's customs efficiency, shipping efficiency, timeliness, and track and trace capability. Following extant trade logistics literature (Marti et al. 2014, Gani 2017), we also include these other four logistics measures in our analysis to provide more holistic insights for country policymakers. In sharp contrast to existing 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 country. However, using AME model, we find that timeliness is not statistically significant either for origin or for destination country regarding bilateral trade. Therefore, our research reveals a fundamentally different story using a different modeling approach, which leads to our next methodological contribution.

Methodologically, 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 the prevalent gravity model to study global trade (Silva and Tenreyro 2006, Head and Mayer 2014). 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, Çelebi 2019) 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 (Section 5.3.3). Different from gravity model, we adopt a recent advancement in social network analysis to deal with these two deficiencies. Despite social network analysis has been increasingly popular in operations management for studying relational data (Appendix A), 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, therefore, yields more reliable and less biased estimates. To this end, our research contributes to advancing the application 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 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 (Appendix A) 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 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. We attribute this insignificant finding to the continuous improvement achieved by local government and international logistics service providers in the past decades such that timeliness, shipping efficiency, and track and trace capability have become order qualifiers, rather than order winners, to compete in the global trade, hence, the non-significant findings. Further investment in these three logistics dimensions is not encouraged as it seems that the law of diminishing returns has started to have an effect – 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 0.61% less exports and 0.47% less imports. However, developing countries do benefit more from improving their logistics infrastructure and logistics competence: compared with developed countries, a same 1% improvement in the quality of logistics infrastructure and logistics competence enables developing countries to enjoy 3.9% and 3.6% more exports respectively. The effect of improving the quality of logistics infrastructure and logistics competence for developing countries, however, does not apply to imports, which corroborates the long established export-led growth theory for developing countries in macroeconomics (Tyler 1981, Balassa 1985). To this end, we call for policymakers in developing countries to continue investing to improve their logistics infrastructure and logistics competence. 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 trade flows, which, in hindsight, reinforces the decision of Brexit as UK probably will not benefit from increased trade flows at all by staying in the EU.

In the following sections, we first review the relevant literature to develop hypotheses. Then, we present our data sources and variables followed by statistical analysis. Robustness tests were conducted to evaluate model fit. Various contributions were discussed before we conclude our paper and call for future research.

2. RELATED LITERATURE AND TESTABLE HYPOTHESES

We first use the World Bank's definition to define logistics infrastructure and logistics competence. Logistics infrastructure refers to "the quality of trade and transport infrastructure" (Word Bank 2023). Logistics competence refers to "the competence and quality of logistics services—trucking, forwarding, and customs brokerage" (World Bank 2023). The World Bank collects data and generates these measures to rank all countries on a biannual basis since 2007 (more details in data section).

2.1 Logistics Infrastructure and Bilateral Trade

The prevalent research on the relationship between logistics infrastructure and bilateral trade is in the economics field. Previous economics researchers have done a comprehensive literature review on this topic (Farhadi 2015). Our focus hence is not to present a comprehensive literature review on this specific topic. Rather, we present a brief summary of the key findings from the literature and use them as the basis for our hypothesis development.

First, logistics infrastructure has long been considered a key antecedent to economic growth (Pradhan and Bagchi 2013). Better logistics infrastructure helps to reduce transaction costs on trade, thus leading to pecuniary and allocative externalities (Banister and Berechman 2017). Second, at the aggregated level, logistics infrastructure has been found to positively contribute to global trade (Wang et al. 2021). A scrutiny of operations management literature reveals a very limited amount of related research. Among the few logistics infrastructure related research in operations management field, Handfield and Withers (2003) compared different logistics attributes in Hungary, South Korea, China, and Japan, with distribution infrastructure being one of the logistics attributes. Handfield and Withers (2003) subsequently found that firms in Hungary and China lack strong managerial skills to manage these logistics attributes. In most recent years, the research on logistics infrastructure in operations management field focuses on specific topics such as public–private partnerships in cross boarder logistics management (Davis and Friske 2013). Other scattered research on infrastructure itself examines the role of IT infrastructure in supply chain management and firm performance (Byrd et al. 2008, Gardner et al. 2015).

Previous research has adopted different measures of logistics infrastructure. Early research of logistics infrastructure adopts an aggregated measure inclusive of a wide range of infrastructures such as electricity, telecommunication, IT infrastructure, and transportation (Loree and Guisinger 1995), which cannot be described as "logistics" infrastructure per se. Other research that specifically measured logistics infrastructure only used proxy measures, such as cost of roads/construction (Canning and Bennathan 2000) , length of total highway/paved roads (Kumar 2006), density of roads (Khadaroo and Seetanah 2009). In addition, research examining the relationship between logistics infrastructure and economic development focused on a very limited number of countries (Limão and Venables 2001, Wang et al. 2021), making the generalizability of the findings very limited.

In contrast to previous research, we adopt a logistics infrastructure measure that was meticulously collected and compiled by the World Bank across 163 countries (Hausman et al. 2013). The World Bank's logistics infrastructure measure surveys managers who rate the quality of a country's logistics infrastructure for all the countries they conduct business in. Compared with static logistics infrastructure measures used in the extant literature, the World Bank's measure is biannually derived from managers who have first-hand experience of each country's logistic infrastructure in their day-to-day business operations across the globe. We consider the World Bank's measure a more accurate and updated reflection of the relationship between logistics infrastructure and economic activities. The World Bank counts ports, roads, and railroads as logistics infrastructure. From a pure logistics operations perspective, better railroads and roads facilitate faster and more efficient domestic shipment flows while better ports facilitate faster exporting of the outbound shipments and more efficient importing of the inbound shipments. The recent Pandemic is a great witness to this in that countries with poorer port facilities have been struggling with exporting and importing while those countries with better port facilities have recovered from the Pandemic more quickly. Coupled by the findings from the literature, we hypothesize:

H1: Better logistics infrastructure will increase exports as well as attract more imports.

2.2 Logistics Competence and Bilateral Trade

Logistics competence or logistics competency is a well-researched topic in operations management field. At firm level, Closs et al. (1997) investigated the antecedents to firm logistics competence across 111 firms and found that timeliness and flexibility are the key factors driving overall logistics competence. Goldsby and Stank (2000) found strong support for a positive relationship between overall logistics competence and the implementation of environmentally responsible logistics practices by surveying 2,680 managers. Bagchi and Helge (2000) studied 30 Norwegian firms and found that four components of logistics competence, i.e., competitive costs, timeliness, process improvement, and customer service, positively impact firm's return on assets.

Country level research on logistics competence also drew researcher's attention in recent years. Using cluster and discriminant analysis across 155 countries, Burmaoglu and Sesen (2011) found that logistics infrastructure and customs capability are the two key drivers to achieve country competitiveness. Çemberci et al. (2015) found that to rank higher in global competitive index, countries should strive to improve shipping quality, track and trace quality, and timeliness. A few research also focuses on the impact of logistics competence on international trade. Using gravity model, Marti et al. (2014) revealed that improving logistics competence can help increase exports for almost all the countries in their study. Çelebi (2019) also found a positive relationship between logistics competence and bilateral trade across 118 countries.

Resource-based view (RBV) has been frequently used to explain the impact of logistics performance on international trade (Halldórsson and Skjøtt-Larsen 2004, Burmaoglu and Sesen 2011). However, scholars have argued that RBV is a predominantly inward-focused view where a firm focuses on its internal resources and protects its know-how to succeed (Dyer and Singh 1998). The increasingly integrated global economy operates against the inward-focused RBV as all countries are intertwined in a network of dyadic and triadic interdependent relationships. Therefore, we adopt an extension of RBV, the relational view, to explain why countries need to improve their logistics competence to promote bilateral trade. Advocated by Dyer and Singh (1998), relational view posits that a firm's critical resources may span firm boundaries and be embedded in inter-firm resources and routines. Hence, to achieve competitive advantage, firms will have to reach out to share their know-how with other firms, instead of protecting their know-how. Relational view treats firm at the dyad and network level rather than at a single firm level. Consequently, relational view posits that it is the collaboration between firm that generates rent.

Applying relational view to logistics competence at country level, we see that countries are increasingly expanding and exchanging their logistics competencies with other countries, such as the ever-increasing foreign direct investment in logistic sector (World Bank 2023) and the most recent "one belt one road" initiatives by China (Chatzky and McBride 2020). These initiatives can be explained by the relational view where countries span their logistics boundaries to expand exports and attract more imports. The recent Biden infrastructure bill also reinforces the importance of renewing and updating logistics competences to "compete against China and other nations vying for dominance of 21st century emerging industries" (Tankersley 2021), which is another complementary view to RBV – dynamic capability, proposing that "the capacity to renew competences" (Teece et al. 1997, p. 515) is also key to achieve sustained success. Combined with findings from the literature, we posit:

H2: Better logistics competence will increase exports as well as attract more imports.

2.3 The Differentiating Role of Logistics Infrastructure and Logistics Competence

Trade economics has long established that a country's economic status is closely associated with its ability to export and import (Tyler 1981, Balassa 1985). Similarly, we argue that a country's economic status should also impact the extent to which a country can increase its trade flows by improving its logistics infrastructure and competence. The rationale can be explained by the classic microeconomic law of diminishing returns (Schmenner and Swink, 1998). If a country has relatively low quality of logistics infrastructure and competence, improvement on these two logistics dimensions might bring in significant and immediate effects, such as drastic increase of exports and imports. However, if a country already enjoys a very high level of logistics infrastructure and competence, further improvement on these two dimensions might bring in less significant effect in promoting trade flows. As developing countries are normally associated with poorer logistics infrastructure and logistics competence, we argue:

H3a: Developing countries should expect to benefit more from improving their logistics infrastructure.

H3b: Developing countries should expect to benefit more from improving their logistic competence .

3. 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 the International Monetary Fund (IMF 2023). At the time of writing, IMF provides global trade data up to December 2022. The two logistics measures, however, have 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 logistics measures up to 2018. Accordingly, we set the timeframe of bilateral trade data from 2007 to 2018. The discontinuous data of logistics measures makes it challenging to conduct a longitudinal analysis. So, we take the average exports and imports between 2007 and 2018 to conduct a cross-sectional analysis. However, follow existing practice (Zhou 2011, 2013), we also conduct 6 separate analysis for the years of 2007, 2010, 2012, 2014, 2016, and 2018 when logistics measures are available (more in Section 5). After data cleaning, we have 163 countries in our observations.

The operationalization of our dependent variable bilateral trade is fundamentally different from how bilateral trade (i.e., exports and imports) was operationalized as a dependent variable in related literature. A common practice in related literature using gravity model is to use one single dependent variable (total exports) or two separate dependent variables (export and import) to model the relationships of trade flows (Table 1). As the "bilateral" trade flow is compressed into a single column of data (Table 1), 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. In addition, separating exports and imports in two regression 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.

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	-

Trade adjacency matrix is log-transformed following standard econometrics practice (Wooldridge 2010) and economic development literature (Frankel and Romer 1999). Our dependent variable, therefore, is a 163*163 matrix capturing true bilateral trade among 163 countries. Table 2 (untransformed values) is a mini version to illustrate our adjacency matrix. Take Austria (AUS) for example, each cell on the row of AUS represents Austria's exports to its counterparts. 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 Austria's imports from its counterparts. For example, during the period of 2007 to 2018, Austria on average imported $297 million/year from Algeria (ALG).

3.1.2.Independent Variables

The main independent variables are a country's logistics infrastructure and logistics competence. We compile these two measures from the World Bank who derives these measures biannually since 2007. World Bank uses a 1 – 5 Likert scale to rank a country's logistics infrastructure and logistics competence with 5 being the best and 1 being the worst. The rating of these two measures was assessed by thousands of managers who are doing businesses in those countries. Hausman et al. (2013) elaborated the process and methodology the World Bank adopted to derive these measures. We averaged the scores of these two measures for the six years of 2007, 2010, 2012, 2014, 2016, and 2018 to conduct a cross-sectional analysis. We also did a robustness test for each year in Section 5 following extant trade literature (Zhou 2011, 2013).

To capture the intertwined trade relationships, we construct both dyadic level and nodal level variables for logistics infrastructure and logistics competence. A dyadic level variable is a 163*163 difference matrix to specifically control for dyadic relationships between each pair of countries, i.e., how the difference in logistic infrastructure and competence among different countries affect their bilateral trade. The order of the 163 countries on the rows and columns in the dyadic matrix corresponds exactly to the order of 163 countries on the rows and columns in our bilateral trade matrix. To test our hypotheses, i.e., how improving these two logistics measures impacts exports and imports for an individual country, we construct a nodal level variable, meaning the scores for each country on these two measures were assigned at *both* rows and columns in a 163*163 adjacency matrix corresponding to our dependent variable – the bilateral trade matrix. Rows represent how a country's logistic infrastructure and competence impacts its *exports* while columns represent how a country's logistic infrastructure and competence impacts its *imports*. Our modeling approach, therefore, is fundamentally different from gravity model (Table 1).

3.1.3. Dyadic and Nodal Covariates

We identify appropriate control variables following extant trade economics 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 where BEL and BFA crosses each other in the matrix.

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

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. Most of 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 and the source of each variable.

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 to test our hypotheses. 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 international trade and other social 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 consisting 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 modelled 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" (Barabásia 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 single country to all other countries while each column represents imports into one single 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 and standard network model toolkit and require a different modeling approach.

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 hypotheses (i.e., how logistics infrastructure and competence impact exports and imports) test the first-order and second-order dependencies by constructing country logistics measures at the nodal level as both sender effect and receiver effect, where the scores of the logistics measures for each country were assigned at both rows and columns in an adjacency matrix. Rows represent how logistics infrastructure and competence impact exports while columns represent how logistics infrastructure and competence impact imports in the global trade network.

Third order dependency arises when shared attributes among actors affect their probability to interact with each other. A consistent finding from gravity model in international trade 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 in this example. The various dyadic controls we constructed capture the third order dependency.

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 relationships in the data, the model is prone to be a poor model fit and statistical inference also becomes questionable (more in Section 5). 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 heterogeneity across row means (out-degree), heterogeneity along column means (in-degree), correlation between row and column means, and 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 5). 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 the two logistics measures 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 (Appendix A). We calculate these measures for the top 10 countries and report them in Table 5. 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.

Table 5 Nodal Level Measures for Top 10 Countries of Global Trade

Out Degree	Country	In Degree	Country	Total Degree	Country	Betweenness	Country	Closeness	Country	Eigenvector	Country
161	ARG	161	AUL	322	AUL	15,695	ZIM	0.0061	BOS	1.00	USA
161	AUL	161	BEL	322	BEL	8,092	ICE	0.0061	DRC	0.88	CHN
161	AUS	161	CAN	322	CAN	6,833	SAL	0.0061	ALB	0.52	JPN
161	BEL	161	CHN	322	CHN	6,821	MAD	0.0061	MZM	0.51	CAN
161	BUL	161	COS	322	DEN	6,606	ALB	0.0061	PAN	0.49	GMY
161	CAN	161	DEN	322	FRN	5,083	URU	0.0061	TAJ	0.41	MEX
161	CHN	161	FRN	322	GMY	4,346	MNG	0.0061	SOL	0.33	ROK
161	CRO	161	GMY	322	IND	4,208	SYR	0.0061	PNG	0.28	NTH
161	CZR	161	IND	322	INS	4,069	NIR	0.0061	ZIM	0.28	FRN
161	DEN	161	INS	322	IRE	3,429	GAM	0.0061	PER	0.27	UKG

The correlation matrix for the four nodal level centrality measures of the 163 countries is reported in Table 6. The correlation matrix, to a certain extent, explains the differences in rankings in Table 5. All degree measures are weakly and negatively correlated with betweenness and closeness, explaining the very different ranking of countries in these measures in Table 5. 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 depend on how many trade partners a country has or how close a country is to all of the others.

Table 6 Correlation Matrix of Nodal Level Measures for 163 Countries

	Out Degree	In Degree	Total Degree	Betweenness	Closeness	Eigenvector
Out Degree	1.00	0.95	0.99	(0.18)	(0.08)	0.33
In Degree	0.95	1.00	0.99	(0.14)	(0.07)	0.31
Total Degree	0.99	0.99	1.00	(0.16)	(0.08)	0.33
Betweenness	(0.18)	(0.14)	(0.16)	1.00	0.14	(0.16)
Closeness	(0.08)	(0.07)	(0.08)	0.14	1.00	(0.70)
Eigenvector	0.33	0.31	0.33	(0.16)	(0.70)	1.00

We next visualize bilateral trade, logistics infrastructure, and logistics competence to show the overall picture. The average annual exports and imports in million U.S. dollars from 2007 to 2018 was used for the visualization of bilateral trade. Figure 1 and Figure 2 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. Figure 3 and Figure 4 plot the quality of logistics infrastructure and the quality of logistics competence measured by the World Bank. We see that countries are less polarized in these two measures. The two logistics measures present the same picture: U.S., Canada, West Europe, Australia, New Zealand, and Japan are the first-tier countries with the best quality in logistics infrastructure and logistics competence, 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 infrastructure and logistics competence.

Figure 1 Average Exports in $Million/Year (2007 – 2018)

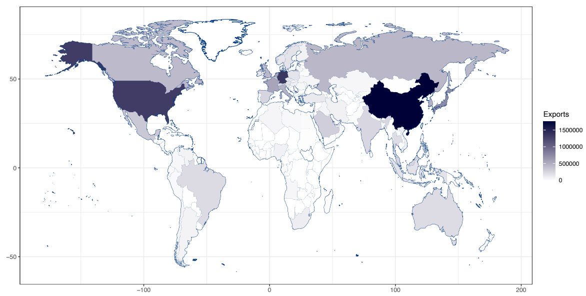


Figure 2 Average Imports in $Million/Year (2007 – 2018)

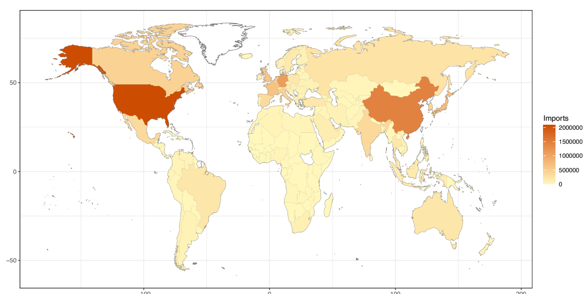


Figure 3 Logistic Infrastructure (1 – 5 World Bank Scale) Averaged Value 2007 – 2018

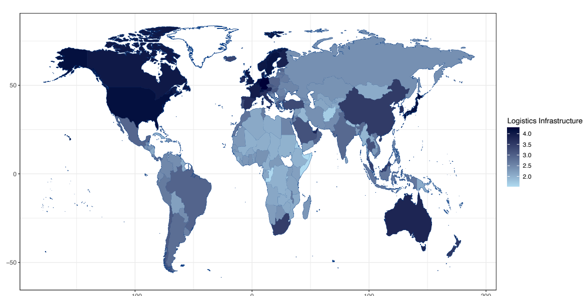
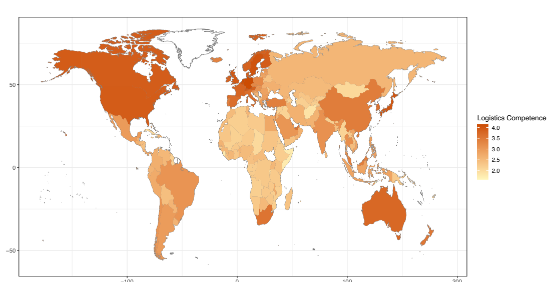


Figure 4 Logistic Competence (1 – 5 World Bank Scale) Averaged Value 2007 – 2018



4. ANALYSIS AND RESULTS

4.1. Main Analysis

We run all analyses in *R* (version 4.3.1) to test our hypotheses. The results are summarized in Table 7. Model 1 only includes the six logistics measures complied by the World Bank at the dyadic level. Model 2 adds all dyadic level covariates. Model 3 further adds all nodal level covariates to test our hypothesized relationships.

Table 7 AME Model Outputs

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	7.37***(0.39)	11.51***(0.40)	-18.64***(2.77)	-14.85***(3.30)	-15.16***(3.47)
Dyad Level Effects					
Customs	0.01 (0.29)	0.75* (0.31)	0.74* (0.30)	0.71* (0.30)	0.71* (0.30)
Logistics Infrastructure	-0.44 (0.33)	0.06 (0.33)	0.02 (0.28)	0.04 (0.30)	0.04 (0.30)
Shipping	-0.68† (0.36)	0.12 (0.34)	0.17 (0.36)	0.19 (0.34)	0.20 (0.34)
Logistics Competence	1.15* (0.45)	0.77† (0.41)	0.72† (0.43)	0.70† (0.42)	0.71† (0.42)
Track and Trace	1.28***(0.37)	0.47 (0.34)	0.51 (0.34)	0.49 (0.34)	0.49 (0.34)
Timeliness	-1.91***(0.45)	-1.94***(0.37)	-1.92***(0.38)	-1.89***(0.38)	-1.89***(0.38)
Political Difference		0.39***(0.04)	0.39***(0.04)	0.39***(0.04)	0.39***(0.04)
Social Connectedness		0.23***(0.01)	0.23***(0.01)	0.23***(0.01)	0.23***(0.01)
Common Language		0.71***(0.05)	0.72***(0.05)	0.72***(0.05)	0.72***(0.05)
Common Religion		0.63***(0.07)	0.65***(0.07)	0.65***(0.07)	0.65***(0.07)
Common Colonial		0.67***(0.16)	0.67***(0.19)	0.67***(0.18)	0.64***(0.18)
Contiguity		1.13***(0.11)	1.19***(0.10)	1.19***(0.10)	1.19***(0.10)
Distance		-0.78***(0.02)	-0.73***(0.02)	-0.73***(0.02)	-0.73***(0.02)
RTA		0.72***(0.06)	0.75***(0.06)	0.76***(0.06)	0.76***(0.06)
Sender Effect					
Customs			-10.80***(2.60)	-8.76***(2.55)	-9.37***(2.56)
Logistics Infrastructure			**10.48***(2.13)**	**9.06***(2.29)**	11.60***(2.32)
Shipping			1.31 (3.02)	-0.07 (2.85)	0.46 (2.86)
Logistics Competence			**5.64† (3.17)**	4.95 (3.06)	**2.44† (3.33)**
Track and Trace			-0.54 (2.67)	-0.05 (2.88)	-0.28 (2.90)
Timeliness			0.09 (2.78)	-0.78 (2.78)	-0.51 (2.80)
GDP			0.05 (0.05)	0.04 (0.05)	0.04 (0.05)
Population			0.53***(0.11)	0.52***(0.11)	0.51***(0.11)
Doing Business			-0.14 (0.16)	-0.16 (0.17)	-0.16 (0.17)
Surface			0.09 (0.07)	0.10 (0.07)	0.10 (0.08)
Landlocked			-0.90***(0.22)	-0.80***(0.22)	-0.82***(0.22)
GATT			-0.29 (0.28)	-0.18 (0.27)	-0.16 (0.27)
WTO			1.18***(0.34)	1.05***(0.34)	1.06***(0.34)
EU			0.18 (0.32)	0.35 (0.31)	0.37 (0.32)
Developing Country			-0.61* (0.29)	**-4.29***(1.27)**	**-4.18** (1.49)**
Developing Country*Infrastructure				**3.92***(1.32)**	
Developing Country*Timeliness					**3.63** (1.50)**
Receiver Effect					
Customs			-9.88***(2.15)	-9.21***(2.29)	-9.62***(2.28)
Logistics Infrastructure			**10.31***(1.90)**	**9.76***(2.19)**	**10.75***(2.19)**
Shipping			-0.09 (2.65)	-0.62 (2.63)	-0.29 (2.63)
Logistics Competence			**4.27 (2.76)**	4.21 (2.85)	**3.44 (3.05)**
Track and Trace			0.73 (2.51)	0.93 (2.56)	0.81 (2.57)
Timeliness			-2.09 (2.59)	-2.61 (2.58)	-2.46 (2.60)
GDP			0.03 (0.04)	0.03 (0.04)	0.03 (0.04)
Population			0.58***(0.09)	0.57***(0.10)	0.57***(0.10)
Doing Business			-0.13 (0.15)	-0.14 (0.16)	-0.14 (0.16)
Surface			0.003 (0.06)	0.009 (0.07)	0.01 (0.07)
Landlocked			-0.93***(0.21)	-0.89***(0.20)	-0.91***(0.20)
GATT			-0.19 (0.25)	-0.16 (0.25)	-0.16 (0.25)
WTO			1.08***(0.29)	1.04***(0.30)	1.06***(0.30)
EU			-0.25 (0.30)	-0.17 (0.28)	-0.18 (0.28)
Developing Country			-0.47† (0.27)	**-2.09* (1.12)**	**-1.68 (1.32)**
Developing Country*Infrastructure				**1.72 (1.17)**	
Developing Country*Timeliness					**1.22 (1.33)**

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

Our first hypothesis proposes that improving logistics infrastructure positively contributes to both exports and imports for an individual country. This hypothesis was tested by the nodal level effect, i.e., the coefficients for "logistics infrastructure" 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 logistics infrastructure on exporting and importing. The coefficient for sender effect is 10.48 ($p=0.000$) while that for receiver effect is 10.31 ($p=0.000$), indicating that a 1% increase in the quality of logistics infrastructure (as measured by the World Bank) will likely increase a country's exports by 10.48% as well as attract more imports by 10.31%. Therefore, Hypothesis 1 is supported. We see that the role of logistics infrastructure is equally important in promoting both exports and imports.

Our second hypothesis proposes that the quality of logistics competence positively contributes to both exports and imports. As with hypothesis 1, this hypothesis was also tested at the nodal level effect by the coefficients for "logistics competence" under both sender effect and receiver effect. The coefficient for sender effect is 5.64 ($p=0.075$) while that for receiver effect is 4.27 ($p=0.123$), indicating that a 1% increase in the quality of logistics competence (as measured by the World Bank) will likely to increase a country's exports by 5.64%. However, improving logistics competence does not have impact on imports. So, hypothesis 2 is partially supported. Different from logistics infrastructure, a country's ability to export more is affected by its logistics competence while a country's ability to import does not have a statistically significant relationship with its logistics competence. One logistics interpretation might be that in a global supply chain, a seller country's logistics competence and its associated logistics service quality impacts its ability to deliver goods on time, which is key to international trade, hence the better competence the more exports. However, as an importing country, how the imported goods are handled by which level of logistics competences domestically might not matter that much for the importing country.

Our third hypothesis posits that developing countries should benefit more from improving their logistics infrastructure (H3a) and logistics competence (H3b) compared with developed countries. To test this hypothesis, we first create two interaction terms between developing country dummy and logistics infrastructure and logistics competence. Model 4 tests the interaction term of developing country×logistics infrastructure while Model 5 tests the interaction term of developing country×logistics competence. In Model 4, we see that under the sender effect, the three terms of logistics infrastructure (9.06, $p=0.000$), developing country (–4.29, $p=0.001$), and developing country×logistics infrastructure (3.92, $p=0.003$) are all statistically significant, indicating that compared with developed countries, developing countries benefit from a 3.92% more exports when improving their logistics infrastructure. However, under the receiver effect, the interaction term developing country×logistics infrastructure (1.75, $p=0.142$) is not statistically significant. Therefore, Hypothesis 3a is only partially supported. Turning our attention to Model 5, we see that under receiver effect, the three terms of logistics competence (2.44, *p=0.063*), developing country (–4.18, *p=0.005*), and developing country × logistics competence (3.63, *p=0.015*) are all statistically significant, indicating that developing countries also benefit 3.63% more exports from improving their logistics competence. Under the receiver effect, however, none of the three terms is statistically significant. Therefore, Hypothesis 3b is also partially supported. In sum, as a developing country, improving logistics infrastructure and logistics competence only helps this country to export more but not import more, echoing the neoclassic export-led growth theory in developing countries (Tyler 1981, Balassa 1985).

4.2. Model Fit Statistics

In Model 3 of Table 7, 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 5. In Figure 5, 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 performs well in capturing variation across row means (out-degrees) in the top left graph and variation across column means (in-degrees) in the top right graph. The model also 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 7 and report the result in Figure 6. From the trace plots in Figure 6, we see that all parameter estimates are approximately normal, indicating a decent model fit.

Figure 5 AME GoF for Model 3 in Table 7

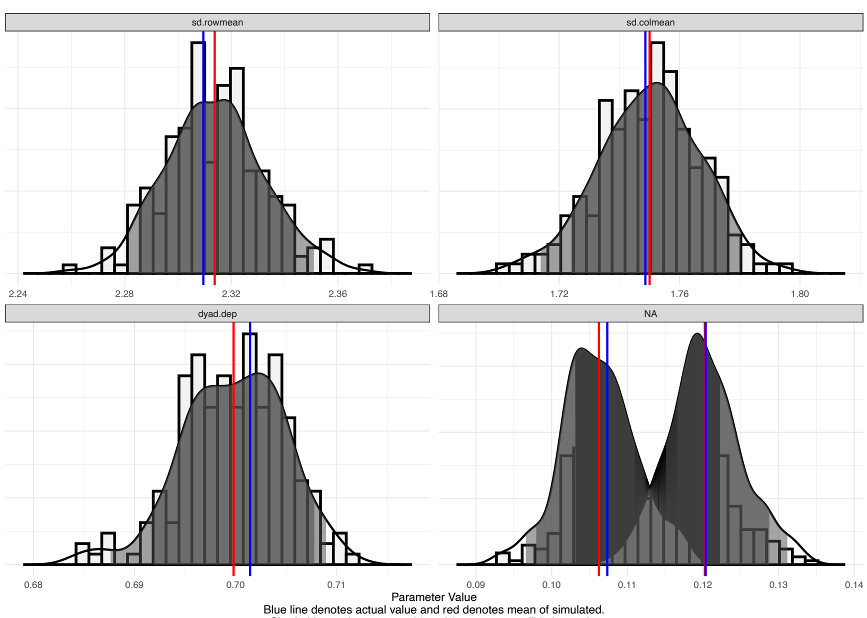
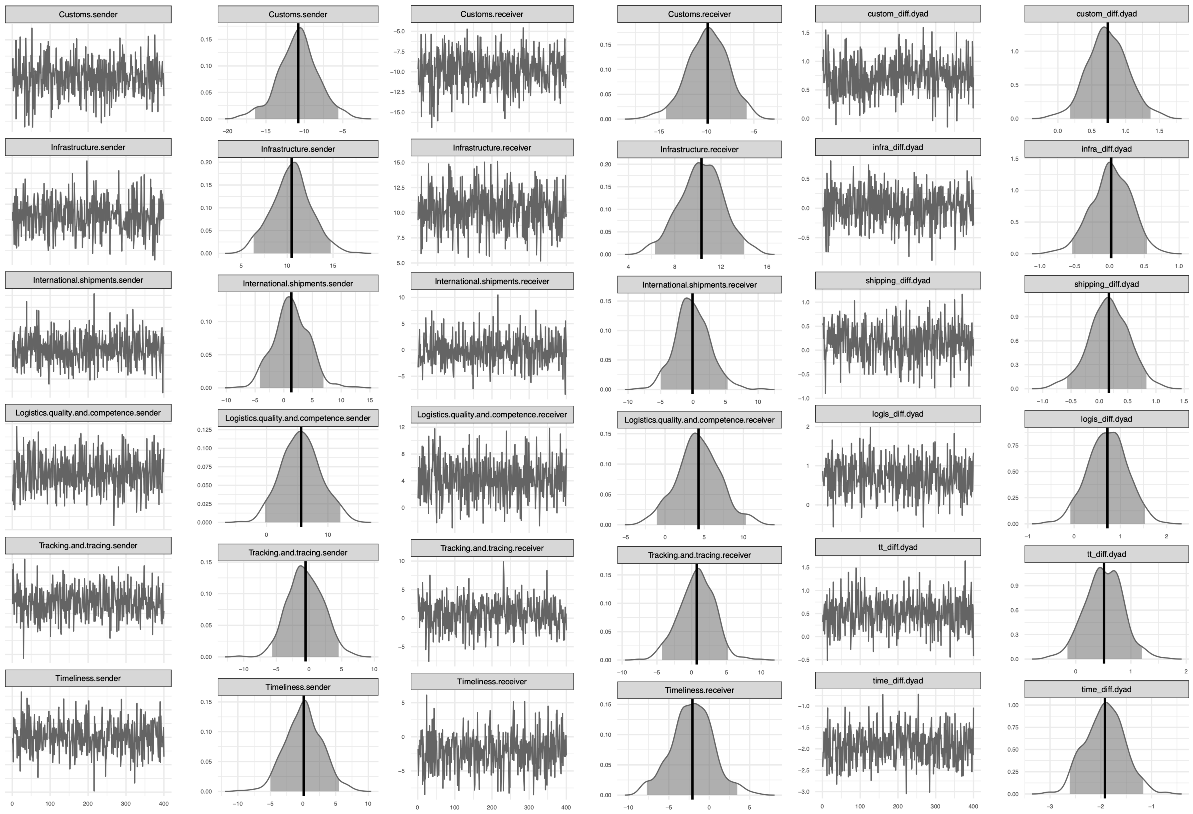


Figure 6 Trace Plots for AME Model 3 in Table 7



4.3. The Six Dimensions of Logistics Performance

The World Bank measures a country's logistics performance on six dimensions. We, accordingly, also include the other four dimensions in our model as controls. 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 dimension of logistics, i.e., shipping efficiency, timeliness, and track and trace capability are statistically non-significant. We attribute this to the fact that shipping efficiency, timeliness, and track and trace capability have become order qualifiers so improvement in these dimensions would be a waste of a country's resources as these improvements will not generate more trade flows. 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 comparison in the next section.

5. ROBUSTNESS TEST

We conduct three robustness tests. First, we test the model specification of AME itself using different latent factors (k in Equation 1). Second, we conduct a longitudinal analysis to re-test our hypothesis. Third, 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.

5.1. AME with Different Latent Factors

From Equation 1, we see 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. We use k=1 for Model 3 in Table 7. Therefore, we accordingly change k to 2, 3, and 4 to test if the change in latent factors impacts our hypothesis testing results and the model fit. Table 8 reports the results of different k values (using Model 3 in Table 7 as an illustration) and Figure 7 plots the model fit using different k values. We see from Table 8 that both Hypothesis 1 and 2 still stand (i.e., same statistical significance for the coefficients of logistics infrastructure and logistics competence across different k values). We also use different k values to re-test Model 4 and Model 5 in Table 7 and the hypothesis testing result remains the same (tables omitted).

Figure 7 Model Fit of Different Latent Factors k in AME Model

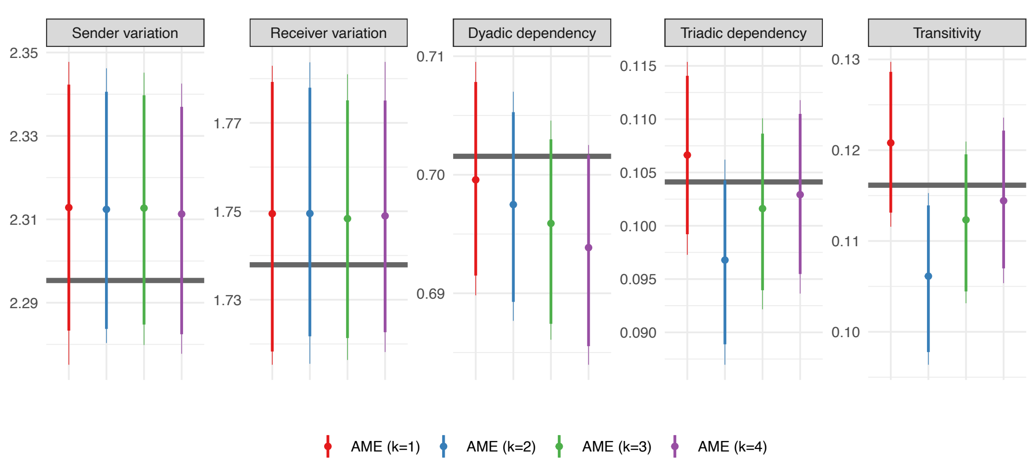


Table 8 Comparison between Different Latent Factors *k* in AME Model

Variable	AME (k=1)	AME (k=2)	AME (k=3)	AME (k=4)
Intercept	-18.64***(2.77)	-16.21***(2.94)	-19.17***(2.55)	-19.39***(2.65)
Dyad Level				
Customs	0.74* (0.30)	1.59***(0.33)	1.66***(0.33)	0.99** (0.32)
Logistics Infrastructure	0.02 (0.28)	-0.60* (0.35)	-0.70* (0.34)	-0.33 (0.32)
Shipping	0.17 (0.36)	-1.60***(0.42)	-1.67***(0.40)	-1.43***(0.39)
Logistics Competence	0.72† (0.43)	0.08 (0.44)	-0.13 (0.43)	0.03 (0.42)
Track and Trace	0.51 (0.34)	0.18 (0.39)	0.49 (0.37)	0.39 (0.37)
Timeliness	-1.92***(0.38)	-1.61***(0.43)	-1.85***(0.42)	-1.76***(0.42)
Political Difference	0.39***(0.04)	0.09***(0.04)	0.07***(0.04)	0.11***(0.04)
Social Connectedness	0.23***(0.01)	0.25***(0.01)	0.22***(0.01)	0.20***(0.01)
Common Language	0.72***(0.05)	0.66***(0.05)	0.62***(0.05)	0.48***(0.05)
Common Religion	0.65***(0.07)	0.53***(0.07)	0.30***(0.07)	0.28***(0.08)
Common Colonial	0.67***(0.19)	0.54***(0.17)	0.52***(0.16)	0.66***(0.16)
Contiguity	1.19***(0.10)	1.09***(0.10)	1.22***(0.10)	1.26***(0.09)
Distance	-0.73***(0.02)	-0.77***(0.02)	-0.59***(0.03)	-0.58***(0.03)
RTA	0.75***(0.06)	0.84***(0.06)	0.86***(0.06)	0.74***(0.06)
Sender Effect				
Customs	-10.80***(2.60)	-10.52***(2.65)	-9.58***(2.33)	-9.42***(2.33)
Logistics Infrastructure	**10.48***(2.13)**	**11.21***(2.28)**	**10.84***(1.97)**	**10.85***(2.09)**
Shipping	1.31 (3.02)	-0.24 (3.01)	0.62 (2.70)	1.02 (2.59)
Logistics Competence	**5.64† (3.17)**	**6.70* (3.25)**	**5.39* (2.64)**	**4.82† (2.64)**
Track and Trace	-0.54 (2.67)	-0.96 (2.93)	-0.80 (2.62)	-0.67 (2.51)
Timeliness	0.09 (2.78)	0.38 (3.12)	-0.31 (2.57)	-0.33 (2.61)
GDP	0.05 (0.05)	0.04 (0.05)	0.05 (0.04)	0.05 (0.04)
Population	0.53***(0.11)	0.53***(0.11)	0.58***(0.11)	0.56***(0.10)
Doing Business	-0.14 (0.16)	-0.20 (0.18)	-0.17 (0.15)	-0.13 (0.15)
Surface	0.09 (0.07)	0.12 (0.08)	0.10 (0.07)	0.10 (0.07)
Landlocked	-0.90***(0.22)	-0.90***(0.22)	-0.90***(0.21)	-0.85***(0.21)
GATT	-0.29 (0.28)	-0.22 (0.30)	-0.23 (0.21)	-0.15 (0.25)
WTO	1.18***(0.34)	1.19***(0.36)	0.89***(0.31)	0.84***(0.29)
EU	0.18 (0.32)	0.21 (0.30)	0.26 (0.29)	0.27 (0.31)
Developing Country	-0.61* (0.29)	-0.72** (0.31)	-0.73** (0.27)	-0.67** (0.27)
Receiver Effect				
Customs	-9.88***(2.15)	-9.51***(2.37)	-8.63***(2.13)	-8.33***(2.09)
Logistics Infrastructure	**10.31***(1.90)**	**11.01***(1.98)**	**10.58***(1.89)**	**10.47***(1.89)**
Shipping	-0.09 (2.65)	-1.70 (2.76)	-0.88 (2.41)	-0.64 (2.27)
Logistics Competence	**4.27 (2.76)**	**5.37 (3.01)**	**4.13† (2.44)**	**3.60 (2.53)**
Track and Trace	0.73 (2.51)	0.30 (2.71)	0.55 (2.35)	0.67 (2.27)
Timeliness	-2.09 (2.59)	-2.63 (2.82)	-2.54 (2.44)	-2.43 (2.29)
GDP	0.03 (0.04)	0.03 (0.05)	0.03 (0.04)	0.03 (0.04)
Population	0.58***(0.09)	0.58***(0.10)	0.63***(0.09)	0.61***(0.09)
Doing Business	-0.13 (0.15)	-0.21 (0.17)	-0.17 (0.13)	-0.14 (0.14)
Surface	0.003 (0.06)	0.03 (0.07)	0.007 (0.06)	0.01 (0.06)
Landlocked	-0.93***(0.21)	-0.93***(0.21)	-0.94***(0.19)	-0.90***(0.19)
GATT	-0.19 (0.25)	-0.15 (0.28)	-0.15 (0.23)	-0.10 (0.23)
WTO	1.08***(0.29)	1.09***(0.33)	0.81***(0.28)	0.76***(0.26)
EU	-0.25 (0.30)	-0.18 (0.30)	-0.14 (0.27)	-0.14 (0.29)
Developing Country	-0.47† (0.27)	-0.59* (0.29)	-0.58* (0.25)	-0.54* (0.25)

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

In Figure 7, 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 7 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 is used in our Table 7 to report hypothesis testing results).

5.2. Alternative Model Specification

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 dummies to re-run our analysis. Result is reported as Model 1 in Appendix B. We see that both H1 and H2 still hold. An interesting phenomena to notice is that compared with other countries, China significantly exports more (3.29, $p=0.001$) and imports more (2.82, $p=0.07$) but U.S. does not.

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 both dependent variables and independent variables are just single columns 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 Appendix B. From Appendix B, we see that Hypothesis 1 holds across all years while Hypothesis 2 holds in some years, indicating that the effect of logistic infrastructure stays the same from 2007 to 2018 while the effect of logistics competence varies from 2007 to 2018. We also test Hypothesis 3 and see that Hypothesis 3 still remain the same (13 models in total and table was omitted).

5.3. Alternative Estimators: Gravity Model, EGRM, and LSM

5.3.1 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).

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

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, Yang et al. 2022).

5.3.2 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 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.

5.3.3 Model Fit Comparison

Since Gravity model, ERGM, and LSM are popular choices in modeling global trade (Zhou 2011, 2013, Ward et al. 2013, Yang et al. 2022), we accordingly specify our Model 3 from Table 7 using MRQAP (gravity model), ERGM, and LSM by constructing both dyadic and nodal level variables for these three models. Model outputs are reported in Table 9. Using logistics infrastructure as an example, we see that logistics infrastructure is still statistically significant in both ERGM and LSM models in generating more exports (sender effect) and attracting more imports (receiver effect) despite ERGM and LSM both estimated a slightly smaller effect size. However, the gravity model does not show any statistically significant relationships between infrastructure and bilateral trade. So, the question becomes: which model to trust, i.e., which model produces the most accurate estimates for the relationship between logistics infrastructure and bilateral trade?

We, therefore, compare the model fit among the four different models in Table 10. The fundamental criteria 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).

Figure 8, Figure 9, and Figure 10 show 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 Figure 8, 9, and 10, 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.

Table 9 Model Comparison between AME, Gravity Model, ERGM, and LSM

Variable	AME (Model 3 in Table 7)	MRQAP (Gravity Model)	ERGM	LSM
Intercept	-18.64***(2.77)	0.019	-16.98***(0.89)	-18.99***[-20.74, -17.32]
Dyad Level				
Customs	0.74* (0.30)	0.03	2.70***(0.65)	-1.08***[-1.81, -0.28]
Logistics Infrastructure	0.02 (0.28)	-0.08	-1.99***(0.60)	2.52***[1.21, 4.00]
Shipping	0.17 (0.36)	0.35***	2.34** (0.73)	1.32***[0.70, 1.80]
Logistics Competence	0.72† (0.43)	0.04	-3.27***(0.75)	-0.88 [-1.83, 0.28]
Track and Trace	0.51 (0.34)	-0.32***	-3.89***(0.66)	0.34***[0.32, 0.35]
Timeliness	-1.92***(0.38)	0.17	0.99 (0.69)	-0.09 [-1.49, 1.46]
Political Difference	0.39***(0.04)	0.03***	0.24***(0.06)	0.39***[0.39, 0.40]
Social Connectedness	0.23***(0.01)	0.008**	0.09***(0.01)	0.05***[0.04, 0.05]
Common Language	0.72***(0.05)	0.04***	1.27***(0.12)	1.12***[1.11, 1.12]
Common Religion	0.65***(0.07)	-0.02	-0.18 (0.13)	-0.44***[-0.44, -0.43]
Common Colonial	0.67***(0.19)	-0.05	0.01***(0.01)	32.16***[8.85, 55.31]
Contiguity	1.19***(0.10)	-0.02	-0.39 (0.35)	0.41***[0.40, 0.42]
Distance	-0.73***(0.02)	-0.02	-0.24***(0.02)	-0.89***[-1.01, -0.77]
RTA	0.75***(0.06)	-0.01***	1.86***(0.44)	1.05***[0.49, 1.65]
Sender Effect				
Customs	-10.80***(2.60)	-0.63***	-8.55***(0.97)	-4.69***[-4.72, -4.66]
Logistics Infrastructure	**10.48***(2.13)**	**0.23**	**6.71***(0.76)**	**6.33***[5.74, 7.00]**
Shipping	1.31 (3.02)	0.61**	7.98***(1.01)	6.27***[5.86, 6.67]
Logistics Competence	**5.64† (3.17)**	**-0.32**	**-0.59 (0.98)**	**-3.98***[-4.33, -3.63]**
Track and Trace	-0.54 (2.67)	0.47*	9.03***(0.88)	10.67***[9.65, 11.89]
Timeliness	0.09 (2.78)	-0.20	-10.33***(0.95)	-6.53***[-8.19, -5.16]
GDP	0.05 (0.05)	0.002	0.07***(0.02)	0.05***[0.05, 0.05]
Population	0.53***(0.11)	-0.004	0.25***(0.04)	0.32***[0.28, 0.37]
Doing Business	-0.14 (0.16)	0.03*	0.28***(0.04)	0.35***[0.30, 0.40]
Surface	0.09 (0.07)	0.005	0.15***(0.03)	0.10***[0.06, 0.13]
Landlocked	-0.90***(0.22)	-0.02	-0.46***(0.07)	-0.54***[-0.56, -0.51]
GATT	-0.29 (0.28)	0.005	0.08 (0.10)	0.12 [-0.12, 0.37]
WTO	1.18***(0.34)	0.08**	0.83***(0.11)	1.50***[1.24, 1.77]
EU	0.18 (0.32)	-0.02	0.07 (0.19)	-0.65***[-0.90, -0.43]
Developing Country	-0.61* (0.29)	-0.002	-0.86***(0.12)	-1.12***[-1.12, -1.11]
Receiver Effect				
Customs	-9.88***(2.15)	-0.48***	-4.96***(0.95)	0.08 [-0.61, 0.79]
Logistics Infrastructure	**10.31***(1.90)**	**0.20**	**6.19***(0.75)**	**5.99***[5.92, 6.05]**
Shipping	-0.09 (2.65)	0.37*	2.48* (1.00)	0.36***[0.22, 0.49]
Logistics Competence	**4.27 (2.76)**	**-0.21**	**0.80 (0.96)**	**-1.18***[-1.79, -0.57]**
Track and Trace	0.73 (2.51)	0.27	5.66***(0.88)	5.37***[5.25, 5.48]
Timeliness	-2.09 (2.59)	0.02	-5.64***(0.95)	-2.79***[-2.81, -2.76]
GDP	0.03 (0.04)	0.002	0.06***(0.01)	0.07***[0.05, 0.08]
Population	0.58***(0.09)	0.0001	0.26***(0.04)	0.33***[0.32, 0.33]
Doing Business	-0.13 (0.15)	0.02*	0.15***(0.04)	0.19***[0.16, 0.21]
Surface	0.003 (0.06)	0.005	0.14***(0.03)	0.11***[0.10, 0.12]
Landlocked	-0.93***(0.21)	-0.02	-0.56***(0.07)	-0.47***[-0.54, -0.40]
GATT	-0.19 (0.25)	0.003	-0.03 (0.10)	-0.02 [-0.21, 0.12]
WTO	1.08***(0.29)	0.07**	0.74***(0.11)	1.33***[1.28, 1.41]
EU	-0.25 (0.30)	-0.005	1.39***(0.23)	2.23***[1.51, 3.09]
Developing Country	-0.47† (0.27)	-0.0005	-0.64***(0.11)	-0.75***[-0.76, -0.72]

Notes: Standard errors are given in parenthesis for AME and ERGM. MRQAP provides no standard errors.
95% posterior credible intervals are provided in brackets for LSM.
*†p < .1; *p < .05; **p < .01; ***p < .001*

Figure 8 MRQAP Gravity Model – Goodness of Fit Assessment

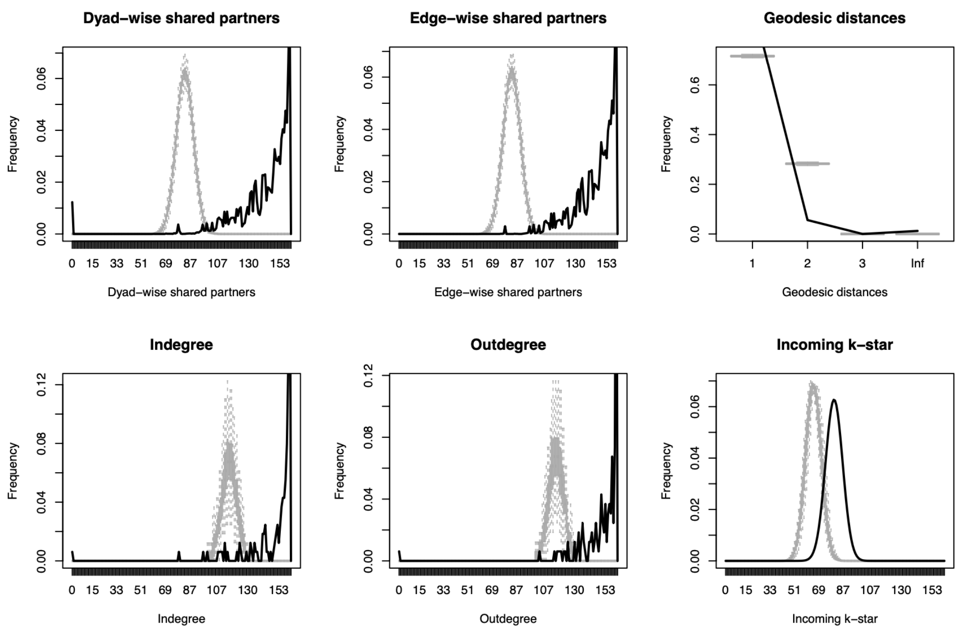


Figure 9 ERGM – Goodness of Fit Assessment

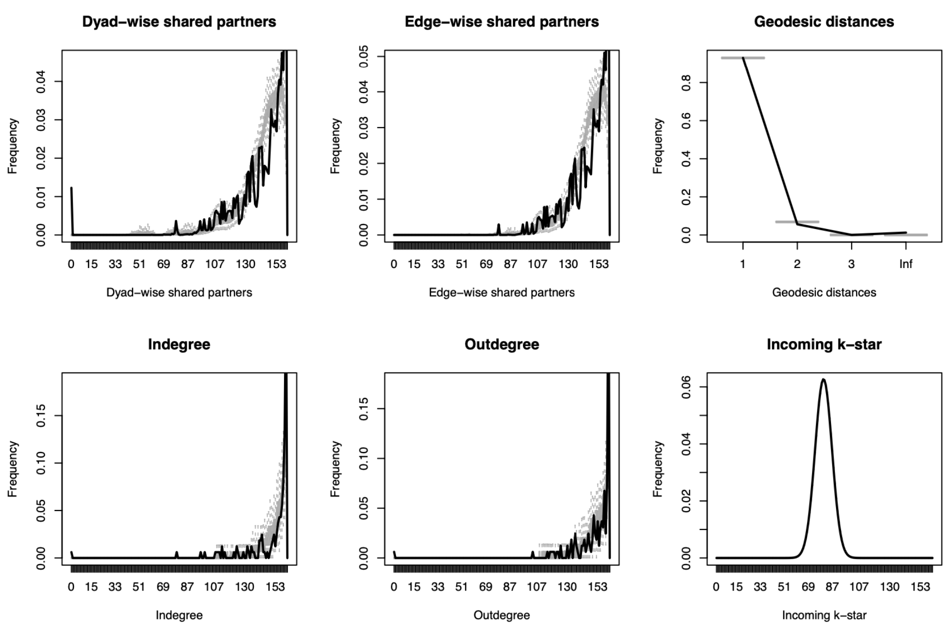
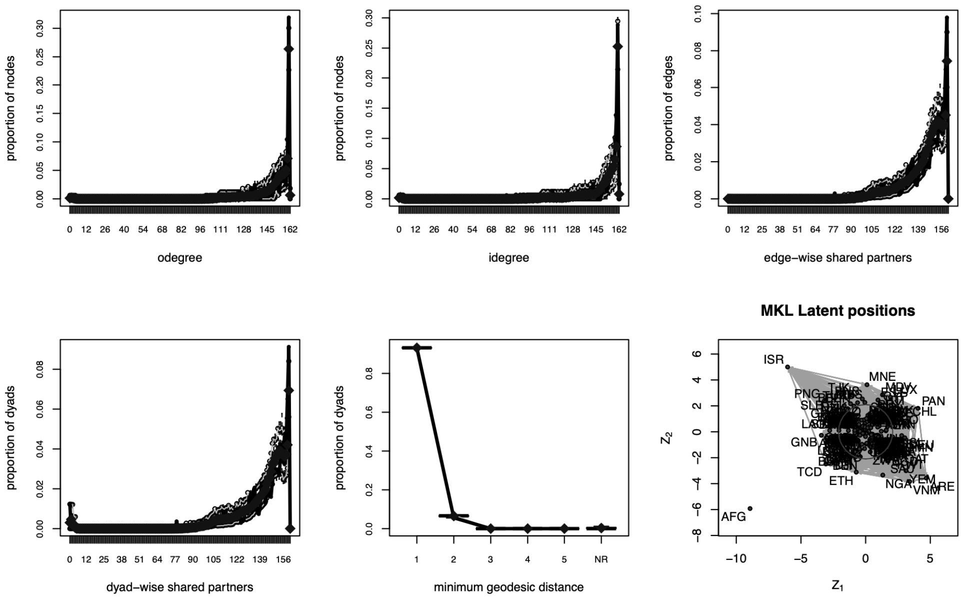
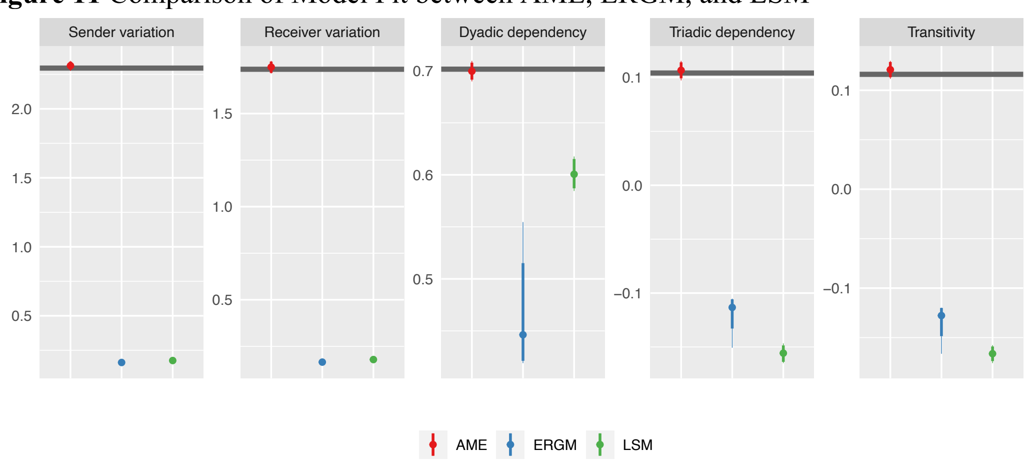


Figure 10 LSM – Goodness of Fit Assessment



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 a better fit between ERGM and LSM by just looking at the graphs in Figure 9 and Figure 10. Therefore, we further use simulation to test a models' ability to reproduce the five network measures previously discussed in Figure 7, such as standard deviation of row means and column means. Figure 11 adds AME and compares how well the simulated networks generated from the models align with the observed values in the data.

Figure 11 Comparison of Model Fit between AME, ERGM, and LSM



The gray horizontal bar in Figure 11 represents values from the observed network. Red, blue, and green dots represent average values in the simulated networks 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 putting ERGM and LSM on these five network parameters, we see that despite ERGM and LSM show relatively good model fit from the previous group of model fit comparison, ERGM and LSM still suffer from 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.

In sum, the model fit comparison between Gravity model (MRQAP), ERGM, LSM, and AME reveals that the gravity model (using 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 accurate statistical inferences.

6. 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 both the hardware and the software of logistics, i.e., logistics infrastructure and logistics competence, are 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 flows. 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 5.3); 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 changed 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 international trade 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 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 separating 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 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. 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 when studying complex relational data.

For policy makers, our research yields the following managerial contributions. First, for an individual country, a 1% improvement in logistics infrastructure increases exports by 10.48 % and imports by 10.31% while a 1% improvement in logistics competence also increases exports by 5.64%. This informs country policymakers that continuous investment to improve logistics infrastructure and competence will help boost both exports and imports. Second, developing countries and developed countries benefit differently from improving these two logistics dimensions. The same 1% improvement in the quality of logistics infrastructure and logistics competence enables developing countries to enjoy 3.9% and 3.6% more exports respectively, although there is no differentiating effect 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 logistics infrastructure and competence 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 service quality. 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 0.90% less and importing 0.93% 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.

7. 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 logistics infrastructure measured by the World Bank. The different modes of logistics infrastructure, such as rail and road, 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 roads, airports, waterways, and 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 infrastructure and global trade. This modal approach might uncover unique patterns or phenomena for different modes and contribute to a more comprehensive understanding of the role logistics infrastructure plays in shaping global trade.

Next, our research aims to answer the overarching question of how logistics infrastructure and logistics competence 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 import/export 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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