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GEBZE TECHNICAL UNIVERSITY
INSTITUTE OF SOCIAL SCIENCES

**A SPATIAL APPROACH TO TRADE AND ECONOMIC
GROWTH**

Hasan KARABOĞA
DOCTORAL DISSERTATION
DEPARTMENT OF ECONOMICS

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Prof. Dr. Halit YANIKKAYA

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2022



DOKTORA JÜRİ ONAY FORMU

GTÜ Sosyal Bilimler Enstitüsü Yönetim Kurulu'nun 18/05/2022 tarih ve 2022/18 sayılı kararıyla oluşturulan jüri tarafından 31/05/2022 tarihinde tez savunma sınavı yapılan Hasan Karaboğa'nın tez çalışması İktisat Anabilim Dalında DOKTORA tezi olarak kabul edilmiştir.

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ÖZET

Bölgelerin ve ülkelerin coğrafi özellikleri ve ticari etkileşimleri iktisadi büyümeleriyle ilişkili midir? Uluslararası ticaret literatüründe, coğrafyanın ticaret üzerindeki etkilerini araştırmak için çekim modeli sıklıkla kullanılmaktadır. Ayrıca ağ modelleri, ticaret akışlarını görselleştirmek ve bu ilişkilerin sonuçlarını yorumlamak için kullanışlıdır. Mekansal ekonometrideki gelişmeler de çeşitli iktisadi birimlerin bağlantılarını daha iyi anlamamıza katkıda bulunmaktadır. Bu tezde farklı yöntemler kullanarak coğrafya, ticaret ve iktisadi büyüme arasındaki bağı araştırmayı amaçlamaktayız.

İkinci bölüm, ikili ticaretin coğrafi belirleyicilerini açıklamak için ANFIS'i temel çekim modeli ile uluslararası ticarete uyarlamaktadır. Bu bölümde ANFIS'i geleneksel OLS ile karşılaştırıyoruz ve kabaca benzer sonuçlar verseler de ANFIS tahminlerinin OLS'e göre çok daha iyi olduğunu buluyoruz. Ayrıca ANFIS'te iki girdi ve bir çıktı değişkeni arasındaki ilişkiyi üç boyutlu şekiller yardımıyla gösterebilmemiz bize daha kapsamlı yorum yapma imkânı sağlamaktadır.

Üçüncü bölüm, uluslararası ticaretin ağ dinamiğini keşfetmekte ve küresel değer zincirleri ile ilişkilendirmektedir. Bu bölümde ülkelerin katma değerli ticaret paylarının ticaret ağındaki konumları ile yakından ilişkili olduğunu buluyoruz. Küresel değer zincirlerine ileri ve geri yönlü katılımların arka planını derece, kümelenme katsayısı, merkez ve otorite gibi ağ endeksleriyle ilişkilendirerek keşfetmenin, ticaret akışlarının doğasını anlamak için önemli bir çaba olacağına inanıyoruz.

Dördüncü bölüm, mekânsal ekonometri tekniklerinden yararlanarak komşuluk ve ticaret bağlantılarının iktisadi büyüme üzerindeki etkisini analiz etmek için ülke içi ticaret verisi kullanmaktadır. Bu bölümde, ülkemizde iller arasındaki mekânsal bağılılığı bulmak için, aralarındaki mesafe, komşuluk ve ticaret etkileşimlerine ilişkin mekânsal ağırlık matrisleri oluşturuyoruz. Kullandığımız teknikler ve ağırlık matrislerinden bağımsız olarak, illerin iktisadi büyümesinin birbirleriyle mekânsal olarak bağlı olduğu sonucuna varıyoruz.

Anahtar Kelimeler: Uluslararası Ticaret, İktisadi Büyüme, Yerçekimi Modeli, Ağlar, Küresel Değer Zincirleri, Mekansal Ekonometri

SUMMARY

Do geographical characteristics and trade interactions of regions and countries are related with their economic growth? In the international trade literature, gravity framework is frequently employed to discover the impacts of geography on bilateral trade. Moreover, network models are more practical to present the trade interactions and interpret the consequences of these relationships. Advances in spatial econometrics also enable us to better understand the connections of various economic units. In this dissertation, using different methods, we aim to explore the nexus between geography, trade, and economic growth.

The second chapter adopts ANFIS to international trade with the basic gravity model to explain the geographical determinants of trade. In this chapter, we compare ANFIS with traditional OLS, and state that although they provide somewhat similar results, ANFIS estimates are much finer than the OLS estimates. Besides, in ANFIS analysis, we are able to evaluate the relation between one output and two inputs variables by the help of three-dimensional figures, which allows us to draw more broad conclusions.

The third chapter explores the dynamics of international trade network and relates the network structure of trade with global value chains. We find that value added trade shares of countries are closely related with their position in trade network in this chapter. We believe that exploring the background of forward and backward participations relating them with specific network indices such as degree centralities, clustering coefficient and hub and authority centralities is a significant effort to realize the nature of trade flows.

The fourth chapter employs domestic trade data to analyze the neighboring and trade partnership effects on economic growth by exploiting spatial econometric techniques. To find out spatial dependence between provinces in Turkey, we construct spatial weight matrices regarding the distance, contiguity, and trade interactions in this chapter. Regardless of techniques and weight matrices we employ, we safely conclude that the economic growth of the provinces is spatially dependent to each other.

Keywords: International Trade, Economic Growth, The Gravity Model, Networks, Global Value Chains, Spatial Econometrics

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Finally, I would like to dedicate this dissertation to my daughter.

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LIST OF ABBREVIATIONS

<u>Abbreviation</u>	<u>Explanation</u>
ANFIS	: Adaptive Network Based Fuzzy Inference System
ANN	: Artificial Neural Network
ARIMA	: Autoregressive Integrated Moving Average
CEPII	: Centre d'Etudes Prospectives et d'Informations Internationales
CES	: Constant Elasticity of Substitution
EIS	: Enterprise Information System
EU	: European Union
FIS	: Fuzzy Inference System
GADM	: Database of Global Administrative Areas
GATT	: General Agreement on Tariffs and Trade
GNP	: Gross National Product
GDP	: Gross Domestic Product
GIS	: Geographical Information Systems
GNP	: Gross National Product
GVCs	: Global Value Chains
HEFST	: Hybrid Ellipsoidal Fuzzy Systems for Time Series Forecasting
HS	: Harmonized System
HITS	: Hyperlink-Induced Topic Search
H-O	: Heckscher-Ohlin
IRS	: Increasing Returns to Scale
ISE	: Istanbul Stock Exchange

<u>Abbreviation</u>	<u>Explanation</u>
ITN	: International Trade Network
MAE	: Mean Absolute Error
MNEs	: Multinational Enterprises
MRIO	: Multi-Region Input-Output Table
NEG	: New Economic Geography
OECD	: Organization for Economic Co-operation and Development
OLS	: Ordinary Least Squares
RMSE	: Root Mean Square Error
RSVMG	: Recurrent Support Vector Machines with Genetic Algorithms
SAC	: Spatial Autoregressive Combined
SAR	: Spatial Autoregressive
SDM	: Spatial Durbin Model
SEM	: Spatial Error Model
SVMG	: Support Vector Machines with Genetic Algorithms
UK	: United Kingdom
UN	: United Nations
UNCTAD	: United Nations Conference on Trade and Development
U.S.	: United States of America
WTN	: World Trade Network
WTO	: World Trade Organization
WTW	: World Trade Web

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1. INTRODUCTION

1.1 Trade, Geography, and Networks

The distribution of economic activities across space is an intriguing subject if we are studying the differences between countries, regions, and cities in terms of economic growth. Depending upon the transportation costs, the geographical location of any economic unit may affect its activities by means of accessing to markets. Besides, whether affected by geography or not, the network links of the economic agents have significant effects on their activities. Therefore, the interactions among economic agents are closely related with their geography, proximity, and their network.

In this dissertation, we deal with interactions related with both foreign and domestic trade. We explain the main subjects related with trade depending on the scope of the thesis in this section. First, we present the literature originated from the location theory. These are economic geography, spatial economics, and new economic geography. Second, we discover the studies on the gravity model of trade concerning especially with distance between trade partners. Third, we review the international trade network literature. Finally, we refer to the related literature that deal with these subjects together.

The theory of location in economics goes back to Thünen (1826), which associates the distance and area with economic activities. Isard (1949) states that the trade theory, general theory of location and space-economy can be explained together, and their meanings are similar. Tobler (1970) points out the first law of geography, “Everything is related to everything else, but near things are more related than distant things.” These kinds of efforts can be evaluated in the scope of location theory or regional science; however, they are also milestones on the road to spatial economics. Krugman (1991) builds the spatial structure of economy on core and periphery concepts, known as the new economic geography. After 1990s, thanks to developments in computer systems, spatial econometric techniques have been widely used with large datasets.

To explain the differences in trade caused by geographical distances between countries, the gravity equation in physics was firstly adapted by Tinbergen (1962) to international trade. This model has been widely used in the literature and developed in many perspectives. The idea is similar with location theory since both are associated with the location of the activities. Anderson (1979) and Bergstrand (1985) are seminal theoretical foundations of the model. An empirical work employing the gravity model, McCallum (1995) finds the negative effect of borders on trade, comparing domestic trade between Canadian provinces and exports of Canada and U.S. Frankel and Romer (1999) suggest geographical variables as the instruments and find that these geographical variables affect trade and in turn trade has the positive effect on income. Another interesting work, Barjamovic et al. (2019), estimates a structural gravity model to locate lost ancient cities of the Bronze Age, by employing large commercial data of Assyrian merchants in the nineteenth century B.C.

Apart from location, we can claim that trade interactions are affected by the links with partners. An increasing number of studies treats international trade as a complex system and employs network techniques to discover the topological properties of the trade network. Hilgerdt (1943) is the first effort defining the world trade as a network. Some works deal with topological properties; that is, they calculate various network metrics for countries, and represent them as graphics to interpret the analysis. Fagiolo et al. (2008) and Barigozzi et al. (2010) are examples of this kind of works. However, efforts such as De Benedictis and Tajoli (2011) and Duenas and Fagiolo (2013) examine trade networks by utilizing applied econometric methods.

Finally, there is a large literature, which deals with the main subjects of this thesis, gravity model, networks, and spatial economics, together. For instance, Almog et al. (2019) employ a maximum-entropy framework and combine gravity equation with a network approach. Rossi-Hansberg (2005) proposes a spatial theory of trade and finds consistent results with gravity model for the regions in the European Union and states in the United States. Barthelemy (2011) explains that considering the network topology with spatial structure provides us a better understanding for networks.

1.2 The Motivation

Countries and regions differ from each other in many aspects. The disparities across countries and within the countries have been frequently discussed in the literature. In the traditional theories of international trade, it has been argued that comparative advantages of countries determine both the level and direction of trade with each other. In these theories, the geographical features of the countries have been generally neglected. However, after 1990s, instead of the traditional Heckscher-Ohlin model, Krugman's new economic geography model becomes widespread.

The starting point of my dissertation is to explore the differences in trade patterns for countries and regions and their interaction in terms of economic growth. Our first research question is how the trade among economic agents is affected by geographical location of these units. This question is also related with the literature on location theory, new economic geography, and spatial economics. With a spatial approach, we can explain the differences among economic units concerning their dependence to each other in terms of location.

However, before dealing with the spatial structure of trade, we decide to investigate the geographical determinants of trade by employing a typical gravity equation. The gravity framework is useful for determining the effects of geography on trade. The main drivers of this equation are geographical distance and total GDP, and it is developed further by including other geographical characteristics. We aim to contribute to gravity and trade literature by developing a new point of view. We thus employ an artificial neural network model, ANFIS, in addition to the simple OLS.

The gravity model successfully explains trade flows, but we also aim to find out the interaction and link formation of the countries and regions. This idea brings us to the international trade network literature. Trade networks are complex systems and explain the interaction of trade partners in terms of their links. The network theory usually deals with the connections irrelevant of geography. Finally, we go back to the starting point of the thesis and try to clarify the relationship between trade and economic growth with a spatial approach.

To conclude, the main motivation of my dissertation is to answer the following research questions related with trade:

- What are the geographical determinants of trade flows, and how can gravity model be improved to clarify these factors with the help of artificial neural network models?
- How the dynamics of international trade network changes, and what are the implications of participation in global value chains to international trade network?
- Are the cities spatially dependent, and does the domestic trade affect the economic growth of the cities?

To answer these questions, we present our models with empirical applications in the second, third and fourth chapters.

1.3 The Scope and Contribution

In this thesis, we start with the gravity model in the second chapter, by outlining its applications in the international trade literature. As an empirical exercise, we estimate the gravity model of trade with the traditional OLS method and the Adaptive Network Based Fuzzy Inference System (ANFIS). Implementing ANFIS to international trade also provides us to interpret the nonlinear relationships among the variables by the help of three-dimensional figures.

Although the gravity model is quite successful in understanding of international trade flows concerning geographical distances, there are also many shortcomings of these models. Recently, the models based on the graph theory have been used in the international trade literature to mitigate these drawbacks. According to these network models, which are defined as “International Trade Network” (ITN), “World Trade Network” (WTN) or “World Trade Web” (WTW), countries are treated as nodes and trade between them is shown as links and network indices are calculated. These models then attempt to explain international trade flows. The network models of trade try to explain international trade as a complex system, and they can evaluate the network’s weighted structural properties as well as the binary topology of the network.

In the third chapter, our aim is to discover the dynamics of the international trade network. We first adapt the basic gravity model to determine whether the network position of the countries affects bilateral trade. Apart from all countries, we also repeat the analysis for the trade interaction between and within developed and developing countries. To avoid the potential endogeneity problems, we then improve our methodology by treating several network indices as the dependent variables and incorporate Global Value Chains (GVCs) to our model. We find that value added trade shares of the countries are closely associated with their positions in the ITN.

Another aim of this dissertation is to analyze the relationship between trade and economic growth by taking the location into consideration. Using location and space concepts in economics is not new, but as the Geographical Information Systems (GIS) and computers become powerful, spatial economics has gained more importance. There are several spatial models employed in the literature such as Spatial Durbin Model (SDM), Spatial Autoregressive Combined (SAC), Spatial Error Model (SEM), and Spatial Autoregressive Model (SAR). By taking advantage of these models, we can investigate how the locations depend on each other in various ways. We evaluate spatial dependence of provinces in terms of trade and economic growth in this thesis.

In the fourth chapter of this thesis, we utilize province-level within country trade data, which differs from the previous two chapters dealing with international trade; and employ spatial econometric methods to estimate whether the geography and trade interactions of provinces affect their economic growth. We consider that a spatial approach enables us to understand the reasons behind the disparities among provinces in terms of trade and economic growth more definitely. Our estimation results from various spatial models imply that both distance, contiguity and trade interactions have significantly positive impact on economic growth of the provinces.

2. THE GRAVITY MODEL OF TRADE

2.1 Introduction

The well-known theory of gravitation in physics is concerned with the interactions of the objects. Fundamentally, the international trade literature pays attention to the interaction of countries in terms of trade. With the understanding that countries' geographical characteristics and the distance between countries determine the volume of bilateral trade, the gravity model has been adapted to the international trade literature. According to the Newton's equation, gravity is calculated proportional with the masses of two objects and inversely proportional with the distance between them. The basic form of the gravity equation is basically as follows:

$$F = \frac{G(m_1 \times m_2)}{R^2}$$

In this gravity equation of Newton, F is the magnitude of the attractive force between two masses, m_1 and m_2 . G is gravitational constant, and R is the distance between these masses. Tinbergen (1962) is the first effort, which employs the gravity model in trade by considering the geographical characteristics of the countries. In his book, he defines the main factors affecting trade flows between countries, and formulates it as follows to estimate by the least squares analysis¹:

$$\log E_{ij} = \alpha_1 \log Y_i + \alpha_2 \log Y_j + \alpha_3 \log D_{ij} + \log \alpha_0$$

In this equation, i and j are origin and destination countries involving in international trade. E_{ij} denotes the export volume from country i to country j , Y_i and Y_j are Gross National Products (GNP) of each country respectively, and D_{ij} is the distance between these countries. The intuition behind this formulation is the dependence of the amount of export (E_{ij}) of the origin country to its economic size (GNP_i), the relation of this amount with destination country's economic size (GNP_j). Since the volume of trade is affected from the transportation costs, the geographic distance between the countries is assumed to be the indicator of these costs.

¹ The equation appears in Appendix VI of the book "Shaping the World Economy".

Since the work of Tinbergen, the gravity model has been developed in many different perspectives in the trade literature to explain the effects of borders, trade blocs, membership of unions like the OECD, EU, and WTO etc. on trade flows. A seminal theoretical study, Anderson (1979) proposes a theoretical foundation of the gravity model by defining the constant elasticity of substitution (CES) expenditure function. Another early example dealing with microeconomic foundation in a general equilibrium framework is Bergstrand (1985), which incorporates price into the gravity model.

There is some other major theoretical general equilibrium literature for the gravity model originating from the well-known international trade theories. First example, based on increasing returns to scale (IRS) models, Helpman and Krugman (1985) develop under the monopolistic competition framework. Besides, Deardorff (1998) develops the equation with the Heckscher-Ohlin (H-O) model. Evenett and Keller (2002) discuss the theories based on IRS and H-O type gravity model. Other studies like Eaton and Kortum (2002) propose heterogeneous models with the Ricardian framework, and Bernard et al. (2003) present a similar model with imperfect competition. Chaney (2008) proposes a gravity model with firm heterogeneity in productivity and makes a distinction between intensive and extensive margin of trade.²

There was a strong idea that distance and the borders between the countries have lost their importance as transportation costs fall. However, the empirical studies based on the gravity model since Tinbergen proved that the distance is still a significant driver for trade. McCallum (1995), employing the gravity model by using the U.S. and Canadian trade data, finds that shared border also has substantial impact on trade. According to this work, intra trade between Canadian provinces is more than 20 times larger than the trade between a Canadian province and U.S. state. Anderson and van Wincoop (2003) present a theoretical framework for the border puzzle of McCallum (1995).

Frankel and Romer (1999) is a seminal paper suggesting several geographical variables as alternative instruments for trade. Basically, they use the gravity model of trade, and argue that the bilateral trade between two countries is related with the distance between them. They use distance, population, area, dummy for landlocked countries and dummy for common border countries data to estimate bilateral trade over

² See Head and Mayer (2014) for the comprehensive theoretical background of gravity models in trade.

GDP of the countries. They find geographical characteristics of the countries affects their trade and trade has important positive effect on their income.

Other empirical studies concerning with geographical variables and international trade also find some interesting results. Dollar and Kraay (2003) claim that growth in the long run, high amounts of trade flow and good institutions are related with each other. However, they state that since the trade and better institutions might be the outcomes of geographical and historical factors, relative importance of them cannot be exactly known. Redding and Venables (2004) argue that income inequalities between the countries result from geographical access to markets and sources of supply. When they control the determinants of per capita income, economic geographical determinants are still highly significant.

Using a constant returns-to-scale function, Rossi-Hansberg (2005) shows how the distribution of economic activity is affected by trade barriers, transportation costs, and technology. Helpman et al. (2008) develop an international trade model with heterogeneous firms, which provides estimates of intensive and extensive margins of trade. Head and Mayer (2011) use world trade data between the years 1965 and 2003; and they find market potential effects the economic development in the long term. Silva and Tenreyro (2006), Wang et al. (2010), Gomez-Herrera (2013), Eaton et al. (2016), and Barjamovic et al. (2019) are for other empirical applications of gravity model in trade.

In this chapter, we contribute to the empirical gravity model literature by employing Adaptive Network Based Fuzzy Inference System (ANFIS) approach to estimate the geographical determinants of bilateral trade. ANFIS is frequently applied in economics and especially in finance, however less effort made in international trade. We argue that this non-linear estimation method will provide us to make more definite interpretations of the determinants of bilateral trade. In the next section, we express the literature on ANFIS. Section 2.3 explains the data used in this work and describes the methodology of this work. Section 2.4 presents the results and makes the comparison of the results of different methods. Finally, Section 2.5 concludes the chapter.

2.2 Literature Review

ANFIS is first developed by Jang (1993), and by the help of the learning procedure with fuzzy if-then rules, this structure is used to model nonlinear functions. Table 2.1 summarizes the Fuzzy Inference System (FIS), which ANFIS is based on. In a basic fuzzy inference system, fuzzy if-then rule base and the database of membership functions compose the knowledge base, and the operations are performed in a decision-making unit. In this framework, input variables are transformed to outputs by fuzzification and defuzzification interface of FIS. ANFIS architecture integrates the fuzzy inference system with artificial neural network.

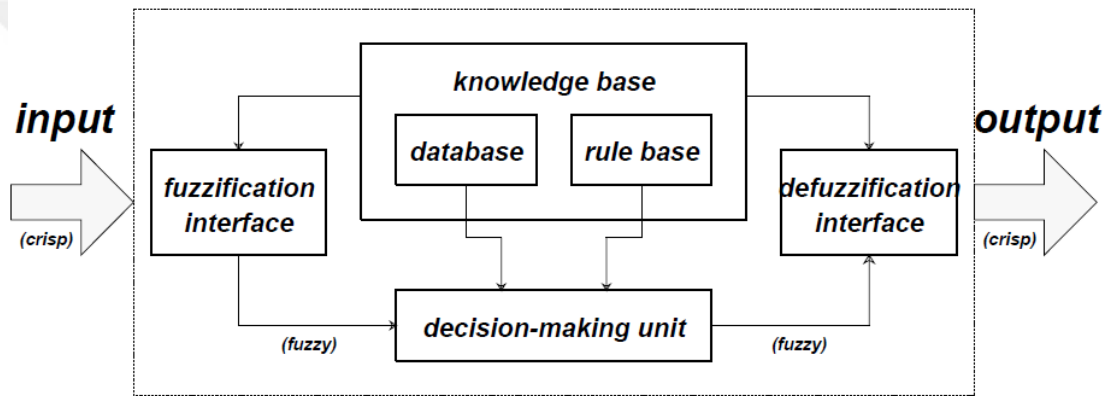


Figure 2.1: Fuzzy Inference System

Source: Jang (1993)

There are several published papers in economics and finance related areas like stock market prediction, trade and economic growth utilizing the ANFIS architecture. For example, Boyacioglu and Avci (2010) employ the ANFIS algorithm for predicting stock market returns. They get monthly data on macroeconomic indicators from January 1990 and December 2008 and divide the dataset into test and training parts. Their ANFIS model predicts monthly return of Istanbul Stock Exchange (ISE) with an accuracy of 98.3%. They argue that this method is practical for economists since it properly forecasts returns.

Sokolov-Mladenovic et al. (2017), use a basic ANFIS methodology to investigate the impact of trade on economic growth. They employ five trade parameters as inputs in ANFIS: trade in services, exports of goods and services, imports of goods and services, trade, merchandise trade. They find that imports of

goods and services has the highest impact on GDP growth rate. Recently, Dokic and Jovic (2017) take output value of industry and agriculture sectors as inputs and GDP growth rates as output for 28 countries in the European Union. By employing ANFIS approach, they find that compared to an industry sector, an agriculture sector has a considerable impact on GDP growth.

Another strand of the literature compares ANFIS with other widely used techniques such as Artificial Neural Network (ANN), Ordinary Least Squares (OLS), and Autoregressive Integrated Moving Average (ARIMA) in different range of areas from exchange rate forecasting discussed in Fahimifard et al. (2009) to demand in football games studied in the work of Şahin and Erol (2018). In these studies, they evaluate the performance of the methods by comparing their statistical values such as Pearson coefficient (r), coefficient of determination (R-Squared), root mean square error (RMSE), and mean absolute error (MAE) values.

Yazdani-Chamzini et al. (2012) employ ANFIS, ANN, and as well as ARIMA to predict the gold price changes, using data from April 1990 and July 2008. They take MAE, R-Squared, and RMSE as performance criteria, and find that ANFIS surpasses the other two methods in forecasting gold prices. Ying and Pan (2008) apply simple regression, ANFIS, ANN, support vector machines with genetic algorithms (SVMG), recurrent support vector machines with genetic algorithms (RSVMG), and hybrid ellipsoidal fuzzy systems for time series forecasting (HEFST) models to forecast the regional electricity loads in Taiwan. They claim that ANFIS is more promising than the other models by looking at the mean absolute percentage errors and statistical results for each method.

ANFIS is commonly employed in the economics and finance literature as shown above. Following these studies, we argue that our understanding about the impacts of geographical features of countries on bilateral trade can well be enhanced by the help of the ANFIS structure. Our work is thus the first effort to analyze the geographical determinants of bilateral trade using ANFIS and compare these estimations with the OLS results. This chapter utilizes a bilateral trade model based on the gravity equation used by Frankel and Romer (1999) and compares the estimation results from the both techniques by comparing R-Squared, RMSE, and MAE statistics.

Combining BACI and gravity datasets of CEPII, we construct a 104-country dataset for the years between 1995 and 2015 in this chapter. In our gravity model, the dependent variable is natural logarithm of export to GDP ratio, and we have

geographical variables as independent variables. We first employ the OLS regressions and then we estimate the same model with ANFIS structure. Our results for two types of analysis are roughly similar and mostly in line with the literature. However, by looking R-Squared, RMSE and MAE values, we conclude that ANFIS performs much better than traditional OLS technique. Besides, the three-dimensional nonlinear figures provided by ANFIS offers us a flexibility when we interpret the relationships between our variables.

2.3 Data

Our dataset is the combination of trade and gravity datasets taken from the CEPII³. Trade dataset of CEPII is called BACI (Gaulier and Zignago, 2010) and based on Comtrade data of the United Nations (UN) Statistical Division. BACI dataset associates the bilateral trade reports of both exporter and importer countries, which results in large coverage of data although there are some countries not reporting in same level of the product classification. This dataset provides export values of more than 200 countries at the Harmonized System (HS) of 6-digit product disaggregation, covering the years since 1995. CEPII gravity dataset that we used apart from trade dataset contains country specific properties (Head et al., 2010; Head and Mayer, 2014). It covers data on contiguity, distance, population, area, GDP, GATT/WTO memberships for 224 countries between the years 1948 and 2015.

Table 2.1: CEPII BACI Dataset Coverage

Harmonized System Version	Covered Years
HS92	1995-2019
HS96	1996-2019
HS02	2002-2019
HS07	2007-2019
HS12	2012-2019
HS17	2017-2019

Source: (Web 1, 2021)

³ CEPII, located at France, is a research center specialized on the world economy (<http://www.cepii.fr/CEPII/en/welcome.asp>).

Before explaining the combined dataset and the methodology we employed in our analysis, we provide some descriptive information about world trade based on CEPI BACI dataset. In Table 2.1, we demonstrate the six versions of CEPII BACI dataset available, which are based on the HS classifications. From HS92 to HS17 revisions, we observe improvements in terms of product codes. For the years 1995-2019, Figure 2.2 illustrates the numbers of the products in HS classification, and revisions differ in terms of numbers. Except from the newest revisions (HS12 and HS17), the number of the products tends to decrease over time.

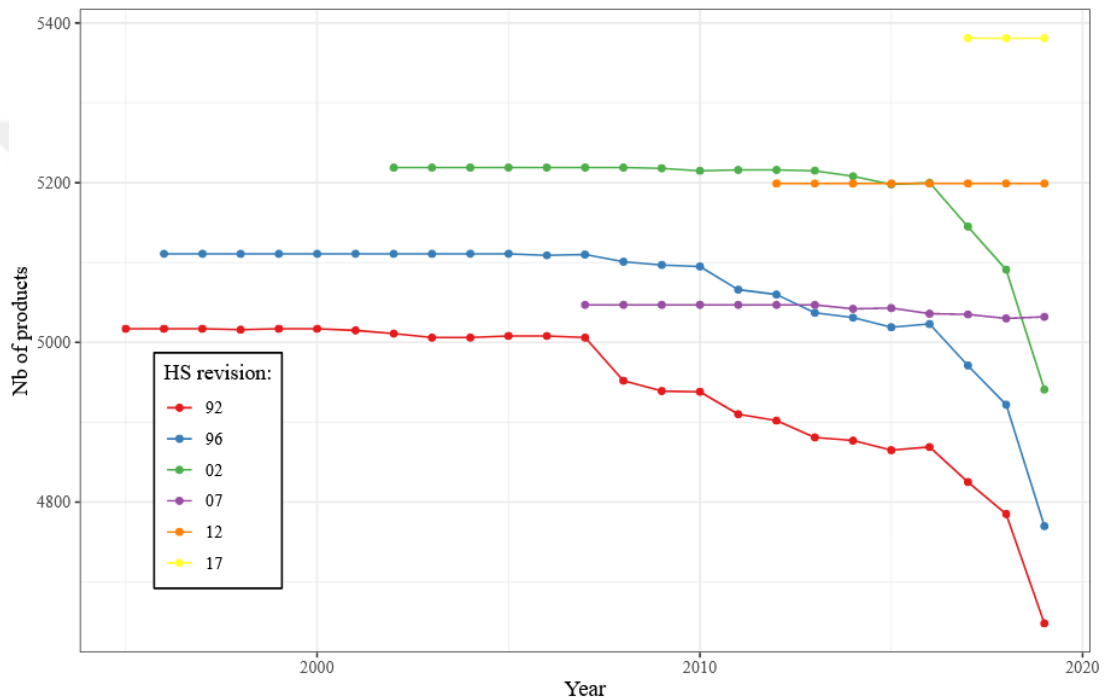


Figure 2.2: The number of products across HS revisions

Source: (Web 1, 2021)

According to Figure 2.3, total trade volumes (in thousand current dollars) between the years 1995 and 2019 for the different HS revisions are similar. Since the first version covers more years, we work with the dataset using HS92 version. For all HS versions, BACI dataset contains only positive trade flows. CEPII does not include zero and missing trade flows in this dataset due to the limit of the volume of the data.

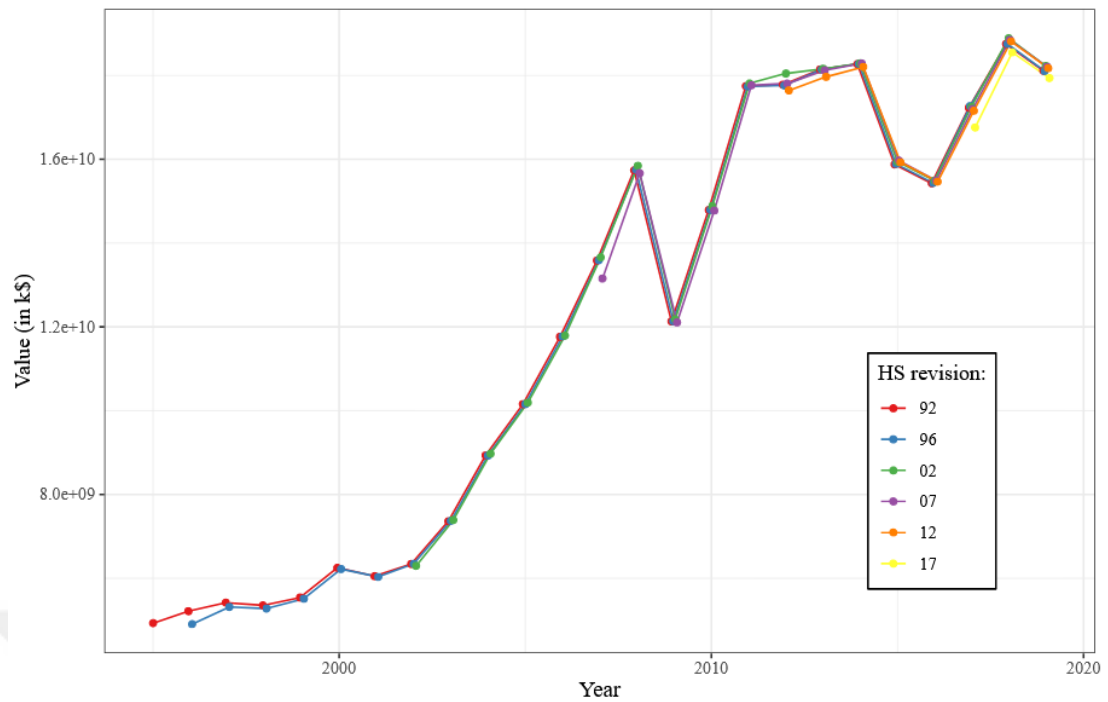


Figure 2.3: Total Trade Values across HS revisions

Source: (Web 1, 2021)



Figure 2.4: Top 5 Exported Products

Source: Author's calculations.

In Figure 2.4, we express five the most exported products for year 2019 with trillion current US dollars, according to the HS2 classification. Electrical machinery

and equipment, mineral fuels, nuclear reactors, vehicles other than railway or tramway, and natural or cultured pearls are exported the most in year 2019, respectively. We then demonstrate exports of these products with 5-year period between 1995 and 2015. Besides, in the Appendix A, the detailed HS2 descriptions for the top 20 exported products and the volumes in current trillion dollars can be found.

We also display the top five exporter countries of year 2019 in trillion current US dollars, and their historical order within 5-year periods in Figure 2.5. China is the top exporter country for the year 2019, and the U.S., Germany, Japan, and France follow it. Chinese export volume was the lowest among these countries in 1995 though. We observe the rapid rise of China in terms of exports from the figure. We also include the top 20 exporter countries' volumes in the Appendix B.



Figure 2.5: Top 5 Exporter Countries

Source: Author's calculations.

2.4 Methodology

As we discussed in the previous section, we employ a combination of two datasets (BACI and gravity) from the CEPII. The BACI dataset covers the years 1995-2019, the gravity dataset lasts in year 2015 though. Thus, we limit our combined dataset between the years 1995 and 2015. Our data sample contains 104 countries. We end up with these 104 countries by merging 62-country-dataset of Frankel and Romer

(1999), and 98-country-dataset of Mankiw et al. (1992). Our dataset contains over 200K observations on bilateral trade and geographical characteristics of countries. Based on the gravity model of trade and following the work of Frankel and Romer (1999), our bilateral trade equation is as follows:

$$\ln\left(\frac{T_{ijt}}{GDP_{it}}\right) = a_0 + a_1 \ln D_{ij} + a_2 \ln N_{it} + a_3 \ln N_{jt} + a_4 \ln A_i + a_5 \ln A_j + a_6 C_{ij} + a_7 L_{ij} + e_{ijt}$$

where “i” is the origin (exporting) country, “j” is the destination (importer) country, and “t” denotes the year. In our model, T_{ijt} denotes total bilateral trade between the countries i and j, and GDP_{it} denotes the gross domestic product of origin country for the specific “t” year. Hereby, the left-hand side of the equation is natural logarithm of bilateral trade over GDP of the exporter country.

At the right-hand side, D_{ij} is the distance between countries having bilateral trade. N_{it} and N_{jt} are populations for the year “t”, and A_i and A_j are the area values of the origin and destination countries, respectively. C_{ij} denotes the contiguity, which takes a value of “1” if the two countries share a common border, and “0” if they do not. The last variable in our analysis L_{ij} , landlocked, is the sum of bilateral landlocked status of the countries. If a country has not a coast, we define it as a landlocked country and valued as “1”, and if it has a coast, it is valued as “0”. We use the landlocked variable as sum of landlocked value of the two countries dealing with trade. Thus, this variable takes values “0”, “1” or “2”. Table 2.2 reports the descriptive statistics of all variables used in the chapter.

Table 2.2: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Trade/GDP	200450	0.65	2.58	1.36	4.88
ln (origin population)	200450	2.92	1.38	-1.32	7.22
ln (destination population)	200450	2.92	1.38	-1.32	7.22
ln (origin area)	200450	12.52	1.84	6.47	16.12
ln (destination area)	200450	12.52	1.84	6.47	16.12
ln (distance)	200450	8.75	0.75	4.74	9.89
Landlocked	200450	0.33	0.52	0	2
Contiguity	200450	0.33	0.17	0	1

This study employs pooled data including all bilateral trade flows for all years in the analysis. Zero trade flows and unrecognized trade data are not incorporated. We divide the dataset into three parts randomly, which is required for the ANFIS procedure: training, test, and validation, with percentages of 60, 20, and 20 respectively. We conduct this separation by using the MATLAB's “*dividerand*” function, which divides the dataset using random indices. While the training part now contains 120,270 observations, the test and validation parts have 40,090 observations each. When estimating our model using the OLS method, we employ both the training and validation parts of our dataset. We then utilize the estimated coefficients obtained from these estimations to get the fitted values of the countries included in the test part, which makes a coherent comparison between the OLS and ANFIS estimations.

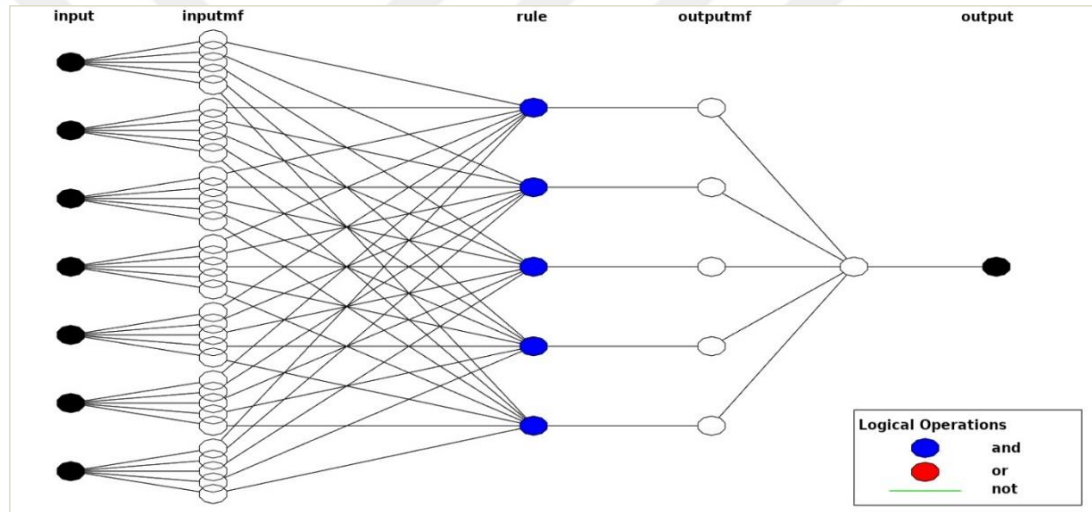


Figure 2.6: ANFIS Structure

In a typical ANFIS structure, there are five layers starting with involvement of inputs in the fuzzy framework by membership functions and ending with the calculation of overall output. Figure 2.6 illustrates the structure of ANFIS analysis in this chapter. We have seven input variables, five membership functions and one output. We apply a subtractive clustering algorithm, which predicts the number of the clusters in the input data. The squash factor is used in ANFIS structure to scale the range of influence of cluster centers and is 1.25 by default.

2.5 Empirical Results

At the first phase, like the ANFIS analysis, we perform the OLS analysis for the pooled dataset of both training and validation parts for the 1995-2015 period, which has 160360 observations. The OLS estimations in Table 2.3 indicate that both higher origin and destination populations have positive effects on bilateral trade. Both origin and destination areas have significantly negative effects. In line with the literature, distance between countries and landlocked status of origin country negatively and the contiguity of the countries positively affect the bilateral trade between the countries. Our results are extremely similar with the results of Frankel and Romer (1999)⁴.

Table 2.3: OLS Regression Results

ln (Trade/GDP)	Coef.	St. Err.	t-value
ln (origin population)	0.045***	0.006	7.52
ln (destination population)	1.091***	0.006	184.28
ln (origin area)	-0.133***	0.004	-30.13
ln (destination area)	-0.326***	0.004	-73.77
ln (distance)	-1.203***	0.009	-128.58
Landlocked	-1.305***	0.012	-105.45
Contiguity	1.182***	0.043	27.79
constant	9.967***	0.102	97.48
R-squared	0.314	Number of obs.	160360
RMSE	2.52	MAE	2.02

Note: ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$ respectively.

At the second phase, we aim to assess the geographical determinants of bilateral trade using the ANFIS analysis. We employ the exact same variables and years as in the OLS estimates. In other words, we utilize the pooled data for the years 1995 to 2015. ANFIS is expectedly successful to indicate the nonlinear relationships from which we can draw comprehensive conclusions. Since we are looking for a better way of expressing the geographical factors affecting bilateral trade, we consider implementing this method in addition to the OLS regressions. In order to compare OLS and ANFIS methods, we employ certain accuracy measures apart from R-squared in evaluating the performance of these analyses.

⁴ Note that Frankel and Romer (1999) employ data from the year 1985 and their dataset contains 3220 observations.

Hyndman and Koehler (2006) provide a critical survey about the accuracy measures, and they state that RMSE is more popular in statistical modelling. Because of its being sensitive to outliers, they recommend using MAE as an accuracy measure apart from RMSE. Like Yazdani-Chamzini et al. (2012), which uses R-Squared, RMSE, and MAE values in comparison of ANFIS, ANN, and ARIMA, we employ the same criteria to compare OLS and ANFIS estimations. Table 2.4 reports these statistics for both estimation techniques. By comparing R-Squared, RMSE, and MAE values, we can easily then evaluate which method performs better in our case.

Table 2.4: OLS and ANFIS Comparison

	OLS	ANFIS
R-Squared	0.314	0.406
RMSE	2.52	1.49
MAE	2.02	1.23
Number of observations	160360	

Since R-Squared in ANFIS is much higher, we can safely claim that ANFIS explains the geographical determinants of bilateral trade much better than the OLS estimates. We then compare RMSE and MAE values from both estimations. While ANFIS reports 1.49 as RMSE and 1.23 as MAE, OLS estimations obtain 2.52 and 2.03 as RMSE and MAE estimates, respectively. Smaller RMSE and MAE statistics suggest that inputs explain the output variable better in the model. Given the substantially smaller RMSE and MAE values, we can safely conclude that the ANFIS method once again performs much better than the linear regression analysis.

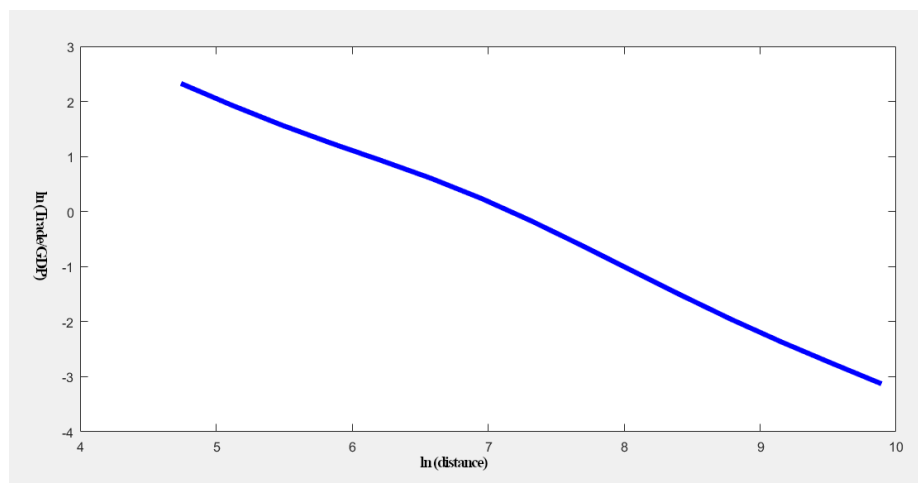


Figure 2.7: Bivariate Relationship of Distance with Bilateral Trade

Furthermore, we evaluate the geographical determinants of total bilateral trade of the origin country by the help of surface viewer of MATLAB. By selecting specific input variables, surface viewer indicates the relationship between them and the output in the ANFIS structure. From the Figure 2.7, we observe that the higher distance between countries lowers trade, which is in line with the literature. To raise the readability of our work, we demonstrate other figures of bivariate relationships in the Appendix C.

As can be seen from the Appendix C, higher origin population decreases bilateral trade unlike the OLS estimates, whereas destination population raises trade similar to the OLS estimates. As also illustrated in the other figures of Appendix C, while bilateral trade decreases by origin area, the estimated relationship between destination area and bilateral trade is different in ANFIS. We actually find that bilateral trade firstly decreases and then increases with the destination area. Being landlocked affects bilateral trade negatively in ANFIS like the results in the OLS regression. Note that the shape of the relationship in last part of Appendix C implies that the most damaging to the bilateral trade is the case in which both countries are landlocked. Finally, we understand that contiguity is positively related with bilateral trade, which is also in line with the OLS results.

In the ANFIS analysis, we can also view three-dimensional graphs, which makes the analysis more powerful when we need to analyze the relationship between any two inputs and the output simultaneously. For example, we can infer the effect of each variable on trade with the change in distance. From the Figure 2.8, when we consider distance and being landlocked together, we can understand which of these variables affects bilateral trade much and how. Based on the observed relationship from this figure, a change in natural logarithm of distance between the countries affects the ratio of trade and GDP much, whereas there is a little effect when the landlocked variable changes throughout the figure. Thus, we can conclude that the impact of the distance on bilateral trade is much more vital than the countries' landlocked status.

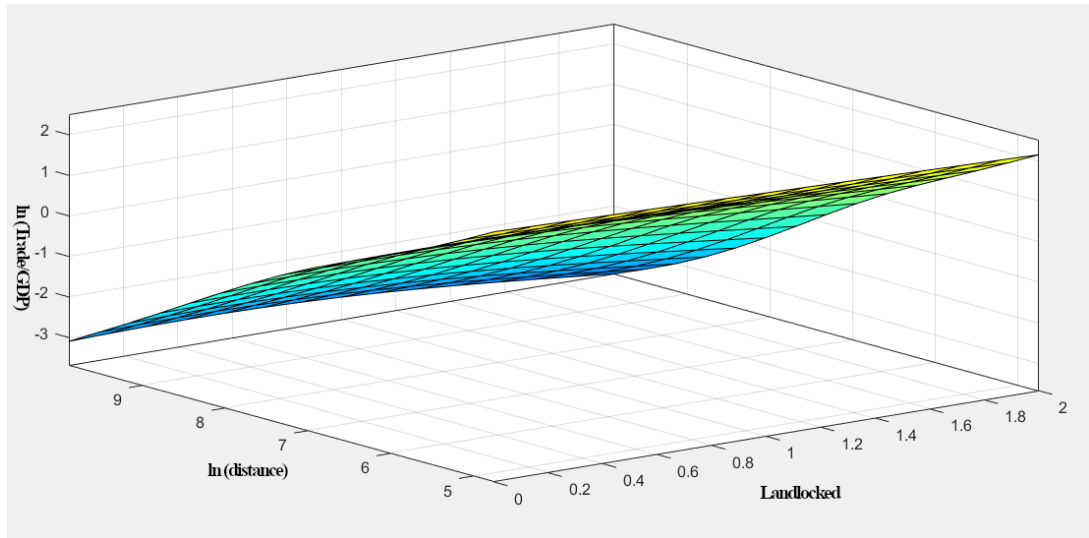
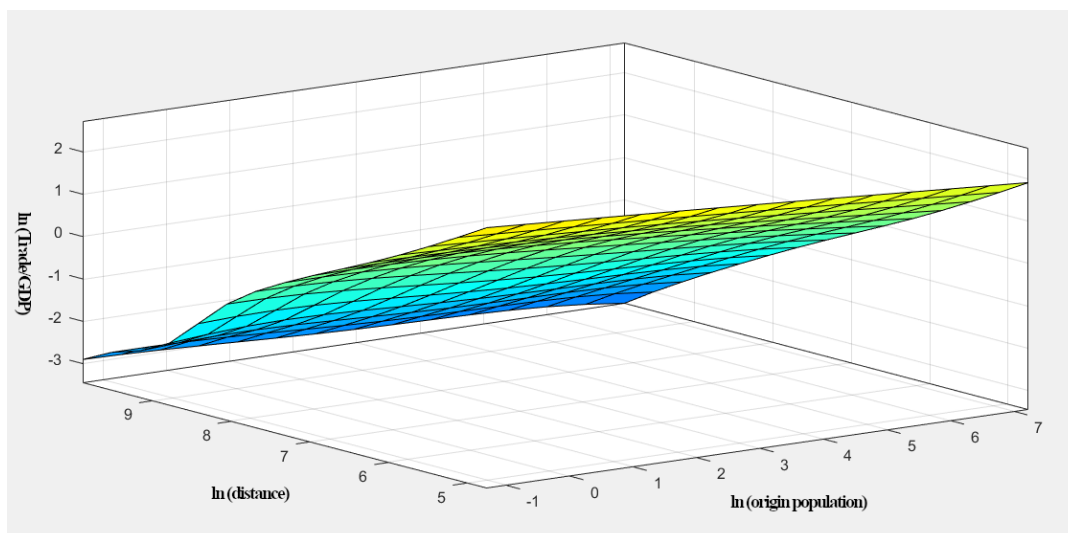


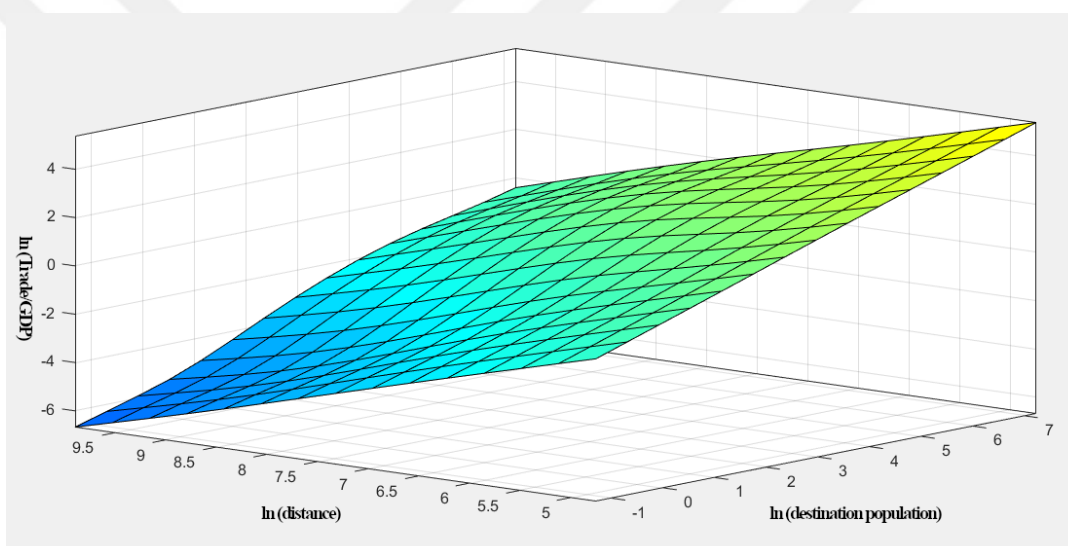
Figure 2.8: Distance vs. Landlocked with Bilateral Trade

From the previous bivariate relationships obtained from the ANFIS structure, we find that the effects of populations of origin and destination countries on trade vary.⁵ However, from the Figure 2.9, we can argue that origin population has limited effect on trade as opposed to destination population when we consider them with the distance. Because, from these figures, we deduct that the change in impact of destination population is much more than origin population for a given distance.

⁵ See Appendix C.

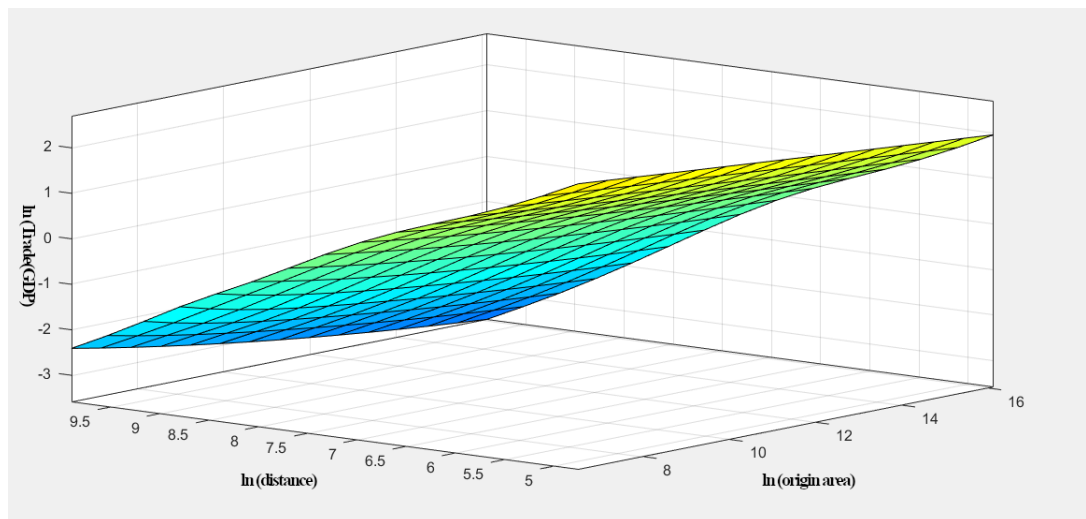


a) Distance vs origin population

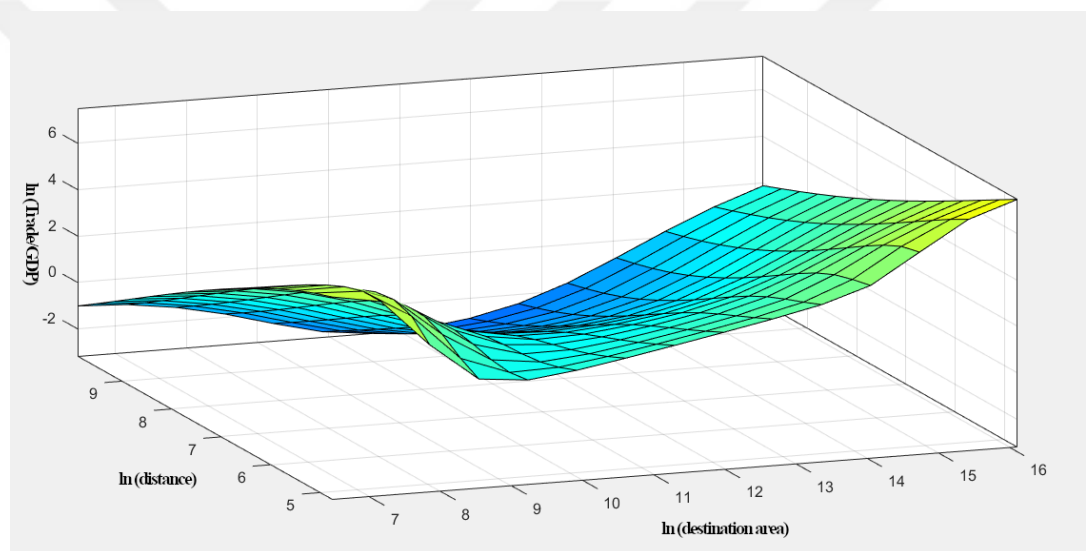


b) Distance vs. destination population

Figure 2.9: Distance vs. Population with Bilateral Trade



a) Distance vs. origin area



b) Distance vs. destination area

Figure 2.10: Distance vs. Area with Bilateral Trade

The area of the origin country has a negative, and that of the destination country has first negative and then positive impact on trade when we analyze them by ANFIS separately.⁶ When we consider each of them with the distance; the effects of origin and destination area of the countries with the change of distance on trade will be like the (a) and (b) part of the Figure 2.10. Whenever the origin country is small in terms of area, there occurs lower trade between the countries. Besides, in the (a) part, we can observe that the change in distance and area in the figure indicates a similar path, thus we can state that the impact of distance on trade is as strong as the effect of area of the origin country. We find that the effect of destination country's area on the trade firstly negative and then positive, according to the bivariate ANFIS analysis. By the help of the (b) part, we can conclude that destination country's area affects bilateral trade much more than the distance between origin and destination countries.

2.6 Conclusion

In this chapter, by employing a new approach, we aim to explain differences regarding bilateral trade between countries caused by the geographical characteristics. We start with the frequently used gravity equation in international trade, and its applications. The idea behind our argument is to improve the inferences from a fundamental gravity model with the help of fuzzy logic system. We decide to employ the ANFIS framework to express the geographical relationships of countries and bilateral trade between them.

We assess the time-invariant geographical determinants of bilateral trade by comparing the OLS regressions and ANFIS analysis. Our analysis combines both the trade and gravity datasets of CEPII and analyze the bilateral trade of 104 countries for the years between 1995 and 2015. We first split the dataset into training, test, and validation parts when performing both the OLS and ANFIS analysis. We report the estimated effects of population, area, distance, landlocked status, and contiguity of countries on their bilateral trade. Our results mainly show that both OLS and ANFIS provide very similar results.

According to the OLS regressions, we find that bilateral trade increases by population of origin and destination countries. However, both origin and distance area

⁶ See Appendix C.

have the significantly negative estimated coefficients. The distance negatively affects trade, as we expected. Also, the countries' being landlocked has negative and contiguity with the destination country positive impacts on trade. ANFIS results differ from the OLS results in some variables. The origin population has negative effect, destination area has first negative, but then positive effect regarding larger areas. We also interpret the results of ANFIS which we evaluate the effects of distance together with landlocked, population and area on trade.

To evaluate the performance of both techniques we used, we compare the R-Squared, RMSE, and MAE statistics from each analysis. They all consistently imply that we can estimate the determinants of bilateral trade with ANFIS approach much finer than the OLS estimation. Furthermore, since the ANFIS is substantially flexible in considering nonlinear relationships among the variables considered, we can easily draw much improved conclusions on relationships by the help of the figures. The ANFIS approach employed in this chapter may also improve the instrumental variable approach utilized in Frankel and Romer (1999).

3. INTERNATIONAL TRADE NETWORK AND GLOBAL VALUE CHAINS

3.1 Introduction

In the previous chapter, we introduce the gravity model of trade and provide an application to estimate the geographical determinants of international trade. The gravity model is widely used in the literature, and considerably successful in examining international trade flows concerning geographical distances. We observe that gravity-related trade literature concerns with the interaction of countries and regions. In this thesis, our aim is not only to understand geographical interaction but also to examine the interactions relevant to their links. Since we know that trade channels have an impact on the Gross Domestic Product (GDP) and the wealth of the countries, the trade links may be influential on the economic growth of countries.

Network models, which are based on the graph theory in mathematics, are exploited to discover interactions in various fields of science like physics, biology, computer, sociology, and economics. Recently, network models are also employed for trade interactions resulted by the links of the countries in the international trade literature. These models are named as “International Trade Network” (ITN), “World Trade Network” (WTN) or “World Trade Web” (WTW), and all of them are used in the same sense. According to these network models, countries or regions are defined as nodes, and trade between them is defined as edges or links and network indices are calculated to explain international trade flows.

In this chapter, we first use the gravity model with the network approach of international trade and try to explore the trade effects of characteristic properties of network indices. For this purpose, we combine gravity, network, and trade datasets from the CEPII and analyze the factors affecting the trade flows in the international trade network. Main innovation of this part is bringing these datasets together and analyzing the trade effects of network indices by considering developed and developing countries separately.

In the rest of this chapter, we then employ network indices as the dependent variables to investigate the relationship between participations of countries in Global

Value Chains (GVCs) and their positions in the International Trade Network (ITN). Our estimates indicate that there is a strong relationship between the GVC participation and the network position of a country. We find that forward participation is associated with more clustered but fewer trade links, whereas backward participation is associated with less clustered but more trade links. We then interpret these results by expressing the background of global value chains, and this provides us a clear understanding for the nexus between the GVCs and ITN.

This chapter is organized as follows. Section 3.2 introduces the basic of networks. Section 3.3 reviews the literature on ITN and GVCs. Section 3.4 presents the data we employed, and represents the graphics related with this data. Section 3.5 explains the methodology and Section 3.6 expresses the estimation results. Finally, Section 3.7 concludes the chapter by the discussions.

3.2 Basics of Networks

In this part, we introduce some basic concepts of graph theory and networks relevant to this chapter. We mention the explanations of nodes and edges utilized in ITN literature above. According to Haggett and Chorley (1969), there are some confusions of terminology in the application of graph theory to the network structure. For instance, apart from “nodes” and “edges”, points of a graph are defined as vertices, junctions, intersections, terminals, or zero-cells; and lines are referred as links, sides, arcs, segments, branches, routes, or once-cells.

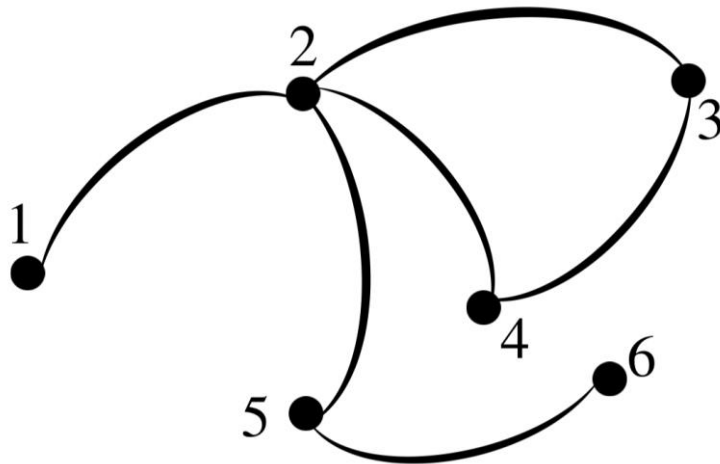


Figure 3.1: A Basic Graph (Network Diagram)

Now, we basically illustrate the nodes and edges of a network as a graph, in Figure 3.1. Here, nodes are denoted as points from 1 to 6; edges are shown as links between them. Besides, these interactions are usually represented as a matrix. Table 3.1 demonstrates the adjacency matrix for our example. Note that, this kind of a graph is called “undirected”, which means that the connection between the nodes is mutual. Social networks may be an example for this since there is a link between two people if they know each other. In trade networks, we have “directed” graphs, since exports and imports are flows between one country to another.

Table 3.1: Adjacency Matrix of the Graph

	1	2	3	4	5	6
1	0	1	0	0	0	0
2	1	0	1	1	1	0
3	0	1	0	1	0	0
4	0	1	1	0	0	0
5	0	1	0	0	0	1
6	0	0	0	0	1	0

Density is the simplest network metric we employ in this chapter. It is calculated as shown in Equation 3.1 below. In a world of n countries, we can find the number of maximum possible links by $n(n - 1)$. So, in an ITN, the density of whole network is the proportion of actual trade links to maximum possible ones. The value of density ranges between 0 and 1.

$$density = \frac{\text{number of links}}{\text{number of maximum possible links}} \quad (3.1)$$

Another type of metrics, which is “centralities”, are calculated for each country, not for the whole network like “density”. To begin with, *degree centralities* are employed for determining the position of countries in the ITN. *Out-degree* and *in-degree* centralities, as shown in Equations 3.2 and 3.3, are related with countries’ export and import links, respectively. In a world of n countries, the number of maximum possible export and import links is $n - 1$ for each country. These centralities range between 0 and 1. We also utilize *strength centralities* or *weighted*

degrees in this thesis, which are weighted with trade volumes, instead of just using the number of trade flows like in degree centralities.

$$\text{out} - \text{degree centrality} = \frac{\text{number of export links}}{\text{number of maximum possible export links}} \quad (3.2)$$

$$\text{in} - \text{degree centrality} = \frac{\text{number of import links}}{\text{number of maximum possible import links}} \quad (3.3)$$

One of the most used network measures is *closeness centrality*. Jackson (2016) defines it as convenience of a node when reaching to other nodes. In a world of n countries, it is defined as in Equation 3.4, where $l(i, j)$ is the shortest topological path between country i and j . If a country reaches another country directly, this value will be 1. However, if it has no trade link with a country, it can reach that country with its other links. We thus calculate the number of steps to reach other nodes in the network. For instance, we can say that if a country has trade links with all countries, $l(i, j)$ will be “1” for each connection, which will result in a sum of $n - 1$ for the denominator. Therefore, the closeness centrality will get the highest value, which is 1.

$$\text{closeness centrality} = \frac{n-1}{\sum_{j \neq i} l(i, j)} \quad (3.4)$$

Moreover, Newman (2018) defines the *clustering coefficient* by the help of transitivity in networks, like in Equation 3.5. We regard the term “path of length two” for the trade link between country A and B, and country B and C. If countries A and C are also connected, we define this triangle path as “closed”. The clustering coefficient gets values between 0 and 1.

$$\text{clustering coefficient} = \frac{\text{number of closed paths of length two}}{\text{number of paths of length two}} \quad (3.5)$$

Newman (2018) explains another metric we used, *eigenvector centrality*, as an extension of degree centrality, which takes the importance of linked neighbors into account. It is calculated by valuation of centrality scores of neighbors. The last

centralities that we are interested in this chapter are *hubs and authorities*, which are developed by HITS (hyperlink-induced topic search) algorithm.⁷

3.3 Literature Review

3.3.1 International Trade Network

The idea of treating international trade flows as a network is not new. Hilgerdt (1943) is a seminal effort defining international trade as a network, as shown in Figure 3.2 below. However, by the help of modern network analysis techniques and big data, in the last two decades, the structure and evolution of ITN is frequently discussed in many perspectives. Smith and White (1992) analyze the structure of the trade network by using the relational distance algorithm and find that the countries are slowly altering from their positions over time, which are defined as the core, semi-periphery, and periphery.

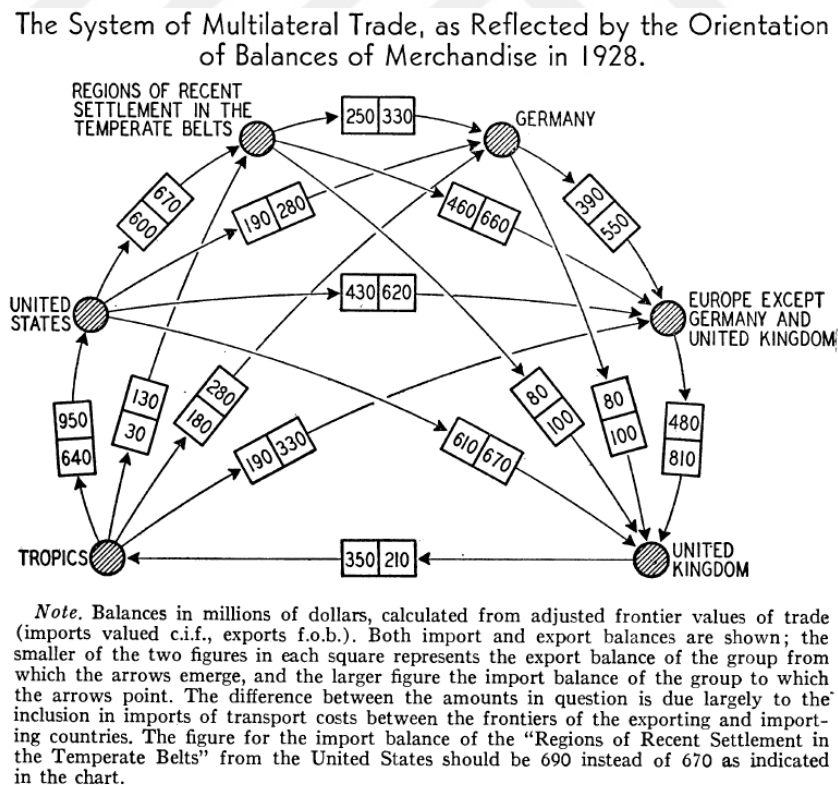


Figure 3.2: Hilgerdt's (1943) chart illustrating trade network

⁷ See, the Chapter 7 of Newman (2018) for the detailed explanations.

Garlaschelli and Loffredo (2005) define the world trade web as a directed and evolving network and affirm the phenomenon of relationship between this topology and wealth of the countries. Serrano and Boguna (2003) find that the international trade network shows complex network features, and it addresses topological features of the network. They argue that international trade must be considered as a whole, complex system since the globalization tends to eliminate most of the geographical, economic, and technical limitations.

Another work, Kali and Reyes (2007) suggest a network approach to international economic integration instead of the classical measures based on trade volumes. They find that a country's economic growth and its network position are strongly related. Schweitzer et al. (2009) concern with challenges originated from the global crisis that affects the whole complex system. They argue that economic policies favoring network structures resistant to economic shocks should be proposed.

Substantial efforts in the ITN literature deals especially with the topological properties of the network. Topology refers to the metrics like degree, strength as we discussed above. They employ various examinations to discuss these networks properties. Fagiolo et al. (2008) examine the topology of trade network by employing a weighted-network analysis. They show that most of the trade links are weak relationships and there is a linear relationship between the intensity of trade connections and clustering.⁸ Barigozzi et al. (2010) and Barigozzi et al. (2011) are another strand of the literature related with the topological properties of ITN, which analyzes the commodity-specific trade relations. De Benedictis et al. (2014) is a comprehensive paper analyzing world trade using network techniques. Working with the CEPII BACI dataset for the years between 1995 and 2010, they calculate local and global centrality measures for the countries and describe the binary and weighted topology of the trade network with supporting network representations both in aggregate and sectoral levels.

As discussed above, the gravity model is widely used in the international trade literature. Some works on the ITN deal with the shortcomings of the gravity model. They argue that the gravity model cannot estimate the zero trade flows, which results in failure in reproducing links in the trade network. To overcome this drawback, Picciolo et al. (2012) employ exponential random graphs and treat distances as

⁸ See Fagiolo et al. (2009) and Fagiolo (2010) for the related work.

constraints. They conclude that trade network does not strongly depend on the distances between countries. Squartini and Garlaschelli (2014) suggest a probabilistic approach taken from the physics, by adopting quantum-mechanical paradigm. Their results indicate that these methods explain binary topological properties much better than weighted metrics of the international trade network.

Another strand of the ITN literature combines network indices with the gravity model for empirical analysis. De Benedictis and Tajoli (2011) utilize network metrics such as density, closeness, betweenness, and degree centrality as well as various country characteristics such as income, population, and geographical location. They employ these network metrics as dependent variables in a classical gravity equation on the traditional country-specific variables to provide additional explanatory power. Duenas and Fagiolo (2013) also explain the international trade network through the gravity model. According to the authors, the gravity model is insufficient to account for the high-level statistics such as clustering. To explain the topological properties of the network, the gravity model and network-related variables should be combined.

Our first contribution in this chapter is to the ITN literature to employ the gravity model with the network approach of international trade and empirically examine the trade effects of characteristic properties and network indices. For this purpose, we combine gravity, network, and trade datasets from the CEPII and analyze the factors affecting flows in the trade network to discover the dynamics of ITN. Main innovation of this work is not only to bring these datasets together but also is to analyze the trade effects of network indices by considering developed and developing countries separately. We interpret the empirical results of this part, Dynamics of ITN, in Section 3.6.1.

3.3.2 Global Value Chains

Since the concept of GVC participation is first developed by Koopman et al. (2011) based on the vertical specialization measures of Hummels et al. (2001), the literature on GVCs has been rapidly growing. It is known that almost half of the global trade involves in global value chains (World Bank, 2020). GVC participation of the countries is thus significant for their welfare. Altomonte et al. (2018) evaluate trade and growth by taking GVCs into account. Applying a new gravity instrument of trade, they find that countries participating in GVCs more over time are positively affected

from exports in terms of growth. Yanikkaya and Altun (2020) find the positive impact of participation in GVCs on output and productivity growth. They compare two different time periods and conclude that the affirmative effect of GVC participation to countries and sector less visible in times of global crisis.

Scholars from various disciplines such as international business, management, economic geography, regional development are also interested in GVC subjects.⁹ Since GVCs are closely related with international trade, there are several studies employing GVCs with a trade network perspective. Amador and Cabral (2017) argue that the interdependence of countries in terms of shock transmission and co-movement of business cycles become significant as the share of the exports in foreign value-added increases. They examine the evolution of networks of value-added trade by employing network indices and visualization techniques. Cingolani et al. (2018) explore global and regional value chains by illustrating them as network graphs. They state that geographical distance and regionalization still play a significant role on production and trade and discovering topology of networks is beneficial for understanding production linkages.

With the availability of above works in the literature, we consider that GVC participation indices described as in Koopman et al. (2011), OECD (2016), and Wang (2017) may provide more comprehensive understanding of the issue by the help of the ITN analysis. For instance, although countries might have relatively higher forward participations due to the mostly exports of mining and extraction of energy producing products, they may not have considerable roles in the coordination of GVCs. Similarly, a country's higher participation may be a result of its trade with very few countries, instead of having more regional and global dimensions. Hence, discovering the relationship between the participation in GVCs and the network positions of the countries in international trade provide robust explanations these kinds of uncertainties.

World Bank (2020) emphasizes that hyper specialization and durable firm-to-firm relationships are the two prominent characteristics of GVCs. They are mainly results of the technological developments, not only by enabling further production fragmentation but also allowing an effective and efficient coordination of GVCs (OECD, 2019). We intuitively think that this may have substantial implications for the

⁹ See Kano et al. (2020) for a multi-disciplinary GVC literature review.

trade networks in both country and firm levels. These advances are beyond the GVC participation indices and thus international trade network analysis is worthwhile for understanding these available and prospective developments.

Our second contribution in this chapter is both to ITN and GVC literature. We prove that there is a strong link between the value-added trade and the ITN. Then, we argue that it is worthwhile to study the association between the ITN and GVC participation since GVCs are not simply bilateral flows between any two countries but organized through trade networks among many countries. Our empirical analysis aims to close the gap in understanding the macro and micro dimensions of GVCs enlargement process. We discuss the empirical results of this part, GVCs and ITN, in Section 3.6.2.

3.4 Data and Graphics

3.4.1 Data

For the “Dynamics of ITN” part of this chapter, we basically combine three datasets together which are taken from the CEPII for 178 countries. Firstly, trade data is from the BACI dataset based on UN Comtrade¹⁰ dataset. Export volumes come from this dataset. Originally, the BACI dataset is disaggregated at the Harmonized System (HS) 6 level, and we then aggregate export shares as of total export of each country to another.

We also make use of the network trade dataset, which includes network indices.¹¹ These are out-degree, out-strength, out-closeness, and out-eigenvector centrality. Lastly, we include the gravity dataset, which is consisted of the geographical characteristics of countries¹²; which are the weighted distance, GDP per capita, population, area, contiguity, common currency, common language, and GATT/WTO membership. Note that, the CEPII BACI dataset covers the years between 1995 and 2015. However, since the network trade dataset lasts by the year 2010, our combined dataset is limited by the years 1995 and 2010.

¹⁰ See Gaulier and Zignago (2010).

¹¹ See the Section 3.2 for the definitions of these metrics.

¹² See Head et al. (2010) and Head and Mayer (2014).

Table 3.2 displays the descriptive statistics. Export and GDP per capita values are in thousand dollars and deflated by 2010 U.S. CPI. In our dataset, export and GDP per capita observations are thus much fewer than the other variables we have since there are some missing values for some of the countries and years. Variables are named as the “origin” for country i , and the “destination” for country j . For these variables, understandably, summary statistics take the same values.

Table 3.2: Descriptive Statistics for Dynamics of ITN

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Export	299186	2.19x10 ⁹	5.49x10 ¹¹	930.91	2.96x10 ¹⁴
Distance (km)	504096	7929.49	4497.06	60.77	19781.39
Origin GDP per capita	434004	38034.39	1201817	207.37	5.95x10 ⁷
Destination GDP per capita	434004	38034.39	1201817	207.37	5.95x10 ⁷
Origin population (million)	503565	35.29	129.08	0.02	1337.71
Destination population (million)	503565	35.29	129.08	0.02	1337.71
Origin area (km ²)	504096	741708.10	1983853	25	1.71x10 ⁷
Destination area (km ²)	504096	741708.10	1983853	25	1.71x10 ⁷
Contiguity	504096	0.02	0.13	0	1
Common currency	504096	0.01	0.10	0	1
Common language	504096	0.14	0.35	0	1
GATT/WTO (origin)	504096	0.74	0.44	0	1
GATT/WTO (destination)	504096	0.74	0.44	0	1
Out-degree centrality	504096	0.65	0.25	0.05	1
Out-strength centrality	504096	1829488	2591063	500.55	9996222
Out-closeness centrality	504096	0.77	0.15	0.51	1
Out-eigenvector centrality	504096	0.07	0.02	0.01	0.11

For the GVCs and ITN part of this chapter, we use the CEPII Gravity dataset for country specific characteristics, such as area, population, and GDP per capita. GDP per capita data is deflated by 2015 U.S. GDP deflator. Countries’ being landlocked and membership to GATT/WTO and the European Union (EU) are added to model as dummy variables. In our model, we control trade for any country by using the following trade weighted distance equation:

$$W_i = \sum_j d_{ij} \left(\frac{export_{ij}}{export_i} \right) \quad (3.6)$$

In the equation above, we employ simple distance d_{ij} between countries' most populated cities, which is taken from CEPII GeoDist. $export_{ij}$ denotes export of country i to j , and $export_i$ denotes country i 's total gross export, and the data come from the CEPII BACI, which is based on the UN Comtrade dataset.¹³ Export data employed here is deflated by 2015 U.S. GDP deflator. We also use this trade dataset to calculate our network indices namely as out-degree centrality, in-degree centrality, clustering coefficient, hub and authority centralities.

To calculate the participations in GVCs, we employ the UNCTAD-EORA Global Value Chain Database generated from the EORA Multi-Region Input-Output Table (MRIOs)¹⁴, which covers 190 countries for the 1990-2017 period. By combining UNCTAD-EORA with CEPII Gravity, GeoDist, and BACI datasets, we obtain a sample of 174 countries for the years between 1995 and 2015. As the widely known in the literature¹⁵, we consider the share of foreign value-added in domestic exports and the share of domestic value-added in foreign exports as backward and forward participation indices, respectively.

Table 3.3: Descriptive Statistics for ITN and GVCs

Variable	Obs	Mean	Std.Dev.	Min	Max
Forward participation	3654	28.71	11.65	0.78	204.20
Backward participation	3654	23.01	14.70	0.15	95.27
Weighted distance	3654	5118.20	2518.93	858.79	14531.49
GDP per capita	3473	12607.14	18018.92	94.50	105827.70
Area (km ²)	3654	756622.80	2002105	25	17075400
Population (millions)	3640	37.08	134.11	0.02	1371.22
Landlocked	3654	0.18	0.39	0.00	1.00
EU	3654	0.12	0.32	0.00	1.00
GATT/WTO	3654	0.75	0.43	0.00	1.00
Out-degree centrality	3654	0.69	0.24	0.11	1.00
In-degree centrality	3654	0.69	0.21	0.15	1.00
Clustering coefficient	3654	0.29	0.07	0.15	0.56
Hub centrality	3654	0.04	0.12	2×10^{-6}	1
Authority centrality	3654	0.03	0.09	1×10^{-5}	1

¹³ See, Head et al. (2010), Mayer and Zignago (2011), and Gaulier and Zignago (2010) for the CEPII datasets used in this paper.

¹⁴ See, Lenzen et al. (2012), Lenzen et al. (2013), and Casella et al. (2019).

¹⁵ See, Kowalski et al. (2015) and Doan and Le (2021)

3.4.2 Network Metrics for 178-Country Dataset

In this section we represent network related figures and tables below by employing our 178-country dataset described in the data section. Since the aim of the first part of our analysis is to explain the dynamic changes in the international trade from the network perspective, we first calculate the density of the whole trade network, following De Benedictis et al. (2014). In the Section 3.2, we define density as the proportion of actual trade links to maximum possible ones. We can observe from Figure 3.3 that, the density of ITN mostly increases between the years 1995 to 2010, except from the years near 2008 financial crisis.

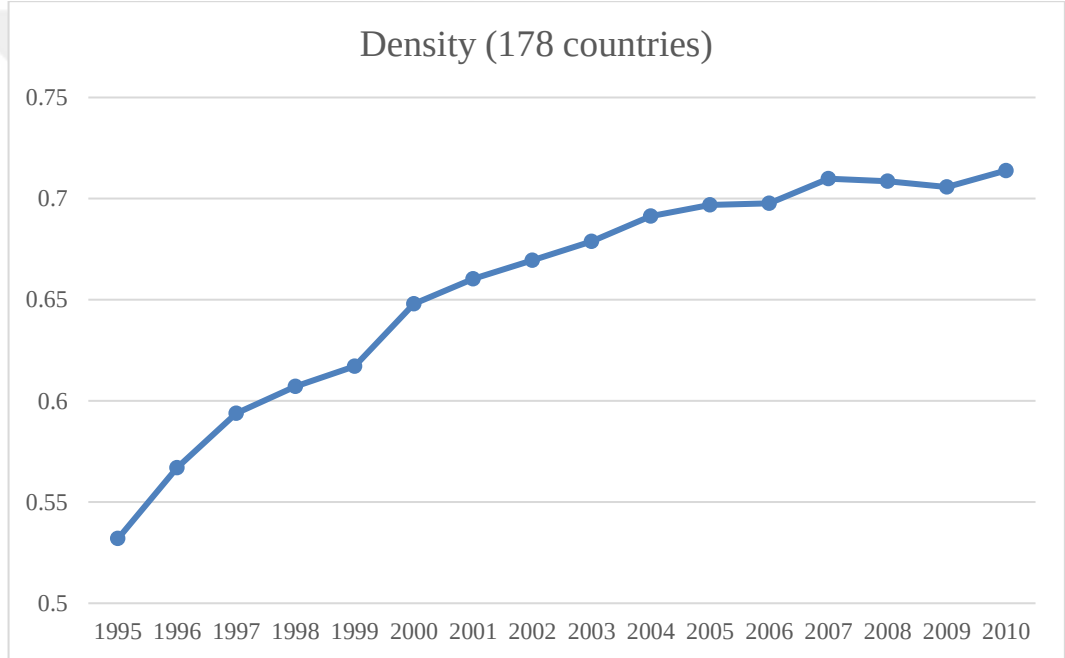


Figure 3.3: Network density of 178 countries

For the links indicating trade flows out and in, we calculate and demonstrate the change in average values of out-degree and in-degree centralities. We have two separate figures, Figures 3.4 and 3.5, to observe the difference between out and in trade flows. We also divide data for 35 developed and 143 developing countries¹⁶ to see how different countries behave over time. Note that, degree centralities are calculated for each country, then we take the averages of these values for 178 countries.

¹⁶ See Appendix D for these countries.

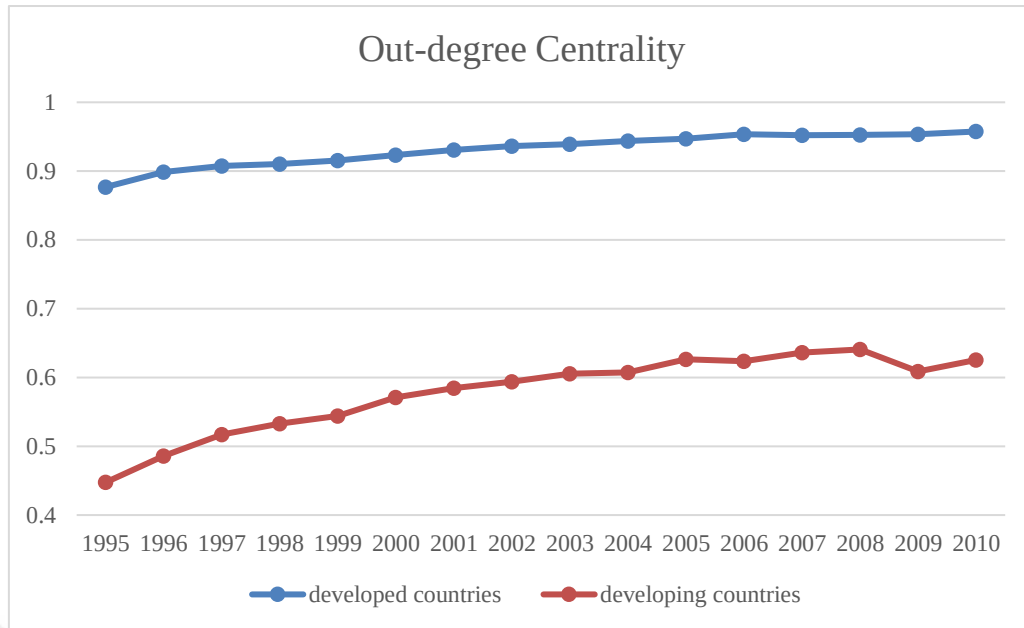


Figure 3.4: Average out-degree centrality

Figure 3.4 shows the average out-degree centralities of developed and developing countries. For the developed countries, values range between 0.88 and 0.95 for the years between 1995 and 2010. Developing countries' average out-degree centrality starts from 0.45 in 1995 and increases to 0.65 in 2008. After the 2008 global crisis, we observe a decline especially for the developing countries though.

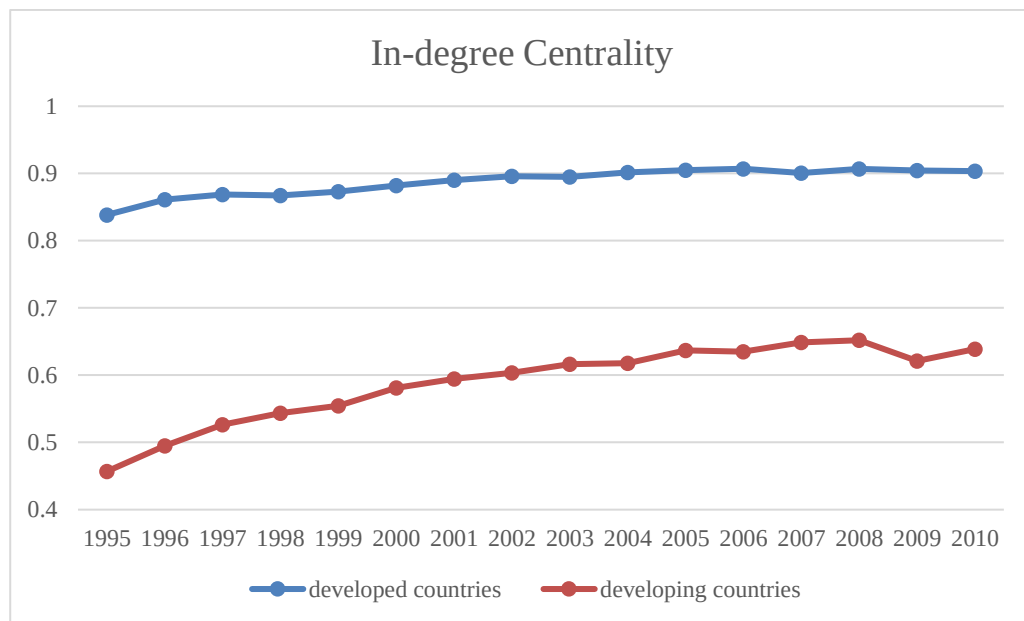


Figure 3.5: Average in-degree centrality

As can be seen from Figure 3.5, similarly, the average in-degree centralities for the developed countries increases from 0.84 to 0.90. Developing countries' in-degree centralities come up against a decline from 0.65 to 0.62 after the crisis, which has increased steadily from 0.45 since 1990. These two figures indicate that developed countries have substantially higher degree centralities and the position of developed countries in the trade network is less affected from the 2008 crisis than that of developing countries is.

Table 3.4: Out-strength Centrality (1995 and 2010)

1995			2010		
Rank	Country	Out-strength	Rank	Country	Out-strength
1	U.S.	3384770	1	China	9996222
2	Germany	2786351	2	Germany	6705292
3	Japan	2579884	3	U.S.	6610431
4	France	1539471	4	Japan	4415181
5	UK	1284979	5	France	2880275
6	Italy	1255030	6	South Korea	2679725
7	China	1151677	7	Italy	2424068
8	Canada	1063366	8	Netherlands	2356322
9	Netherlands	957603	9	UK	2187866
10	Belgium	857750	10	Canada	2142547
...			...		
169	Seychelles	402.882	169	Saint Vincent	786.511
170	Armenia	354.513	170	Maldives	759.471
171	Samoa	324.756	171	Central African R.	686.148
172	Bosnia and Her.	312.950	172	Guinea-Bissau	524.097
173	Antigua and Bar.	265.744	173	Saint Lucia	480.173
174	Rwanda	251.977	174	Samoa	467.743
175	Bhutan	240.245	175	Saint Kitts.	394.072
176	Saint Kitts	234.620	176	Gambia	371.713
177	Marshall Isl.	156.370	177	Dominica	323.509
178	Vanuatu	151.737	178	Micronesia	307.672

In Table 3.4, we list 10 countries with highest and 10 with lowest out-strength centrality for the years 1995 and 2010, which are the first and the last years of our dataset. The strength centrality is simply trade weighted version of degree centrality. Thus, we can claim that countries with high trade volumes and trade links have also high out-strength centralities. For example, we can easily see the surge of China to the first rank in 2010 due to its recent spectacular performance in the world trade.

Table 3.5: Out-closeness Centrality (1995 and 2010)

1995			2010		
Rank	Country	Out-closeness	Rank	Country	Out-closeness
1	Belgium	1	1	China	1
2	Denmark	1	2	Germany	1
3	Germany	1	3	U.S.	1
4	Italy	1	4	France	1
5	Netherlands	1	5	Italy	1
6	Sweden	1	6	Netherlands	1
7	UK	1	7	UK	1
8	China	0.994	8	Spain	1
9	Japan	0.989	9	India	1
10	U.S.	0.989	10	Malaysia	1
...			...		
169	Bhutan	0.550	169	Equatorial G.	0.586
170	Guinea-Bissau	0.550	170	Saint Lucia	0.584
171	Saint Kitts	0.550	171	Saint Kitts	0.582
172	Solomon Isl.	0.546	172	Marshall Isl.	0.577
173	Equatorial G.	0.543	173	Samoa	0.571
174	Iraq	0.538	174	Vanuatu	0.567
175	Samoa	0.536	175	Bhutan	0.567
176	Vanuatu	0.532	176	Solomon Isl.	0.560
177	Marshall Isl.	0.521	177	Guinea-Bissau	0.557
178	Micronesia	0.513	178	Micronesia	0.545

Closeness and eigenvector centralities in principle measure different values. As we discussed in Section 3.2, the former can be defined as easiness of a node when reaching to other nodes, whereas the latter quantifies the importance of linked neighbors of the node. In Table 3.5 and Table 3.6, we demonstrate the top and bottom 10 countries with out-closeness and out-eigenvector centralities in 1995 and 2010. Note that Turkey's rank is rising for both centralities. The ranking for out-closeness centrality of Turkey is 32 in 1995 and 20 in 2010. Besides, her out-eigenvector rank rises to 16th position from 32nd between the years 1995 and 2010.

We rank the countries with their out-strength centrality if their closeness or eigenvector centralities are equal. We observe that although the ranking is somewhat different, both two list consist of very similar countries. The reason for this is probably a country which easily reach to another country, having high closeness centrality, has also important neighbors, having high eigenvector centrality.

Table 3.6: Out-eigenvector Centrality (1995 and 2010)

1995			2010		
Rank	Country	Out-eigenvector	Rank	Country	Out-eigenvector
1	Germany	0.112	1	China	0.096
2	UK	0.112	2	Germany	0.096
3	Italy	0.112	3	U.S.	0.096
4	Netherlands	0.112	4	France	0.096
5	Belgium	0.112	5	Italy	0.096
6	Sweden	0.112	6	Netherlands	0.096
7	Denmark	0.112	7	UK	0.096
8	China	0.112	8	Spain	0.096
9	Switzerland	0.111	9	India	0.096
10	Japan	0.111	10	Malaysia	0.096
...			...		
169	Solomon Isl.	0.029	169	Equatorial G.	0.034
170	Bhutan	0.028	170	Saint Lucia	0.033
171	Aruba	0.025	171	Saint Kitts	0.033
172	Saint Kitts	0.024	172	Marshall Isl.	0.032
173	Equatorial G.	0.024	173	Samoa	0.029
174	Samoa	0.023	174	Bhutan	0.028
175	Iraq	0.022	175	Vanuatu	0.028
176	Vanuatu	0.020	176	Solomon Isl.	0.026
177	Marshall Isl.	0.014	177	Guinea-Bissau	0.024
178	Micronesia	0.009	178	Micronesia	0.020

3.4.3 Network Metrics for 174-Country Dataset

In this section, we represent the figures and tables for centralities in our 174-country dataset. In this dataset, we have the out-degree and in-degree centralities, clustering coefficient, hub and authority centralities. Since we demonstrate the figures related with out-degree and in-degree centralities in previous section for our 178-country dataset, we skip them in this section.

We begin with a graphical representation of international trade network for the year 2015 in Figure 3.6, which is generated by Gephi software (Web 2, 2022). In this figure, we group the countries according to their continents. However, note that their position is not exact geographical position. Besides, the circle and label sizes of the nodes are proportional with the countries' weighted out-degree centralities, and the size of the edges are weighted by the trade volume.

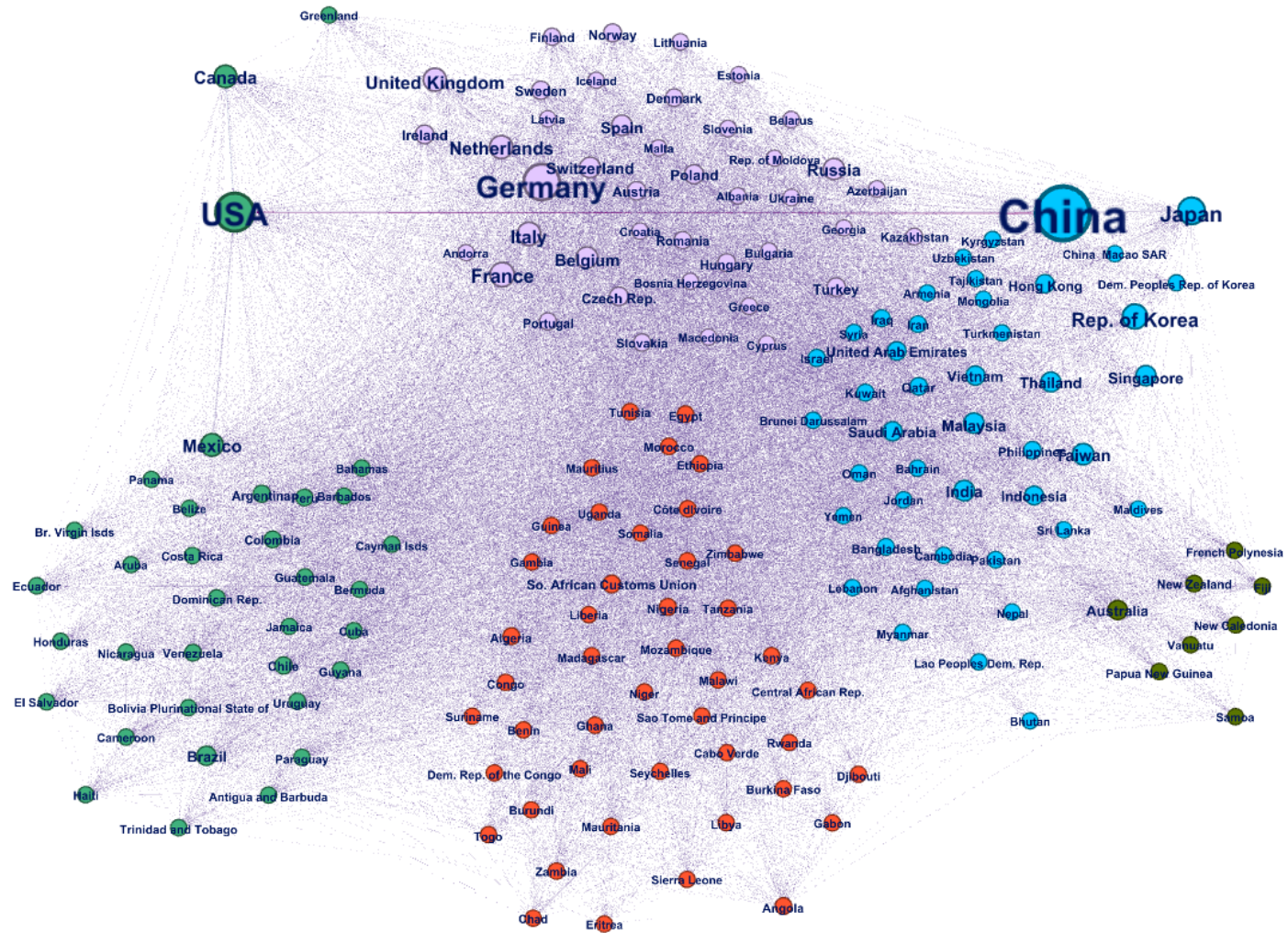


Figure 3.6: International Trade Network (2015)

According to our 174-country dataset, top 5 countries in terms of weighted out-degree centrality are China, the U.S., Germany, Japan, and the Republic of Korea. And from Figure 3.6, we observe that the highest trade volumes in the trade network are between U.S. and China, Mexico, Canada.

Table 3.7: Clustering Coefficient (1995 and 2015)

1995			2015		
Rank	Country	Clustering coefficient	Rank	Country	Clustering coefficient
1	Vanuatu	0.523	1	Greenland	0.448
2	Greenland	0.491	2	Eritrea	0.433
3	Samoa	0.491	3	Vanuatu	0.429
4	Bhutan	0.480	4	Bermuda	0.417
5	Iraq	0.480	5	Samoa	0.417
6	Cape Verde	0.478	6	Aruba	0.409
7	Andorra	0.463	7	Sao Tome and Pr.	0.408
8	Cayman Isl.	0.444	8	Central African R.	0.407
9	Somalia	0.439	9	Burundi	0.406
10	Eritrea	0.428	10	Gambia	0.403
...			...		
165	Italy	0.161	165	Austria	0.203
166	Netherlands	0.157	166	Canada	0.203
167	Switzerland	0.156	167	Thailand	0.203
168	Japan	0.156	168	Switzerland	0.203
169	Spain	0.156	169	Belgium	0.203
170	U.S.	0.156	170	UK	0.203
171	Belgium	0.155	171	Italy	0.202
172	France	0.154	172	Netherlands	0.202
173	UK	0.153	173	Singapore	0.202
174	Germany	0.152	174	France	0.202

In Table 3.7, we present the clustering coefficient of first and last 10 countries in 1995 and 2015. As we can see, mostly small countries have higher clustering coefficients, whereas countries with higher trade volumes have lower. We define this centrality in Section 3.2 as the ratio of *closed path of length two* and *path of length two*. The term “path of length two” is the trade link of country A and B. We call the total path as “closed” if country B and C are also connected. Thus, countries with higher clustering coefficients probably have few trade links but they tend to cluster. Conversely, countries with lower clustering coefficients enjoy lots of trade connections but they are not clustered.

Table 3.8: Hub Centrality (1995 and 2015)

1995			2015		
Rank	Country	Hub centrality	Rank	Country	Hub centrality
1	Japan	1	1	China	1
2	Canada	0.881	2	Mexico	0.418
3	Germany	0.551	3	Canada	0.417
4	U.S.	0.550	4	Germany	0.310
5	China	0.436	5	Japan	0.277
6	Mexico	0.382	6	U.S.	0.245
7	France	0.325	7	South Korea	0.186
8	UK	0.317	8	UK	0.128
9	Italy	0.284	9	France	0.121
10	Taiwan	0.266	10	Taiwan	0.120
...			...		
165	Somalia	4.18×10^{-5}	165	Antigua and Bar.	2.65×10^{-5}
166	Antigua and Bar.	3.03×10^{-5}	166	Central African R.	2.50×10^{-5}
167	Vanuatu	2.97×10^{-5}	167	Gambia	2.45×10^{-5}
168	Samoa	2.59×10^{-5}	168	Burundi	2.04×10^{-5}
169	Iraq	9.47×10^{-6}	169	Bermuda	1.92×10^{-5}
170	Djibouti	9.44×10^{-6}	170	Samoa	1.39×10^{-5}
171	Bhutan	9.40×10^{-6}	171	Cape Verde	1.29×10^{-5}
172	Cape Verde	6.93×10^{-6}	172	Andorra	1.22×10^{-5}
173	Sao Tome and Pr.	6.48×10^{-6}	173	Djibouti	7.81×10^{-6}
174	Eritrea	5.54×10^{-6}	174	Sao Tome and Pr.	2.63×10^{-6}

In Table 3.8 and 3.9, we show 10 countries with highest and 10 with lowest hub and authority centralities for the years 1995 and 2015. Hubs and authorities are calculated with mutual recursion; hub is a node which links to authorities, an authority is a node which is linked by hubs. The term “hub” in trade refers to a country which imports raw material and export them after assembly. Japan is number one hub according to Table 3.8 in 1995, but China takes Japan’s place in 2015. When we look at Table 3.9, we observe that the authority, the United States, does not change after 20 years. However, China, Hong Kong, and Mexico are rising in the authorities list.

Table 3.9: Authority Centrality (1995 and 2015)

1995			2015		
Rank	Country	Authority centrality	Rank	Country	Authority centrality
1	U.S.	1	1	U.S.	1
2	Germany	0.297	2	Hong Kong	0.376
3	Japan	0.260	3	Japan	0.241
4	France	0.234	4	Germany	0.208
5	UK	0.233	5	China	0.200
6	Hong Kong	0.220	6	UK	0.161
7	Canada	0.214	7	South Korea	0.160
8	South Korea	0.171	8	Mexico	0.154
9	Italy	0.156	9	Canada	0.150
10	Netherlands	0.153	10	France	0.140
...			...		
165	Greenland	1.40×10^{-4}	165	Antigua and Bar.	1.50×10^{-4}
166	Armenia	1.32×10^{-4}	166	Burundi	1.42×10^{-4}
167	Sierra Leone	1.20×10^{-4}	167	Andorra	1.20×10^{-4}
168	Tajikistan	1.19×10^{-4}	168	Samoa	1.20×10^{-4}
169	Samoa	9.95×10^{-5}	169	Vanuatu	1.18×10^{-4}
170	Cape Verde	8.13×10^{-5}	170	Central African R.	1.07×10^{-4}
171	Iraq	5.87×10^{-5}	171	Cape Verde	8.70×10^{-5}
172	Somalia	4.76×10^{-5}	172	Bhutan	8.02×10^{-5}
173	Bhutan	2.95×10^{-5}	173	Greenland	5.88×10^{-5}
174	Sao Tome and Pr.	1.82×10^{-5}	174	Sao Tome and Pr.	1.47×10^{-5}

3.4.4 GVC Participations

We present backward and forward GVC participation of China, U.S., Germany, Japan, France, South Korea, which are top 6 exporter countries of 2019, and Turkey in this section. We include the participations between 1995 and 2015, with a five-year interval. We demonstrate backward GVC participations and forward GVC participation in Figure 3.7 and 3.8, respectively. As we discussed before, backward participation refers to the share of foreign value-added in domestic exports and whereas forward participation refers to the share of domestic value-added in foreign exports.

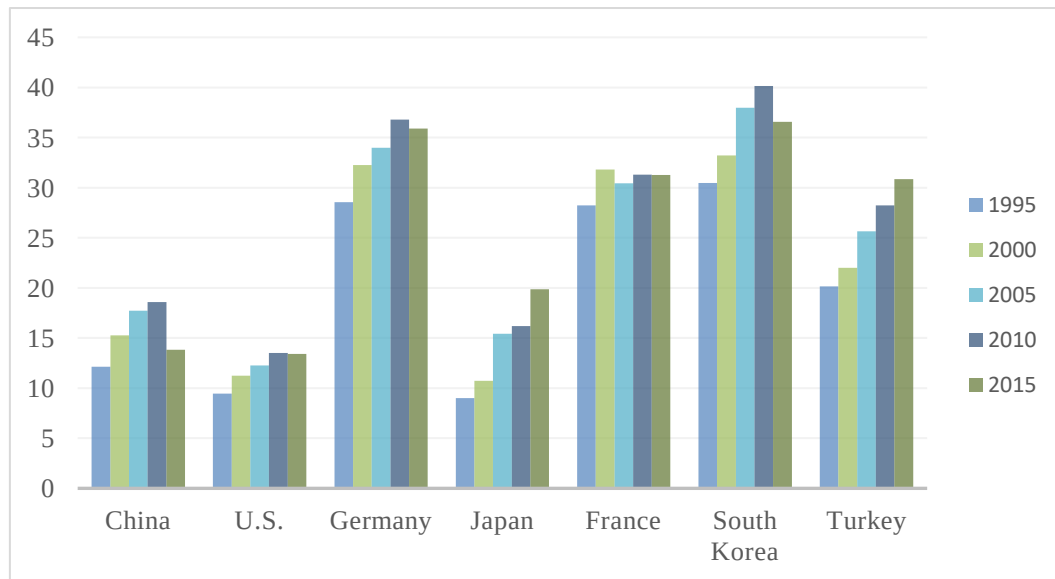


Figure 3.7: Backward GVC Participations

In Figures 3.7 and 3.8, we observe that China, U.S., and Japan have higher forward GVC participations than backward GVC participations for all years. Thus, we can state that these countries participate in partner countries' exports much more than they participate in their exports. While Germany and South Korea have higher backward participations, France have similar backward and forward participation rates in most years. Turkey has relatively higher forward participations in 1995 and 2000; but backward participations are rising, and it is higher in the years 2010 and 2015. This might be result of rising intermediate imports and inward FDI in Turkey.

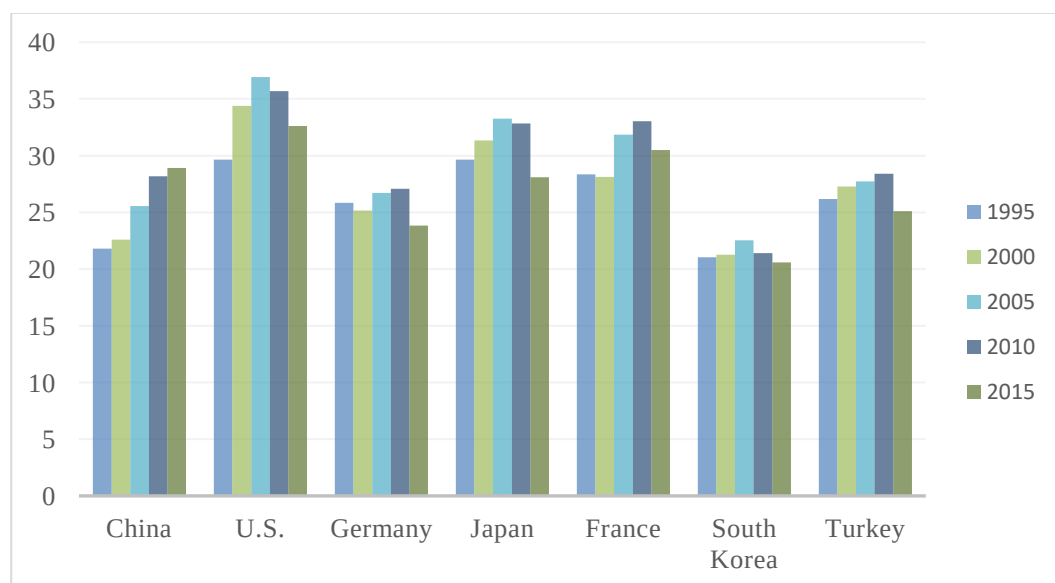


Figure 3.8: Forward GVC Participations

3.5 Methodology

To discover the dynamics of ITN, we first combine both network indices and country-specific characteristics with the gravity model, based on the earlier studies such as De Benedictis and Tajoli (2011). Network indices used in this part are degree, strength, closeness, and eigenvector centrality.¹⁷ Country characteristics such as GDP, population, and geographical properties are also put in the gravity equation.

$$\ln T_{i,j} = \beta_0 + \ln \beta_1 X_{i,j} + \ln \beta_2 C_i + \ln \beta_3 C_j + \beta_4 D_{i,j} + \ln \beta_5 N_{i,j} + \epsilon_{i,j} \quad (3.7)$$

In this model, T denotes trade flow from country i to country j . The distance between the countries is shown as X in the model. C_i and C_j are country-specific properties such as GDP per capita, population, and area. Dummy variables are also added to the model, which are contiguity, common currency, common language, and GATT/WTO membership, denoted by $D_{i,j}$. Finally, $N_{i,j}$ denotes network indices, and we only use “out” values of these indices since we assume trade flows as exports from country i to country j .

By combining gravity model with network indices, we can examine the impact of both the geographical characteristics and network position of the countries on international trade. However, these network metrics are mainly calculated by trade flows between countries, which may cause endogeneity problems. We then think intuitively that it would be a good idea to study the determinants of trade network formations. In contrast to the studies like De Benedictis and Tajoli (2011), utilizing the gravity model to assess the effects of network indices on trade, we aim to evaluate the formation of trade links in the network.

Following Fracasso et al. (2018), which employs network measures as dependent variables which investigates the determinants of out-degree centrality and HITS-hub score in the oil trade network, we build our model to estimate the relationship between GVC participation and ITN. By incorporating participation indices with network measures, we principally try to assess the impact of participation in GVCs more accurately. Thus, our model for the GVCs and ITN part of this section is as follows.

¹⁷ See the Section 3.2 for the definitions of these metrics.

$$\ln network_{i,t} = \beta_0 + \beta_1 \ln GVC_{i,t} + \beta_2 \ln W_{i,t} + \beta_3 \ln C_{i,t} + \beta_4 D_{i,t} + \varepsilon_{i,t} \quad (3.8)$$

where $network_{i,t}$ is the out-degree centrality, in-degree centrality, clustering coefficient, hub centrality or authority centrality.¹⁸ $GVC_{i,t}$ is forward or backward participation, $W_{i,t}$ is the trade weighted distance, $C_{i,t}$ is country specific properties such as GDP per capita, area and population, and $D_{i,t}$ denotes several dummy variables which are countries' being landlocked, membership to GATT/WTO and the European Union (EU). We include year dummies, and the regressions are clustered at the country level.

We initially choose out-degree centrality and clustering coefficient measures to simply compare the number of export links of countries (out-degree) and their concentrated links (clustering) and relate these with GVC participations. Inherently, connecting to several links and concentrating on a few are opposite behaviors. Thus, we intuitively consider that the contrast of these two centralities might be worthwhile to interpret. Then, we also include the analysis for the other network indices; in-degree centrality, hub centrality, and authority centrality.

3.6 Empirical Results

3.6.1 Dynamics of ITN

We separate our analysis regarding dynamics of ITN into two steps. Firstly, we perform the OLS regressions with four centrality measures for all countries. We then estimate our model for four different country groupings. We begin with our regression results concerning the geographical and network effects on exports with our dataset for all countries, which are displayed in Table 3.10.

We perform the regressions for out-degree, out-strength, out-closeness, and out-eigenvector centralities individually and report the results in four columns in the table respectively. All centralities have positive effect on exports, and the coefficient of out-closeness centrality is the greatest one. It is interesting that the coefficient of out-strength centrality is lower than out-degree centrality. That is, if we weigh trade links by trade volumes for strength centrality instead of calculating degree centrality using

¹⁸ See the Section 3.2 for the definitions of these metrics.

the number of trade links, the effect of network on trade would be lower. We also find that out-eigenvector centrality has positive impact on exports.

As expectedly, the distance between the countries negatively affects the trade volume. GDP and population of both the origin and the destination countries have positive and significant coefficients. The areas of the countries have negative effects on the bilateral trade. Almost all dummies apart from a GATT membership of the origin country have significantly positive coefficients.

For the second step, we estimate our model for the two groups of countries with each four centrality measures. In Tables 3.11 to 3.14, we report the regressions for out-degree, out-strength, out-closeness, and out-eigenvector centralities, respectively. The first column of each table (1-1) shows the trade flows between developed countries, and the second column (0-0) displays trade flows between developing countries. The third column (1-0) is the regression results for the export flows from developed countries to developing countries, and the fourth column (0-1) is vice versa.

Like the full sample regressions, we obtain very similar results for these four sub-groups for the distance, GDP per capita, and the population. However, areas of the origin and the destination country now raise bilateral trade volumes when the flow is between developed countries, otherwise it has negative trade effect as we report regressions for all countries. Almost all dummy variables have positive and significant effects on trade. When the trade flows from developing country to developed country, both country's GATT memberships negatively affect the trade. If the trade flows from developed to developing country, the origin country's GATT membership has negative effect whereas the destination has positive effect on bilateral trade.

All centralities positively affect the export volumes except out-strength centrality when the flow is between developing to developed country. In this case, out-strength centrality of developing country has statistically significant and negative effect on export of developing country to developed country. Like in all country regressions, the coefficient of out-strength centrality is smaller than other centralities for all versions of trade flows between developed and developing countries.

Table 3.10: ITN and Exports (All Countries)

ln (export)	(1)	(2)	(3)	(4)
ln (weighted distance)	-1.146***	-1.170***	-1.150***	-1.145***
	(0.006)	(0.006)	(0.006)	(0.006)
ln (origin GDP per capita)	0.976***	1.139***	0.845***	0.990***
	(0.004)	(0.003)	(0.004)	(0.004)
ln (destination GDP per capita)	0.916***	0.895***	0.925***	0.911***
	(0.003)	(0.003)	(0.003)	(0.003)
ln (origin population)	0.987***	1.171***	0.873***	1.003***
	(0.004)	(0.004)	(0.005)	(0.004)
ln (destination population)	1.021***	1.002***	1.027***	1.020***
	(0.004)	(0.004)	(0.004)	(0.004)
ln (origin area)	-0.067***	-0.094***	-0.052***	-0.071***
	(0.003)	(0.003)	(0.003)	(0.003)
ln (destination area)	-0.139***	-0.136***	-0.139***	-0.140***
	(0.003)	(0.003)	(0.003)	(0.003)
contiguity	1.233***	1.175***	1.243***	1.225***
	(0.028)	(0.029)	(0.028)	(0.028)
common currency	0.848***	0.726***	0.787***	0.874***
	(0.035)	(0.035)	(0.034)	(0.035)
common language	1.057***	0.982***	1.080***	1.054***
	(0.012)	(0.012)	(0.012)	(0.012)
GATT/WTO (origin)	0.083***	0.329***	-0.030**	0.135***
	(0.012)	(0.012)	(0.012)	(0.012)
GATT/WTO (destination)	0.283***	0.278***	0.288***	0.300***
	(0.012)	(0.012)	(0.012)	(0.012)
ln (out-degree centrality)	1.387***			
	(0.019)			
ln (out-strength centrality)		0.034***		
		(0.002)		
ln (out-closeness centrality)			4.488***	
			(0.043)	
ln (out-eigenvector centrality)				1.589***
				(0.023)
Constant	6.745***	4.553***	8.458***	10.22***
	(0.078)	(0.078)	(0.081)	(0.107)
Observations	265,154	265,154	265,154	265,154
R-squared	0.667	0.661	0.674	0.666

Notes: Standard errors in parentheses. ***, **, and * denote 1, 5, and 10 percentages of significance levels, respectively.

Table 3.11: Out-Degree Centrality and Exports

ln (export)	1-1	0-0	1-0	0-1
ln (weighted distance)	-1.006***	-1.232***	-1.203***	-0.685***
	(0.008)	(0.009)	(0.012)	(0.015)
ln (origin GDP per capita)	0.893***	0.965***	1.180***	0.974***
	(0.011)	(0.006)	(0.011)	(0.008)
ln (destination GDP per capita)	0.827***	0.711***	0.879***	1.033***
	(0.010)	(0.005)	(0.005)	(0.014)
ln (origin population)	0.822***	0.926***	1.045***	0.982***
	(0.008)	(0.007)	(0.008)	(0.010)
ln (destination population)	0.780***	0.980***	1.015***	1.342***
	(0.006)	(0.006)	(0.006)	(0.008)
ln (origin area)	0.019***	-0.068***	-0.095***	-0.048***
	(0.006)	(0.005)	(0.005)	(0.006)
ln (destination area)	0.031***	-0.184***	-0.151***	-0.262***
	(0.006)	(0.005)	(0.004)	(0.007)
contiguity	0.539***	1.430***	1.339***	2.389***
	(0.032)	(0.038)	(0.094)	(0.121)
common currency	0.0912***	1.206***	0.872***	0.722*
	(0.026)	(0.052)	(0.322)	(0.413)
common language	0.690***	0.864***	1.007***	1.246***
	(0.030)	(0.018)	(0.023)	(0.031)
GATT/WTO (origin)	0.089*	0.173***	-0.385***	-0.271***
	(0.048)	(0.018)	(0.056)	(0.023)
GATT/WTO (destination)	0.292***	0.245***	0.088***	-0.355***
	(0.039)	(0.017)	(0.016)	(0.062)
ln (out-degree centrality)	1.189***	1.590***	2.664***	1.757***
	(0.104)	(0.030)	(0.115)	(0.035)
Constant	5.527***	10.02***	6.378***	3.358***
	(0.159)	(0.134)	(0.169)	(0.201)
Observations	19,036	126,861	61,250	58,007
R-squared	0.857	0.549	0.727	0.672

Notes: Standard errors in parentheses. ***, **, and * denote 1, 5, and 10 percentages of significance levels, respectively.

Table 3.12: Out-Strength Centrality and Exports

ln (export)	1-1	0-0	1-0	0-1
ln (weighted distance)	-1.011***	-1.212***	-1.205***	-0.724***
	(0.008)	(0.009)	(0.012)	(0.015)
ln (origin GDP per capita)	0.843***	1.135***	1.090***	1.152***
	(0.013)	(0.006)	(0.013)	(0.007)
ln (destination GDP per capita)	0.827***	0.691***	0.875***	1.018***
	(0.010)	(0.005)	(0.005)	(0.014)
ln (origin population)	0.795***	1.188***	0.989***	1.294***
	(0.009)	(0.006)	(0.009)	(0.008)
ln (destination population)	0.779***	0.955***	1.011***	1.312***
	(0.006)	(0.006)	(0.006)	(0.008)
ln (origin area)	0.0276***	-0.116***	-0.0787***	-0.110***
	(0.006)	(0.004)	(0.005)	(0.006)
ln (destination area)	0.0331***	-0.180***	-0.150***	-0.254***
	(0.006)	(0.004)	(0.004)	(0.007)
contiguity	0.530***	1.370***	1.372***	2.468***
	(0.032)	(0.039)	(0.094)	(0.123)
common currency	0.0992***	1.015***	0.709**	1.117***
	(0.026)	(0.052)	(0.322)	(0.422)
common language	0.679***	0.867***	0.971***	1.227***
	(0.030)	(0.018)	(0.023)	(0.031)
GATT/WTO (origin)	0.342***	0.393***	0.149***	0.0112
	(0.040)	(0.017)	(0.048)	(0.022)
GATT/WTO (destination)	0.295***	0.232***	0.0909***	-0.183***
	(0.039)	(0.017)	(0.016)	(0.064)
ln (out-strength centrality)	0.0934***	0.0654***	0.188***	-0.00731*
	(0.008)	(0.003)	(0.008)	(0.004)
Constant	4.505***	6.928***	4.184***	1.249***
	(0.143)	(0.134)	(0.150)	(0.209)
Observations	19,036	126,861	61,250	58,007
R-squared	0.858	0.540	0.727	0.657

Notes: Standard errors in parentheses. ***, **, and * denote 1, 5, and 10 percentages of significance levels, respectively.

Table 3.13: Out-Closeness Centrality and Exports

ln (export)	1-1	0-0	1-0	0-1
ln (weighted distance)	-1.003***	-1.275***	-1.203***	-0.737***
	(0.008)	(0.009)	(0.012)	(0.015)
ln (origin GDP per capita)	0.860***	0.818***	1.128***	0.890***
	(0.011)	(0.007)	(0.012)	(0.008)
ln (destination GDP per capita)	0.829***	0.726***	0.880***	1.035***
	(0.010)	(0.005)	(0.005)	(0.013)
ln (origin population)	0.797***	0.705***	1.015***	0.863***
	(0.008)	(0.008)	(0.008)	(0.010)
ln (destination population)	0.781***	0.996***	1.016***	1.334***
	(0.006)	(0.006)	(0.006)	(0.008)
ln (origin area)	0.021***	-0.020***	-0.092***	-0.020***
	(0.006)	(0.005)	(0.005)	(0.006)
ln (destination area)	0.030***	-0.185***	-0.151***	-0.255***
	(0.006)	(0.004)	(0.004)	(0.007)
contiguity	0.544***	1.418***	1.341***	2.228***
	(0.032)	(0.038)	(0.094)	(0.120)
common currency	0.083***	1.156***	0.934***	0.744*
	(0.026)	(0.051)	(0.322)	(0.409)
common language	0.687***	0.864***	1.008***	1.198***
	(0.030)	(0.018)	(0.023)	(0.030)
GATT/WTO (origin)	0.048	0.059***	-0.381***	-0.298***
	(0.046)	(0.017)	(0.054)	(0.022)
GATT/WTO (destination)	0.285***	0.259***	0.088***	-0.399***
	(0.039)	(0.017)	(0.016)	(0.062)
ln (out-closeness centrality)	2.287***	5.995***	4.414***	5.416***
	(0.153)	(0.072)	(0.163)	(0.089)
Constant	5.966***	12.31***	6.992***	5.090***
	(0.165)	(0.136)	(0.174)	(0.205)
Observations	19,036	126,861	61,250	58,007
R-squared	0.858	0.563	0.728	0.678

Notes: Standard errors in parentheses. ***, **, and * denote 1, 5, and 10 percentages of significance levels, respectively.

Table 3.14: Out-Eigenvector Centrality and Exports

ln (export)	1-1	0-0	1-0	0-1
ln (weighted distance)	-1.010***	-1.227***	-1.207***	-0.676***
	(0.008)	(0.009)	(0.012)	(0.015)
ln (origin GDP per capita)	0.919***	0.981***	1.266***	0.936***
	(0.011)	(0.006)	(0.010)	(0.008)
ln (destination GDP per capita)	0.829***	0.703***	0.873***	1.055***
	(0.010)	(0.005)	(0.005)	(0.013)
ln (origin population)	0.849***	0.959***	1.128***	0.932***
	(0.007)	(0.008)	(0.007)	(0.010)
ln (destination population)	0.778***	0.976***	1.013***	1.348***
	(0.006)	(0.006)	(0.006)	(0.008)
ln (origin area)	0.017***	-0.078***	-0.104***	-0.046***
	(0.006)	(0.005)	(0.005)	(0.006)
ln (destination area)	0.033***	-0.186***	-0.152***	-0.267***
	(0.006)	(0.005)	(0.004)	(0.007)
contiguity	0.532***	1.420***	1.325***	2.438***
	(0.032)	(0.039)	(0.095)	(0.120)
common currency	0.122***	1.199***	0.706**	0.647
	(0.026)	(0.052)	(0.323)	(0.411)
common language	0.690***	0.858***	0.997***	1.255***
	(0.030)	(0.018)	(0.023)	(0.030)
GATT/WTO (origin)	0.289***	0.224***	0.168***	-0.270***
	(0.043)	(0.018)	(0.050)	(0.022)
GATT/WTO (destination)	0.355***	0.255***	0.099***	-0.199***
	(0.040)	(0.017)	(0.017)	(0.062)
ln (out-eigenvector centrality)	0.864***	1.705***	0.811***	2.495***
	(0.123)	(0.038)	(0.123)	(0.044)
Constant	6.922***	13.72***	6.703***	9.137***
	(0.348)	(0.183)	(0.360)	(0.241)
Observations	19,036	126,861	61,250	58,007
R-squared	0.857	0.546	0.725	0.676

Notes: Standard errors in parentheses. ***, **, and * denote 1, 5, and 10 percentages of significance levels, respectively.

3.6.2 GVCs and ITN

In this section, we analyze the relationship between GVC participation and ITN. We have two GVC participation variables, forward and backward participations. We have also several network indices, out-degree centrality, in-degree centrality, clustering coefficient, hub centrality or authority centrality. We first present the regression results for out-degree centrality and clustering coefficient since these metrics have naturally opposite behaviors and we would like to interpret their results by making a comparison. Then, we explain the estimation results for the other centralities; in-degree, hubs and authorities.

Table 3.15 reports the results for out-degree centrality in the first two columns and those for the clustering coefficient in the last two columns. Not surprisingly, trade weighted distance reduces out-degree centrality. Besides income, population, and GATT/WTO memberships have positive and being landlocked has negative and significant signs. We do not find significant results for area and the EU membership. Our results indicate that countries having higher forward participations tend to have fewer outward links. Unlike forward participation, countries with higher backward participation have more export partners.

The estimated coefficients on the country specific properties and the trade weighted distance take mostly the opposite signs in the regressions in the columns 3 and 4 compared to the first two columns. For example, the clustering coefficient is positively associated with the weighted distance in both columns. We can comfortably claim that distance is an influential driver of countries' making more clustered trade connections. Unlike out-degree centrality, we observe a positive relationship with forward participation, whereas it is negatively associated with backward participation. Fracasso et al. (2018) employ multilateral measure of distance and find a negative effect on out-degree centrality, which is in line with our results of trade weighted distance. The finding of a positive relationship between output and out-degree centrality is also similar with this study.

Our overall estimations suggest that the nature of an association between GVC participation and trade network differs according to the type of network metrics employed. Countries with higher forward participation are more likely to have lower out-degree centrality and higher clustering coefficient, which means fewer outward but more clustered links. We have also the exact reverse of these results for the

backward participation. This is probably because countries might have different incentives to take more partnership links or concentrating on more clustered trade connections.

Table 3.15: GVC Participations and Network Measures

Variables	ln (out-degree centrality)		ln (clustering coefficient)	
	(1)	(2)	(3)	(4)
ln (forward participation)	-0.071** (0.027)		0.029** (0.014)	
ln (backward participation)		0.107*** (0.02)		-0.09*** (0.01)
ln (weighted distance)	-0.069** (0.03)	-0.047* (0.028)	0.045*** (0.015)	0.023* (0.013)
ln (GDP per capita)	0.114*** (0.011)	0.109*** (0.011)	-0.084*** (0.006)	-0.08*** (0.005)
ln (area)	-0.009 (0.009)	-0.006 (0.009)	0.008 (0.005)	0.003 (0.005)
ln (population)	0.142*** (0.012)	0.146*** (0.012)	-0.096*** (0.006)	-0.098*** (0.006)
Landlocked dummy	-0.065* (0.037)	-0.076** (0.037)	0.02 (0.017)	0.028* (0.016)
GATT/WTO dummy	0.2*** (0.04)	0.202*** (0.039)	-0.076*** (0.018)	-0.077*** (0.015)
EU dummy	0.043 (0.043)	-0.015 (0.042)	-0.058*** (0.021)	-0.014 (0.019)
Constant	-1.116*** (0.285)	-1.851*** (0.293)	-0.939*** (0.147)	-0.371** (0.149)
Number of observations	3473	3473	3473	3473
R-squared	0.724	0.737	0.799	0.832

Notes: Clustered robust standard errors are in parentheses. Year dummies are included in the model, but they are not represented here. ***, **, and * denote 1, 5, and 10 percentages of significance levels, respectively.

When we evaluate these results along with the architecture of GVCs, we can obtain a clearer picture. Regarding the current algorithm of GVC revolution, in general, Multinational Enterprises (MNEs) engage in production sharing or outsourcing. The sub-stages of production are performed in various countries, which

leads to the fact that the bulk of the global trade is in intermediate goods. By the forward participation, countries seek to spread production efficiently, which means more durable relationship along value chains. This may cause more clustered destination locations by fewer trade links, instead of fully spreading production across countries. The organization of GVCs driven by MNEs thus imply the clustering role of forward participation. Furthermore, at the end of production process, many countries where final assembly occurs generally sell these products to everywhere in the world. In other words, foreign value added in domestic exports, namely higher backward participation led to more trade links and inherently less clustering. These are fully in line with our analysis results.

We also report the regression results for other network measures, in-degree centrality, hubs centrality and authority centrality in Table 3.16. As we define before, in-degree centrality is calculated by the import links of the country, whereas out-degree is about the export links. And here, we have similar results for in-degree centrality with out-degree centrality, in terms of backward participation, weighted distance and other geographical variables, GDP per capita, the GATT/WTO and EU dummies. However, the coefficient of forward participation is negative but insignificant, which differs from the results of out-degree centrality. The backward participation of the country positively affects the in-degree centrality. Since the backward participation is defined as foreign value-added in domestic exports, positive relationship between backward participation and in-degree centrality shows that countries having more foreign value-added shares tend to have more import partners.

In the international trade literature, the term “hub” is usually referred to the country that imports large amounts of raw materials and intermediate goods and export them to the other countries after assembling (Deguchi et al., 2014). In the network theory, hub and authority centralities are calculated with mutual recursion, by employing HITS algorithm. We can simply explain that a hub with high score links to many high-scored authorities, and an authority with high score is linked by many high-scored hubs.

Table 3.16: GVC Participations and Network Measures

Variables	ln (in-degree centrality) ln (hub centrality) ln (authority centrality)					
	(1)	(2)	(3)	(4)	(5)	(6)
ln (forward participation)	-0.010 (0.025)		-0.354** (0.147)		-0.272** (0.119)	
ln (backward participation)		0.114*** (0.022)		0.096 (0.112)		0.399*** (0.087)
ln (weighted distance)	-0.071*** (0.023)	-0.042* (0.022)	0.326*** (0.118)	0.320** (0.123)	-0.075 (0.071)	0.007 (0.079)
ln (GDP per capita)	0.096*** (0.009)	0.091*** (0.009)	1.161*** (0.061)	1.159*** (0.063)	0.946*** (0.046)	0.930*** (0.044)
ln (area)	-0.007 (0.006)	0.001 (0.006)	0.055 (0.047)	0.035 (0.047)	-0.092*** (0.033)	-0.082*** (0.030)
ln (population)	0.108*** (0.008)	0.109*** (0.008)	0.979*** (0.054)	0.997*** (0.055)	0.950*** (0.040)	0.963*** (0.038)
Landlocked dummy	-0.057 (0.038)	-0.065* (0.035)	-0.332* (0.169)	-0.360** (0.169)	-0.254* (0.136)	-0.297** (0.134)
GATT/WTO dummy	0.192*** (0.036)	0.192*** (0.034)	0.306* (0.180)	0.312* (0.181)	0.050 (0.126)	0.055 (0.125)
EU dummy	0.013 (0.031)	-0.039 (0.029)	-0.065 (0.198)	-0.161 (0.208)	0.008 (0.136)	-0.209 (0.147)
Constant	-1.071*** (0.226)	-1.743*** (0.255)	-19.178*** (1.314)	-20.312*** (1.450)	-12.556*** (0.715)	-15.306*** (0.896)
Number of observations	3473	3473	3473	3473	3473	3473
R-squared	0.67	0.697	0.862	0.86	0.915	0.921

Notes: Clustered robust standard errors are in parentheses. Year dummies are included in the model, but they are not represented here. ***, **, and * denote 1, 5, and 10 percentages of significance levels, respectively.

Our regression results regarding hubs and authorities are important since we examine their relationship with GVC participations. For the hub centrality, we find negative association with forward participation, and insignificant result for backward participation. That means if the value-added share of a country in other countries' export increases, it's hub score decreases. Some countries participate in global value chains and act like a hub in international trade. This means that they especially import intermediate goods and raw materials and export them as a final good. If we evaluate this fact with our results, we can argue that countries with higher forward participations would gradually abandon its role as a hub in international trade.

The results for the authority centrality are also interesting. The forward participation is negatively linked with the authority centrality, whereas the backward participation and authority centrality are positively associated. Countries participating more in other countries' exports in terms of value-added have less authority score, whereas countries having much foreign value-added in domestic exports has more authority score, according to our regression results. We expect the opposite results because countries with higher authority scores have also high forward participations in GVCs. However, an increase in forward participation might not be associated with high authority for all countries. For instance, if a country's forward participation increases as a result of natural resource exports, the authority score of that country probably does not increase. Thus, for both forward and backward participations, evaluating with disaggregated sectors would give us a better insight when we interpret their relationship with authority centrality.

3.7 Conclusion

In this chapter, we begin with defining the basic concepts of network theory, and then we make two applications related with trade network. For the first analysis, we combine gravity, network, and trade datasets from the CEPII, and we employ country-specific properties and network indices to explain the dynamic changes in the ITN. We also separate our data into developed and developing countries to observe the differences between the groups of countries. By using the gravity model with the network indices, we first analyze the factors affecting export volumes for all countries, and then for the flows between developed and developing countries.

When we look at the trade flows for all countries, we find that centrality measures, which are out-degree, out-strength, out-closeness, and out-eigenvector centrality, significantly raise countries' bilateral trade. These measures are related to the position of the countries in the network. Thus, countries with high centralities are more likely to have higher trade volumes than the others have. We re-run the regressions for the four sub-group of countries and evaluate the differences when the flow is from a developed or a developing country. Our results show that apart from developed countries, developing countries with high centrality measures tend to have higher trade volumes.

In our second econometric analysis in this chapter, we examine the relationship between GVC participation and the network characteristics of the countries, by combining very large datasets from the CEPII and EORA MRIO. For this purpose, using the data from 1995 to 2015 for 174 countries, we first calculate out-degree centrality, in-degree centrality, clustering coefficient, hub and authority centralities as network indices, and forward and backward participations in GVCs as value added trade shares. We then evaluate the impact of GVC participation on the international trade network.

Our overall findings indicate that the value-added trade shares of countries are significantly associated with their positions in the ITN. Our estimation results imply that the nature of the relationship differs for the types of participations. Higher forward participation stands for a decrease in the number of the outward trade connections and leads to more clustered trade network. On the contrary, an increase in backward participation implies higher out-degree centrality and lower clustering coefficient, which means more outwards links but less clustered trade connections.

We also report the regression results for in-degree centrality, hub centrality, and authority centrality. Forward participation has the negative link with hub and authority centralities, whereas has no significant relation with in-degree centrality. Backward participation has the positive association with in-degree and authority centrality, and the insignificant coefficient in the regression with hub centrality.

We argue that exploring the background of GVCs may provide us better understanding of the results of our study. In the production stages of intermediate and final goods, the way in which countries' forward and backward participations to GVCs differs. In accordance with our analysis, the differing relationship between GVC participation and five types of network indices can be validated when we think of the

architecture of the GVCs. Thus, regarding the nexus between trade network and GVC participation is a substantial effort to understand the contemporary nature of global trade flows.

In the light of relevant literature and our empirical results, we suggest that policies should be designed not only by considering participation indices, but also their associations with trade network indices for countries to efficiently integrate to the global value chains. For further research, since the complexity of products and whether countries and industries participate in high value-added activities such as conception and design can be assessed by the GVC length and upstreamness measures, it would be a worthwhile effort to evaluate their impacts on trade network.



4. DOMESTIC TRADE AND GROWTH IN TURKISH PROVINCES: A SPATIAL APPROACH

4.1 Introduction

Spatial economics mainly deals with the location of the economic activities. In the literature, this branch of economics is mostly attributed to “Location Theory” of Thünen (1826). According to Fujita (2010), the evolution of spatial economics starts from Thünen to the New Economic Geography (NEG). Blaug (1985) states that Thünen was the first researcher who analyses economic subjects related with space by a spatial analysis perspective. In his book “The Isolated State”, Thünen attracts attention on the effects of distance and area on the economic activities. The theory of location is based on transportation costs of the factors of production.

There are number of studies involved in location theory especially in Germany after Thünen. However, Fujita (2010) claims that the works of Walter Isard switched the center of the spatial economics from Germany to the United States in 1950s. Space component had usually ignored in the neoclassical economy and traditional international trade theories. Isard (1949) argues that the trade theory and general theory of location and space-economy are equivalent terms. Isard’s “General Location Theory” and later works are regarded as the part of the Regional Science discipline.

Although there are lots of efforts made in economic geography literature, spatial aspects remained as a small part in the mainstream economics until 1990s. Krugman (1991) tries to reconsider economic geography bearing in mind that the new models and techniques of the industrial organization theory. Krugman’s theory is named as “New Economic Geography”, and it defines the spatial structure of the economy based on industrialized “core” and agricultural “periphery”. Krugman (1998) and Fujita and Krugman (2004) are two of the works about the evolution of NEG. Moreover, there are some other efforts about this subject such as Martin (1999) and Garretsen and Martin (2010).

Although using location of economic activities in the literature dates to Thünen and continues with regional science and new economic geography, spatial

econometrics is relatively new term in economics. Anselin (2010) claims that the first comprehensive work in this area is Paelinck and Klaassen (1979). Three stages - preconditions, take off and maturity- are defined for the 30-years history of spatial econometrics in Anselin (2010). The author argues that spatial econometrics has reached to the maturity stage at the beginning of the twenty-first century.

In this thesis, previous two chapters are primarily related with the international trade. The gravity model in the second chapter investigates the trade flows regarding partners' distance and geographical characteristics. And the network model in the third chapter relates with the trade links that the countries form. Unlike these two chapters, instead of analyzing foreign trade we mainly deal with domestic trade in this chapter. Our main aim is to discover how spatial interactions affect the economic growth of the provinces within a country. Employing spatial econometric methods, we find that both neighborhood and trade interactions are effective on economic growth of Turkish provinces.

This chapter is structured as follows. The following section briefly reviews the literature. Section 4.3 presents the data we employ in this chapter, then displays related tables and figures. Section 4.4 explains the estimation methodology. Section 4.5 reports the empirical results. And final section discusses the results.

4.2 Literature Review

We introduce the gravity model of trade in the second chapter. This model basically examines the implications of distance on trade. So, our assumption is the geography of the economic units matters in their interaction. The gravity model successfully explores the trade flows between countries or regions in various ways. However, employing spatial econometrics in the economic geography and regional science literature may provide better understanding for these interactions. Anselin and Bera (1998) provide a review of methods concerning spatial dependence in linear regression models, and Gibbons and Overman (2012) discuss the identification problems in applied spatial economic research.

According to Fotheringham and Webber (1980), the interaction in the fundamental gravity model is composed of masses and distances. However, they claim that employing spatial structure might result in accurate estimates for the parameters of the gravity model. Fotheringham and O'Kelly (1989) provide detailed formulations

and applications of spatial interaction models. Anselin and Griffith (1988) also argue that incorporating spatial effects to the econometric analysis of regional science and geography would prevent measurement problems in regressions. Another theoretical contribution modelling spatial distribution of economic activity, Rossi-Hansberg (2005), finds consistent results with the gravity equation. The developments in the literature of spatial econometrics provide newer insights for scholars studying trade models.

Porojan (2001) accounts spatial effects into gravity model to test the empirical performance. Unlike the traditional approach, employing spatial specification brings that trade flows are wrongly estimated, and trade blocs do not have large explanatory power. LeSage and Fischer (2008) extend the gravity model used for explaining origin destination flows of trade, transportation, and migration, suggesting spatial dependence. In a newer contribution, Allen and Arkolakis (2019) claim that the gravity model is a significant element of the spatial theory for understanding the effects of space on economic growth and economic activities. Conducting an empirical model of interstate highway network, they argue that the mobility of goods and labor across the country can be modelled in spatial structure.

In the third chapter, we undertake the application of network analysis in the international trade. In these types of models, the interactions of the economic agents are evaluated in a system of network. We discuss the related literature utilizing distance-based specifications like gravity model in the network analysis. Besides, some other works in the geography literature involve in location-based analysis, gathering the spatial structure analysis and topological properties. The book “Network Analysis in Geography” is one of the first efforts employing network analysis in space (Haggett and Chorley, 1969). The interaction between economic units at the regional level can also be analyzed in a network structure. Van den Bergh and Nijkamp (1996) use multiregional and spatial price equilibrium models to formulate externalities in networks of commodity flows which take place in space by physical transport.

Barthelemy (2011) is a comprehensive review for spatial networks, in which nodes and edges of the graph are embedded in space. In this work, various models and empirical applications of networks related with space like transportation, internet, social, and neural network are discussed. When we deal with trade, transportation costs, which is associated with the infrastructure, gain importance. Fajgelbaum and

Schaal (2020) build up a framework and apply it to the European road network to indicate the connection of infrastructure and transport network in spatial equilibrium.

We discuss the spatial econometrics literature especially related with the gravity model and network analysis thus far. Since trade is about interaction of countries or regions, spatial models successfully explore these kinds of flows. Another strand of the literature focuses on subjects such as agglomeration economies, and firm or industry level productivity, inequalities and convergence in regional level, economic growth, and trade. These subjects are attracted more attention by the scholars thanks to large spatial datasets, which becomes widespread. Understanding exactly the differences of the countries, regions, or cities may offer us a better picture of economic growth and development by a spatial point of view.

Venables (2005) relates development with changing spatial disparities between regions and becoming more export oriented large industrial clusters in developing countries. Einio and Overman (2016) find that the displacement effects of spatially targeted interventions in disadvantaged areas of UK decreases after the program ends. Using the firm and plant-level French data for the years between 1996 and 2004, Martin et al. (2011) examine the impacts of spatial agglomeration on firm productivity. They discover that productivity gains resulted from geography is not much in the short run.¹⁹

Lastly, this chapter especially focuses on the spatial economics literature, which concerns the economic growth effects. Studies such as Abreu et al. (2004), Gallo and Ertur (2005), Yildirim et al. (2009), Hering and Poncet (2010), Akçagün (2017) deals with the convergence and growth affected by the geography. Other works including Ho et al. (2013), Alaya (2020), Amidi and Majidi (2020) investigate the spatial relationship between international trade and economic growth. Our work contributes to this literature by analyzing the spatial effects of trade on economic growth in regional level by employing domestic trade data.

¹⁹ See Fazio and Piacentino (2010), Ahlfeldt and Feddersen (2018), and Rosenthal and Strange (2020) for other efforts related with spatial effects on productivity.

4.3 Data

In this chapter, we employ three different types of datasets. Firstly, demographic and macroeconomic variables such as population and GDP per capita are collected from the Turkish Statistical Institute (Web 3, 2022) while public investment data is gathered from the Presidency of Strategy and Budget of Turkey (Web 4, 2022). Public investment data is consisting of starting allowance of investment program provided by the government. Secondly, we utilize domestic trade dataset of the Enterprise Information System (EIS), from the Ministry of Industry and Technology of Turkey (Web 5, 2022). And lastly, we make use of spatial dataset (shapefiles) in our econometric analysis from Database of Global Administrative Areas (GADM) website (Web 6, 2022).

Table 4.1 represents the descriptive statistics for our demographic and macroeconomic variables. We include level forms of the variables with natural logarithms. Our dataset is consisted of 81 provinces of Turkey for the years between 2006 and 2019. However, we also use 2005 population data to calculate population growth of the year 2006, and 2005 GDP per capita data when evaluating the previous years' values. We assume the sum of g (the growth rate of technology) and δ (the depreciation rate of capital) as 0.05.²⁰ Since the dataset in this analysis consists of province-level data, unfortunately we do not have capital accumulation data in this level. Instead, we incline to utilize public investment data. Both GDP per capita and investment variables are in Turkish Liras and deflated by 2009 constant GDP deflator.

Table 4.1: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
$\ln(n+g+\delta)$	1134	-1.843	0.123	-3.17	-1.162
$\ln(\text{GDP per capita})$	1134	9.431	0.448	8.141	10.805
$\ln(\text{GDP per capita (t-1)})$	1134	9.356	0.442	8.141	10.713
$\ln(\text{Investment})$	1134	11.682	1.05	7.679	15.775

Our domestic trade dataset is the aggregate version of firm and regional level confidential dataset, the EIS. This dataset originally integrates datasets from Social Security Institution, the Ministry of Treasury and Finance, the Ministry of Trade, the

²⁰ We use log transformation by adding 0.1 to $(n+g+\delta)$, so that we avoid negative natural logarithmic values.

Scientific and Technological Research Council of Turkey, the Turkish Patent and Trademark Agency, Small and Medium Enterprises Development and Support Administration, and the Turkish Statistical Institute. We employ the aggregate domestic trade dataset, which consists of interprovincial and cross-industry trade. Table 4.2 defines the main industry codes in domestic trade dataset. We also provide province names and codes in Appendix E.

Table 4.2: Industry Codes

Code	Industry
1	Agriculture, Forestry and Fishing
2	Mining and Quarry
3	Manufacturing
4	Generation and Distribution of Electricity, Gas, Steam and Air Cond.
5	Construction
6	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles
7	Transport and Storage
8	Accommodation and Food Service Activities
9	Information and Communication
10	Finance and Insurance Activities
11	Real Estate Activities
12	Professional, Scientific and Technical Activities
13	Administrative and Support Service Activities
14	Human Health and Social Work Activities

In spatial econometrics analysis, we utilize ‘shapefiles’ containing coordinates and other spatial characteristics for a specified geographical region, such as world, country, and province. In this chapter, since we deal with Turkey, we employ province-based country shapefiles from GADM. We import related files to STATA to perform our empirical analysis concerning geographical effects and economic growth.

Before performing spatial econometric analysis in the next sections, we present various descriptive tables, figures and maps illustrating the domestic trade interactions in Turkey, both in province and industry levels. Our dataset not only includes trade data between provinces and industry, but it also contains within transactions. By picking the first and last years of our dataset, 2006 and 2019, we observe that in terms of total trade²¹ top 5 provinces are identical: İstanbul, Ankara, İzmir, Kocaeli, and Bursa.

²¹ Total trade refers to all transactions from a province to another plus within province trade.

Then, in Table 4.3, we demonstrate top 10 domestic trade volumes between provinces, for the years 2006 and 2019.²² In the (a) part of the table, we see that within province trade in İstanbul is the largest trade for both years. We also observe a tremendous increase in 14 years in terms of trade, for the same connections. If we remove the trade within provinces, we get the (b) part of the table. Again, most of the trade is originated from İstanbul.

Table 4.3: Domestic Trade between Provinces

a) Trade within province included

2006			2019		
origin	destination	volume	origin	destination	volume
İstanbul	İstanbul	246	İstanbul	İstanbul	1141.3
Ankara	Ankara	27.2	Ankara	Ankara	176.9
İstanbul	Ankara	24.9	İstanbul	Ankara	112.6
İzmir	İzmir	18.8	Kocaeli	İstanbul	102.2
Kocaeli	İstanbul	18.4	Ankara	İstanbul	101.0
Ankara	İstanbul	17.0	İzmir	İzmir	84.5
İstanbul	İzmir	14.6	İstanbul	İstanbul	57.2
Bursa	Bursa	12.1	Bursa	Bursa	56.0
İzmir	İstanbul	9.5	İstanbul	İzmir	53.7
İstanbul	Bursa	9.3	Bursa	İstanbul	41.6

b) Trade within province not included

2006			2019		
origin	destination	volume	origin	destination	volume
İstanbul	Ankara	24.9	İstanbul	Ankara	113
Kocaeli	İstanbul	18.4	Kocaeli	İstanbul	102
Ankara	İstanbul	17.0	Ankara	İstanbul	101
İstanbul	İzmir	14.6	İzmir	İstanbul	57.2
İzmir	İstanbul	9.5	İstanbul	İzmir	53.7
İstanbul	Bursa	9.3	Bursa	İstanbul	41.6
Bursa	İstanbul	9.0	İstanbul	Kocaeli	40.5
İstanbul	Kocaeli	8.9	İstanbul	Bursa	38.6
İstanbul	Antalya	5.6	İstanbul	Antalya	25.7
İstanbul	Adana	4.1	İstanbul	Gaziantep	19.2

We present a map of the total trade volumes of the provinces in Turkey in Figure 4.1. We both include within and between province trade data when calculating these

²² All values are in billion Turkish Liras and deflated with 2009 GDP deflator.

volumes. The maps are for the years 2006 and 2019, respectively. These values are in terms of deflated 2009 constant Turkish Liras. In both maps, we have four ranges and darker colors indicates the range with higher trade volumes. The highest trade volume range is 2.5 billion to 377 billion Turkish Liras in 2006, whereas it is between 18.7 billion and 1.69 trillion in 2019. We observe that trade volumes of the provinces increase in 13 years, however, most of the provinces remains in the same range.

In Table 4.4, we list the total trade volumes, out-degree and weighted out-degree centralities of first and last 10 provinces in terms of weighted out-degree centralities in Turkey for the year 2019. Total trade volumes are deflated with 2009 Turkish Liras and weighted out-degree values are total trade weighted versions of out-degree centralities. Both out-degree and weighted out-degree centralities are calculated by the Gephi software (Web 2, 2022), a representation tool for graphs and networks. We also generate domestic trade network in Turkey in Figure 4.2 and trade network of industries in Turkey in Figure 4.3 with the same software.

Total trade in Table 4.4 is the total trade flows from an origin province to all destination provinces, and we do not include the trade within the province. We observe that İstanbul has more than 4.5 times trade flows than its successor, Ankara, has in 2019. The top 10 provinces have out-degree centrality of 1, which means they are connected to all other 80 provinces. Some provinces in the last 10, such as Sinop, Bingöl, Iğdır, and Kars, have out-degrees higher than 0.9. However, since they face very low trade flows, their weighted out-degree centralities are more than 100 times lower than the top 10 provinces.

When generating domestic trade network in Turkey in Figure 4.2, we represent the node circle size proportional with the provinces' weighted out-degrees. We locate the top 10 provinces in Table 4.4 to be close to each other, and the other provinces to the right-hand side of the graph. Note that the positions of the provinces in the trade network are not their exact geographical location.

Table 4.4: Total Trade, Out-degree and Weighted Out-degree Centralities (2019)

Rank	Province	Total Trade	Out-degree	Weighted Out-Degree
1	İstanbul	1.69×10^{12}	1	5.53×10^{11}
2	Ankara	3.69×10^{11}	1	1.92×10^{11}
3	Kocaeli	1.66×10^{11}	1	1.38×10^{11}
4	İzmir	1.99×10^{11}	1	1.15×10^{11}
5	Bursa	1.27×10^{11}	1	7.11×10^{10}
6	Gaziantep	7.49×10^{10}	1	3.45×10^{10}
7	Adana	4.84×10^{10}	1	3.16×10^{10}
8	Konya	6.00×10^{10}	1	3.11×10^{10}
9	Antalya	5.99×10^{10}	1	2.81×10^{10}
10	Hatay	4.07×10^{10}	1	2.80×10^{10}
...				
72	Sinop	7.83×10^8	0.99	5.73×10^8
73	Bingöl	1.04×10^9	0.93	5.71×10^8
74	Iğdır	7.29×10^8	0.95	4.58×10^8
75	Kars	6.21×10^8	0.94	3.75×10^8
76	Hakkari	6.78×10^8	0.79	3.64×10^8
77	Kilis	4.70×10^8	0.81	3.39×10^8
78	Gümüşhane	3.19×10^8	0.89	2.19×10^8
79	Tunceli	2.81×10^8	0.79	2.11×10^8
80	Bayburt	1.48×10^8	0.76	9.21×10^7
81	Ardahan	1.13×10^8	0.74	6.61×10^7

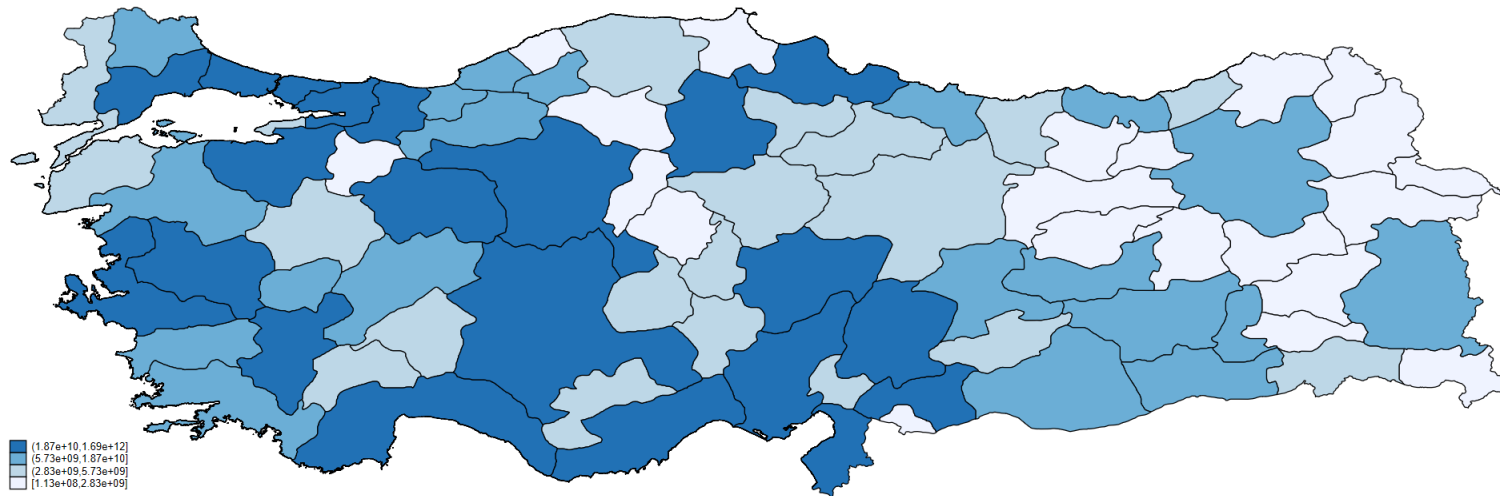
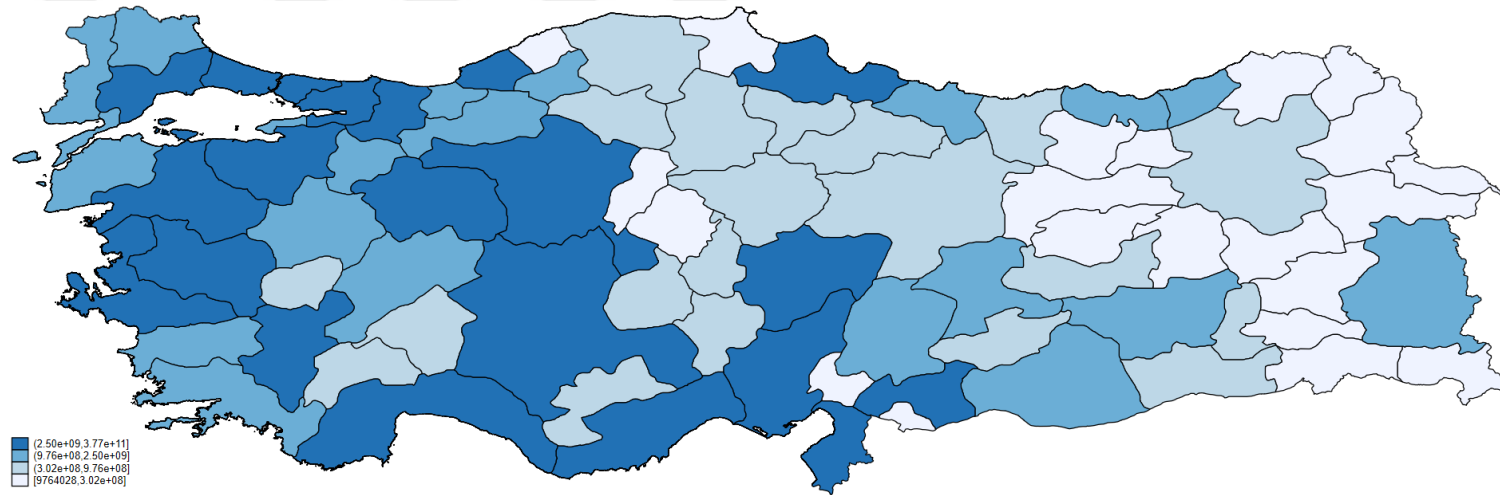


Figure 4.1: The Map of Total Trade Volumes for Turkey (2006 and 2019)

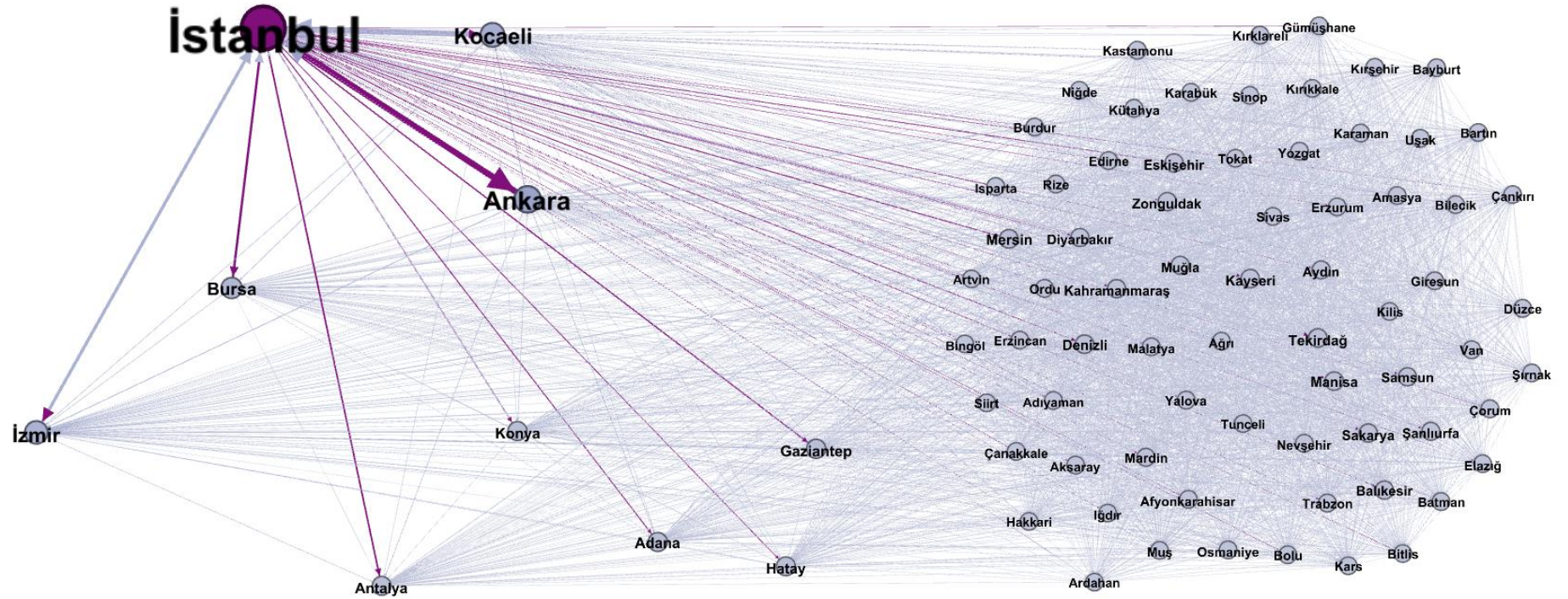


Figure 4.2: Domestic Trade Network in Turkey (2019)

Similar to trade flows between provinces, we show the trade volumes²³ of industry in Table 4.5. We use the specified codes of industries shown in Table 4.2. For both years 2006 and 2019, Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles (code: 6) and Manufacturing (code: 3) industries have the largest trade volume between them and within each other.

Table 4.5: Domestic Trade between Industries

(a) Trade within industry included

2006			2019		
origin	destination	volume	origin	destination	volume
6	6	171	6	6	864
3	6	144	3	6	620
3	3	98.7	3	3	393
6	3	60.5	6	3	285
6	5	13.5	4	4	88.4
4	4	12.5	5	5	83.7
5	5	10.2	6	5	74.3
7	3	10.1	7	7	61.3
3	5	10	4	10	46.4
7	4	9.03	6	7	45.5

(b) Trade within industry not included

2006			2019		
origin	destination	volume	origin	destination	volume
3	6	144	3	6	620
6	3	60.50	6	3	285
6	5	13.50	6	5	74.30
7	3	10.10	4	10	46.40
3	5	10.00	6	7	45.50
7	4	9.03	10	4	42.60
6	7	8.87	7	3	40.60
9	6	6.89	3	5	39.70
7	6	5.42	7	6	32.00
5	3	4.59	6	8	27.70

²³ All values are in billion Turkish Liras and deflated with 2009 GDP deflator.

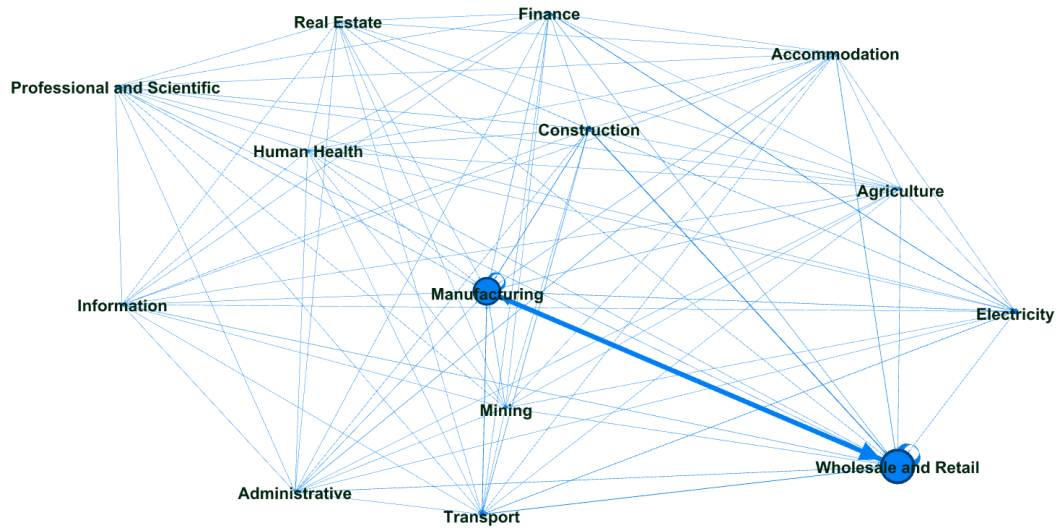


Figure 4.3: Trade Network of Industries in Turkey (2019)

In Figure 4.3, we demonstrate trade flows among industries as a trade network, including within industry trade. Node and edge size in the network are proportional with trade volume in the figure. Since the highest trade volume is for the within industry trade of wholesale and repair industry, we observe that its node and edge size are the highest in the network.

4.4 Methodology

Our main purpose in this chapter is to show how the geographic positions of the provinces and their trade interactions within country affect their economic growth. We employ spatial econometric techniques to analyze the determinants of economic growth within the country. The provincial data enables us to grasp a clearer picture for this. Before performing spatial analysis, we ought to produce spatial weight matrices. These specified spatial weight matrices are related with the relationship between these units. In the spatial economics literature, distance or contiguity are often used for weighting.

Apart from distance and contiguity parameters, we also employ domestic trade data for spatial weighting in this chapter.²⁴ For the distance and contiguity parameters, we employ province-level spatial data for Turkey. We begin with constructing distance

²⁴ All three types of weight matrices are row normalized.

based spatial weight matrices. The distances are calculated by the coordinates of the provinces, and these data are obtained from shapefiles. We use 5 distance bands for Turkey, 0-2, 2-4, 4-6, 6-8, and 8-10, and construct spatial weight matrices for each band. Note that, the distance specified in these bands is inverse distance and equivalents in kilometers are as follows. The distance band limits 0, 2, 4, 6, 8, and 10 are equal to 0, 192, 384, 576, 768, and 960 in kilometers, respectively.

After constructing weight matrices, we demonstrate the Moran's I test results of distance-based weight matrices in Table 4.6, which are used to measure global spatial autocorrelation. We employ three different measures to find the spatial dependence of the provinces in terms of economic growth: the growth of per capita GDP for the year 2019, the mean growth value per capita GDP for 2006-2019, and the natural logarithm of the mean growth per capita GDP for the years between 2006-2019. The idea behind employing different growth measures is to test whether the results are consistent. The significantly positive Moran's I value for the distance bands in the table indicates the existence of spatial autocorrelation.

Table 4.6: Moran's I Tests for Distance Based Spatial Weight Matrices

a) Growth measure: the growth of per capita GDP, for the year 2019.

Distance band	I	E(I)	sd(I)	z	p-value
0<d<=2	0.220	-0.013	0.057	4.073	0.000
2<d<=4	0.126	-0.013	0.033	4.203	0.000
4<d<=6	0.011	-0.013	0.036	0.652	0.257
6<d<=8	-0.038	-0.013	0.040	-0.644	0.260
8<d<=10	-0.073	-0.013	0.047	-1.301	0.097

b) Growth measure: the growth of per capita GDP, mean value for 2006-2019.

Distance band	I	E(I)	sd(I)	z	p-value
0<d<=2	0.232	-0.013	0.058	4.245	0.000
2<d<=4	0.255	-0.013	0.033	8.039	0.000
4<d<=6	0.036	-0.013	0.037	1.326	0.092
6<d<=8	0.006	-0.013	0.040	0.456	0.324
8<d<=10	-0.106	-0.013	0.047	-1.963	0.025

Table 4.6: (continued)

c) Growth measure: $\ln$ (growth of per capita GDP), mean value for 2006-2019.

Distance band	I	E(I)	sd(I)	z	p-value
$0 < d \leq 2$	0.218	-0.013	0.058	3.985	0.000
$2 < d \leq 4$	0.235	-0.013	0.032	7.426	0.000
$4 < d \leq 6$	0.029	-0.013	0.037	1.120	0.131
$6 < d \leq 8$	0.013	-0.013	0.041	0.637	0.262
$8 < d \leq 10$	-0.094	-0.013	0.047	-1.726	0.042

Moreover, by the help of Moran's I test, we can select appropriate distance bands for spatial weighting, which are used in spatial analysis. To do so, we first evaluate z and p-values for each growth measure. Then, within the statistically significant rows, we select the distance band with the maximum z value. We get maximum of 4.203, 8.039 and 7.426 z values among statistically significant distance bands, for (a), (b), and (c) parts respectively. Thus, for each growth measure, $2 < d \leq 4$ distance band is the appropriate one. When we perform the spatial analysis with distance based spatial weights, provinces in these ranges can be regarded as spatially dependent in terms of economic growth.

In our empirical analysis, apart from distance-based weight matrices, we also use the spatial weights gathered from contiguity of the provinces, and the average bilateral trade volumes between them. Similar with distance, contiguity matrix is obtained from spatial data. In the contiguity weighted matrix, $w_{ij} = 1$ if the provinces share a common border and $w_{ij} = 0$ if they are not neighbors. Since the contiguity is constant in the years between 2006 and 2019, we create one contiguity matrix. However, trade volumes differ by years. Ho et al. (2013) employ a time-varying bilateral trade spatial weight matrix. Following Ertur and Koch (2011), which takes the average imports over the 10-year period to prevent endogeneity problems, we take the 14-years average (2006-2019) bilateral trade volumes between the provinces to obtain a single spatial weighting matrix. We neglect trade within provinces and deflate the trade volumes between the provinces by 2009 GDP deflator.

Our spatial econometric methodology is a type of empirical growth model with spatial autoregressive term, based on Ho et al. (2013). We modify this specification as

follows and perform our estimations by the Spatial Durbin Model (SDM). We choose the SDM, since it also includes spatially lagged variable (W_x), which might clarify our research question regarding the economic growth relationship between the provinces better. We also adapt our model to frequently employed the Spatial Autoregressive Combined (SAC), Spatial Error Model (SEM), Spatial Autoregressive (SAR), and include their estimates below. The SAC Model works only with fixed effects, and we estimate both fixed and random effects for the SEM, SAR, SDM models.

$$\ln Y_{it} = \rho \sum_{j=1}^k w_{ij} \ln Y_{jt} + \gamma \ln Y_{i,t-1} + \beta_1 \ln(n_{it} + 0.05) + \beta_2 \ln I_{it} + \delta_i + \mu_t + u_{it}$$

In this model, all our variables are province level data. The dependent variable Y_{it} denotes provincial GDP per capita. $Y_{i,t-1}$ is the previous year's GDP per capita, and n_{it} is population growth rate. We assume $g + \delta$ as 0.05, in line with the economic growth literature. Investment variable (I_{it}) is the public investments instead of capital accumulation in traditional growth model. We include this variable since we have no capital accumulation data on provincial base. Spatial autoregressive term $\rho \sum_{j=1}^k w_{ij} \ln Y_{jt}$ estimates the spillover effect of economic growth of a province from its trade partner. We also include province δ_i and year μ_t dummies and error term u_{it} in the model.

4.5 Empirical Results

We first perform spatial econometric estimations by employing the Spatial Durbin Model (SDM). The number of the groups in the tables denotes the provinces, and our balanced panel length is 14, which denotes the years between 2006 and 2019. We test whether the growth of any province affected by the growth of its trade partners. We report the estimation results with both fixed and random effects for spatial weight matrices based on distance, contiguity, and bilateral trade between provinces. We also include the results of regressions employed by the Spatial Autoregressive Combined (SAC), Spatial Error Model (SEM), Spatial Autoregressive (SAR) in this section.

In Tables 4.7, 4.8 and 4.9, we have spatially lagged variable (W_x) estimates in SDM Model. These variables are for the partner provinces, which are the same

variables as the origin provinces, but they are weighted with spatial weight matrices. Spatially lagged variables exhibit the impact of neighboring provinces to the origin province. In both fixed and random effects, for all weight matrices we employ, one-year lagged growth rates have the positive effect on the growth, which is in line with the literature.

If we examine the estimations of spatially lagged (W_x) variables with random effects, we observe that the neighbor provinces' lagged growth has a negative association with the origin provinces' current growth. For the distance and trade weighted fixed effect estimations, we get the positive but insignificant results. If we employ contiguity weight matrix with fixed effects, we find the negative and significant effects, as in the regressions with random effects.

Public investment has the positive and significant coefficients in all forms of the SDM model estimations as we expect. However, the estimated coefficients on the investment are relatively small. Population has the negative and significant coefficients except the distance weighted regressions with fixed effects. Overall, we get similar results whatever the type of spatial weight matrix is used.

Finally, we examine spatial ρ values, which is the coefficient of spatial lag, to test the spatial dependence of the provinces. Given the positive and significant spatial ρ values for all three weights, we find significant spatial dependence in terms of economic growth. That is, the economic growth of a province is affected by its partners through the distance, contiguity, and trade linkages between them. Ho et al. (2013) report the positive effect through trade flows but no effect through distances, unlike our estimations. Thus, we conclude that the SDM model proves the positive effects of distance, neighborhood, and trade interaction on GDP per capita of the provinces.

Table 4.7: SDM Model with Distance Weight Matrix

Dependent variable: ln (GDP per capita)	Spatial Weight: Distance	
	Fixed Effects	Random Effects
ln (GDP per capita t-1)	0.683*** (0.022)	0.983*** (0.005)
ln (Investment)	0.004** (0.002)	0 (0.001)
ln (n+g+ δ)	-0.016 (0.011)	-0.027*** (0.01)
Constant		-0.042 (0.074)
Wx ln (GDP per capita t-1)	0.013 (0.084)	-0.676*** (0.038)
Wx ln (Investment)	0.008 (0.009)	-0.012*** (0.003)
Wx ln (n+g+ δ)	-0.141*** (0.035)	-0.015 (0.028)
Spatial ρ	0.238*** (0.074)	0.705*** (0.036)
Number of observations	1134	1134
Number of groups	81	81
Panel length	14	14

Notes: Standard errors are in parentheses. ***, **, and * denote 1, 5, and 10 percentages of significance levels, respectively.

Table 4.8: SDM Model with Contiguity Weight Matrix

Dependent variable: ln (GDP per capita)	Spatial Weight: Contiguity	
	Fixed Effects	Random Effects
ln (GDP per capita t-1)	0.691*** (0.022)	0.978*** (0.007)
ln (Investment)	0.004* (0.002)	-0.001 (0.001)
ln (n+g+ δ)	-0.025** (0.01)	-0.033*** (0.011)
Constant		0.042 (0.055)
Wx ln (GDP per capita t-1)	-0.169*** (0.046)	-0.545*** (0.028)
Wx ln (Investment)	0.012*** (0.004)	-0.006** (0.002)
Wx ln (n+g+ δ)	0 (0.022)	0.037* (0.019)
Spatial ρ	0.32*** (0.038)	0.575*** (0.027)
Number of observations	1134	1134
Number of groups	81	81
Panel length	14	14

Notes: Standard errors are in parentheses. ***, **, and * denote 1, 5, and 10 percentages of significance levels, respectively.

Table 4.9: SDM Model with Trade Weight Matrix

Dependent variable: ln (GDP per capita)	Spatial Weight: Trade	
	Fixed Effects	Random Effects
ln (GDP per capita t-1)	0.691*** (0.022)	0.98*** (0.005)
ln (Investment)	0.005** (0.002)	0 (0.001)
ln (n+g+ δ)	-0.021** (0.011)	-0.033*** (0.01)
Constant		-0.021 (0.141)
Wx ln (GDP per capita t-1)	0.079 (0.194)	-0.763*** (0.046)
Wx ln (Investment)	0.021** (0.01)	-0.004** (0.002)
Wx ln (n+g+ δ)	-0.411*** (0.156)	0.019 (0.078)
Spatial ρ	0.300** (0.134)	0.787*** 0.043
Number of observations	1134	1134
Number of groups	81	81
Panel length	14	14

Notes: Standard errors are in parentheses. ***, **, and * denote 1, 5, and 10 percentages of significance levels, respectively.

Apart from the SDM estimates, we report the results of other spatial models in Tables 4.10, 4.11 and 4.12. According to Table 4.10, by employing distance, contiguity and trade spatial weight matrix, the SAC Model predicts that given the significantly estimated coefficients on the lagged growth rates, provincial growth persists across time. Public investment has the significantly positive effect except with contiguity matrix, whereas population has the negative impact on growth for all specifications. The significantly positive spatial ρ statistics for distance and contiguity show that the economic growth of the neighbors' affects the growth of origin province. Insignificant spatial ρ and autocorrelation term λ indicate that bilateral trade between the provinces has no impact on their economic growth according to the SAC Model.

Table 4.11 demonstrates the results estimated by the SEM Model. If we test the model with the distance and contiguity weights, we observe similar results for fixed and random effects, whereas the coefficients on λ are greater in random effects. However, the estimated coefficients on public investment are significantly positive when we perform fixed effects under the distance and trade weighted spatial matrix, which differs from the results of contiguity weight. The positive and significant λ values indicate that the spatial effects originated from proximity, neighborhood and trade flows are effective on economic growth of neighbor provinces. Thus, we can infer that the trade interactions between the provinces have substantial spillover effects on the economic growth of each other.

In Table 4.12, for all three spatial weights, the SAR Model predicts the positive and negative impact of public investment on growth, in fixed and random effects, respectively. Population growth has the insignificant coefficients when we employ random effects with distance and contiguity spatial weights in this model. The persistency of provincial growth is still high. We have also positive spatial ρ values in all the SAR estimations. Consequently, we can claim that economic growth of the provinces is positively affected by their neighbors and trading partners.

Table 4.10: SAC Model

Dependent variable: ln (GDP per capita)	Spatial Weight: Distance Fixed Effects	Spatial Weight: Contiguity Fixed Effects	Spatial Weight: Trade Fixed Effects
ln (GDP per capita t-1)	0.68*** (0.023)	0.695*** (0.022)	0.709*** (0.022)
ln (Investment)	0.004* (0.002)	0.003 (0.002)	0.004** (0.002)
ln (n+g+ δ)	-0.023** (0.011)	-0.024** (0.01)	-0.027** (0.011)
Spatial ρ	0.267*** (0.081)	0.097* (0.058)	0.1 (0.146)
Spatial λ	0.023 (0.127)	0.242*** (0.068)	0.1 (0.095)
Number of observations	1134	1134	1134
Number of groups	81	81	81
Panel length	14	14	14

Notes: Standard errors are in parentheses. ***, **, and * denote 1, 5, and 10 percentages of significance levels, respectively.

Table 4.11: SEM Model

Dependent variable: ln (GDP per capita)	Spatial Weight: Distance		Spatial Weight: Contiguity		Spatial Weight: Trade	
	Fixed Effects	Random Effects	Fixed Effects	Random Effects	Fixed Effects	Random Effects
ln (GDP per capita t-1)	0.693***	0.986***	0.699***	0.993***	0.709***	0.981***
	(0.022)	(0.005)	(0.022)	(0.005)	(0.021)	(0.004)
ln (Investment)	0.004*	0.001	0.003	-0.001	0.004**	0.002
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
ln (n+g+ δ)	-0.018*	-0.025**	-0.023**	-0.038***	-0.026**	-0.038***
	(0.011)	(0.01)	(0.01)	(0.011)	(0.011)	(0.01)
Constant		0.149***		0.075		0.136***
		(0.05)		(0.054)		(0.039)
Spatial λ	0.333***	0.772***	0.331***	0.596***	0.252***	0.834***
	(0.07)	(0.031)	(0.038)	(0.027)	(0.075)	(0.03)
Number of observations	1134	1134	1134	1134	1134	1134
Number of groups	81	81	81	81	81	81
Panel length	14	14	14	14	14	14

Notes: Standard errors are in parentheses. ***, **, and * denote 1, 5, and 10 percentages of significance levels, respectively.

Table 4.12: SAR Model

Dependent variable: ln (GDP per capita)	Spatial Weight: Distance		Spatial Weight: Contiguity		Spatial Weight: Trade	
	Fixed Effects	Random Effects	Fixed Effects	Random Effects	Fixed Effects	Random Effects
ln (GDP per capita t-1)	0.679*** (0.022)	0.708*** (0.031)	0.668*** (0.021)	0.711*** (0.025)	0.7*** (0.022)	0.75*** (0.035)
ln (Investment)	0.004* (0.002)	-0.007*** (0.002)	0.004* (0.002)	-0.006*** (0.002)	0.005** (0.002)	-0.004* (0.002)
ln (n+g+ δ)	-0.023** (0.01)	-0.015 (0.012)	-0.024** (0.01)	-0.017 (0.011)	-0.026** (0.011)	-0.021* (0.011)
Constant		-0.273*** (0.052)		-0.245*** (0.05)		-0.629*** (0.057)
Spatial ρ	0.278*** (0.052)	0.332*** (0.03)	0.245*** (0.031)	0.325*** (0.024)	0.3*** (0.116)	0.308*** (0.034)
Number of observations	1134	1134	1134	1134	1134	1134
Number of groups	81	81	81	81	81	81
Panel length	14	14	14	14	14	14

Notes: Standard errors are in parentheses. ***, **, and * denote 1, 5, and 10 percentages of significance levels, respectively.

4.6 Conclusion

In this chapter, we investigate trade and economic growth nexus with a spatial approach, employing provincial domestic trade data in Turkey between the years 2006 and 2019. We construct three spatial weight matrices, distance, contiguity, and trade, and use the last two measures in our empirical analysis. Our main finding is that all distance, contiguity, and trade interactions between the provinces affect their economic growth.

Our trade data is the aggregate version of a firm and regional level confidential dataset. We represent the descriptive tables and visualizations to demonstrate province and industry level trade within Turkey. We generate distance and contiguity weight matrices by importing spatial dataset. By utilizing Moran's I test, we select appropriate distance band which we regard as spatially dependent in our analysis. The contiguity weight matrix is gathered from coordinates of the provinces, gets 1 and 0 values if the provinces are neighbors and not. We also construct trade spatial weight matrix by employing mean bilateral trade data between the provinces for the years 2006-2019. In our model, these three weight matrices are utilized to indicate the geographical and trade effects on economic growth.

In the econometric model, we have GDP per capita growth as the dependent variable, and lagged growth, public investment, and $(n + g + \delta)$ as independent variables. We also employ three spatial weight matrices that we mentioned above for each model. We estimate the model first with SDM. We also include the estimation results for frequently used spatial econometric models SAC, SEM, and SAR. In the SAC Model, we employ with fixed effects, whereas in the other models we work with both fixed and random effects.

In all models, per capita growth in the provinces is very persistent over time. Public investment has a small effect on growth, and it is not statistically significant in some models. Population growth has significantly negative estimates in almost all regressions, except the random effects in SAR Model with distance and contiguity spatial matrix. Except from the SAC Model with trade weight matrix, we also get positive and significant effects of spatial ρ or autocorrelation term λ on GDP per

capita. Thus, we can state that the distance, contiguity, and trade partnership is an outstanding driver for the provincial growth.

Unlike other models, in the SDM Model, we have spatially lagged variable (W_x). These variables are defined as the lagged values of partner province, so that we can gauge the effect of neighboring provinces to the origin province. We can thus evaluate the effects of the variables of origin province and lagged versions of partner province together on economic growth. Our estimation results show that even a province's one-year lagged growth has the positive impact on the current year, the neighbor provinces' lagged growth negatively effects the origin provinces' current growth.

To conclude, our results in this chapter substantially prove the spatial dependence between the provinces in Turkey in terms of economic growth and have significant policy recommendations regarding trade links and growth of the provinces. While total trade volumes are increasing over time in Turkey, some provinces and regions lag in terms of trade. We show that domestic trade is an important driver for provincial growth, thus provisions supporting domestic trade partnerships of these provinces enhance economic growth for the provinces which are suffered from regional disparities.

5. GENERAL CONCLUSION AND DISCUSSION

5.1 Conclusion

The complex relationship between trade and economic growth has been discussed in different aspects in the literature for a long time. Since the trade flows are affected by geography through the channels such as transportation costs and agglomeration, growth is also related with geography. Thus, we start this thesis by thinking of the economic disparities among countries and regions caused by their geographical characteristics.

The prominent gravity equation of trade is a convenient way of investigating the geographical effects, and we first implement a particular form of the gravity model estimated by both the OLS and ANFIS methods. Trade flows are apparently bilateral; however, they are not purely the transaction of two economic agents. Then, this idea takes us to investigate the complex network structure of international trade. We not only employ the gravity equation in a network structure, but also analyze the link between GVCs and ITN. And finally, by a spatial point of view, we investigate the relationship between domestic trade and economic growth.

We think that the main subjects in second, third and fourth chapters of this thesis are closely related to each other, we observe numerous studies in the literature which proves our idea. For instance, Squartini and Garlaschelli (2014) state that although the network approach in trade is recently popular, the gravity model recognizes the importance of the socio-economic networks. Almog et al. (2019) combine the gravity model with network approach within a maximum-entropy framework. Rossi-Hansberg (2005) argues that the border effects and gravity equation are proved if we understand trade by discovering spatial distribution of activities. Barthelémy (2011) draws attention on spatial network, explaining that various types of networks cannot be understood without considering their topology and spatial structure together.

After introducing the key concepts of my dissertation in *Chapter 1*, we begin *Chapter 2* by explaining the gravity model and its implementations in economics, especially in international trade. The gravity equation in trade simply relates the trade flows with economic size of origin and destination countries, and distance between them. The model is developed in many alternative ways; however, the distance affects

the trade flow negatively, in principle. The most significant reason for that is the existence of transportation costs. Based on the gravity model applied in Frankel and Romer (1999), we propose the Adaptive Neuro Fuzzy Inference System (ANFIS), which is an uncommon way to analyze the determinants of international trade.

The main structure of ANFIS is composed of fuzzy inference system and a kind of artificial neural network. By a framework with fuzzy if-then rules, input variables are converted to output variables. Thanks to its forecasting capability, it has applied mostly in the finance literature. Nevertheless, there are few studies utilizing ANFIS in the empirical analysis related with trade and economic growth. We consider taking advantage of the opportunity of inferring nonlinear relationships of fuzzy system to international trade.

We combine BACI trade and gravity datasets of CEPII and employ our model to 104 countries for the years between 1995 and 2015 for the second chapter. One of our aims is to compare traditional analysis in economics with ANFIS. We thus first undertake our analysis with the OLS regressions. Then, we divide the data into three parts, training, test, and validation, before performing ANFIS. While both relationships gathered from the OLS and ANFIS are similar and mostly in line with literature, we conclude that ANFIS performs much better in determining the geographical factors of international trade, when we compare their R-Squares, RMSE, and MAE values. Moreover, in ANFIS analysis, we also interpret conclusions for the relationship between two inputs and one output variables in addition to bivariate relationships by the help of three-dimensional figures, which makes this system more flexible.

Even though the gravity model successfully explores the trade effects of geography, we propose network models in *Chapter 3*, to better understand the complex structure of international trade. Some studies in International Trade Network (ITN) literature examine the networks under the context of gravity models. In this chapter, employing a form gravity model, we first try to explore the dynamics of ITN by explaining trade flows in relation with geographical properties of the countries and their network positions in the ITN. However, to mitigate the potential endogeneity concerns, we introduce a new model having dependent variable of several network indices and examining the relationship between Global Value Chains (GVCs) and ITN.

For the first part of the analysis of the third chapter, we study with data for 178 countries, combining BACI, Network, and Gravity datasets of CEPII for the years

between 1995 and 2010. We find that bilateral trade decreases by distance, which is in line with the literature. GDP per capita and population of the origin and destination countries, contiguity and other dummy variables have positive impacts on trade, whereas population of both countries has the negative coefficients. Besides, all network indices (out-degree, out-strength, out-closeness, out-eigenvector) we employed affect trade positively. Then we also extend this analysis by separating the trade flows between developing and developed countries.

The second part of the analysis in the third chapter consists of 174-countries and 21-years (1995-2015) data, with a combination of CEPII BACI, Gravity, GeoDist with GVC data obtained from the UNCTAD-EORA. In the GVC literature, forward participation refers to the share of domestic value-added in foreign exports, whereas backward participation means the share of foreign value-added in domestic exports. We think that higher participation in GVCs might not mean a significant role in regional or global trade, since it may be result of exporting higher amounts of natural resources, or high-volume trade with only a few countries. Thus, we include participation indices to our model to relate them with ITN, which provides a better understanding of GVCs.

According to our empirical analysis related with GVCs and ITN, we find a strong link between them. Our results suggest that higher forward participation is related with lower out-degree centrality and higher clustering coefficient, whereas higher backward participation is associated with higher out-degree centrality and lower clustering coefficient. The trade-weighted distance affects out-degree centrality negatively, and clustering coefficient positively. GDP per capita has positive impact on out-degree centrality, whereas negative impact on clustering coefficient. We also include regression results for in-degree centrality, hub centrality, and authority centrality. We can conclude that value-added trade shares of countries relate with ITN, and the association changes by the type of network metrics.

In *Chapter 4*, our aim is to find out the connection between trade and economic growth in a spatial econometric framework. The location of economic activities and their interaction is the main subjects of the spatial economics, and this field has attracted more attention in the last decades by the help of large datasets and improvements in computer systems. In our work, we employ province-level data of Turkey, and spatial approach helps us to figure out how geography and trade effects economic growth of the provinces.

The data for the spatial analysis in the fourth chapter covers the years between 2006 and 2019, and includes domestic trade, GDP per capita and population data for 81 provinces of Turkey. We construct spatial weight matrices related with location and domestic trade. Employing the SAC, SEM, SAR, and SDM models, our estimates provide substantial evidence that contiguity and trade partnership between provinces has significant and positive effects on regional economic growth.

5.2 Discussion

We exploit both international and domestic trade in this thesis, and we consider that any trade flow is a kind of interaction, whether it is affected through geography or network. Therefore, the first policy implication can be drawn from our work is to ensure the continuity of the interaction among economic agents. In the international trade, this can be achieved by reducing the geographical barriers and transportation costs as well as promoting open trade policies. Besides, the network position of a country in international trade can be improved by connecting to new markets or becoming stronger in existing partnerships. A way of accomplishing this can also be through international and regional trade agreements.

Participation to global value chains is strongly associated with international trade network, according to our findings. Our second policy recommendation is thus to discover the potentials of GVCs which is related with network position of the country. Various countries contribute to sub-production stages, and their participation in GVCs may differ in these stages. For instance, producing intermediate goods or final goods are distinct stages, and the countries' formation of network connections during these processes may vary. To benefit more from the GVC participations, these trade networks may play a crucial role for the countries.

In a spatial point of view, trade interactions in the country level are affected by the location of the economic agents. We learn from our analysis that location and trade partnership within country positively affect the economic growth of the provinces. Our third policy suggestion is that reducing disparities among cities in a country in terms of economic growth is possible by the help of improving trade partnership between provinces. In most countries, government interventions are usually applied to subsidize investment. These kinds of incentives may shift the location of production and result in eliminating the disadvantages originated from the geography. Besides,

policies promoting agglomeration of specific industries may provide higher productivity. Moreover, the improvements in transportation infrastructure in a country is another way to provide equality between the cities and regions. These kinds of improvements might first direct the investments to the disadvantaged regions, then promote trade partnerships between provinces, and hence provide economic growth for the provinces.

5.3 Directions for Future Research

In this section, we present the limitation of this dissertation, and suggest some directions for the future research. First, we employ a typical gravity model and estimate the geographical determinants of trade by the OLS regressions and ANFIS. However, trade shares can be endogenous in the model. Following Frankel and Romer (1999), instrumented trade shares can also be calculated through the ANFIS framework.

Second, we work with datasets such as trade volumes and GVC participations to find out the relationship between GVCs and ITN. Our analysis is limited with aggregate trade data and total forward and backward participation rates of the countries. For the future research, by the help of GVC length and upstreamness measures, the effect of participating in high or low value-added trade on trade networks can be studied.

Third, our spatial analysis is undertaken by an aggregate version of firm-level domestic trade data. This work may well be extended by employing the disaggregated firm and industry level dataset, to discover the relationship between domestic trade and economic growth.

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BIOGRAPHY

Hasan Karaboğa first graduated from the management department of Boğaziçi University with bachelor's degree, then completed master's degree in economics at Gebze Institute of Technology. His main research areas are international trade, economic growth, economic geography, spatial economics, and network theory.



APPENDIX

Appendix A: Top 20 Exported Products in 2019

HS2 Code	HS2 Section	Exports (trillion \$)
85	Electrical machinery and equipment and parts thereof; sound recorders and reproducers, television image and sound recorders and reproducers, and parts and accessories of such articles.	2530
27	Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes.	2210
84	Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof	2170
87	Vehicles other than railway or tramway rolling-stock, and parts and accessories thereof.	1510
71	Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal and articles thereof; imitation, jewellery; coin.	654
90	Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; parts and accessories thereof	641
30	Pharmaceutical products.	636
39	Plastics and articles thereof	628
29	Organic chemicals.	436
72	Iron and steel.	380
73	Articles of iron or steel.	307
94	Furniture; bedding, mattresses, mattress supports, cushions and similar stuffed furnishings; lamps and lighting fittings, not elsewhere specified or included; illuminated signs, illuminated nameplates and the like; prefabricated buildings.	257
88	Aircraft, spacecraft, and parts thereof.	253
26	Ores, slag and ash.	251
61	Articles of apparel and clothing accessories, knitted or crocheted.	234
62	Articles of apparel and clothing accessories, not knitted or crocheted.	230
38	Miscellaneous chemical products.	201
40	Rubber and articles thereof	189
48	Paper and paperboard; articles of paper pulp	186
76	Aluminum and articles thereof	179

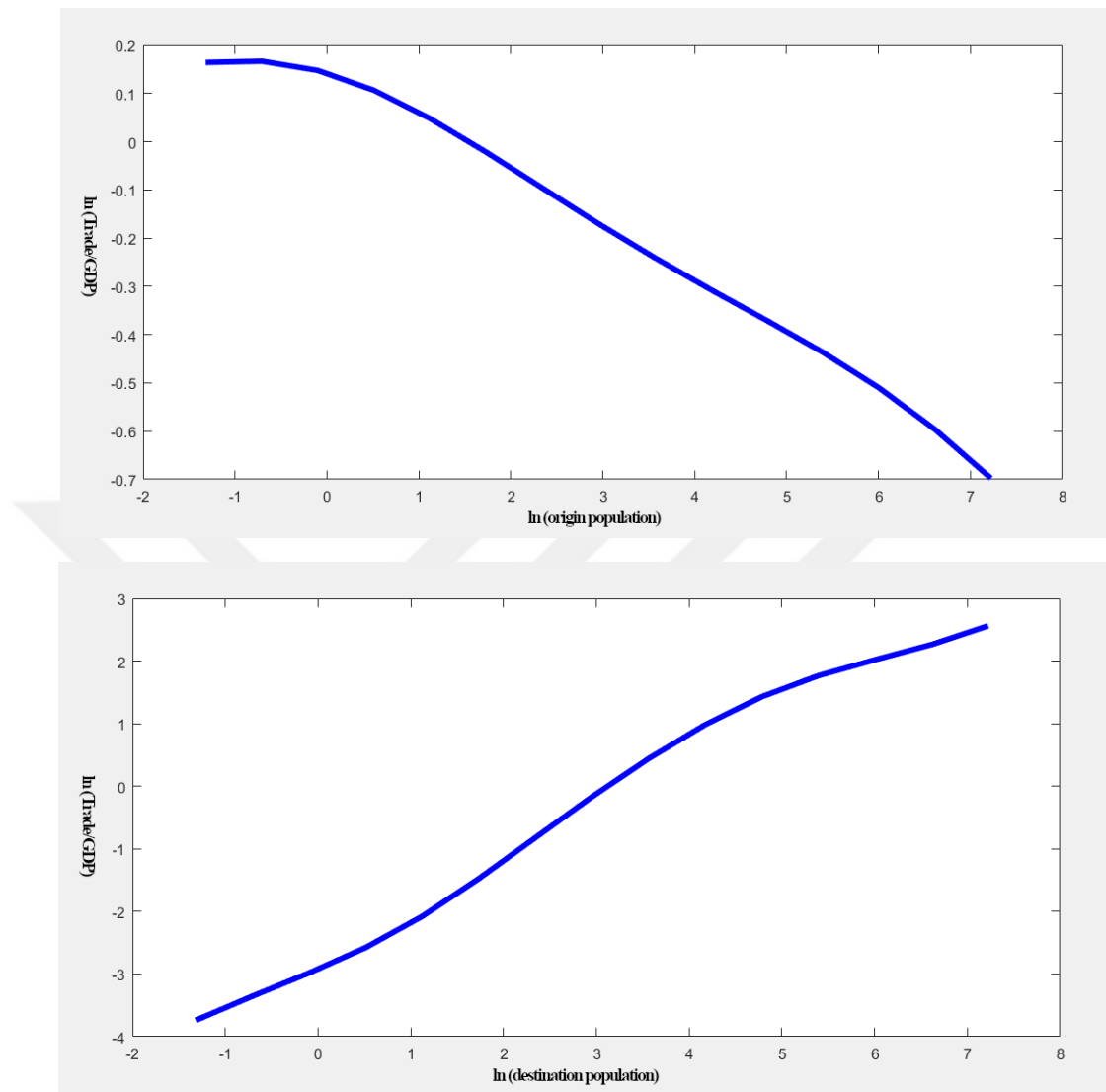
Source: Author's calculations.

Appendix B: Top 20 Exporters in 2019

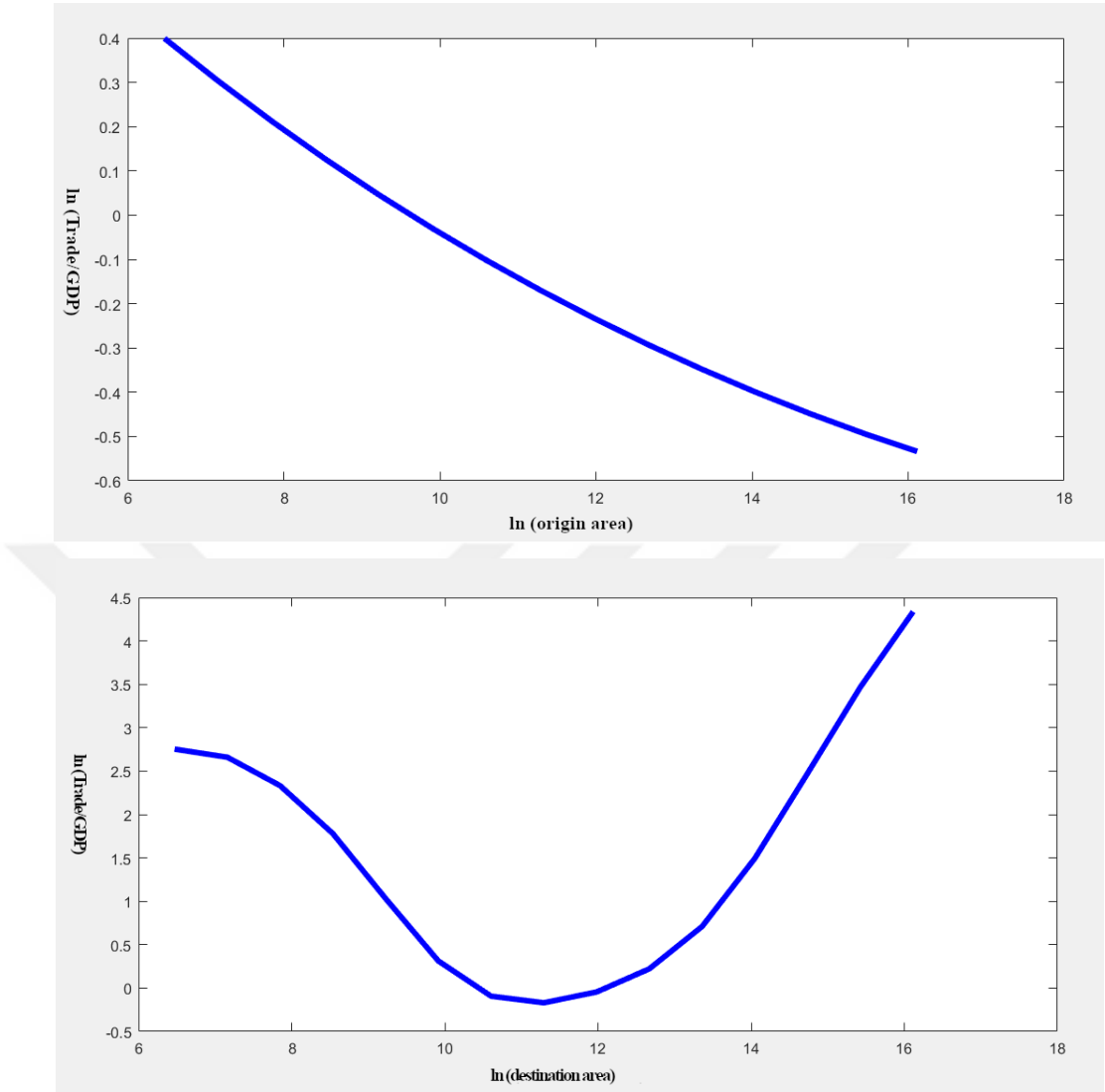
Country Code	Country Name	Exports (trillion \$)
156	China	2570
842	U.S.	1510
276	Germany	1440
392	Japan	696
251	France	558
410	The republic of Korea	555
528	Netherlands	534
381	Italy	525
484	Mexico	480
826	The United Kingdom	446
124	Canada	431
56	Belgium	411
643	The Russian Federation	407
490	Taiwan	351
699	India	330
724	Spain	319
757	Switzerland	310
702	Singapore	301
36	Australia	284
704	Vietnam	280

Source: Author's calculations.

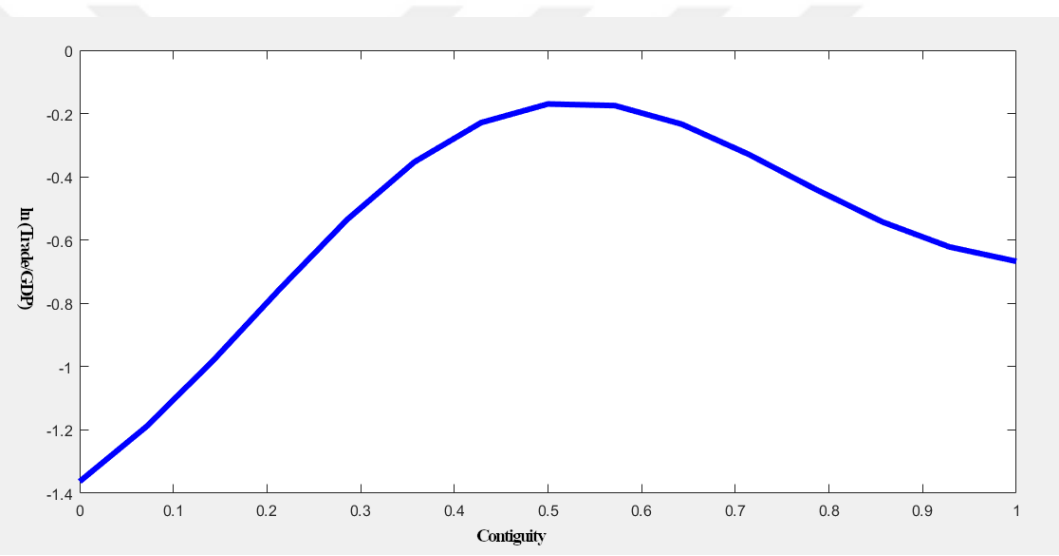
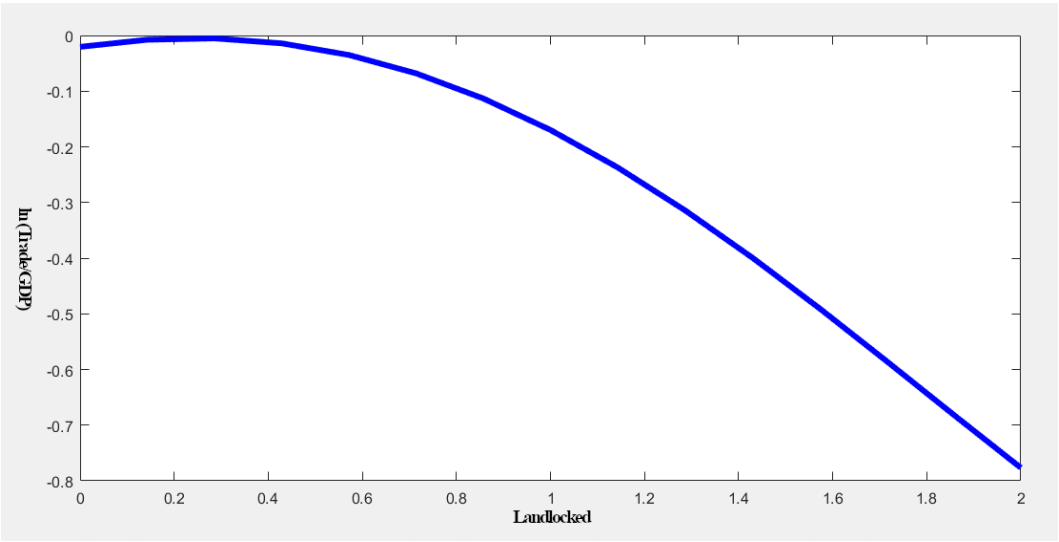
Appendix C: Bivariate Relationship of Bilateral Trade



Appendix C: (continued)



Appendix C: (continued)



Appendix D: Developed and Developing Countries

Developed Countries		
Australia	Germany	Norway
Austria	Greece	Poland
Belgium	Hungary	Portugal
Bulgaria	Iceland	Romania
Canada	Ireland	Slovakia
Croatia	Italy	Slovenia
Cyprus	Japan	Spain
Czech Republic	Latvia	Sweden
Denmark	Lithuania	Switzerland
Estonia	Malta	United Kingdom
Finland	Netherlands	United States
France	New Zealand	

Appendix D: (continued)

Developing Countries	
Afghanistan	Dem. Peop. Rep. of Korea
Albania	Dem. Rep. of the Congo
Algeria	Dominica
Angola	Dominican Rep.
Antigua & Barbuda	Ecuador
Argentina	Egypt
Armenia	El Salvador
Aruba	Equatorial Guinea
Azerbaijan	Ethiopia
Bahrain	Fiji
Bangladesh	FMR Sudan
Barbados	FS Micronesia
Belarus	Gabon
Belize	Gambia
Benin	Georgia
Bermuda	Ghana
Bhutan	Guatemala
Bolivia	Guinea
Bosnia Herzegovina	Guinea-Bissau
Br. Virgin Isds	Guyana
Brazil	Haiti
Brunei Darussalam	Honduras
Burkina Faso	Hong Kong
Burundi	India
Cambodia	Indonesia
Cameroon	Iran
Cayman Isds	Iraq
Central African Rep.	Israel
Chad	Jamaica
Chile	Jordan
China	Kazakhstan
Colombia	Kenya
Congo	Kuwait
Costa Rica	Kyrgyzstan
Côte d'Ivoire	Lao Peop. Dem. Rep.
Cuba	Lebanon

Appendix D: (continued)

Developing Countries	
Liberia	Saint Vincent & Grenadines
Libya	Samoa
Macao	Saudi Arabia
Madagascar	Senegal
Malawi	Serbia and Montenegro
Malaysia	Seychelles
Maldives	Sierra Leone
Mali	Singapore
Marshall Isds	So. African Customs Union
Mauritania	Solomon Isds
Mauritius	Somalia
Mexico	Sri Lanka
Mongolia	Suriname
Morocco	Syria
Mozambique	Taiwan
Myanmar	Tajikistan
Nepal	TFYR of Macedonia
Neth. Antilles	Thailand
New Caledonia	Togo
Nicaragua	Trinidad and Tobago
Niger	Tunisia
Nigeria	Turkey
Oman	Turkmenistan
Pakistan	Uganda
Panama	Ukraine
Papua New Guinea	United Arab Emirates
Paraguay	United Rep. of Tanzania
Peru	Uruguay
Philippines	Uzbekistan
Qatar	Vanuatu
Republic of Korea	Venezuela
Republic of Moldova	Viet Nam
Russian Federation	Yemen
Rwanda	Zambia
Saint Kitts and Nevis	Zimbabwe
Saint Lucia	

Notes: We take the classification from WESP (World Economic Situation and Prospects), (United Nations, 2014). We include transition countries to developing countries in our sample due to simplicity.

Appendix E: Province Names and Codes in Turkey

Code	Province	Code	Province	Code	Province
1	Adana	28	Giresun	55	Samsun
2	Adıyaman	29	Gümüşhane	56	Siirt
3	Afyonkarahisar	30	Hakkari	57	Sinop
4	Ağrı	31	Hatay	58	Sivas
5	Amasya	32	Isparta	59	Tekirdağ
6	Ankara	33	Mersin	60	Tokat
7	Antalya	34	İstanbul	61	Trabzon
8	Artvin	35	İzmir	62	Tunceli
9	Aydın	36	Kars	63	Şanlıurfa
10	Balıkesir	37	Kastamonu	64	Uşak
11	Bilecik	38	Kayseri	65	Van
12	Bingöl	39	Kırklareli	66	Yozgat
13	Bitlis	40	Kırşehir	67	Zonguldak
14	Bolu	41	Kocaeli	68	Aksaray
15	Burdur	42	Konya	69	Bayburt
16	Bursa	43	Kütahya	70	Karaman
17	Çanakkale	44	Malatya	71	Kırıkkale
18	Çankırı	45	Manisa	72	Batman
19	Çorum	46	Kahramanmaraş	73	Şırnak
20	Denizli	47	Mardin	74	Bartın
21	Diyarbakır	48	Muğla	75	Ardahan
22	Edirne	49	Muş	76	Iğdır
23	Elazığ	50	Nevşehir	77	Yalova
24	Erzincan	51	Niğde	78	Karabük
25	Erzurum	52	Ordu	79	Kilis
26	Eskişehir	53	Rize	80	Osmaniye
27	Gaziantep	54	Sakarya	81	Düzce

Appendix F: Publications Made within the Dissertation

Yanikkaya, H., Karaboga, H., Altun, A., (2021), “Implications of Participation in Global Value Chains for International Trade Network.”, *Applied Economics Letters*, 28(14), 1169-1173.

Yanikkaya, H., Karaboga, H., (2018), “Dynamics of World Trade Network.”, 12th International Days of Statistics and Economics, 1962-1971, Prague, Czech Republic, September 6-8.

