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TURKISH – GERMAN UNIVERSITY

INSTITUTE OF SOCIAL SCIENCES

INTERNATIONAL FINANCE DEPARTMENT

Foreign Trade Flows Estimations of RCEP Countries Using Neural Networks and Panel Data Analysis

MASTER'S THESIS

Pashton BAHA

ADVISOR

Prof. Dr. Elif NUROĞLU

ISTANBUL, SEP 2022

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DEDICATION

It is with my utmost pride and enthusiasm that I present you hereby the fruit of my extensive labor to research, process and new developments in economics and trade. I assure the reader of this thesis that no effort was spared and no stone was left unturned throughout conducting this inquiry. By this means, I express my gratitude and appreciation to all individuals and institutions that helped me in this quest. In particular, I want to thank my fiancé Yasemin Mirana Öztürk, my parents Mohammad Shah Baha and Sadia Hotaki Baha for their absolute support, my advisor Prof. Dr. Elif Nuroğlu for her guidance and mentorship at all times, Prof. Dr. Ferda Halıcıoğlu for sparing his valuable time to instruct, review, comment and correct my progress during this process, Prof. Dr. Kersten Kellermann for her constructive insight and thought provoking comments and the Turkish-German University for providing valuable resources and tools through their progressive and fostering licensing attitude. May this thesis provide answers to the questions regarding matters within its bounds.

Pashton Baha
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TABLE OF CONTENTS

Page NO

ÖZET

BKEO Ülkelerinin Ticaretlerinin Panel Veri ve Yapay Sinir Ağları Yöntemleri ile Tahmin Edilmesi

Bölgesel Kapsamlı Ekonomik Ortaklık, Güneydoğu Asya ve Okyanusya bölgelerinden, çeşitli ekonomik büyüklükteki 15 ülke arasında yapılan nispeten yeni bir çok taraflı serbest ticaret anlaşmasıdır. Dünyanın, son dönemlerde en önemli ekonomilerinin ve en büyük tüketici pazarlarının bazılarını kapsayan bu anlaşma, araştırmacılar ve analistler arasında haklı olarak bir merak konusu haline gelmiştir. Çeşitli çalışmalar, bu anlaşmanın küresel tedarik zincirleri, ticaret, gelir ve diğer ilgili konular üzerindeki potansiyel etkisini araştırmıştır. Bu tezde, yer çekimi modeli yaklaşımı kullanılarak bölgedeki ticaret akımlarının arkasındaki itici güçlerin araştırılmasına ve ayrıca gelecekteki ihracat büyüklüklerini tahmin etme yöntemlerinin değerlendirilmesine gayret edilmiştir. Bu çerçevede, elde ettiğimiz sonuçlar uluslararası ticareti yer çekim modeli ile inceleyen önceki çalışmaların çıkarımları ile uyumludur. Çalışma sonucunda ihracatçı ve ithalatçı ülke GSYİH'larının ticareti olumlu yönde etkilediği tespit edilmiştir; ticaret yapan ülkelerin nüfus büyüklüklerinin ise ticaret akımları üzerindeki etkisinin çok yönlü olduğu görülmüştür. Ticaret ağırlıklı göreli mesafenin ticaret akımlarını teşvik ettiği tespit edilmiştir. İhracatı etkileyen faktörlerin ne ölçüde ve ne yönde bir etkisi olduğu panel data analizi ve yapay sinir ağları yöntemleri ile yapılmış ve ayrıca bu iki modelin açıklama gücü birbiri ile karşılaştırılmıştır. Düzeltilmiş R-Kare ve kök ortalama kare hata baz alınarak değerlendirildiğinde, yapay sinir ağlarının doğrusal regresyon modeline kıyasla daha üstün bir tahmin performansı gösterdiği tespit edilmiştir. Çalışmada yapay sinir ağlarının sınırlamalarına da değinilmiştir. Son olarak, bazı çıkarımlar ileriye sürülmüş ve bundan sonraki araştırmalar için önerilerde bulunulmuştur.

Anahtar Kavramlar : BKEO, Yer Çekim Modeli, Doğrusal Regresyon, Sinir Ağları

Tarih : 07/09/2022

ABSTRACT

Foreign Trade Flows Estimations of RCEP Countries Using Neural Networks and Panel Data Analysis

Regional Comprehensive Economic Partnership is a relatively new multilateral free trade agreement among 15 countries of various economic size from the Southeast Asia and Oceania regions. Covering some of the world's recently most influential economies and largest consumer markets it has rightfully invoked curiosity among researchers and analysts. Several studies have investigated the agreement's potential effect on global supply chains, trade, income and other relevant subjects. In this study it is attempted to investigate the driving forces behind trade flows in the region using a gravity approach and also, to evaluate methods to estimate future export magnitudes. In this context, the findings of this thesis are consistent with the previous findings of the gravity model of international trade literature. Exporter and importer's GDPs are found to positively stimulate trade between trading partners; population sizes of the trading countries is found to have a multi-directional effect; trade weighted relative distance is observed to have a stimulating effect on exports. In order to estimate magnitude and direction of the impact of dependent variables on trade flows between RCEP countries a linear regression model and artificial neural networks model is used. Moreover, both approaches are compared in terms of explanatory power. Based on Adjusted R-Squared and root mean squared error benchmarks the artificial neural network is found to have shown superior predictive performance compared to the linear regression model. The limitations of neural networks' applications are also touched upon. Finally, some implications are put forward and suggestions for further research are made.

Key Words : RCEP, Gravity Model, Linear Regression, Neural Networks

Date : 07/09/2022

LIST OF SYMBOLS

%	: Percent
$\boldsymbol{\varepsilon_{ijt}}$	: Error Term
$\mathbf{Dist}_{ij}$	: Distance Between Exporter and Importer's Major Population Centers
$\mathbf{Exp}_{ijt}$	: Exports
$\mathbf{GDP}_{it}$	: Exporter Country's Gross Domestic Product
$\mathbf{GDP}_{jt}$	: Importer Country's Gross Domestic Product
$\mathbf{Pop}_{it}$	: Exporter Country's Population
$\mathbf{Pop}_{jt}$	: Importer Country's Population
Q1	: First Financial Quarter
$\mathbf{R}^2$	: Coefficient of Determination

LIST OF ABBREVIATIONS

ADJ.	: Adjusted
AIC	: Akaike Information Criterion
ASEAN	: Association of South-East Asian Nations
CGPA	: Cumulative Grade Point Average
CPTPP	: Comprehensive and Progressive Agreement for Trans Pacific Partnership
E.G.	: Exempli Gratia (For Example)
ELU	: Exponential Linear Unit
ET AL.	: Et Alia (And Others)
EU	: European Union
EXPGDP	: Exporter Country's Gross Domestic Product
EXPPOP	: Exporter Country's Population
FDI	: Foreign Direct Investment
FTA	: Free Trade Agreement
FTSE	: Financial Times Stock Exchange
GDP	: Gross Domestic Product
GELU	: Gaussian Error Linear Unit
I.E.	: Id Est (That Is).
IMF	: International Monetary Fund
IMPGDP	: Importer Country's Gross Domestic Product
IMPPOP	: Importer Country's Population
MSE	: Mean Squared Error
RCEP	: Regional Comprehensive Economic Partnership
RELU	: Rectified Linear Activation Unit
RMSE	: Root Mean Squared Error
SELU	: Scaled Exponential Linear Unit
SME	: Small and Medium Sized Enterprises
SNARC	: Stochastic Neural Analog Reinforcement Calculator
TANH	: Hyperbolic Tangent Activation Function
TWRD	: Trade Weighted Relative Distance
US	: United States
USD	: United States Dollar

LIST OF FIGURES

Page No.

LIST OF TABLES

CHAPTER 1: INTRODUCTION

Researchers across many disciplines have witnessed the recently intensified development of many new forecasting methods. Evolution in computer technology has helped downscale otherwise impractical methods of calculation and paved the way for individual researchers to be more creative in model configuration in their studies. It has helped researchers break free from the drawbacks from which traditional estimation methods suffer. Normal distribution of the population is a strict assumption of traditional statistical methods. However, with novel forecasting methods such assumptions are open for discussion -artificial neural networks is one such method.

This study is an effort to estimate bilateral trade flows among Regional Comprehensive Economic Partnership nations using artificial neural networks and conventional panel data analysis. It examines bilateral trade figures of RCEP member nations from 1991 until 2020, utilizing both artificial neural networks and traditional panel data analysis method. Using available data, one empirical model is developed for each approach. The study tests the estimation and explanatory power of both models by cross checking predicted outputs with realized figures and make a comparative analysis of estimation capabilities of two models. The aim of the study is to reach a credible conclusion regarding the explanatory power of both models. Both models utilized in this study are based on a modified version of the gravity model of international trade (Tinbergen 1962) that additionally takes into consideration the populations of trading countries.

The course pursued in this study is as follows. First, the relevant concepts, terms and models used in this study are introduced and explained. In the second chapter, a review of existing literature in the fields of artificial neural networks and its utilization in economics and trade; its application to the gravity model as well as its comparison to traditional statistical models such as multiple linear regression model are presented. Then, in Chapter 3, the models and their configurations are discussed, the data processing methods are explained, the main research question is hypothesized, the results of both approaches are presented and a comparative analysis is conducted. In the last chapter, the results achieved by both models alongside their statistical and theoretical strengths and weaknesses are discussed, some final remarks are made and a few suggestions for the direction of further research in the field are provided.

1.1. REGIONAL COMPREHENSIVE ECONOMIC PARTNERSHIP

Regional Comprehensive Economic Partnership is a free trade agreement among 15 South-East Asian and Asia-Pacific countries of Australia, Brunei, Cambodia, China, Indonesia, Japan, South Korea, Laos, Malaysia, Myanmar, New Zealand, the Philippines, Singapore, Thailand and Vietnam. The member countries account for 29.46% of the world's population as of 2020 and 29.33% of global GDP as of 2018 (World Bank, 2022). Although many FTAs already exist in the region, RCEP is the only FTA that unites China, Japan and South Korea under the same agreement which are three of the four largest economies in Asia. Instead of replacing the existing FTAs, RCEP aims to raise the level of regional integration to a higher level. The agreement's framework consists of 20 chapters related to inter alia, trade in goods and services, efficiency in custom procedures, trade facilitation, sanitary and phytosanitary measures, technical regulations and standards, labour mobility, investment, intellectual property, e-commerce, competition, SMEs, economic and technical cooperation and dispute settlement.

The agreement's main purposes are to develop a contemporary, inclusive, mutually valuable, market-consistent economic cooperation environment to enable and support the growing intra-region economic activity, trade and flow of investment and therefore contribute to economic growth and development internationally, whilst also focusing on development of the member states and attending to their economic needs, particularly economic needs of the relatively less developed members. In a progressive manner, the agreement will supposedly liberalize and positively stimulate trade of goods within the pact by using different strategies one of which is phasing out tariff and non-tariff barriers on an extensive portfolio of goods from countries withing the agreement. Moreover, it tackles the issue of favouritism and aims to take counter measures against restrictive practices in trade in the services sector. It seeks to convert the region into an encouraging, liberal and competitive habitat for investment, which will ease, promote and enhance investment opportunities among member states.

1.1.1. ORIGIN AND PROGRESSION OF RCEP

The concept and framework for a Regional Comprehensive Economic Partnership was first introduced at the 19th ASEAN summit held in Bali between 14-19 November 2011 (ASEAN 2011). At the 21st ASEAN summit, which was held between 18-20 November 2012 in Phnom Penh, Cambodia, negotiations were launched and guidelines and objectives were drawn for RCEP through a joint declaration by heads of ASEAN and its free trade agreement partner nations (RCEP 2012). The first round of negotiations were held in Brunei in May of 2013. This was the start of a lengthy chain of negotiations held in different stakeholder countries over a course of seven years. The latest of which were the 31st round of negotiations, held in July of 2020 as an online video conference due to traveling complications brought by the Covid-19 pandemic. Countries that have hosted the negotiations for RCEP includes Australia in 2013, 2016 and 2019; Brunei in 2016; China in 2014, 2016 and 2019; Indonesia in 2016, 2018 and 2019; Japan in 2015 and 2017; South Korea in 2015 and 2017; Malaysia in 2014; Myanmar in 2015; New Zealand in 2016 and 2018; Philippines in 2017; India in 2014 and 2017; Singapore in 2014 and 2018; Thailand in 2015 and 2018 and Vietnam in 2016 and 2019.

The first ever RCEP summit was held on 14 November 2017 in Manila, Philippines. Regarded as the world’s largest trading pact, RCEP was signed on 15 November 2020 by the ministers of 15 member nations in a ceremony held virtually due to the Covid-19 pandemic (J.T. 2020).

1.1.2. CURRENT TRADE IN THE RCEP REGION

Southeast Asia and Oceania is arguably, the centre of global trade in goods. The region represents almost a third of the world population, it contributes to the global economy in the same proportion. Due to the low-cost nature of the region’s labour market, it has become progressively more price competitive in the global economy.

Southeast Asian economies collectively are the biggest participants in maritime freight-logistic activities which facilitates more than 80% of international trade. The top five countries best connected to global network of shipping lines are located within the RCEP region. In 2020, 62% of global port container traffic was processed in developing economies of Asia and Oceania. The region has; and continues to develop extensive and capable infrastructure for trade and freight-logistics. The shipbuilding industry of China, Japan and South Korea accounted for 94% of the industries global activity. Therefore, Asia's ownership of half of the world's shipping fleet is unsurprising (UNCTAD, 2021).

Becoming a global manufacturing powerhouse has also transformed Southeast Asian economies to become large consumer markets with expanding middle classes (Brueckner et al., 2018). Although demand for consumer goods from outside the region has been increasing for the past two decades; raw materials, fuels, intermediate goods, capital goods, machine and electronics have consistently maintained their position as the region's biggest imports in the same period. On the other hand, consumer products, textile and clothing, and intermediate goods have been the region top exports for the last two decades (WITS, 2022).

Countries in the Southeast Asian region have a total of 227 free trade agreements between themselves and with the outside world (Asian Development Bank, 2022), many of which overlap each other. RCEP can be seen as an attempt to consolidate many individual FTAs under a single comprehensive umbrella, to promote integration and economic interdependence. RCEP is the latest in a series of substantial multilateral economic unions and trade blocks, the region has witnessed in the modern history. It stands on the shoulders of Association of Southeast Asian Nations, founded in 1967, which was itself inspired by the Association of Southeast Asia formed in 1961 (Tarling, 1993).

Recently the pandemic caused by the Covid-19 virus and its variants, has led to contractions in economic activities, and brought disruptions to supply chains all over the world. In RCEP region trade volumes started to recover in the final quarter of 2020. It continued expanding through 2021, and they seem to be plateauing rather than declining in 2022. Indonesia, Malaysia, Thailand, Vietnam, and China have exceeded their pre-pandemic merchandise export volumes. The region's path to full recovery is still a challenging one though. The disruption in supply of semiconductors has persisted, and it is expected to discourage growth in supplier countries. The war between Ukraine and Russia is expected to have a negative impact in the foreseeable future. The global upwards trend in inflation has also been creating cost pressure for various industries in the region. The rise in inflation was expected, however, the recent surge in the prices of oil and other commodities, in combination with varying levels of currency depreciation in the region has resulted in headline inflation raising beyond the expected level. Despite the challenges, trade and economic activity is projected to expand in the region. Real GDP of the ASEAN countries is forecasted to grow by 5.8% in 2022, and 5.2% in 2023 (OECD, 2022). Table 1.1 presents a macroeconomic indicators of the RCEP countries for 2020.

Table 1. 1

Macroeconomic indicators of RCEP countries in 2020

Country	*GDP (billion USD)*	*Exports (million USD)*	*Imports (million USD)*	*Population (million)*	*GDP per Capita*	*Inflation CPI*	*Growth*
Australia	1,542.66	251922.7	214734.6	25.74	59934.13	2.86	1.47
Brunei	14.01	6607.141	5342.373	0.44	31722.66	1.73	-1.60
Cambodia	26.96	17767.03	19833.28	1412.36	19.08937	0.98	8.10
China	17,734.06	2598014	2060258	276.36	64169.73	1.56	3.69
Indonesia	1,186.09	163306.5	141568.8	125.68	9437.285	-0.23	1.62
Japan	4,937.42	638167	631195.4	16.95	291354.4	2.92	3.02
Korea	1,798.53	512644.8	467645.5	51.74	34757.72	2.49	4.02
Lao	18.83	6331.808	6483.104	7.38	2551.326	3.75	2.52
Malaysia	372.70	233959	190320.7	54.81	6800.373	-	-17.98
Myanmar	65.07	16998.94	17568.48	32.78	1985.215	2.47	3.13
New Zealand	249.99	38824.43	37205.02	5.12	48801.69	3.94	4.64
Philippines	394.09	63583.03	89792.36	111.05	3548.828	3.92	5.70
Singapore	396.99	287884.2	261351.6	5.45	72794	2.30	7.61
Thailand	505.98	229256.1	207092.2	69.95	7233.389	1.23	1.56
Vietnam	362.64	277270.8	258784.4	98.17	3694.019	1.83	2.58

Source: IMF direction of trade and World Bank database.

1.1.3. RATIFICATION OF RCEP

On April 9th, 2021, a press release by the ministry of trade and industry of Singapore announced the country's ratification of RCEP. By depositing the Instrument of Ratification with the Secretary-General of ASEAN it became the first country to fully complete the official ratification process (Ministry of Trade and Industry Singapore 2021). Following Singapore, on April 15th 2021 China deposited the Instrument of Ratification with the Secretary-General of ASEAN and thereby completed the official ratification process (Zhang 2021). Japan completed the ratification process on June 25th 2021 (Ministry of Foreign Affairs of Japan 2021). The National Assembly of Cambodia ratified RCEP on September 9th 2021 (Huaxia 2021), Brunei and Thailand completed their ratification processes on October 11th and 28th 2021 respectively (Bandial 2021), (Ministry of Foreign Affairs of Kingdome of Thailand 2021). Australia and New Zealand ratified RCEP on the same day of 2nd November 2021 (Ministry of Foreign Affairs of Australia 2021; Ministry of Foreign Affairs and Trade New Zealand 2021). South Korea's National Assembly voted to ratify RCEP on December 2nd 2021 (Graceoh 2021). Laos and Vietnam have also ratified the agreement.

Malaysia, Indonesia, Philippines and Myanmar have yet to fully ratify the agreement. Malaysia has been intensifying efforts to implement alterations to the present legislations that would allow it to ratify the agreement and become the 12th nation to do so. Philippines' government is also determined to rapidly complete the ratification process as the president has already approved the documents necessary for the procedure in September 2021. However, the agreement has been facing resistance from non-government institutes and individuals primarily in the agriculture industry. It is expected to be an important subject in the country's general elections planned for May 2022. As the elections approaches closer, Philippine's ratification of RCEP remains to be done (Malindog-Uy 2022). Indonesia is expected to complete all stages of RCEP ratification by the end of Q1-2022. Despite being one of the main drivers behind the agreement, issues related to the Covid-19 pandemic had slowed the country's efforts towards ratification (Suroyo and Christina 2021). On the other hand, Myanmar has not shown any progress or intentions towards ratification of RCEP. Development is not expected -

particularly after the recent military coup- in the country's ratification process anytime soon.

On November 4th 2019 India withdrew from the RCEP agreement stating the agreement's potentially negative impact on its vulnerable citizens and core domestic industries. However, representatives of other major economies within the pact namely China and Japan hope for India's return to the agreement (Akimoto 2021; Kyodo 2019).

RCEP would come into effect sixty days after a minimum of six ASEAN-member signatories and three non-ASEAN-member signatories have deposited their Instruments of Ratification. This condition was satisfied on 2nd November 2021 when Australia and New Zealand deposited their Instruments of Ratification on the same day. As a result, RCEP became effective on 1st January 2022, among signatories that have ratified the agreement.

1.1.4. PERCEPTION AND POTENTIAL OF RCEP

After RCEP was signed it was lauded as a victory of multilateralism, a significant move forward for the region and as an indicator of mutual expression of positive attitude towards free trade, economic interdependence and regional harmony. It is expected to contribute to the shifting of global economic gravity back towards Asia. Some analysts interpreted this aspect of the agreement as a miss out, for the current global powerhouse; the U.S. While the development of such dynamic-changing trade pact has pushed many individuals of diverse backgrounds and professions to consider the growing importance of the region in their analysis and strategies, it has also aroused the interest of trade academics in the newly born subject.

RCEP is expected to generate 245 billion USD incremental income for its member states. The agreement's total generated income for the world, is expected to amount to 263 billion USD. At the sectoral level trade of durable and non-durable goods is expected to experience the most growth. It is anticipated that alongside CPTPP, RCEP will enhance the quality of logistics and supply chains, make enterprises of the region more productive, increase income and diminish unemployment. East-Asian region is expected to become even more competitive in the global economy. Improvement and refinement of its standards and disciplines is also foreseen (Park et al., 2021).

As a major partner and promoter of the agreement, its influence on China’s economy is of great interest. China’s regional economy is expected to benefit from RCEP. While its positive impact is expected to be concentrated in the coastal areas, inland provinces will also gain from the agreement. Data simulations suggest that the indirect impact of the agreement will be relatively strong. Due to relatively bigger tariff reductions for agricultural and food products, labor intensive and agricultural manufacturing industries are expected to gain from the agreement. However, it might have some negative effects on technology focused industries and the services sector (Zhou et al., 2021). Li et al. (2017) simulate RCEP’s impact on foreign direct investments of China through a direct effect of FDI liberalization and an indirect effect of trade liberalization. They conclude that RCEP will encourage FDIs in via trade effect and the direct FDI effect. Xiaohan et al. (2022) find that RCEP’s liberalization of the forestry industry will pave the way for trade with protectionist countries. However, a tax revenue source of considerable size will be diminished for the Chinese government and the welfare of Chinese forestry product consumers can be expected to reduce.

Marikan et al. (2020) find that joining the RCEP will place Malaysia in a position to become even more competitive in international markets. Malaysian Minister of International Trade and Industry expects his country to enjoy the preferential treatment advantage through progressive reduction and abolishment of tariffs. Research by the MIDF, national finance company, projected the agreement to add 4 billion USD to the country’s annual GDP. The Malaysian External Trade Development Corporation expects exports to RCEP region to reach 5.25 billion USD (Jalil, 2020).

Indonesian Minister of Trade expressed confidence that the pact would benefit Indonesian businesses, and stated that the agreement has the potential to increase the country's exports to participating countries by 8-11 % and investment to Indonesia by 18-22 % (Tambun & Olavia 2020). For Indonesia, its GDP and the GDP of its partners are significantly influential on its trade volume. Hence, for Indonesia to achieve and sustain a noticeable gain from trade, collective regional developments are needed. As for most of other members, tariff reduction brought by the RCEP shall positively contribute to Indonesia’s trade volume (Aprilianti, 2020).

South Korean President expects RCEP to open the world's biggest e-commerce market. He was quoted saying that the agreement will "contribute to the recovery of multilateralism and the development of free trade around the world, beyond the region." (Yonhap, 2020)

Kishore Mahbubani, Singapore's former permanent representative to the United Nations stated that "future of Asia will be written in four letters: RCEP." He also considers India's withdrawal from the pact to have benefited China. He also stated that in the absence of India and the United States a 'massive economic ecosystem centred on China is evolving in the region."

Itakura (2015) runs a tariff policy simulation for RCEP countries with special focus on ASEAN members. The results reveal that through liberalization of trade and promotion of investment, all participating parties of the RCEP will gain in terms of real GDP; investment in all of RCEP member countries will rise and because of high rates of return more foreign capital will be attracted as well. A positive link was observed between tariff reductions by participant countries and volume of trade.

Textile, clothing, apparel and the accessories market has for long been synonymous with East Asia. Due to lower cost and increasingly better quality of manufacturing, most major global producers have outsourced considerable amount of their production processes to the region. However, with the implementation of RCEP changes to the current balance of trade is expected. A supply chain strengthened by the RCEP would encourage member states to procure more of industry products and raw materials from within the bloc, hence generating a trade creation effect. The trade diversion effect of the RCEP, is expected to reduce imports from outside the bloc, mainly the EU and the US, to the RCEP region. Better integration of the industry facilitated by the RCEP will lead its member states to demonstrate more competitiveness in the world's leading apparel markets (Lu, 2018).

Erokhin et al. (2021) expect the implementation of RCEP to further widen the inequality gap between high- and low-income countries in trade in the fish and seafood products industry. It could increase outward orientation of fish supplies at the expense of interregional trade, degrade the competitive advantages of smaller economies and endanger economic and social stability in communities dependant on the industry. They state that RCEP would position some countries more favourably than others in the industry. They then divide the fifteen member states into four groups and rank them from most favourable to least favourable.

Considering the differences in demographic, social, cultural, historical, geographical, linguistic, economical, administrative and other important characteristics of its member states, RCEP is different than any other regional trade agreement before in many aspects. At times, this has led to disagreement on the bloc's potential among researchers and media analysts. Fukunari Kimura reflects on RCEP's assessment by the general media and states that it tends to go towards two extremes. He comments "One camp says that RCEP is the largest agreement ever concluded in the world and thus is to be celebrated. The other claims that the quality of the agreement is low and thus it will not make much impact" (Kimura, 2021, p.163). He expects the agreement to have a certain level of trade liberalization effect despite its unconventional tariff removing schedule across countries and also to work as a forum that reduces policy risks and forms a pro-trade middle power coalition in East Asia.

1.1.5. PROMINENT REGIONAL INTEGRATION THEORIES

Many factors of various origins are at play in the dynamics of regional integration. Economists often focus only on the economic aspect of regional integration, however, to fully comprehend the diverse driving forces behind regional integration or regionalization a broad perspective of the phenomenon is necessary, which incorporates, beside economic factors, the social, political, historical, cultural and other dynamics of the region. Different scholars have put forward their theories on reasons, conditions and classifications of regional integration.

Functionalism, inspired by the writings of Immanuel Kant, emerged as a theory of international relations in the first half of the 20th century. It argues that the materialistic needs of everyday life, provided by scientists and experts of international actors could promote cooperation and interaction among the leaders of states to solve political and military tensions. It suggests that technological progress would renders any single states' capacity to fulfil its security tasks inefficient, and therefore, international cooperation was a necessity. Haas (2004) contributes to this cooperation-centric theory with his Neo-functionalist ideas. The spill over effect is the main point of focus in Haas's argument. His theory implies that, as interdependency increases in several areas a sense of movement is created. During this movement, the sense of adherence begin to differentiate and the proposition of a region with relatively stronger institutions or perhaps even supranational ones starts to appear real. Neo-Functionalism suggests that the gains of an interdependent sector shall create a positive spill over effect which would in turn motivate leaders and policy makers to evaluate the possibility of integration in other areas and eventually integrate. Haas believes in plurality of actors, according to him the drivers of the integration movement are not only the leaders of states but also the society elites and the business community, therefore the economic and rational characteristics usually associated with state leadership is not thought of as primary. In neo-functional theory regional integration is expected when societal actors, led by their self-interest, prefer to rely on supranational institutions rather than their own governments to materialize their demands. As these institutions would become the source of policies meeting the demands of societal actors, they would represent legitimacy and authority. From that point-on, the theory assumes integration would continue almost automatically as the demand for additional central services intensifies, and eventually services associated with the initially integrated sector would spill over to neighbouring non-integrated sectors (Haas 2004). Neo-functionalism has at times been criticised for being too Europe oriented. Even Haas himself have limited the chances of his ideas' applicability to other regions with different configurations (Santos 2009). Functionalism and Neo-functionalism both, describe regional integration in an organic bottom-to-top approach, and therefore assumes the presence of basic human freedoms such as basic human rights, freedom of doing business and so on.

The Security Communities approach or Transactionalism of Deutsch (1968) is another perspective at the process of integration. Transactionalism can be seen as close to neo-functionalism in its stance, but particularly focused on order and security (Santos 2009). Transactionalism also accepts the existence of driving forces for integration other than the state; it sees integration as a process during which merits of evaluation and societal behaviour based in political decisions is subject to change. Deutsch implies that during the initial phases of the integration process a psychological anti-war atmosphere develops; the idea of military conflict among potential future partners is disregarded and preparations for such a scenario loses public support. And even in situations when parties of the process do find themselves on opposing sides in a larger international conflict, they would act in a manner that minimizes the magnitude of mutual damage and hostilities to a minimum. Besides linking balance in power distribution and repressed urge of war to the prevailing of peace, he also attributes the formation of security community and cooperation to psychological elements and factors concerning identity. The theory puts forward two types of communities: amalgamated communities and pluralistic communities. In the former case, different states gather around one regional centre which eventually leads to the rise of a supranational entity; in case of the latter, sovereign and independent states agree to establish a decision-making process and more importantly renounce the use of force as a means of dispute settlement. The theory also suggests that interaction among diverse members of community shall result in an increasing cross border solidarity and sense of community (Deutsch 1968).

Hegemonic stability theory, first espoused by Charles Kindleberger (Milner 1998), attempts to explain regional integration with a hegemon at the centre of the region. Kindleberger (1973) states that "for the world economy to be stabilized, there has to be a stabilizer, one stabilizer" (Kindleberger 1973, p.305). This theory bridges realist ideas such as security and power with cooperation related elements. At first glance it appears similar to Deutsch's amalgamated communities because of its hegemon centric nature. However, hegemonic stability theory completely denies the possibility of establishing or maintaining a cooperative regime in the absence of a hegemon which provides a stronghold and efficacy. The theory foretells the emergence of two different types of hegemon; a benevolent hegemon and a coercitive one. Mattli (1999) conducts a detailed review of regional integration theories and later provides his own explanation to the failure or success of some regional integration processes. He too, emphasizes on the presence of a hegemon in the region that shows interest in integration. He proposes three pillars on which the success of an integration process would depend. Firstly, in order to ensure the demand for regional regulations and norms, the potential for economic gains arising from the integration must be significant. Secondly, for political leaders to be willing and able to fulfil the demand for regional regulations, a suitable socio-political climate must be predominant, in other words supply conditions must be fulfilled. Thirdly, one state must assume the leadership role or that of a benevolent hegemon. i.e., showing responsibility and assuming the costs of coordination and the development process (Santos 2009).

Moravcsik (1995) combines his studies of regionalism with his realist and liberal ideas and synthesizes what is commonly referred to as liberal intergovernmentalism. Contrary to functionalism and neo-functionalism, liberal intergovernmentalism views integration as a top-to-bottom process with state situated at the top and in charge of making all the decisions. Moravcsik makes three assumptions in explaining the integration process. Firstly, he assumes that states act rationally, therefore, when a state initiates or becomes part of an integration process it is aware of doing so in order to achieve its goals. Secondly, international preferences are affected and driven by intranational politics, and they are obliquely determined by economic interdependence. Thirdly, governments are the key actors. The theory claims that the decisions of states depend primarily on the material capability of each state. Moravcsik’s theory attempts to explain the integration process from the viewpoint of the state and national interest and denies any possibility of supranationality or cooperation based politics, unless subjected to intergovernmental requirements (Santos 2009).

Hettne (1991) offers another perspective at the regional integration phenomenon. His *new regionalism approach* bridges globalization and regionalism in a normative pluri-thematic framework. Hettne distinguishes between the concepts of regionalism from economic integration. According to Hettne, the main goal in the regionalist approach is to establish a viable region, whereas economic integration is neutral in its stance regarding the specific value of the region. This approach factors-in characteristics that are not only economic but also political, social and cultural. It recognizes, the political effort and drive of establishing regional identity and coherence, as the main factor in regional integration. Hettne also proposes a five level system of measurement for ‘regionness’, which according to him represents a region’s position on the spectrum of regional identity and coherence. The first level is regional space or geographical land. Second is the regional complex, which suggests the existence of some level of interdependence. Third is the regional society, which can encompass different aspects e.g., economic, political, cultural, military and so on. Fourth is the regional community, which implies the emergence of a transnational civil society that stimulates the convergence of values. Fifth is the regional institutionalized polity, which would possess some level of decisive authority (Hettne and Söderbaum, 2006).

Balassa (1961) defines integration in a liberal-economic framework, as the abolition of discrimination among economic actors of different nations. he presents a similar classification system of the level of integration. Starting from no tariff or quotas (free trade area), common external tariff (custom union), free flow of factors (common market), coherence in economic policies (economic union) to unification of policies and political institutions (total economic integration). Balassa primarily focuses on the economic aspects of the integration process. He touches upon the political characteristics of the procedure only at the last stage of integration, which implies economic success during previous stages. This approach is criticized for its ignorance of domestic political factors and social dynamics (Santos, 2009).

In light of the theories mentioned in this section some aspects of the RCEP become relatively more apparent. Firstly, the hegemonic stability theory seems to fit well into the case of RCEP. China as a global and regional economic power certainly has the capacity and will to lead the region and assume the role of a hegemon in the integration process. Despite the participation of other major developed economies such as Australia, South Korea and Japan in the agreement, China has shown several times that it is eager to take a leading role in this process, as demonstrated by its hosting of the negotiation talks on several occasions. From China's perspective being a leader in the RCEP, in combination with its belt and road initiative might be the key to their global economic dominance.

Secondly, it should be noted that RCEP is the latest in a series of major economic cooperation and partnership agreements. Since the end of world war II, the number and sphere of economic partnership agreements has only been growing in Southeastern Asia. In fact, RCEP itself is the result of expansion on the existing ASEAN association, as it was initially proposed as 'ASEAN+6'. This highlights the growing interest among nations in economic integration in the Southeast Asia region; or in functionalist and neo-functionalist terminology, the gains from a limited form of integration are encouraging leaders to pursue the integration process in a broader perspective. It can be argued that the existence of RCEP can be attributed in some way or form to the spillover effect, caused by regional cooperation in the past.

The process of regional integration and the idea of regionalism has been thoroughly discussed and explored by numerous scholars in fields of international relationships, political science and economics. Haas (2004), Balassa (1961) and Kindleberger (1973) provide in depth ontological and epistemological study of the theories mentioned in this thesis and other theories of regional integration of varying relevance.

1.1.6. TRADE CREATION AND TRADE DIVERSION EFFECTS OF THE RCEP

The term, trade creation describes a situation where, as a result of economic integration and tariff reduction the cost of goods is decreased, resulting in an increase in efficiency and production and incremental trade. As a result of economic integration or participating in a trade agreement, the countries within an agreement may experience an increase in trade that was not happening before the agreement but happens after the agreement as a result of increased efficiency, which is triggered by economic integration and tariff reduction.

On the other hand, countries may also experience a decrease in their amount of trade as a result of economic integration or participating in a cooperative agreement. This happens when trade is diverted from more efficient producers outside the agreement to less efficient producers inside the agreement, due to cheapening of their goods, as a result of the agreement and the tariff reductions associated with it.

The creation of trade blocs and participating of nations in any sort of trade agreement is generally evaluated based on -inter alia- its trade creation versus trade diversion effects. The balance between these two opposites, is an indicator of the agreements' overall effect on individual nations' welfare (Suranovic, 2010).

A 2% increase in intra-regional trade, amounting to 42 billion USD, is expected in the RCEP region, as a result of the bloc's formation. A significant portion of the incremental trade would be the result of diverging trade away from non-member countries. Approximately 40.5% of the increase in intra-regional trade would be the result of lower tariffs i.e., trade creation (UNCTAD, 2021).

Figure 1.1 shows how trade among members of the RCEP is expected to be affected by implementation of the RCEP agreement. Japan's exports to other RCEP member countries are expected to increase by 5.5% compared to its 2019 magnitude. In this regard, Japan is followed by China, South Korea, Australia and New Zealand. The increase in exports of the aforementioned countries predominantly driven by trade diversion effect of the agreement. On the other hand, Cambodia, Indonesia, Philippines and Vietnam will experience a reduction in exports to other RCEP member countries as a result of the agreement's tariff concessions. Due to tariff liberalization, the exports from these countries are expected to be diverted to other RCEP member countries. However, it does not imply that these countries would be better off by not participating in the agreement; as trade would be diverted, nevertheless. For example, some of Vietnamese exports to China would be replaced by Japanese exports as a result of tariff reduction regardless of Vietnam's participation in the agreement. Despite the loss in exports, trade

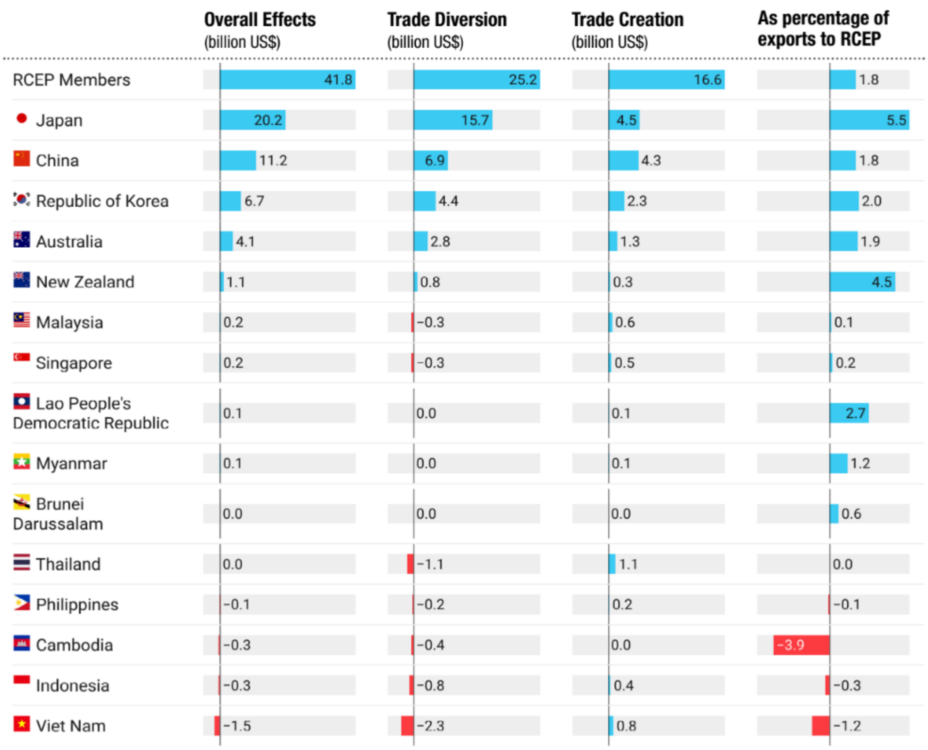


Figure 1. 1

RCEP members export changes due to tariff concessions

Source: (UNCTAD, 2021, p.13)

creation prospects associated with the agreement mitigate the trade diversion effects. In case of Thailand for example, the loss in exports due to trade diversion is wholly covered by gains stemming from the trade creation effect (UNCTAD, 2021).

Trade liberalization in the RCEP region would divert trade from outside the bloc

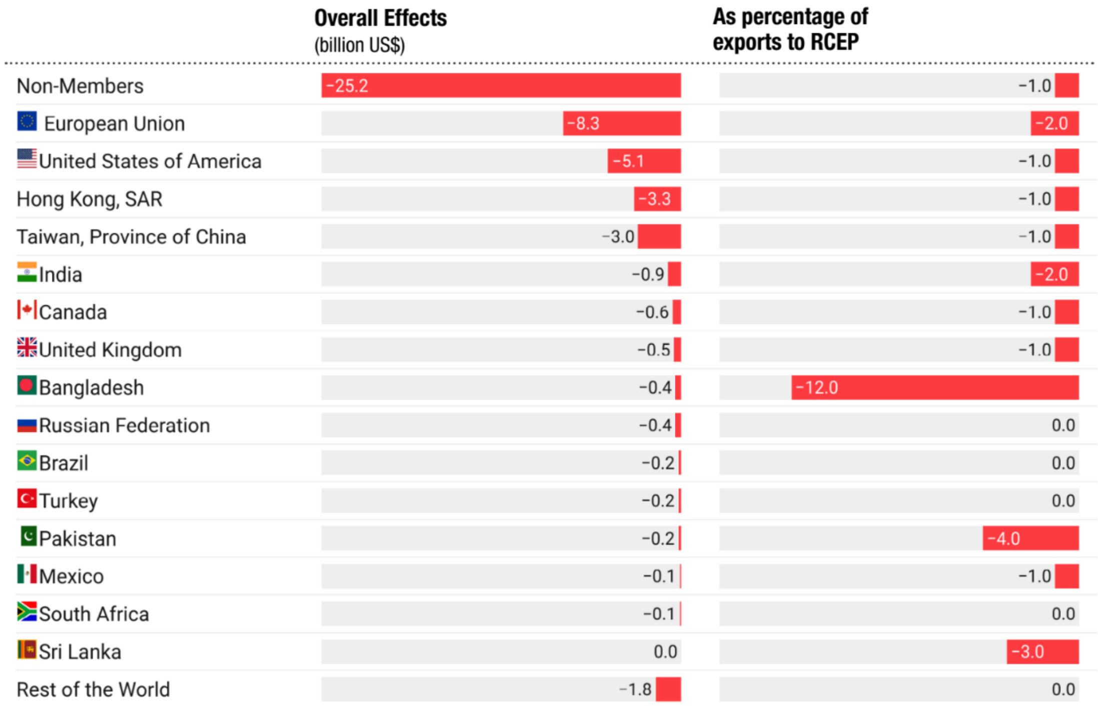


Figure 1. 2

Non-RCEP members: export changes due to tariff concessions

Source: (UNCTAD, 2021, p.14)

to inside the region. Figure 1.2 illustrates how trade diversion effect of the agreement is expected to affect exports from non-member countries. European Union, the United States, Taiwan and Hong Kong are expected to bear the largest losses in terms of export value. The magnitude of losses are related to the exposure level of individual countries to the RCEP region. When the loss of exports as a result of RCEP's implementation is calculated relative to total exports to the RCEP; then Bangladesh, Sri Lanka, and Pakistan appear to be more significantly negatively affected by the agreement. For example, Bangladesh's exports to RCEP countries are expected to shrink by 12% as this portion is diverted to favour RCEP member countries. Trade creation and trade diversion effects of the RCEP are expected to become more magnified as the region integrates further (UNCTAD, 2021).

RCEP is on track to become the world's largest trading bloc. It has also been referred to as ‘a new centre of gravity’ around which, trade and economic relations of the future would take shape. The agreement has large potential for gains for its member countries; even those that may be slightly negatively affected by the trade diversion effect in the beginning. They’re better off inside the bloc, not only because of the agreement’s trade creation potential but also the benefits that comes with it, such as, foreign direct investment, cooperation in development and technology, structural transformations and ease of doing business inside the region. (UNCTAD, 2021).

1.2. GRAVITY MODEL IN INTERNATIONAL TRADE

The Gravity Model of International Trade was first introduced in 1962 by Dutch economist Jan Tinbergen (Tinbergen 1962). It has since been widely adopted by economists to understand trade patterns in an ever-globalizing world. When Tinbergen proposed an econometric exercise to a team of colleagues from the Netherlands Economic Institute “to determine the normal or standard pattern of international trade that would prevail in the absence of trade impediments, he came up with the idea of an economic model formulated along the lines of Newton’s Universal Gravitation” (Benedictis and Taglioni, 2011, p.56). Inspired by Newton's Law of Universal Gravitation which proposes that every particle is attracted to every other particle in the universe with a force that is directly proportional to the product of their masses and inversely proportional to the distance between them. Similarly, Tinbergen’s Gravity Model of International Trade states that the volume of trade between two countries is proportional to the product of their economic mass (i.e., gross national product) and negatively related to the physical distance between them. It should be noted that models inspired by Newton’s theory of gravity were used in research long before Tinbergen’s application, not only in economics but in other disciplines as well.

Ravenstein (1885) used the gravity approach to study the laws that govern the flow of migration in the United Kingdom. Zipf (1946) used the gravity model to study the intercity movement of individuals in the United States and found that the rate of movement among two communities is directly proportional to the product of their populations divided by the transportation between them (Benedictis and Taglioni 2011).

Isard (1956) frequently benefits from the gravity model in his book, in the urban-economic discipline. Deutch and Isard (1961) mention “the ‘well-known’ mutual energy concept of gravitational (Newtonian) physics” and among other things they find that the frequency of a given type of transaction between two economic actors “ought to be directly proportional to the product of the masses of the two actors and inversely proportional to the distance separating the actors”.

After Tinbergen, Pöyhönen (1963) using a similar approach, aimed to study “some structural features of international trade.” After observing the flow of goods between 10 European countries, he validated the inspiration behind the gravity model by stating that “economic activity is governed by rules of which analogies are to be found in natural sciences.” Linnemann (1966), a student of Tinbergen, published a study in which he aimed “to explain why size of international trade flows differ so much between different pairs of countries.” He used regression analysis on a dataset of eighty countries and concludes that the trade flows between any two countries can be explained with a simple log-linear relationship with specific variables that affect the potential supply of the exporting country, the potential demand of the importing country or the “resistance” to trade flows between the two countries.

The gravity model was well-known by the 1970s. Leamer and Stern (1970) in their book on international trade, greatly emphasize on the need for its further research and theoretical refinement. Around the same period, the term “resistance to trade” was introduced and it drew interest of many economists and international trade analysts of that period, and it was widely proxied by economic distance and similar factors, in studies that utilized the gravity model.

Michael Greenwood utilizes a ‘gravity-type’ model to research the internal migration in the U.S. and finds that when a migrant is processing the decision to move, he “takes into account private costs and benefits of his move but does not take into account his social cost” (Greenwood, 1975, p.422). Anderson (1979) referred to the gravity equation as “probably the most successful empirical trade device of the last twenty-five years”. In the same paper he intends to provide a theoretical explanation for the gravity equation. While Tinbergen’s work was plausibly the first application of the Gravity Model in international trade, trade economists, however, seem to be in unanimous agreement that the first theoretical foundation of the gravity equation of trade, as it is know it today, belongs to Anderson (Yotov 2022).

Despite gaining popularity among its adherents the gravity model was not immune to critique. The 1970s, 1980s and even 1990s marks a period in its history in which the model was unable to satisfy expectations of trade economists (Yotov 2022). “The gravity model fell into disrepute in the 1970s and 1980s” (Baldwin and Taglioni 2006) While testing trade theories and predicting trade flows in his book, Deardorrf (1984) refers the theoretical heritage of gravity type models as “somewhat dubious” and points to the handicap of gravity equation for only being able to explain what is happening in international trade but unable to explain the reason behind it. Despite his criticism of the gravity approach, Deardorrf, could not ignore its success, he appreciated the empirical results of the model by referring to them as “extremely successful.” Leamer and Levinsohn (1995) entirely disregarded the model’s contributions to the international trade literature by stating that the gravity theory “had virtually no effect on the subject of international trade”. They highlighted the fact that gravity model had failed to bring the distance factor into relevance in trade textbooks and educational courses. And that it had failed to convince trade economists to admit the effects of distance into their thinking. However, they do appreciate the model’s empiric results by defining them as “some of the clearest and most robust empirical findings in economics.”

Another attempt to enrich the microeconomic foundations of the gravity model was made by Bergstrand (1985). He addressed the model’s ‘weak’ theoretical foundations restraining it from being used as a predictive tool. “He developed a theoretical connection between factor endowments and bilateral trade. He did not manage to reduce the complicated price terms to an empirically implement-able equation” (Baldwin and Taglioni 2006). Many remarkable studies such as Krugman (1980), Bergstrand (1989), Bergstrand (1990) and Deardorrf (1998) continued to be conducted around the gravity model in the 1970s and 1980s (Yotov 2022). It was during this period when “the gravity model went from having too few theoretical foundations to having too many” (Baldwin and Taglioni 2006). Yet it had still not made its way into the mainstream “until the early 2000s when the magic happened” (Yotov 2022).

Eaton and Kortum (2002) developed a Ricardian model that incorporated the effects of level of technology and geographic barriers in explaining bilateral trade. In their study they assume and later find that bilateral trade volumes share structural resemblance with the gravity equation. They claim that global trade volume would have been much larger in a 'zero-gravity' world. As a result, their findings confirm the gravity and resistance effects of distance on trade. Anderson and Van Wincoop (2003) developed a method "that consistently and efficiently estimates a 'theoretical gravity equation'". They also provided an explanation to McCallum's famous Border Puzzle (McCallum 1995) by stating that "national borders reduce trade between industrialized countries by moderate amounts of 20–50%".

Contributions to the gravity model, in the early 2000s, sealed the gap of pessimism in its theoretical foundations. During this period the gravity model became widely patronized as trade economists and academics of all levels employed it in their applications of various types. It has started to appear more often and has become inseparable part of trade textbooks authored by respected economists as well as in studies conducted by young academicians. (Feenstra 2004), (Van Bergeijk and Brakman 2010), (Schernhammer 2011), (De Benedictis and Salvatici 2011), (Melitz, Obstfeld and Krugman 2012), (Grath 2016), (Krueger 2020) and many other books over the years have featured the gravity model. It is also used to research how trade is influenced by factors such as GDP (Kien 2009), immigration (Piperakis, Milner and Wright 2003), FDIs (Gopinath and Echeverria 2004), openness of economy (Rahman 2010), WTO membership (Bino, Ghunmi and Qteishat 2014), cultural proximity (Balogh 2015), RTAs (Ekanayake, Mukherjee and Veeramacheneni 2010), exchange rate volatility (Karemera et al., 2015), linguistic distance (Hutchinsin 2005), complying with HACCP standards (Yunus 2009), trade liberalization (Badinger and Breuss 2004), cultural similarity and political developments (Shrestha and Upadhyay 2004), economic sanctions (Caruso 2005).

Santos Silva and Tenreyro (2006) introduced the Poisson Pseudo Maximum Likelihood estimator. This method was able to account for heteroskedasticity and zero trade flows when estimating the gravity model. It therefore was able to quickly establish itself as a reliable alternative gravity model estimator.

Batra (2007) investigates India’s global trade potential and estimates an augmented gravity model from a dataset of 146 countries to analyse India’s trade flows with the world. She finds that India has unfulfilled trade potential with its neighbouring countries. Khadaroo and Seetanah (2008) utilize the gravity model to study the significance of transportation infrastructure in determining the volume of tourism flows to a country. They find that transportation infrastructure, besides tourism infrastructure and other conventional factors, are important determinants of tourism inflows into a destination.

Olivero and Yotov (2012) contribute to the development of the gravity model by introducing a dynamic gravity model. They argue that trade flows are dynamic in nature and therefore a dynamic model is preferrable to study them rather than the standard gravity model with its static characteristics. Nuroğlu (2014) is among the earliest studies to integrate machine learning elements into the gravity model. She uses artificial neural networks to estimate a modified gravity model.

Natale et al. (2015) develop a gravity model to investigate the influence of primary production, food consumption, population, income, GDP, trade agreements and geographical distance over seafood trade. They find that the trade in seafood portfolio is mainly driven by commercial characteristics of individual products. As an aggregate however, seafood trade is attracted either by countries with well-established seafood preferences and or by countries with low labor costs of further processing. The trade in meat products, in comparison, is attracted by high per capita income and high primary production of the exporting country.

Kea et al. (2019) use a dynamic gravity model in their attempt to determine the factors driving Cambodia’s rice exports. They estimate the model using Generalized Least Squares, Poisson Pseudo Maximum Likelihood and Heckman Sample Selection methods. Their results suggest that historical ties, exchange rate policy and agricultural land reform promote rice exports, especially to the EU, China and ASEAN region.

Yao et al. (2019) use a gravity model to study the effects free trade agreements on bilateral carbon emissions of the bounded countries. They find a positive impact of free trade agreements on carbon emission levels. In an income-based country group context, they find that upper middle income and lower middle income countries are hit the hardest with increase in air pollution due to their lenient environmental laws.

Greaney and Kiyota (2020) contribute to the gravity model literature by concluding that the model performs extremely well in explaining bilateral trade, even when the dual nature of some goods that can be used as, both final and intermediary, is accounted for. Anderson and Yotov (2020) introduce the Short Run Gravity model of bilateral export trade.

Since its emergence in the international trade arena by Tinbergen, the gravity model of international trade has only become more popular in tandem with globalization and ever-more economic integration. As economies around the globe become more connected and trade expansion is used as one of the many means of economic growth, literature on the subject has also grown in abundance, as well as utilization of- and praise for the gravity model. The model is crucial to almost all debates of trade in the modern day. The model's merit and success has asserted it as "the work-horse" model of trade (Yotov, 2022). While the gravity model still is very faithful to its theoretical foundations and initial form, it has undergone a phase of academic evolution to earn its place in international trade literature.

1.2.1. ESTIMATION OF THE GRAVITY MODEL

A panel data structure is used to investigate the factors influencing trade flows in the RCEP region. Pooled OLS, fixed effects model and random effects model are generally used in analysing panel data. However, to account for -otherwise unobservable-partner specific effects a fixed effects method of panel data analysis is used in this thesis (Karagöz and Karagöz, 2009). According to Antonucci and Manzocchi (2006) when estimating trade flows between a predetermined selection of countries fixed effects model is preferrable to the random effects model which shall be used when estimating trade flows between a randomly selected group of trading partners. Egger (2000) suggests that the appropriate econometric configuration of a gravity model in most cases would be with fixed country and time effects. The decision to employ the fixed effects model in this thesis is also supported by the Hausman test.

A handicap of the fixed effects model is that it cannot directly estimate coefficients for variable that do not change through time such as geographical distance (Antonucci and Manzocchi, 2006). To circumvent this obstacle proxy variables for distance, trade costs and trade resistance can be improvised. To be able to work with fixed effects model, the geographical distance variable is substituted for trade weighted relative distance in this thesis, Karagöz and Karagöz (2009) uses a GDP weighted relative distance.

1.3. ARTIFICIAL NEURAL NETWORKS

An artificial neural network is a mathematically programmed web of computing processes. It is inspired by the biological neural network in living creatures, and it attempts to imitate the workings of the biological nerve system and the brain. An artificial neural network consists of nodes, also referred to as artificial neurons, it mimics the functions of a nerve cell, and it is the main processing unit of the network. Artificial neurons are connected with each other via bridges called 'edges,' they transmit signals (i.e., numerical values) produced by one artificial neuron, to, the next. Edges have specific weights dedicated to them. Their weights determine the strength of the signal they carry which is fed to the next neuron. Artificial neurons compute their output signals based on a function of the sum of its input signals, also referred to as activation function. A certain degree of bias may also be attached to the signal transmitted by a neuron, which is summed up before it enters the next neuron. This process of feeding the signal forward is called 'forward propagation' (Nielsen, 2018).

For the neural network to be a useful estimation tool it must predict outputs to a specified level of accuracy. The network learns to predict more accurately through a process called 'back propagation' (Nielsen, 2018). It is a loop of feedback mechanism which re-adjusts the network's weight and bias parameters until it starts predicting outputs accurately enough. This is an over simplified explanation of the intricate mechanism and combination of the weights, bias and activation function that enables the network to recognize patterns and eliminate noise in data. Detailed explanation regarding the workings of the aforementioned components and the network is provided in the following parts of this subchapter.

Starting in the late 1980s and intensifying in the early 2000s, artificial neural networks have gradually established themselves as a reliable alternative to statistical estimators. Though, it should be noted that they are more versatile and multi-purpose rather than only being statistical tools, as some studies inaccurately imply. Despite seeking to achieve the same results neural networks and traditional statistical methods such as regression analysis differ in many aspects. The two methods have different terminologies which at times have caused confusion among researchers attempting to compare them. Elements of a regression model such as independent variable, dependent variable coefficient and standard error are similar but not exactly interchangeable with input, output, weight, and error elements of a neural network model. While regression analysis seek to provide an estimator and explanation regarding the marginal effects of variables and prioritizes interpretability, neural networks aim for increased efficiency and pattern recognition. Regression models are derived a well-defined step-based process, in contrast, the derivation of neural network models do not have universally agreed upon rules, and the process is mostly left to the researcher's satisfaction.

The reason neural networks seem so promising is that they can automatically approximate any non-linear mathematical function. This feature is most relevant when the relationship between the dependant and independent variables is complex, noisy or unknown. Neural networks are also known for their ability to retrieve whole data from a fragment (Hopfield 1982; Hornik et al., 1990).

On the other hand, working with neural networks has challenges of its own. There is no standard method of determining the network structure, the number of hidden layers or the number artificial neurons in the layers. Although neural network packages and extensions have recently been produced for use with existing statistical software there is no standard software application. Its black-box character of solving problems is not as insightful as the step-based process in a liner regression, hence reducing the interpretability of the model's output.

1.3.1. ARCHITECTURE OF ARTIFICIAL NEURAL NETWORKS

Topologically, artificial neural networks have a layered structure. The layers are organized in three sections, the left, the right and the middle. Assuming the flow of data occurs from left to right, then the leftmost layer is called the input layer, it consists of input neurons, and it is where data from outside the network is fed in. The rightmost layer is the output layer, it contains output neurons which emit the result of calculations performed by the previous layers. The layer or group of layers in between, are hidden layers. The neurons in this layer receive signals from the input layers and after applying a certain mathematical function to them, forward them to the neurons in the next layer (Basheer and Hajmeer, 2000). The hidden layer is also referred to as the black box (Nelson and Illingworth 1991).

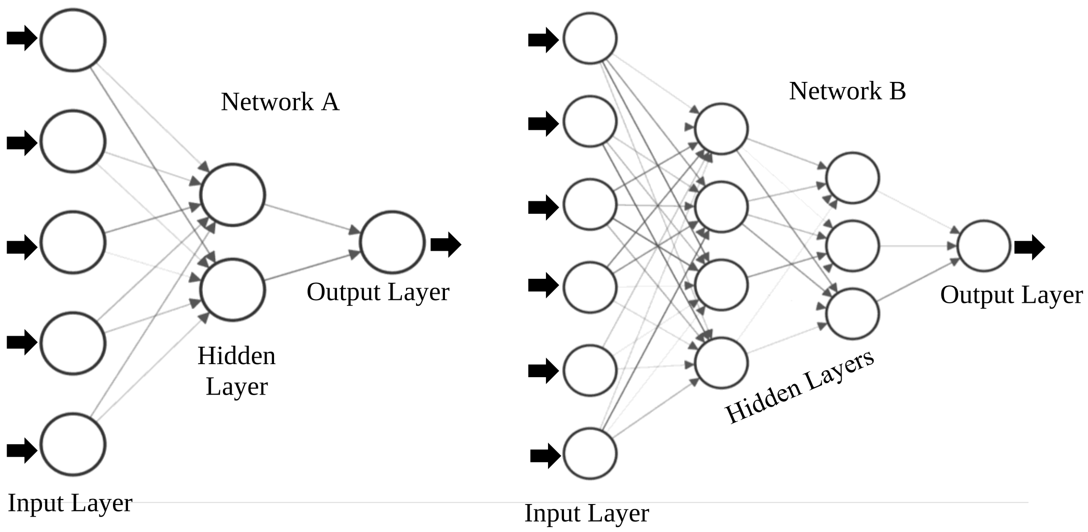


Figure 1. 3

Topologies of single and multiple hidden layered networks

Source: Author’s own graphical illustration

Figure 1.3 shows two different neural networks. Network A is a simpler design with only one hidden layer. Network B on the other hand, is more complex and sophisticated with two hidden layers. Any number of hidden layers can be added to a network. As the number of hidden layers increases the network becomes more intelligent and its design becomes longer and deeper, resulting a deep-learning network. However, for relatively simpler tasks such as empirical research and estimations a conservative number of hidden layers is encouraged. The pointing arrows represent edges and the difference in their shades of colour is supposed to illustrate their weight. The circles represent artificial neurons which are the building blocks of the network.

Artificial Neuron

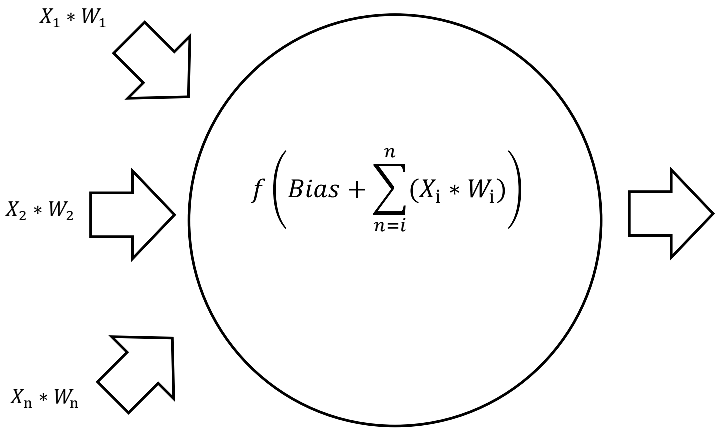


Figure 1. 4

Activation function’s application to the incoming signal inside a neuron.

Source: Author’s own graphical illustration

Figure 1.4 illustrates how neurons process signals they receive. The signals are first summed up together with the bias value. Then they are treated according to an activation function. Finally, the neuron transmits its own signal. Activation function dictates the level of sophistication of the network and its behaviour. In a way it is the mathematical DNA of the network and perhaps, its most vital component. Currently, there are several types of activation functions used in different areas of neural networks’ application. These include Sigmoid, Tanh, ReLU, ELU, Softmax, Swish, GELU and SELU (Baheti, 2022). In comparative academic research such as the present study sigmoid activation function is more commonly used.

Artificial neural networks are versatile and creative tools with unlimited area and potential of applications. The introduction given above shall provide sufficient understanding of the concept, to comprehend the flow and methodology of this study.

1.3.2. EVOLUTION OF ARTIFICIAL NEURAL NETWORKS

Interest in making machines smarter and capable of logic can traced back to the invention of the Chinese Abacus. Counting and computation devices have become more logical in parallel with human species' understanding of laws and logic of our universe. The development of an artificial neural network is one of the countless endeavours by humans to replicate or enhance a human ability in a machine.

Alan Turing is credited with being the first scientist to have thought of computer programming and human brain in the same context. The earliest study found to have attempted to illustrate the 'network-like' behaviour of the human brain was conducted by McCulloch and Pitts (1943). They studied neural activities of the brain from a propositional-logic perspective. Their characterization of neural activity as all-or-none is the base on which the modern active-or-inactive artificial neuron is based.

Hebb (1949) made an important contribution to the field of neurocomputing. He pointed out certain physiological aspects of psychological phenomena. He asserted that when a neural pathway is used repeatedly it becomes more efficient and stable over time. "When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased" (Hebb 1949). Although this statement was made to highlight the physiological changes in brain, it became the groundwork for learning ability of artificial neural networks since certain paths in an artificial neural network also become relatively stronger as the network is fed with more data. Hebb's work solidified the place of artificial neural networks in theoretical realm which was followed by real world applications in a relatively short amount of time.

Nelson and Illingworth (1991) refer to 1950s as the gestation era for neural networks. Due to progress made in computer technology in that period, from which neurocomputing fairly benefited, simulations of artificial neural networks became possible. In the summer of 1951 Minsky and his graduate student Edmonds assembled the first neural network machine from three hundred vacuum tubes and spare auto-pilot equipment from a B-24 airplane. The machine was named SNARC, and it consisted of a network of forty artificial neurons, simulating the brain of a rat that had to learn its way out of a maze (Crevier 1993).

In 1955 McCarthy et al. proposed a "2-month, 10-man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study was to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (Russel and Norvig 1995). Despite involving some of the best minds of that period the program produced mixed results. It did, however, bring momentum to research in the field of neurocomputing.

Rosenblatt (1958) developed the first perceptron. He built upon and improved McCullah and Pitt's (1943) work by incorporating weights into the equation, using an IBM 704 machine he succeeded in getting the computer to learn how to distinguish between cards marked on the left and cards marked on the right (IBM Cloud Education, 2020). Although Rosenblatt's Perceptron was a linear system, it was efficient in solving many problems and led to what is known as the 1960s ANNs hype (Basheer and Hajmeer, 2000).

Widrow and Hoff (1960) developed adaptive filter systems meant to eliminate echoes on telephone lines. Their system could "modify their own structure to optimize performance based on past experiences". The system designer would 'teach' the system by showing it examples of input signals or patterns and their desired output for each input simultaneously. The system in turn would organize and adjust itself to comply as well as possible with the wishes of the designer. This was the first neural networks related solution applied to a real-world problem (Nelson and Illingworth 1991).

In the early 1960s optimal control problems were also explored. Kelley (1960) and Bryson and Denham (1962) developed the gradient-solution procedure for optimal control problems, which in essence, sparked the eventual development of the back propagation method. "Though neural-net researchers have come to recognize that multistage feedforward nets fit into the optimal control theory mold and that [backpropagation] is a gradient procedure, proper credit for the [backpropagation] method of solution has not been accorded to Kelley and Bryson. Often the 1974 doctoral dissertation of Werbos (1974) is cited as the earliest reference" (Dreyfus 1990).

Ivakhnenko and Lapa (1966) introduced the first functional multilayer network. In their study, they propose multidimensional prediction devices based on multilayer networks to be used in research in different fields of science and daily operations such as meteorology, power systems management, agriculture, medical diagnosis, industrial processes and even organizing and planning of the national economy.

Researchers experimented with neural networks throughout the 1960s. Concepts such as continuous speech recognition and teaching motor commands to robotic arms were toyed around with. "Affected by the predominantly rosy outlook of the time, some people exaggerated the potential of neural networks. Biological comparisons were blown out of proportion" (Nelson and Illingworth 1991). The hype of the 1960s was put an end to by Minsky and Pappert (1969) when they published their book; the Perceptrons. Their book in which they greatly emphasized on Rosenblatt's Perceptron's inability of solving non-linear problems, negatively influenced neural networks' growth. Although this handicap was well-known from the beginning, the book deterred researchers from working with artificial neural networks in the early 1970s. As a result, researchers turned their focus to Artificial Intelligence which was seemingly more promising and safer at the time.

A few determined researchers however did continue to experiment with artificial neural networks around the globe. Benefiting from existing research on gradient-solution procedure, Werbos (1974) applied backpropagation process to the neural networks in his PhD thesis. The momentum for interest in neural networks was in the making throughout the 'quiet years' of the 1970s, it resurged when Hopfield (1982) introduced the Hopfield Network. His network could retrieve a complete set of data or an image from its fragments. In contrast with the majority of applications based on neural networks before him, which were attempts at modeling the brain, Hopfield's network was a practical and useful device. His network's abilities "intrigued military minds" (Nelson and Illingworth 1991). Hence, the topic of neural network's potential was again on the table, marking a turning point in its evolution. A series of major developments in the field were soon to follow this renewed interest.

In 1982 the US-Japan Joint Conference on Cooperative/Competitive Neural Networks was held in Kyoto, Japan. Fujitsu later began development of the “thinking computer” for robotic applications.

Rumelhart et al. (1986) redefined the backpropagation process, which escalated the popularity of multilayered neural networks. In 1987 the Institute of Electrical and Electronics Engineering held their first ever International Conference on Neural Networks. The International Neural Network Society was formed later in the same year with divisions based in US, Finland and Japan. In 1988 the first Neural Networks Journal was published by the INNS.

LeCun (1989) illustrated how implementing constrained backpropagation into neural networks can be useful in optimizing algorithms. His research was later successfully applied in training a neural network to recognize handwritten zip code digits for the US Postal Services.

Hornik et al. (1989) illustrated how neural networks, with as few as one hidden layer, consisting of sufficient hidden neurons, can be used as universal approximators. Hornik et al. (1990) demonstrated that a multilayer feedforward neural network with appropriate activation function is capable of arbitrarily accurate approximation of an arbitrary function and its derivates.

The International Joint Conference on Neural Networks held in June of 1989 produced 430 papers, sixty-three of which focused on application developments. The Neural Networks for Defense meeting held in conjunction with the conference gathered more than 160 representatives of government defense agencies and defense contractors giving presentations on their neural network efforts. (Nelson and Illingworth 1991).

The 1980s was a period of astonishing growth for the neural networks. The multipurpose character of the model earned it unprecedented attention from various disciplines. Weng et al. (1992) introduced a self-organizing, adaptively growing neural network called the Cresceptron, which could detect new concepts automatically and grow its neural structure accordingly. It was one of the earliest examples of self-learning structures. Weng et al. (1993) was able to tune the Cresceptron to recognize threedimensional objects in two-dimensional photographs. After many tests with real world images, they reported to have demonstrated the feasibility of learning in the Cresceptron.

Since the late 1980s the field of artificial neural networks has grown stronger and richer; and has expanded in all directions such as visual and vocal pattern recognition, robotics, machine learning, optimization problems and so on.

Neural networks' ability to detect non-linearities in very large and noisy datasets drove financiers to explore its potential in forecasting financial indicators across different markets. Kimoto et al. (1990) developed a buy and sell timing prediction system based on neural networks. They provide the system various learning algorithms and forecasting instructions for the Tokyo Stock Exchange Prices Indices. The program was able to conduct accurate estimations and the stock trading simulation appeared to have yielded extraordinarily good returns.

Trippi and Desieno (1992) developed a system for trading S&P 500 index futures, their system would narrow down the results of several neural network calculations to a single Boolean decision. During testing the system outperformed passive investment in the index.

Kuan and Liu (1995) use neural networks to forecast exchange rates and they conclude that "network models have significant market timing ability and/or significantly lower out of sample mean squared prediction error relative to random walk model."

Verkooijen (1996) finds that neural network-based models are able to predict a higher percentage of exchange rate direction movements and remarks that in his multiple trials, neural networks were never outperformed by the linear models.

Neural networks have also been applied in more complex calculations such as option pricing and the prediction financial crisis and bankruptcies for risk evaluation. Ghaziri et al. (2000) used neural networks to price S&P 500 index call options. They conclude that neural networks outperformed the well-established Black-Scholes option pricing model. Bennell and Sutcliffe (2004) confirms neural networks' superiority to Black and Scholes model in their findings on pricing European style call options on FTSE 100 index. Anders et al. (1998) conduct a similar study for the German Stock Index and find neural networks to have better out of sample performance compared to Black-Scholes model.

Banks use neural networks to evaluate, classify and grade credit and loan applications in order to get as much insight on the applicant's ability to payback. Coats and Fant (1993) developed a system to distinguish between healthy and financially distressed firms using neural networks. Their purpose was to receive early warning signals of future financial distress.

Fernandez and Olmeda (1995) compare the performance of neural networks against decision trees generating algorithms, Multi-Asset Risk System, Discriminant Analysis and Logit in bankruptcy prediction. They found the neural network model to have generally produced better results.

Neural networks have been astonishingly successful in all areas of economics where it has been patronized. Since the early 2010s it has caught the eye of international trade economists and researchers as well. Hence, research publications around neural networks in international trade have steadily started to emerge. Nuroğlu (2014) investigated the determinants of bilateral trade among fifteen European countries. She used a modified gravity model of trade that incorporates population and volatility of exchange rates. While estimating her modified model, using both neural networks and conventional panel data analysis she reported that the former had demonstrated superior ability of learning and explaining the relationship between inputs and outputs as well as out of sample forecasting performance.

Today, neural networks are used in many fields of scientific research. It has proven itself to be a reliable, robust and sophisticated tool to understand the behavior of humans and modern-day civilization from economic, environmental, medical, political and various other perspectives. Artificial neural networks are expected to rapidly evolve further and become even more sophisticated, whilst also becoming more user friendly and easier to implement. The comparison between artificial neural networks and conventional statistical models will be further elaborated in the literature review chapter of this study.

1.4. CONTRIBUTION OF THIS THESIS TO THE LITERATURE

The goal of this study is to contribute to the literature in two ways. Primarily, it is attempted to analyse trade patterns among participants to the relatively novel RCEP agreement. Framework of the RCEP agreement is explained, and its expected effects on economic activity in the region are summarized. The influence of certain gravity related elements on trade will also be investigated. A fixed effects model of panel data analysis is used.

Secondly, it is attempted to present a comparative analysis between forecasting performance of artificial neural networks and the panel data analysis. A summarized yet comprehensive introduction to neural networks is provided and the working mechanism of its components and the network as a whole is explained. Due to the socio-economic diversity, and the variation in data keeping history and standards among members of the agreement, this application is supposed to present a tough challenge to artificial neural networks. However, as explained in the following parts of this thesis, the ability to work with missing data is one of neural networks' strength. A rich and consolidated review of existing literature on the subject is presented and directions for further research in the area are suggested.

CHAPTER 2: LITERATURE REVIEW

Since artificial neural networks were attempted mathematical recreations of the brain, their potential use as statistical tools was evident from the beginning. Literature considering neural networks as complementary or an alternative to the traditional statistical methods first appeared in late 1980s. Hornik et al. (1989) is often considered to be the first in this regard. They establish neural networks to be satisfyingly accurate universal approximators; implying that lack of success in its application must be arising from inadequate learning, insufficient numbers of hidden units or the lack of deterministic relationship between the input and the output.

Statistical aspects of neural networks make it a novel, sophisticated and flexible tool to work with across disciplines. Its area of application has virtually no boundaries. It can potentially be used in aviation sector to help carry out human-logistics operations more efficiently; medical practitioners can use it to accurately diagnose health conditions from a variety of symptom inputs; engineers of all sorts can utilize it to predict the wear and tear in their products even before manufacturing them; it can help human resources managers pick the ideal candidate; it can be programmed to project future energy and resources consumption for cities; or car traffic on highways and junctions. Its potential in the economic realm is unlimited. It can be used to research and optimize a country's economic affairs internationally and internally, on both macro and micro levels. Therefore, the background variation in neural network literature is unsurprising and it will be a common theme in this review.

The use of neural networks as statistical estimators in business and economics initially focused on finance, accounting and marketing areas. Using financial ratios, Salchenberger et al. (1992) develop a neural network model to predict the financial health and risk of failure for saving and loan associations. They compare its predictive ability with that of logistic regression and conclude that in all examined cases the neural network model performed as well or better than the logit model in classifying institutions failed or surviving.

When predicting consumer choices, West et al. (1997) compare neural networks to traditional statistical methods such as Discriminant Analysis and Logistic Regression, they find that neural networks exhibit better out of sample predictive accuracy compared to conventional methods. They highlight the model's flexible nature and its ability to 'learn' complex relationships between product attributes.

Despite being a relatively newcomer to the statistics arena in the early 2000s, neural networks were already being studied with scrutiny. Sargent (2001) elaborates on 28 existing studies that compare the performances of neural networks against regression models. He finds that in 36% of the cases neural networks outperformed regression analysis; gets outperformed in 14% of the cases; and in 50% of the cases the models tied against each other. The author suggests the desired sample size for neural networks optimal performance to be between 200 – 2000 and points out the existence of publication bias in the studies he covered.

Dvir et al. (2006) employs neural networks and the regression analysis to determine using a pool of 400 managerial variables, the critical managerial factors that affects the success or failure of projects in the defense industry. They report the neural network to have produced better predictive results than linear regression.

Ibrahim and Rusli (2007) analyze how the demographic profile and first semester CGPA of undergraduate students, impact their CGPA upon graduation. They use artificial neural networks, decision trees and linear regression methods in their study. Although all three models yield more than 80% accurate results, the neural network model outperforms the other two.

Bakar and Tahir (2009) use linear regression and neural networks to predict bank performances i.e., return on assets, from data on variables such as liquidity, credit risk, cost to income ratio, size, concentration ratio, inflation and GDP. The prediction made by neural networks produces much lower mean squared prediction error compared to that of regression analysis. Therefore, it is found that neural networks are relatively more powerful in predicting bank performances. They suggest attention to be paid in determining the ideal number of neurons for the network since a high number of them would lead to memorizing by the network while an insufficient number would make generalization unfeasible.

In order to improve storage, transportation and disposal facilitation of waste produced by hospitals, Jahandideh et al. (2009) attempt to predict the amount of waste generated by hospitals. Using data received from 50 hospitals they estimate an artificial neural network and a multiple regression model. Based on merits such as root mean squared error and R-Squared score, they find the neural network model to have significantly outperformed the regression model.

Schlechtingen and Santos (2011) develop two neural networks and one linear regression model to predict operation failures in wind turbine generators prior to the failure happening. While all three models were able to detect incipient faultiness, the non-linear neural network-based models outperform the regression model.

The ability to accurately predict meteorological and geological events is crucial to today's highly interdependent global economy. Thanks to the extensive efforts in data keeping, neural networks has received plenty of employment in these fields. Sahoo and Jha (2013) compare neural networks with multiple linear regression in their study to predict transient water levels over a groundwater basin. They estimate the models, using data from 17 sites in Japan, with variables such as rainfall, ambient temperature, river stage, lags of rainfall, groundwater level and 11 seasonal dummy variables. Performance of the two models was compared based on statistical merits and graphic representations. It is observed that the actual ground water levels fit better to the levels predicted by the neural network, compared to the levels predicted by the regression model. Neural networks predicted more accurate results for almost all seventeen sites with remarkably high R-Squared score. The authors attribute neural networks superiority in this case to predictive limitations of the regression model in the presence of nonlinearity. Zare Abyane (2014) compares neural networks and regression analysis in their study to predict two important water quality parameters in a wastewater treatment plant. He concludes that neural networks outperformed regression analysis based on root mean squared error and remarks that even when provided with minimum input data neural networks can be used to predict the two specific water quality parameters.

To avoid performing comprehensive experiments which can be lengthy and costly, Tiryaki and Aydın (2014) design an artificial neural network model to predict the compression strength parallel to grain, also known as maximum crushing strength of wood, of heat-treated wood. Afterwards they compare results of the prediction with results produced by a multiple linear regression model. According to their findings it can be concluded that artificial neural network model provided relatively better prediction results. They highlight the speed and accuracy of neural networks and its usefullness in understanding wood species for structural and other purposes. In the business side of the industry, Nummelin and Hänninen (2016) use neural networks and other machine learning models to analyze and forecast global bilateral trade flows of soft sawn wood by countries. They conclude that machine learning methods such as neural networks can be a practical way to perform predictive analysis for trade in the industry.

Khademi and Behfarnia (2016) aim to predict 28 days compressive strength of concrete from variables such as sand, cement content, gravel, water cement ratio and so on. They use artificial neural networks and multiple linear regression models to explain the relationship. They find neural networks to have shown better prediction performance based on R-Squared score. They point out that neural networks can be easily and frequently retrained as new data become available.

Neural networks' application in predicting trade patterns has been growing recently. Circlaeys et al. (2017) attempt to improve the prediction accuracy of bilateral trade flows using a gravity model, they find that the model's accuracy is improved by an R-Squared score of 0.15 when it is estimated by using neural networks, compared to the linear regression method. Wohl and Kennedy (2018) also estimate the gravity model using linear regression, poisson pseudo maximum likelihood method and a neural network. They observe that neural networks have the most accurate out of sample estimates in test dataset. Neural network's superiority also holds in their prediction dataset, it estimates outputs, that are reasonably close to actual trade values even ten years beyond the training period. Nuroğlu (2019) uses panel data analysis and neural networks to estimate a modified gravity model in order to analyse trade flows between Turkey and its major business partners. She finds that the models estimated by neural networks has a higher R-Squared value than the one estimated by panel data analysis. Dumor and Yao

(2019) predicts trade flows between China and its Belt and Road Initiative partners. Using the traditional regression, poisson pseudo maximum likelihood and neural network models they conclude that neural networks had demonstrated relatively superior predictive performance. They also report that neural networks have improved performance of the gravity model by an R-Square score of 0.15. Related to the same topic, Koffi and Gbongli (2021) use 27 years of trade data to estimate a gravity model and a neural network-based model to estimate the potential effect of China's Belt and Road Initiative. They find the neural networks approach to have outperformed traditional methods in explaining the variability in the dependant variable. i.e., a higher R-Square score.

Lee et al. (2017) predict profits for schooling companies using linear regression and a neural network model. They find neural networks to be slightly superior to the regression model and point that a higher number of hidden layers result in an overfitting model, and in order to solve this problem they suggest data size to be increased or the number of hidden layers to be decreased.

In the earlier stages of neural networks development as a machine learning tool it was expected to be heavily relied upon, in the fields of power and utility management for urban planners and researchers (Ivakhnenko & Lapa, 1966). This has become a reality as neural networks have occasionally outperformed conventional statistical methods employed in these fields. Kim et al. (2020) attempt to predict electric energy consumption on working and non-working days, for different buildings on Penn State University's main campus. Using data on variables such as occupancy rate, weather temperature, humidity ratio, solar radiation, cloud type and wind speed, they estimate a regression model as well as an artificial neural network model. In their results, the neural network model had produced more accurate and stable results compared to the linear regression model for working days. Panklib and Prakasvudhisarn (2015) aim to predict electricity consumption on a grand scale. By using GDP, population, maximum ambient temperature, and electricity demand as independent variables and inputs, they develop a regression model and an artificial neural network. Their results show that the neural networks provide more accurate results compared to that of the linear regression model, which was outperformed on statistical parameters such as mean absolute percentage error and root mean squared error. Ghanbari et al. (2009) conduct a similar study to forecast annual electricity load for Iran, using real GDP and population size as independent variables. After estimating and comparing both artificial neural networks and the linear regression models they conclude that neural networks model yields to have significantly improved results. Nedic et al. (2014) employ neural networks in a different area of urban planning. They design a neural network model and feed it with the traffic flow structure and traffic speed data to predict noise level caused by the flow of traffic. Later, they compare the model's predictive capability with a regression model and conclude that artificial neural networks show much better predictive capabilities.

Its unmatched ability of pattern recognition in complex data has brought neural networks in close competition with established research and analysis approaches in real estate economics. For instance, Nghiep and Al (2001) use artificial neural networks and multiple regression analysis to predict housing prices in Rutherford Tennessee, from observing sales of single-family residential property for eighteen months. They use living area, number of bedrooms, number of baths, age of the property, financial quarter in which the sale was made and the presence of garage space as independent variables and inputs for the respective models. Using mean absolute percentage error and absolute percentage error as benchmark they find that when sufficiently sized training data is provided, and an ideal neural network structure is determined, artificial neural network will outperform multiple regression analysis. The performance of artificial neural networks appears to be positively related to the sample size. They present artificial neural networks as the overall superior estimator; however, they also suggest the ideal sample size and network topology to be researched and experimented with. Selim (2009) investigates the attributes of housing prices in Turkey, using Household Budget Survey Data for Turkey on 41 house-structure and design characteristics. He estimates an artificial neural network and a hedonic regression model, which is the mainstream tool used for researching real estate pricing attributes. Whilst comparing performance of the models he finds the neural network model to have outperformed the regression model based on statical measures such as mean squared error, root mean squared error and mean absolute error.

Andres et al. (2021) use deep learning neural network model to predict the Knowledge Economy Index of seventy-one developing and emerging economies. In their conclusion they praise the neural network-based model for its robust results and high predictive power.

Neural networks are extensively used in agricultural activities. They have been subject to comparison with regression models in numerous studies in the field of agricultural economics as well. To predict Safflower seed yielding and help breeders produce stronger seeds of the flower, Abdipour et al. (2019) develop a variety of neural network models as well as a linear regression model from data collected by observing the seed's growth patterns for a period of two years. Based on statistical quality parameters such as R-squared, root mean squared error and mean absolute error, they conclude that the multilayer perceptron network model outperformed its competitors. In a similar study for another pharmaceutically important plant, Niazian et al. (2018) also find neural networks to have shown superior results, an 18% increase in R-squared score over the linear regression model. Abrougui et al. (2019) attempt to study the extent to which some soil properties such as microbial mass, resistance to penetration, organic matter, and tillage system affect the yield of organic potato crop. In doing so, they also compare neural networks and a multiple regression model. They find the neural network-based model to have produced more accurate results compared to the regression model, the former explained 6.26% more of the volatility in dependant variable. Using historical yield data from different locations in Maryland, Kaul et al. (2005) develop an artificial neural network and a multiple linear regression model to estimate corn and soybean yield. When comparing predictive performance of the two models they find the neural network-based model to have consistently predicted yield figures more accurately than the regression model. Compared to the regression model, neural networks produced an 83% higher R-squared score and 24% lower root mean squared error in predicting corn yield. In case of soybean yield it produced a 76% higher R-squared score and a 31% lower root mean squared error. To predict daily solar radiation, Bocco et al. (2010) uses the data on variables such as relative sunshine duration, maximum and minimum temperatures, rainfall and extra-terrestrial solar radiation to develop a neural network model as well as a linear regression model. In a comparative analysis of the models, they conclude that the neural network-based model had produced overall more accurate results.

Gámez et al (2016) compare a type of neural network to a multiple regression model in their quest to find the connection between a firm's reputation and its stock market value. Using data gathered by Spain's Monitor of Corporate Reputation on firms enlisted in the Spanish stock exchange they conclude that a higher placement in the corporate reputation rankings, or even a firm's mere presence in the rankings is positively related to its market value. They also find that the neural network-based model had produced more robust results than the regression model.

In light of the comparative studies reviewed above, some evaluations of both approaches are found to be relatively more frequent. Firstly, artificial neural networks' incremental value to any analysis is non-negligible. In worst case scenario it has been a beneficial complementary tool to the main approach. In majority of the studies, it has improved and surpassed the performance of traditional statistical estimators. Benchmarks such as R-Squared score, root mean squared error, mean squared error, and mean absolute error were mostly used as comparison references. Neural network-based models consistently outperformed regression-based models by emitting less error and showing higher rates of explanatory power. Its ability to handle non-linear relationships between variables better than the traditional statistical approaches was proven on several occasions and its tolerance of missing data was praised. Secondly, challenges reported in working with artificial neural networks were mainly stemming from its unspecified parameters and configuration. Network components such as the number of layers, neurons, epochs, activation function and learning algorithm were frequently determined using a trial-and-error approach. The lack of interpretability of results produced by the network-based models, was also mentioned frequently, however, it did not affect the model's predictive capabilities. Lastly, some studies suggested that the performance of neural network-based models is positively related to the number of observations. To better utilize the potential of neural networks, research on determining the optimal network structure and number of observations was suggested. The enormous potential of neural networks and its ability to work with missing data was commonly highlighted and almost all of the mentioned studies unanimously suggested and expected artificial neural networks to be applied extensively in the future.

CHAPTER 3: METHODOLOGY AND RESEARCH

In this chapter, information on data used in this study is presented and the model configurations for each of the two approaches are introduced. Estimation of the two models is also explained in a gradual narrative. In order to conduct a comparative analysis between the two approaches, performance benchmarks are selected and the question of neural networks' forecasting capabilities is hypothesized. Afterwards, the models' predictive abilities are tested and their results are presented and explained. This is followed by a comparative analysis of the two approaches.

3.1. DATA AND MODELS

Starting from 1991, the data covers 30 years of trade activity and fluctuations in population and production size. Trade and export volume figures are obtained from IMF's Direction of Trade Statistics Database (IMF, 2022). Data on GDP and population are gathered from World Bank's World Development Indicators database (World Bank, 2022). Trade volumes and GDP figures are calculated in terms of 2010 fixed prices. The distance between major population centers was measured in kilometers using Google's Distance Measurement Tool (Google 2022). A fixed effects model is used to estimate the gravity model parameters for each country. The model for each country is estimated from 357 observations, which accounts for 85% of the total observations over the time period for each country; the remaining 15% of observations are used to test each model's forecasting capability. Similarly, a neural network is developed for each country to simulate the gravity model. 70% of observations from each country are used to train the network; 15% of the observations are used to validate the network; and the last 15% of observations are used to test its forecasting capabilities. Due to lack of trade data for some countries in the early years of the study period, observations with missing trade values are excluded from the analysis and therefore the actual number of observations used to estimate the gravity model for each country averages at 322. A Hausman test is performed on the datasets for each country and based on its results the fixed effects model is found to be the appropriate model to use for the analysis rather than the random effects model which the test proposes in its null hypothesis. Results of the Hausman test for data of each country are presented in Table 3.1.

Figure 3. 1

Hausman test probability values

Country	*Prob > chi2*	*Country*	*Prob > chi2*	*Country*	*Prob > chi2*
Australia	0.00	**Japan**	0.00	**New Zealand**	0.00
Brunei	0.00	**Korea**	0.00	**Philippines**	0.00
Cambodia	0.00	**Lao PDR**	0.00	**Singapore**	0.00
China	0.06	**Malaysia**	0.00	**Thailand**	0.00
Indonesia	0.00	**Myanmar**	0.04	**Vietnam**	0.00

Source: Author's own calculations

3.1.1. THE LINEAR REGRESSION MODEL

In addition to conventional gravity model variables such as GDPs of the trading countries, the model in this analysis also incorporates the effects of exporter and importer population sizes on exports. To overcome the multicollinearity issue that emerges whilst using the fixed effects model due to the static nature of geographical distance, a trade-weighted relative distance variable will be used to represent resistance to trade and the costs associated with it (Nitsch, 2000; Berthelon & Freund, 2008). The gravity model configuration used in this study can be presented as:

$$\ln Exp_{ijt} = \beta_0 + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 \ln Pop_{it} + \beta_4 \ln Pop_{jt} + \beta_5 \ln Twrd_{ijt} + \varepsilon_{ijt}$$

Equation (3.1)

Where, *i* represents exporter country, and *j* represents importer country.

Exp_{ijt} represents the real value of exports from country *i* to country *j* in year *t*,

GDP_{it} represents exporter's real GDP in year *t*,

GDP_{jt} represents importer's real GDP in year *t*,

Pop_{it} represents exporter country's population size in year *t*,

Pop_{jt} represents importer country's population size in year *t*,

Twrd_{ijt} represents the trade-weighted relative distance between country *i* and *j* in year *t*,

And ε_{ijt} is the error term.

Trade-weighted relative distance is calculated as:

$$Twrd_{ijt} = \ \%(j's\ share\ of\ i's\ total\ foreign\ \ trade) * distance\ between\ i\ and\ j$$

Equation (3.2)

From implications of the gravity model, the size of exporter and importer GDPs are expected to positively affect exports. Trade weighted relative distance is expected to have a significant effect on exports. However, the influence of exporter population and importer population on exports, is not unanimously agreed upon in literature. It varies depending on the country's level of development, position in economies of scale, internal market, trading partners and their characteristics. The findings of Dinh et al. (2014); Martinez-Zarzoso (2003); Kumar and Ahmed (2015); Emikönel (2022) and Vu et al. (2020) present various conclusions on population's potential effects. The RCEP region is home to some of the most productive and competitive economies in the world and when aggregated, it has generally been a net exporter region. Therefore, it can be argued that while population may positively stimulate a member country's exports to outside the region, an inverse effect of population maybe the case in intra-regional trade. Thus, population is expected to have a small or even negative effect on exports to countries inside the region.

3.1.2. THE ARTIFICIAL NEURAL NETWORK MODEL

After testing various combinations of layers and neurons in a trial and error approach, a feedforward backpropagated network with one hidden layer, 28 neurons and Levenberg-Marquardt backpropagation training algorithm with a logistic sigmoid activation function is found to yield ideal results (da S Gomes et al., 2011). Moody and Utans (1994) and Hunter et al. (2012) provide more sophisticated approaches for determining the optimal network architecture. However, for relatively simpler tasks applying a trial and error approach seem more convenient and just as productive. Figure 3.1 illustrates a summarized configuration of the employed network.

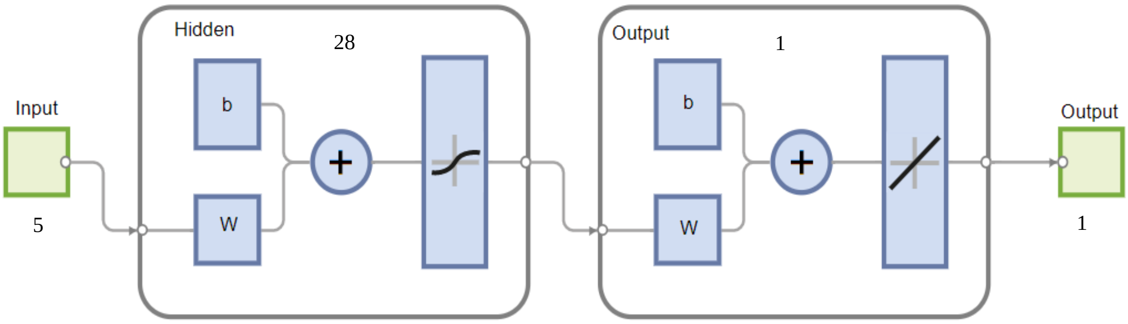


Figure 3. 1

A single layer, 28 neurons network with logSigmoid activation function.

Source: Author's own graphical illustration generated in MATLAB 2022a

Similar to how the five exogenous variables are regressed on exports in the linear regression, the output of the network is also a product of the same five inputs, their weights and added biases. The network uses logistic sigmoid activation function in the hidden layer and linear function in output layer. The choice of determining the right activation function for neurons of a hidden layer varies depending on the application and preference of researchers. The choice of using the logistic sigmoid activation function for the network in this study is inspired by the works of Karlik and Olgac (2011) and Sibi et al. (2013) and it can be mathematically presented as:

$$f(x) = \frac{1}{1 + \mathrm{e}^{-\mathrm{x}}}$$

Equation (3.3)

The neurons in the network at hand, process inputs within the following formulation:

$$I_k = b_k + \sum_{i=1}^{n} x_i w_i$$

Equation (2.4)

$$O_k = f(I_k)$$

Equation (3.5)

Where, I_k represents the input of neuron *k*,

O_k, represents the output of neuron *k*,

$x_i w_i$, represents the weighted signal of variable x_i, and

b, represents bias of neuron *k*.

Before the data was fed to the network it was normalized using feature scaling technique (Nuroğlu, 2014; Beale et al., 2010). For experimental purposes, unscaled data was also used to train the network, which produced fairly convincing results. However, in this analysis the focus is on the network trained using scaled data.

3.1.3. HYPOTHESIS

One of the main objectives in this study is to examine whether the claims declaring neural networks as the superior approach to forecasting can be empirically validated and also to reach a reliable judgement regarding its predictive abilities against the linear regression method. In order to achieve that goal, forecasting performances of the two approaches are compared based on benchmarks such i.e., adjusted R-Squared and root mean squared error (Abrougui et al., 2019). If neural network is found to be the superior forecasting approach, it must be able to explain a higher proportion of the volatility in exports as well as emit less error in predicting future values. The hypothesis of this thesis can be denoted as:

H_0: Adj. $R^2_{\text{Neural Network}}$ < Adj. $R^2_{\text{Linear Regression}}$; $RMSE_{\text{Neural Network}} > RMSE_{\text{Linear Regression}}$

H_a: Adj. $R^2_{\text{Neural Network}}$ > Adj. $R^2_{\text{Linear Regression}}$; $RMSE_{\text{Neural Network}} < RMSE_{\text{Linear Regression}}$

3.2. RESULTS

Stata17 is used to perform the fixed effects method of panel data analysis and conduct the Hausman test; the neural network is developed, trained and tested using MATLAB R2022a.

3.2.1. LINEAR REGRESSION RESULTS

The results of the fixed effects regression analysis for each country are presented in Table 3.2. Largely, they are in accordance with implications of the gravity model. Economic mass of two trading partners is found to generally have a positive significant effect on exports; trade-weighted relative distance also has a consistently positive effect on exports. On the other hand, the effect of exporter and importer country’s population sizes on exports is inconsistent and its coefficients are individually insignificant in some cases as demonstrated by their t-statistics. However, as the F-statistics suggest, the model for each country as a whole is statistically meaningful. The lower t-values might also be the result of the small observation sample for each country in which case, interpretation of the F-statistic becomes more credible.

Table 3. 2 (The table continues into the next page).

Results of the fixed effects regression model.

	Variables	*Coefficient*	*Std. Err.*	*t*	*p*	*Model Specifics*	
Australia	Exporter GDP	0.8693	0.1226	7.09	0	Number of obs.	344
	Importer GDP	0.0729	0.063	1.15	0.251	Prob>F	0
	Exporter Population	2.022	0.485	4.16	0	Adj.R-Squared Within	70%
	Importer Population	-2.027	0.343	-5.9	0	Adj.R-squared Between	1%
	Trade weighted Dist.	0.5992	0.047	12.72	0	Adj.R-Squared Overall	0%
	Constant	-9.1	3.93	-2.32	0.021		
Brunei	Exporter GDP	1.37	0.31	4.33	0	Number of obs.	309
	Importer GDP	0.14	0.23	0.65	0.51	Prob>F	0
	Exporter Population	0.13	1.34	0.1	0.92	Adj.R-Squared Within	64%
	Importer Population	-0.66	1.28	-0.52	0.6	Adj.R-squared Between	89%
	Trade weighted Dist.	1	0.05	19.38	0	Adj.R-Squared Overall	82%
	Constant	-16.06	13.72	-1.17	0.24		
Cambodia	Exporter GDP	1.42	0.7	2.01	0.046	Number of obs.	281
	Importer GDP	-0.8	0.21	-3.78	0	Prob>F	0
	Exporter Population	5.11	2.56	2	0.047	Adj.R-Squared Within	71%
	Importer Population	-1.33	1.17	-1.14	0.257	Adj.R-squared Between	-2%
	Trade weighted Dist.	0.88	0.06	14.24	0	Adj.R-Squared Overall	2%
	Constant	-62.78	27.28	-2.3	0.02		
China	Exporter GDP	1.02	0.1	9.29	0	Number of obs.	344
	Importer GDP	-0.2	0.07	-0.34	0.73	Prob>F	0
	Exporter Population	0.47	1.89	0.25	0.802	Adj.R-Squared Within	92%
	Importer Population	1.01	0.38	2.66	0	Adj.R-squared Between	75%
	Trade weighted Dist.	0.58	0.05	10.35	0	Adj.R-Squared Overall	77%
	Constant	-38	36.02	-1.06	0.29		
Indonesia	Exporter GDP	0.66	0.05	11.72	0	Number of obs.	342
	Importer GDP	-0.02	0.06	-0.45	0.653	Prob>F	0
	Exporter Population	-1.76	0.39	-4.47	0	Adj.R-Squared Within	44%
	Importer Population	0.25	0.35	0.71	3477	Adj.R-squared Between	88%
	Trade weighted Dist.	0.51	0.04	11.41	0	Adj.R-Squared Overall	87%
	Constant	29.44	4.3	6.84	0		
Japan	Exporter GDP	0.86	0.18	4.59	0	Number of obs.	346
	Importer GDP	0.27	0.05	4.59	0	Prob>F	0
	Exporter Population	18.41	2.97	6.2	0	Adj.R-Squared Within	72%
	Importer Population	1.3	0.21	6.05	0	Adj.R-squared Between	74%
	Trade weighted Dist.	0.72	0.05	14.11	0	Adj.R-Squared Overall	73%
	Constant	-382.4	52.72	-7.25	0		
South Korea	Exporter GDP	0.71	0.12	5.94	0	Number of obs.	334
	Importer GDP	0.11	0.06	1.92	0.05	Prob>F	0
	Exporter Population	4.36	0.84	5.18	0	Adj.R-Squared Within	86%
	Importer Population	0.33	0.29	1.12	0.26	Adj.R-squared Between	91%
	Trade weighted Dist.	0.86	0.04	20.02	0	Adj.R-Squared Overall	90%
	Constant	-91.05	10.42	-8.74	0		
Lao	Exporter GDP	1.44	0.09	15.48	0	Number of obs.	269
	Importer GDP	0.27	0.22	1.20	0.233	Prob>F	0
	Exporter Population	0.34	1.03	0.34	0.737	Adj.R-Squared Within	65%
	Importer Population	0.81	1.12	0.72	0.47	Adj.R-squared Between	80%
	Trade weighted Dist.	1	0.08	-12.41	0	Adj.R-Squared Overall	69%
	Constant	-51.24	11.8	-4.34	0		
Mala ysia	Exporter GDP	0.88	0.11	7.83	0	Number of obs.	344
	Importer GDP	-0.23	0.04	-4.87	0	Prob>F	0
	Exporter Population	0.86	0.34	2.52	0.012	Adj.R-Squared Within	84%

	Importer Population	0.05	0.32	0.16	0.87	Adj.R-squared Between	89%
	Trade weighted Dist.	0.84	0.04	19.26	0	Adj.R-Squared Overall	89%
	Constant	-17.61	3.32	-5.3	0		
Myanmar	Exporter GDP	0.39	0.14	2.79	0	Number of obs.	238
	Importer GDP	-0.89	0.21	-4.09	0	Prob>F	0
	Exporter Population	-1.02	2.01	-0.51	0.61	Adj.R-Squared Within	56%
	Importer Population	-1.86	1.03	-1.8	0.07	Adj.R-squared Between	-1%
	Trade weighted Dist.	0.93	0.05	15.91	0	Adj.R-Squared Overall	-2%
	Constant	74.77	24.9	3	0		
New Zealand	Exporter GDP	0.68	0.21	3.17	0.02	Number of obs.	339
	Importer GDP	0.05	0.07	0.7	0.48	Prob>F	0
	Exporter Population	1.07	1	1.07	0.28	Adj.R-Squared Within	67%
	Importer Population	-0.38	0.47	-0.81	0.41	Adj.R-squared Between	64%
	Trade weighted Dist.	0.58	0.03	15.77	0	Adj.R-Squared Overall	63%
	Constant	-14.65	7.61	-1.92	0.05		
Philippines	Exporter GDP	-0.53	0.15	-3.54	0	Number of obs.	336
	Importer GDP	-0.19	0.09	-2.07	0.03	Prob>F	0
	Exporter Population	2.27	0.44	5.13	0	Adj.R-Squared Within	56%
	Importer Population	0.5	0.53	0.94	0.34	Adj.R-squared Between	85%
	Trade weighted Dist.	0.52	0.04	11.68	0	Adj.R-Squared Overall	80%
	Constant	-15.95	4.62	-3.45	0		
Singapore	Exporter GDP	1.31	0.18	7.31	0	Number of obs.	334
	Importer GDP	0.02	0.05	0.37	0.711	Prob>F	0
	Exporter Population	-0.23	0.47	-0.49	0.627	Adj.R-Squared Within	80%
	Importer Population	-0.97	0.33	-2.91	0	Adj.R-squared Between	3%
	Trade weighted Dist.	0.81	0.04	16.56	0	Adj.R-Squared Overall	9%
	Constant	1.23	4.08	0.3	0.76		
Thailand	Exporter GDP	0.65	0.08	8.38	0	Number of obs.	345
	Importer GDP	-0.1	0.04	-2.23	0.02	Prob>F	0
	Exporter Population	8.63	0.71	12.03	0	Adj.R-Squared Within	88%
	Importer Population	-0.43	0.32	-1.32	0.18	Adj.R-squared Between	0%
	Trade weighted Dist.	0.71	0.03	19.7	0	Adj.R-Squared Overall	17%
	Constant	-147.26	8.32	-17.7	0		
Vietnam	Exporter GDP	1.37	0.51	2.66	0	Number of obs.	331
	Importer GDP	-0.78	0.1	-7.43	0	Prob>F	0
	Exporter Population	3.74	3.13	1.19	0.23	Adj.R-Squared Within	78%
	Importer Population	0.79	0.69	1.13	0.25	Adj.R-squared Between	72%
	Trade weighted Dist.	0.86	0.05	15.92	0	Adj.R-Squared Overall	72%
	Constant	-82.96	43.33	-1.91	0.05		

Source: Result of author's own calculations

The coefficient of a variable indicates the direction and average percentage change in exports value, as a result of one percentage change in that independent variable. For example, exporter GDP’s coefficient for Australia is positive and 0.86. In other words, 1 percentage increase in Australian GDP will, on average, result in 0.86% increase in Australian exports in the same direction; 1 percentage increase in GDP of Australia’s trading partner will on average increase Australia’s exports to that partner country by 0.07%; 1% increase in Australian population will on average increase its exports by 2.02%; an increase of the same magnitude in importer’s population will decrease

Australia's exports to that country by 2.02% on average; 1 percentage increase in a county's share of Australia's total global trade will increase Australia's exports to that country by 0.5%.

Exporter's GDP is a crucial driver of exports for all countries of the RCEP region. Despite the low number of observations this effect is statistically significant for all countries. In 14 out of 15 cases exporter's GDP has a positive impact on exports. Laos' GDP has the strongest positive effect on the country's exports relative to other members of the agreement; on the other hand, Myanmar's GDP has the weakest positive effect. Philippines is the only country in the group whose exports are negatively related to its GDP.

Importer's GDP is also an important determinant of exports in RCEP. On average, its effect is smaller than that of exporter's GDP, and less consistent and statistically less significant. In 7 out of 15 cases it has a positive effect. Its effect is statistically significant for 8 out of 15 countries. Within that group, only Japan's exports are positively affected by the importer's GDP; exports of the remaining 7 countries are significantly negatively affected by importer's GDP. It can be argued that importer's GDP has a discouraging effect on exports for some countries.

Exporter's population is observed to have positive effect on exports in general. Only in 3 out of 15 cases it has a discouraging effect on exports, out of which only one is statistically significant, i.e., Indonesia, whose exports are on average decreased by 1.76% in response to 1% increase in its population. Exporter population's effect on exports is significant for 8 out of 15 countries. The effect is generally greater than the effect of the other variables. Exports of Japan, Thailand, Cambodia and Australia are, on average, increased by 18.41, 8.63, 5.11 and 2% in response to 1% increase in their population. It should be noted that the variable's effect for the aforementioned countries is statistically significant, the ability to benefit from the growth of population to such extent is remarkable especially for less developed countries such as Cambodia and Thailand.

Contrary to the effect of exporter's population, the effect of importer's population on exports is less convincing. It is statistically significant only in 4 out of 15 cases, of which, two are negative and the other two are positive. Interestingly, exports of both

China and Japan are significantly positively affected by importer's population. Their exports would increase by 1.01 and 1.3% respectively, in response to 1% increase in importer's population. Australia on the other hand, would experience, on average, a decrease of 2.02% in exports in response to 1% increase in importer's population. Australia's inability to utilize the population growth in other countries of the region might be putting it in a disadvantageous position. On an individual level importer's population is the variable with the least statistical significance. However due to the small size of the observation sample for each country it is more preferable to judge the model's performance as a whole based on its F-statistic.

Trade-weighted relative distance between trading partners has, a statistically significant, positive effect for all countries. From the exporter's point of view, it indicates that as the share of trade with a specific country increase, exports to that country also increase. In this regard, China's exports are the least affected by trade-weighted relative distance, the relatively small effect might be explainable with China's competitiveness and the demand for Chinese goods in the global and regional market. However, smaller economies such as Brunei and Laos experience the effect of trade-weighted relative distance to a much greater extent.

The probability values corresponding to the F-statistics of each country's model are zero, indicating that all five independent variables are jointly and significantly affecting the dependent variable. In other words, in some cases where some variables might be statistically insignificant individually, their effect -when combined with the effect of other variables- is still statistically significant.

Three separate adjusted R-squared values generated by Stata17 as the result of the fixed effects model estimation. The adjusted R-squared within value, represents the portion of volatility in the dependent variable explained by the independent variables, within each trade partner country. In other words, it shows how well the independent variables explain the volatility in the dependent variable within the data for each importing country. The adjusted R-squared between value, represents the portion of volatility in the dependent variable explained by the independent variables between trading partner countries. The adjusted R-squared overall value is a weighted average of the former two adjusted R-squared values. For the purpose of comparing the model's forecasting capabilities, the main value of interest is the adjusted R-squared within. See (StataCorp, 2013) for in-depth mathematical explanation of their computing methods.

In forecasting performance, when averaged for the 15 countries in the analysis, the regression model emits, 1.91 mean absolute error; 0.35 mean absolute percentage error; 52.26 mean squared error and 7.01 root mean squared error. For the purpose of comparing the model's forecasting capabilities, root mean squared error is chosen as the benchmark. Table 3.3 presents the exact error parameters for forecasting within each country's dataset.

Table 3. 3

Forecasting performance results of the regression model.

	Error Parameter	*Error Magnitude*		*Error Parameter*	*Error Magnitude*		*Error Parameter*	*Error Magnitude*
Australia	MAD	3.58208328	**Japan**	MAD	1.72588	**New Zealand**	MAD	1.44196819
	MSE	51.4169689		MSE	80.3188095		MSE	44.5772218
	RMSE	7.17056266		RMSE	8.96207618		RMSE	6.67661754
	MAPE	0.31639195		MAPE	0.39477887		MAPE	0.35221025
Brunei	MAD	1.56102266	**Korea**	MAD	0.74180012	**Philippines**	MAD	1.19109053
	MSE	37.4333916		MSE	46.9566342		MSE	47.0595098
	RMSE	6.11828338		RMSE	6.8524911		RMSE	6.85999343
	MAPE	0.35541419		MAPE	0.3141524		MAPE	0.36550853
Cambodia	MAD	2.43447167	**Lao**	MAD	1.59744656	**Singapore**	MAD	1.64260093
	MSE	71.9198126		MSE	63.9117383		MSE	19.0339838
	RMSE	8.48055497		RMSE	7.99448174		RMSE	4.36279541
	MAPE	0.53192183		MAPE	0.50915211		MAPE	0.18680827
China	MAD	4.66967538	**Malaysia**	MAD	0.62068543	**Thailand**	MAD	1.23387984
	MSE	132.648868		MSE	22.8490527		MSE	30.1444211
	RMSE	11.517329		RMSE	4.78006827		RMSE	5.49039353
	MAPE	0.5216962		MAPE	0.2205484		MAPE	0.25224941
Indonesia	MAD	0.92662554	**Myanmar**	MAD	4.40526008	**Vietnam**	MAD	0.93764302
	MSE	38.7128866		MSE	66.8688195		MSE	30.1664132
	RMSE	6.22196806		RMSE	8.17733572		RMSE	5.49239594
	MAPE	0.30253906		MAPE	0.42646637		MAPE	0.27018695

Source: Result of author's own calculations.

In Figure 3.2, exports are forecasted using parameters of the estimated linear regression model, and they are plotted against their realized figures for each country. The orange line represents forecasted exports; the blue line represents realized export values.

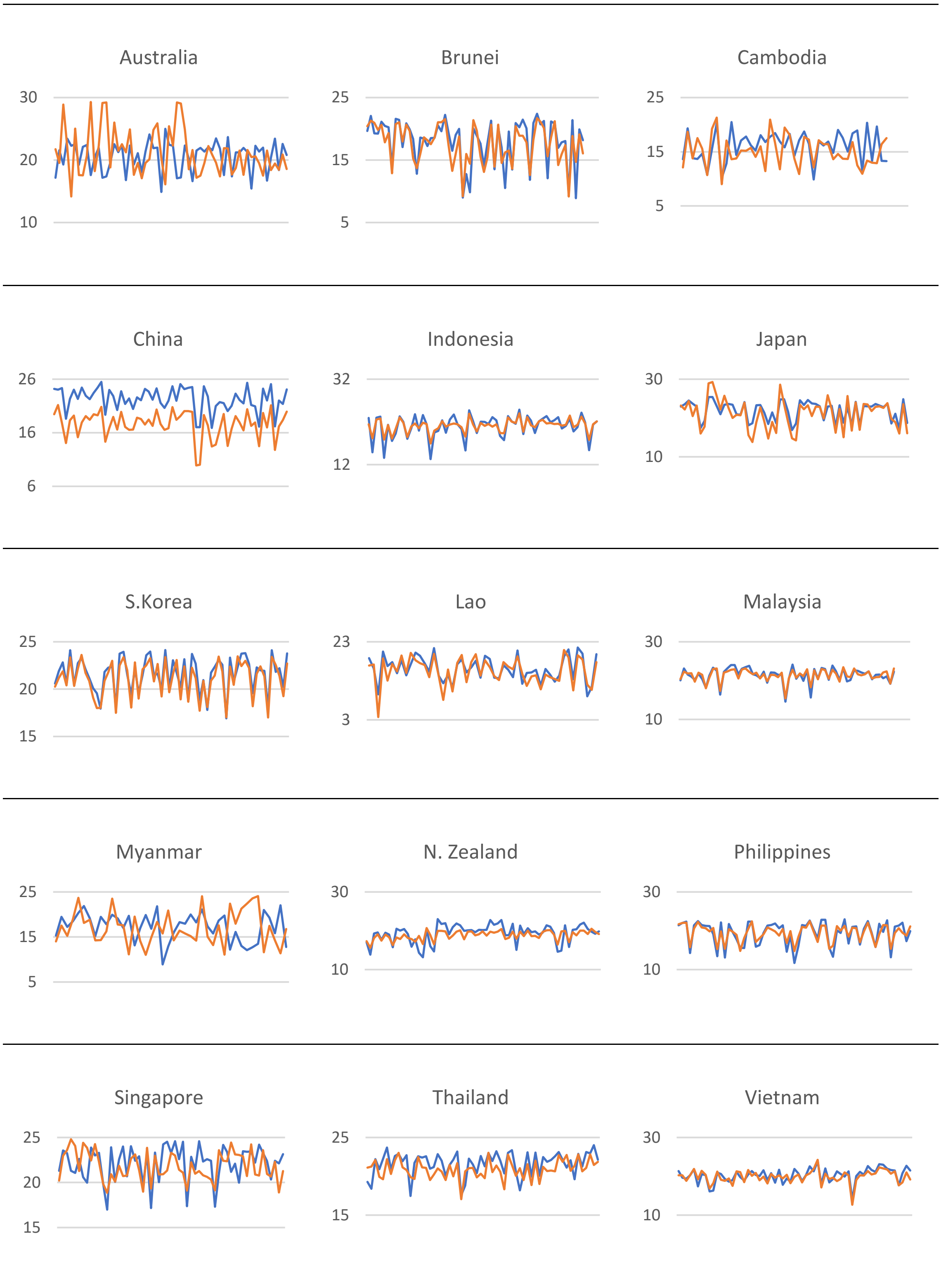


Figure 3. 2

Linear regression plots of estimated exports against actualized exports

Source: Product of author’s own calculations

3.2.2. RESULTS OBTAINED BY USING ARTIFICIAL NEURAL NETWORK

As mentioned, the artificial neural network models are trained using 70% of the data. To ensure that the trained network had actually recognized the potential relationship between the input and output variables rather than memorizing the training data, a further 15% of data is used to validate the network. Validating the network gives the network the ability to generalize the learned relationship to new data, thus, making it a useful prediction tool. The validation process also determines the optimal amount of training and weight adjustment for the network. The model is at its most generalizable and suitable for forecasting when the error in the validation set of data is minimum. Training the model beyond this point will result in overfitting (West et al., 1997). The total number of observations used to train and validate the model amounts to 85% of the total data, which equates to the portion of data used to estimate the linear regression model. Lastly, the remaining 15% of the data is used to test the network's predictive capabilities. Performance indicators for the neural network models are given in Table 3.4.

Table 3. 4 (The table continues into the next page).

Results of the neural network model.

	Dataset	*Observations*	*MSE*	*RMSE*	*Adj. R-Squared*
Australia	Training	282	1.2E-04	0.011	98%
	Validation	61	2.3E-04	0.015	97%
	Test	61	2.3E-04	0.015	97%
Brunei	Training	259	4.1E-07	0.001	99%
	Validation	56	7.6E-07	0.001	88%
	Test	56	4.4E-07	0.001	97%
Cambodia	Training	226	5.4E-07	0.001	65%
	Validation	49	1.9E-07	0.000	59%
	Test	49	4.2E-07	0.001	55%
China	Training	282	3.2E-05	0.006	100%
	Validation	61	3.4E-04	0.018	98%
	Test	61	7.9E-04	0.028	98%
Indonesia	Training	282	2.2E-04	0.015	91%
	Validation	60	2.2E-04	0.015	98%
	Test	60	4.0E-04	0.020	94%

Japan	Training	282	3.0E-04	0.017	99%
	Validation	61	7.0E-04	0.026	96%
	Test	61	1.3E-03	0.036	97%
S.Korea	Training	278	3.4E-05	0.006	100%
	Validation	59	1.1E-04	0.011	99%
	Test	59	2.8E-04	0.017	98%
Lao	Training	223	8.0E-08	0.000	99%
	Validation	48	2.1E-07	0.000	97%
	Test	48	1.2E-07	0.000	97%
Malaysia	Training	282	9.9E-05	0.010	95%
	Validation	61	1.4E-04	0.012	93%
	Test	61	1.6E-04	0.013	95%
Myanmar	Training	196	2.3E-06	0.002	93%
	Validation	42	2.5E-05	0.005	35%
	Test	42	1.4E-05	0.004	82%
New Zealand	Training	282	3.3E-06	0.002	97%
	Validation	60	2.6E-06	0.002	88%
	Test	60	1.1E-05	0.003	91%
Philippines	Training	277	3.5E-06	0.002	98%
	Validation	60	1.0E-05	0.003	94%
	Test	60	2.1E-05	0.005	96%
Singapore	Training	273	3.1E-04	0.018	93%
	Validation	59	3.1E-04	0.018	95%
	Test	59	6.5E-04	0.026	87%
Thailand	Training	283	9.3E-05	0.010	92%
	Validation	61	1.6E-04	0.013	86%
	Test	61	1.1E-04	0.010	94%
Vietnam	Training	274	1.6E-05	0.004	97%
	Validation	59	2.4E-05	0.005	96%
	Test	59	2.3E-05	0.005	93%

Source: Result of author’s own calculations.

The network initially starts training with randomly assigned weights and biases and they converge towards their desired value throughout the training process. As shown in Figure 3.3, the mean squared errors in all three datasets is large in the initial phase of

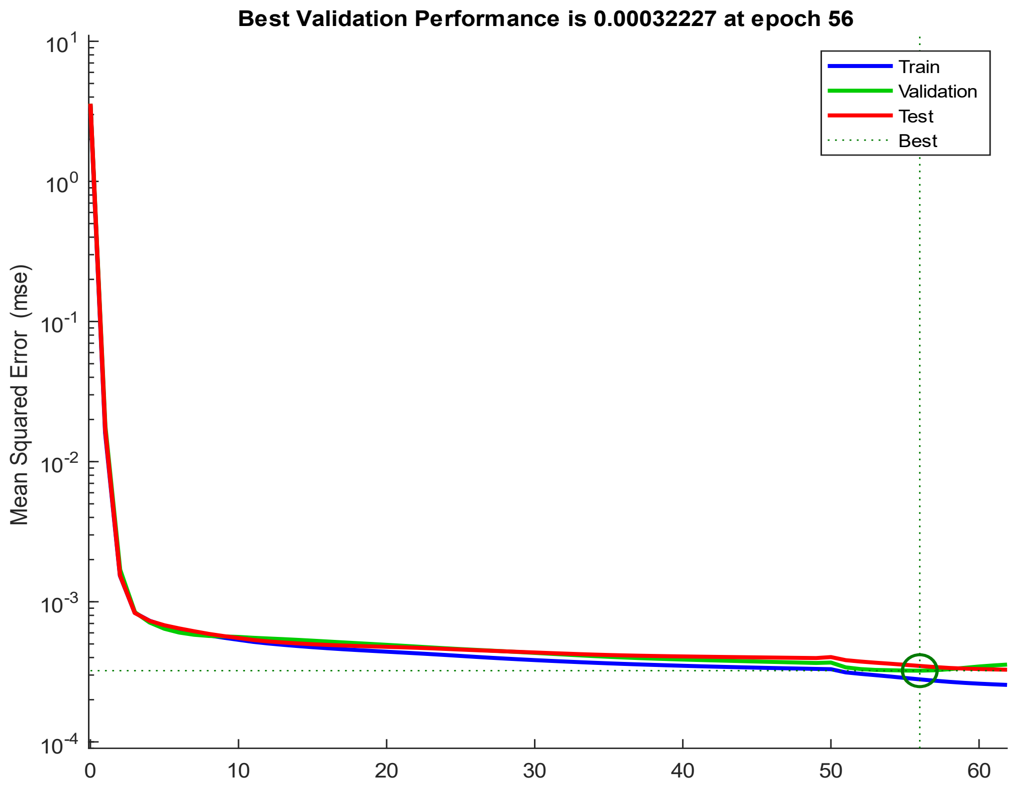


Figure 3. 3

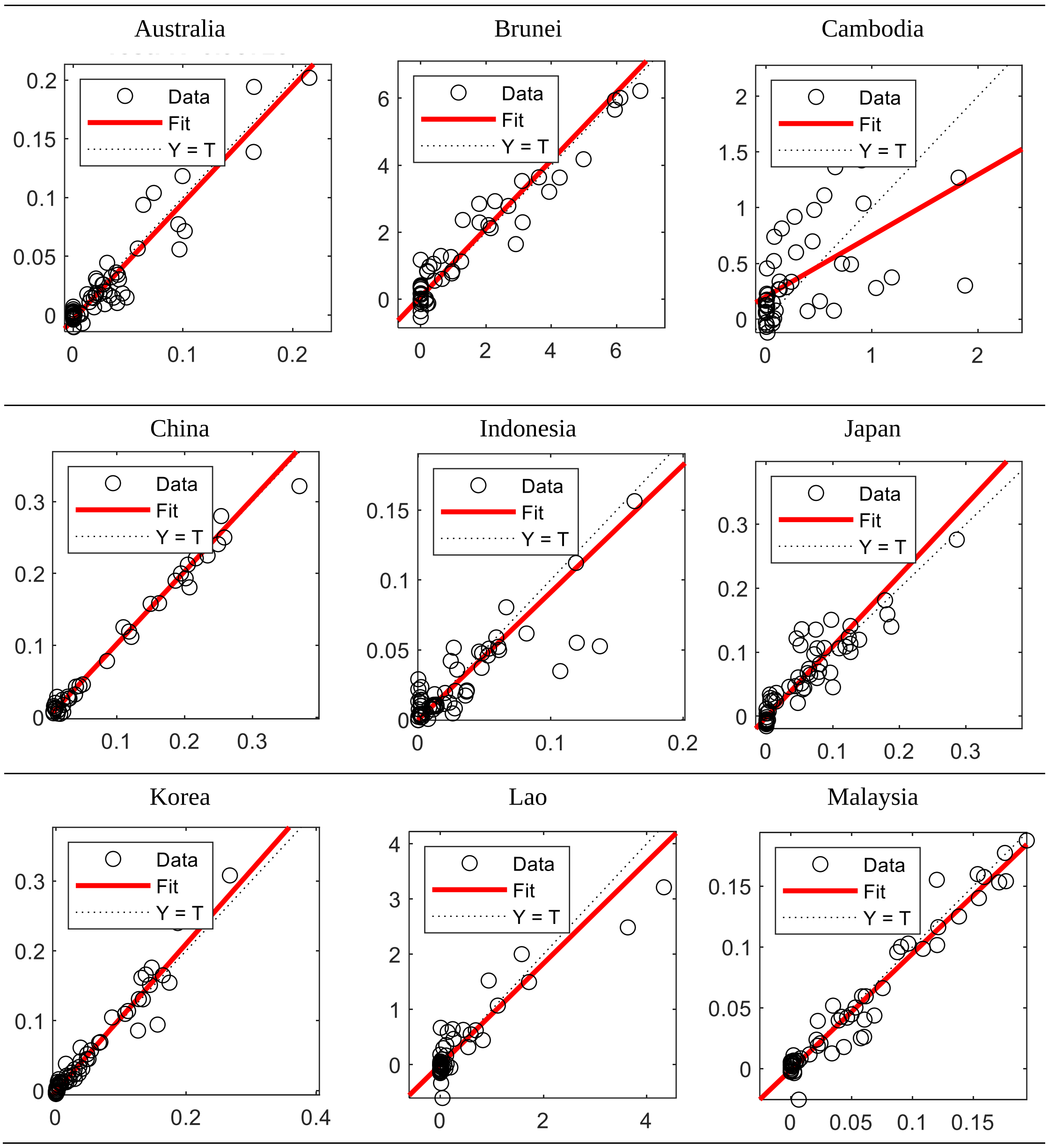
Error minimization during the training process of the network.

Source: Author's own graphical illustration generated in MATLAB 2022a

training due to randomly assigned weights and biases: and as these parameters converge towards more efficient values the mean squared error decreases significantly. The training is stopped when MSE in validation dataset is at its minimum.

The predicted outputs for the test set of each country are compared to their actual values in Figure 3.4. The circular datapoints represent predicted outputs; the dashed line represents perfect prediction where outputs predicted by the network are equal to their realized values; the redline represents the best linear fit for the predicted values. The gap between the two lines should decrease as the network's prediction capability increases. As illustrated the neural networks have predicted the exports figure highly accurately, with the exception of only one case i.e., Cambodia; whose case cannot be confidently attributed to the small number of observations, as the observation number for countries such as Lao and Myanmar is even lower but their adjusted R-Suared values are higher than that of Cambodia. This highlights one of the neural networks' handicaps, its complex workings and inability to troubleshoot.

(Figure continues into the next page).



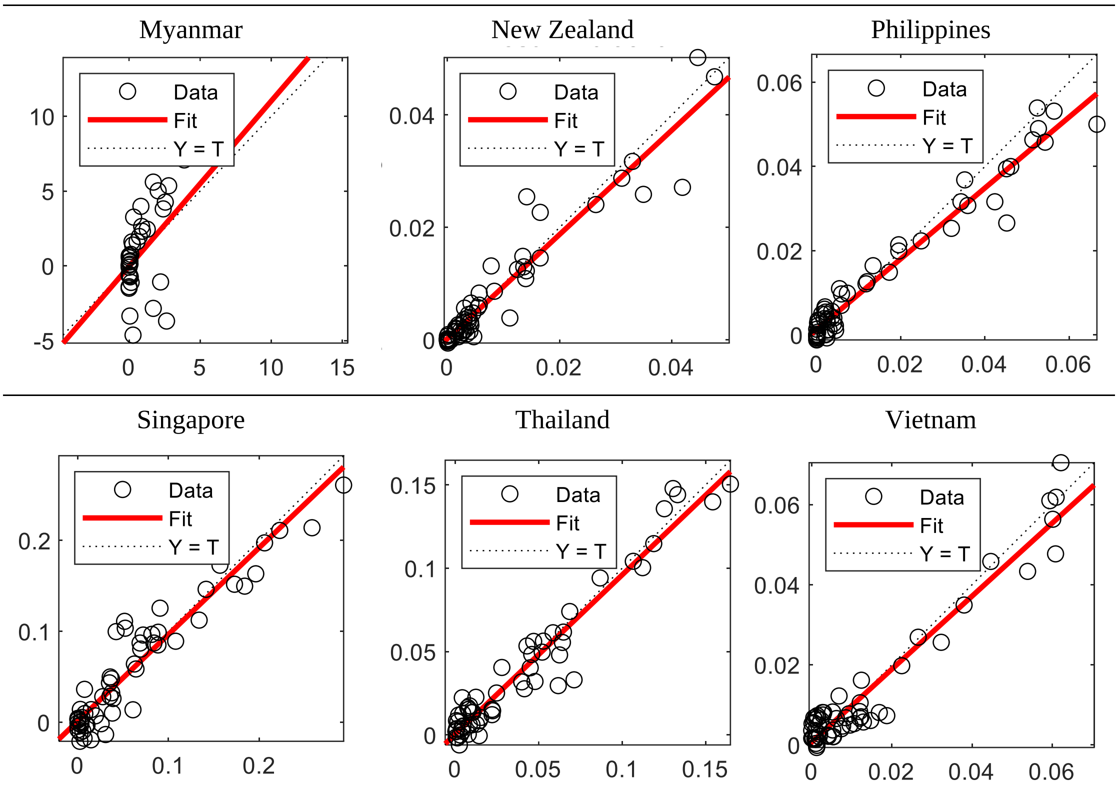


Figure 3. 4

Neural network plots of estimated exports against actualized exports

Source: Product of author's own calculations

3.3. COMPARISON OF ESTIMATION AND FORECASTING PERFORMANCE

In addition to studying the driving forces behind trade flows in the RCEP region, this thesis also compares the forecasting performance of the panel data regression analysis against neural networks based on their adjusted R-Squared score and root mean squared error. However, there are some facts to consider besides the empirical performance of the two models. One major point is that; while almost all aspects of the linear regression model are interpretable, the neural network model does not offer the same level of insight regarding its parameters or configuration. Another shortfall experienced by neural networks was the nonstandard approach to determining the network configuration. While the process of designing and determining the strongest regression model is well defined and clearly understood, the responsibility to find the optimal neural network model and configuration lies on researcher's shoulders and it is often determined through a trial and error approach. A neural network performs best when it is fed with large amount of data as input, therefore, in smaller datasets it might produce unstable or inconsistent results on rare occasions. Forecasting capability and efficiency indicators of the two approaches are presented and compared in Table 3.5.

Table 3. 5

Forecasting performance results of the neural network model.

		Panel FE Model	*Neural Networks*
Australia	Adj. R-Squared	70%	97%
	RMSE	7.171	0.015
Brunei	Adj. R-Squared	64%	97%
	RMSE	6.118	0.001
Cambodia	Adj. R-Squared	71%	55%
	RMSE	8.481	0.001
China	Adj. R-Squared	92%	98%
	RMSE	11.517	0.028
Indonesia	Adj. R-Squared	44%	94%
	RMSE	6.222	0.020
Japan	Adj. R-Squared	72%	97%
	RMSE	8.962	0.036
Korea	Adj. R-Squared	86%	98%
	RMSE	6.852	0.017
Laos	Adj. R-Squared	65%	97%
	RMSE	7.994	0.000
Malaysia	Adj. R-Squared	84%	95%
	RMSE	4.780	0.013
Myanmar	Adj. R-Squared	56%	82%
	RMSE	8.177	0.004
New Zealand	Adj. R-Squared	67%	91%
	RMSE	6.677	0.003
Philippines	Adj. R-Squared	56%	96%
	RMSE	6.860	0.005
Singapore	Adj. R-Squared	80%	87%
	RMSE	4.363	0.026
Thailand	Adj. R-Squared	88%	94%
	RMSE	5.490	0.010
Vietnam	Adj. R-Squared	78%	93%
	RMSE	5.492	0.005

Source: Result of author's own calculations.

Despite its mentioned theoretical shortcomings, the neural network performs more efficient than the linear regression model in predicting future values of exports for all countries. It also explains a higher portion of the volatility in exports with the in input variables, compared to the panel fixed effects model; except only in the case of Cambodia, where the panel fixed effects model has a higher explanatory power. On average neural networks have a 20% higher adjusted R-squared score; in other words, neural networks are, on average, 20% more capable of explaining the volatility in exports with the volatility in exporter and importer GDP, population size and the trade-weighted relative distance between them.

Both models are used to predict 15% of the total observations from data on independent variables. The network model is found to emit smaller amounts of error than the linear regression model in predictive tasks as well. panel fixed effects model on average produces a RMSE of 7.01. The neural network model on the other hand, on average produces a RMSE of 0.012, which is significantly lower than that of the regression model.

After gathering empirical evidence on key parameter of both approaches, the hypothesis question which aimed to examine the forecasting performance of the two approaches, can be answered. The null hypothesis, which states that the artificial neural network has a lower adjusted R-Squared and a higher RMSE compared to linear regression model, can be rejected. And the alternative hypothesis, which states the network model has a higher adjusted R-Squared and a lower RMSE compared to the regression model, can be accepted, thus, suggesting neural networks' superiority in forecasting efficiency and explanatory power.

FINAL CHAPTER: CONCLUSION

This study investigates the driving forces behind trade flows in the RCEP region and explores a relatively novel method of employing neural networks to understand the relationship between dependent and independent variables. Extensive study of the existing literature in the field suggests that in most cases artificial neural networks outperform the panel fixed effects model. The contribution of this thesis to literature is the results of the attempt to evaluate performances of the two approaches in the context of RCEP countries in the framework of the gravity model. Using data collected from 1991 until 2020, a modified gravity model with panel fixed effects model as well as the neural network model is estimated. In addition to traditional gravity related variables such as the GDPs of trading countries and other trade resistance factors, the gravity model employed in this study also includes population sizes of the two countries.

4.1. TRADE PATTERNS AND OUTLOOK FOR RCEP

Economic size i.e., GDP, is found to generally have a positive effect on exports, exporter's GDP especially has a stronger effect on exports compared to importer's GDP. Nevertheless, outcomes of the analysis largely confirm gravity model's implications which suggests that countries of higher economic mass trade more with each other. Population size, however, has controversial effects for different countries of the region. While exporter's population size, mostly has a stable and positive effect on exports; importer populations' effects are not as clear. On one hand, some countries are able to take advantage of population growth in partner countries within the region; other countries, on the other hand, are discouraged from making exports, by the population growth in partner country. Trade-weighted relative distance has a consistent positive effect on exports of a country. It implies that as the share of a specific country's trade in exporter's total foreign trade grows, then exports to that specific country would be positively affected as a result.

Despite its novelty in the global arena, RCEP builds upon a strong heritage of economic ties. It is an important step in the direction of multilateralism and shall contribute to the current trend of regionalization. It can be considered as the successor to the currently relevant ASEAN agreement. Through tariff reduction, improving the quality of supply chains and increasing productivity and employment the agreement is expected to generate incremental income for the regions and the world. Growth is expected in trade of durable and non-durable goods as well as in industries such as textile, clothing, apparel and accessories, forestry, seafood products, agriculture and e-commerce.

Concerns regarding the agreement mostly stems from its lack of emphasis on protection of intellectual property rights and the worsening of wealth and income inequality in the region as a result of the agreement. Geo-political aspects of the agreement are also non-negligible as it is perceived as by some as a sign of Asia's long awaited revival as the global economic center. For disputable reasons, its formation around China is also viewed by some as potential threat to the stability and security of supply chains.

4.2.ARTIFICIAL NEURAL NETWORKS

From the comparison of network models against panel fixed effects model it is apparent, that the artificial neural network models are more capable of detecting and explaining the relationship between the input and output variables. In this analysis neural network models on average explain 32% more variability of the relationship between input and output variables.

The neural network models outperformed the panel fixed effects model in forecasting as well. Both approaches were tasked with estimating 15% of export values from the data in hand. Whilst doing so, the linear regression model, on average emitted a root mean squared error of 7.01; the neural network models on the other hand, made relatively more efficient prediction and emitted a root mean squared error of only 0.012. Hence, based on these criteria it is concluded that compared to the panel fixed effects model, artificial neural networks are more capable and effective in detecting relationships between dependent and independent variables, and they're also more efficient in forecasting and prediction.

Explanatory power is an important quality of any statistical tool and can heavily influence the decision of choosing the most suitable approach for an analysis. It is particularly important in fields such as portfolio management and market risk analysis. However, it should be noted that drawbacks such as, lack of interpretability, nonstandard methods of configuration and difficulty of implementation are still relevant issues in applications of artificial neural networks.

4.3.IMPLICATIONS AND FURTHER RESEARCH

This analysis confirms that artificial neural networks are reliable alternatives or complements to the conventional linear regression method in forecasting tasks and can be used to obtain superior results. Per findings of this thesis, neural networks are more effective in determining the relationship between variables and more efficient in predicting and forecasting tasks. Its use is encouraged in economic research and analysis as complementary, or even alternative if necessary, to traditional methods of panel data analysis.

The study also acknowledges the limitations of artificial neural networks and suggests further research be conducted to set guidelines for determining an effective network configuration. The development of more user friendly software for working with the neural networks as well as their integration in the existing mainstream statistical software is also suggested. Further research in exploring RCEP's potential effects on economies in the region is also encouraged; its effect on the global economy as well as the impact of certain variables on trade flows in the region. As most of RCEP's member countries are highly populated, population's effect on trade flows and other economic variables is of great interest.

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APPENDICES

APPENDIX A

MATLAB (2022a) Script for developing and training a 28 neuron, single hidden layered, backpropagated network with Levenberg-Marquardt learning algorithm is presented below. The script is generated by MATLAB's neural network fitting tool.

Note: The Deep Learning Toolbox add-on is required in order to design a neural network in MATLALB. Simulink add-on is helpful in visualizing the network but not necessary to get results. Statements starting with the percentage symbol are comments.

```
% Solve an Input-Output Fitting problem with a Neural Network
% Script generated by Neural Fitting app
% Created 02-Sep-2022 08:40:49
%
% This script assumes these variables are defined:
%
%   ALLINPUTS - input data.
%   ALLOUTPUTS - target data.

x = ALLINPUTS;
t = ALLOUTPUTS;

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. Suitable in low memory situations.
trainFcn = 'trainlm';  % Levenberg-Marquardt backpropagation.

% Create a Fitting Network
hiddenLayerSize = 28;
net = fitnet(hiddenLayerSize,trainFcn);

% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivision
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Choose a Performance Function
```

```
% For a list of all performance functions type: help nnperformance
net.performFcn = 'mse';  % Mean Squared Error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
    'plotregression', 'plotfit'};

% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, ploterrhist(e)
%figure, plotregression(t,y)
%figure, plotfit(net,x,t)

% Deployment
% Change the (false) values to (true) to enable the following code blocks.
% See the help for each generation function for more information.
if (false)
    % Generate MATLAB function for neural network for application
    % deployment in MATLAB scripts or with MATLAB Compiler and Builder
    % tools, or simply to examine the calculations your trained neural
    % network performs.
    genFunction(net,'myNeuralNetworkFunction');
    y = myNeuralNetworkFunction(x);
end
if (false)
    % Generate a matrix-only MATLAB function for neural network code
    % generation with MATLAB Coder tools.
    genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
    y = myNeuralNetworkFunction(x);
end
if (false)
    % Generate a Simulink diagram for simulation or deployment with.
    % Simulink Coder tools.
    gensim(net);
end
```

APPENDIX B

Table B.1 present data for exports, imports and total trade as a percentage of GDP. Tables longer than two pages are not permitted to be presented withing the main body of the thesis.

Table B. 1

Foreign trade flows of countries and its share of GDP

year	Australia			Brunei Darussalam			Cambodia		
	Total X	Total M	(X+M/GDP)%	Total X	Total M	(X+M/GDP)%	Total X	Total M	(X+M/GDP)%
1991	67946.96	69114.65	26%	3109.55	1400.94	97%	145.88	157.47	6%
1992	68199.74	71930.04	27%	4872.75	3008.30	151%	402.34	1827.80	40%
1993	67139.89	73695.16	29%	4338.00	3648.52	163%	622.39	2285.44	49%
1994	73452.67	85217.43	32%	3835.43	3217.55	148%	541.58	2566.47	50%
1995	78379.16	93482.79	32%	3727.16	3255.62	134%	802.38	3535.08	56%
1996	86893.31	97564.48	32%	3957.69	3792.49	140%	613.82	3421.97	55%
1997	90775.00	97716.49	30%	4212.29	3344.30	137%	1215.44	2168.30	51%
1998	79824.83	95282.69	31%	2108.71	2485.78	106%	1579.18	1909.67	66%
1999	78992.59	101025.22	33%	2729.10	1420.13	84%	1691.64	2021.67	65%
2000	85405.39	96233.49	33%	2964.18	1221.86	66%	2243.99	2315.72	76%
2001	81659.64	82965.57	34%	3672.39	1165.30	83%	2469.06	2400.43	74%
2002	81559.56	92200.25	35%	3820.80	1627.55	87%	3160.85	2640.85	82%
2003	86307.55	109329.87	34%	4726.75	1457.06	88%	3441.89	2701.03	81%
2004	102481.27	130767.88	32%	5648.97	1599.33	87%	4368.88	3177.21	90%
2005	121685.62	146145.70	33%	7056.86	1379.82	85%	4427.74	3733.08	88%
2006	136281.13	157425.26	35%	7970.43	1770.58	81%	4947.35	4127.41	90%
2007	154642.63	182779.50	36%	7965.19	2199.70	80%	4504.45	4526.69	82%
2008	194413.16	212089.57	37%	10719.48	2638.09	92%	4476.22	4541.73	85%
2009	158125.57	173518.87	35%	7197.41	2436.70	89%	5183.81	4055.69	85%
2010	211654.52	204749.53	36%	8886.81	2526.90	83%	5584.63	4889.89	93%
2011	262149.30	240643.80	37%	12446.32	3582.79	87%	6359.20	5820.97	100%
2012	244947.63	252793.16	34%	12948.64	3537.33	87%	7224.03	6507.60	106%
2013	235423.72	229107.57	32%	11363.45	3570.74	83%	8275.63	8252.04	121%
2014	218013.51	218723.90	33%	10569.10	3559.11	83%	5928.58	8840.37	103%
2015	168207.26	190054.85	30%	6357.03	3232.16	74%	7300.43	9545.01	110%
2016	168570.19	177223.53	33%	4926.44	2673.48	66%	8344.13	10657.37	115%
2017	198199.08	196649.99	34%	5675.73	3131.41	71%	9081.91	11881.53	118%
2018	216026.66	204338.46	35%	6608.43	4181.82	79%	9981.11	14205.16	126%
2019	227529.56	189449.67	36%	7323.21	5093.45	91%	11425.67	16184.68	133%
2020	208525.15	177743.30	35%	6545.08	5292.19	100%	13265.03	14807.71	145%

year	China, P.R.: Mainland			Indonesia			Japan		
	Total X	Total M	(X+M/GDP)%	Total X	Total M	(X+M/GDP)%	Total X	Total M	(X+M/GDP)%
1991	171835.97	152528.59	35%	210835.21	187284.45	47%	322685.78	242456.59	15%
1992	192226.69	183817.55	39%	228283.24	183257.19	48%	342250.34	234487.35	15%
1993	179620.78	203003.52	44%	225653.78	173516.35	41%	360770.36	240363.66	14%
1994	190548.99	182417.28	42%	226141.58	180673.77	41%	390366.49	270908.29	13%
1995	201076.13	178406.96	38%	234442.67	209559.82	43%	438300.31	332381.03	14%
1996	188393.43	173170.26	34%	238319.90	204943.09	41%	406407.79	345282.29	15%
1997	221794.40	172373.27	34%	240358.34	187517.64	44%	409035.67	328719.70	17%
1998	224532.21	171544.11	31%	138656.29	77620.81	80%	374119.47	270791.37	16%
1999	241588.66	205377.73	33%	114640.77	56544.55	52%	405792.77	300651.57	16%
2000	307891.59	278096.36	39%	141075.90	76107.92	58%	465933.75	369718.66	17%
2001	327045.83	298663.61	38%	114622.33	63294.61	54%	395969.70	342556.90	17%
2002	402382.95	364941.69	42%	103905.47	56965.16	45%	412806.10	333951.48	18%
2003	535617.12	504585.23	51%	104050.93	55513.80	40%	468599.75	380272.43	19%
2004	698413.56	659782.69	59%	115011.02	74681.69	46%	561893.65	451665.91	21%
2005	881082.35	763157.58	62%	124596.87	84004.59	50%	592435.79	513092.74	23%
2006	1101962.90	900410.17	64%	129615.22	78513.93	44%	642528.12	574925.19	27%
2007	1321262.01	1037468.69	61%	137870.25	89749.22	44%	709126.66	617438.94	29%
2008	1463505.51	1159353.73	56%	150198.16	141079.98	52%	765850.60	746795.21	30%
2009	1240217.31	1035769.58	43%	122353.35	101095.11	39%	576490.18	547940.64	21%
2010	1578428.16	1393909.27	49%	157777.87	135662.89	39%	769767.45	694051.69	25%
2011	1799230.22	1649801.28	48%	193134.10	168410.12	43%	824775.66	857333.20	27%
2012	1892510.98	1677771.59	45%	172962.03	174477.15	42%	801124.03	888846.95	27%
2013	1988681.20	1753628.88	43%	156142.82	159630.49	40%	714466.24	832111.49	30%
2014	2068184.59	1732710.46	41%	141726.72	143245.97	40%	671542.54	790273.58	31%
2015	1984320.19	1393779.07	35%	113672.38	107854.32	34%	603098.32	625504.20	29%
2016	1822652.67	1355956.64	33%	99909.61	98965.64	29%	623323.06	586558.72	25%
2017	1914590.79	1538463.04	33%	118623.52	110141.43	32%	671426.65	645565.79	28%
2018	2057690.00	1755549.55	33%	118617.82	131051.88	35%	702829.46	712753.29	30%
2019	1997496.44	1654059.86	32%	110792.09	112932.33	30%	668931.81	683327.14	28%
2020	2027964.84	1608201.58	32%	105987.61	91879.60	29%	605139.15	598528.28	25%

year	Korea, Rep. of			Lao People's Dem. Rep.			Malaysia		
	Total X	Total M	(X+M/GDP)%	Total X	Total M	(X+M/GDP)%	Total X	Total M	(X+M/GDP)%
1991	148576.12	167989.04	47%	1972.07	3705.41	23%	58027.69	61989.54	145%
1992	149464.80	160336.85	45%	2261.57	5648.29	32%	65533.04	64289.71	136%
1993	158276.27	159777.95	44%	4947.67	8885.24	51%	73276.10	70946.42	139%
1994	175926.43	177636.88	44%	5787.32	10867.61	56%	88064.76	89286.00	159%
1995	218184.64	224443.13	47%	5013.12	9484.98	51%	106827.21	112493.87	171%
1996	218006.89	237730.80	47%	4570.83	9828.65	54%	109515.64	109855.98	155%
1997	218475.87	219256.58	51%	2147.37	4566.24	34%	107623.49	107828.38	158%
1998	187298.78	131652.42	59%	2170.23	3772.57	79%	95189.44	75582.79	183%
1999	201286.51	167471.34	53%	1201.70	2101.56	87%	106618.69	82597.53	190%
2000	235491.59	219299.77	58%	697.81	1361.20	57%	121901.40	102093.76	192%
2001	197608.61	185294.08	53%	595.49	1312.03	56%	108010.47	89836.46	174%
2002	207084.57	193494.44	50%	541.59	1196.48	57%	112331.40	95643.70	171%
2003	239357.28	220833.28	53%	495.64	1153.55	54%	124900.11	98454.45	170%
2004	302639.01	267500.42	60%	529.27	1364.30	59%	148422.56	122373.49	185%
2005	329928.18	303062.42	58%	707.08	1529.48	64%	160611.50	129435.28	177%
2006	369158.90	350964.48	60%	1234.37	1869.37	75%	176655.71	143474.42	179%
2007	411009.22	394720.36	62%	1230.37	2278.63	73%	189915.07	158413.19	167%
2008	446143.49	460287.03	82%	1404.98	2861.34	74%	203935.21	160371.79	154%
2009	373958.27	332565.37	73%	1357.63	2917.93	69%	159886.88	125835.15	139%
2010	466379.96	425174.05	78%	1897.95	3448.70	75%	198746.16	164735.37	143%
2011	533886.15	504030.53	86%	2613.99	4110.72	83%	221260.39	181866.32	140%
2012	515376.61	488785.21	83%	2706.81	5447.79	90%	217144.16	187424.19	135%
2013	519673.97	478792.83	78%	2987.25	5893.95	88%	213252.97	192454.19	134%
2014	525084.69	481868.31	74%	3526.72	6179.33	91%	212055.01	189162.93	131%
2015	479602.75	397440.05	66%	3031.68	5746.25	77%	177282.48	156012.64	125%
2016	447123.79	366141.84	60%	3274.12	5010.17	67%	164496.39	146221.56	119%
2017	497134.06	418019.16	64%	3728.52	5364.11	69%	182130.01	163103.04	129%
2018	527987.68	466111.43	66%	4332.29	5575.62	72%	205004.66	180592.71	130%
2019	471176.95	436578.63	63%	4311.43	5350.04	70%	196029.54	168640.01	121%
2020	442784.96	403917.85	60%	4434.00	4539.95	68%	194835.99	158494.95	126%

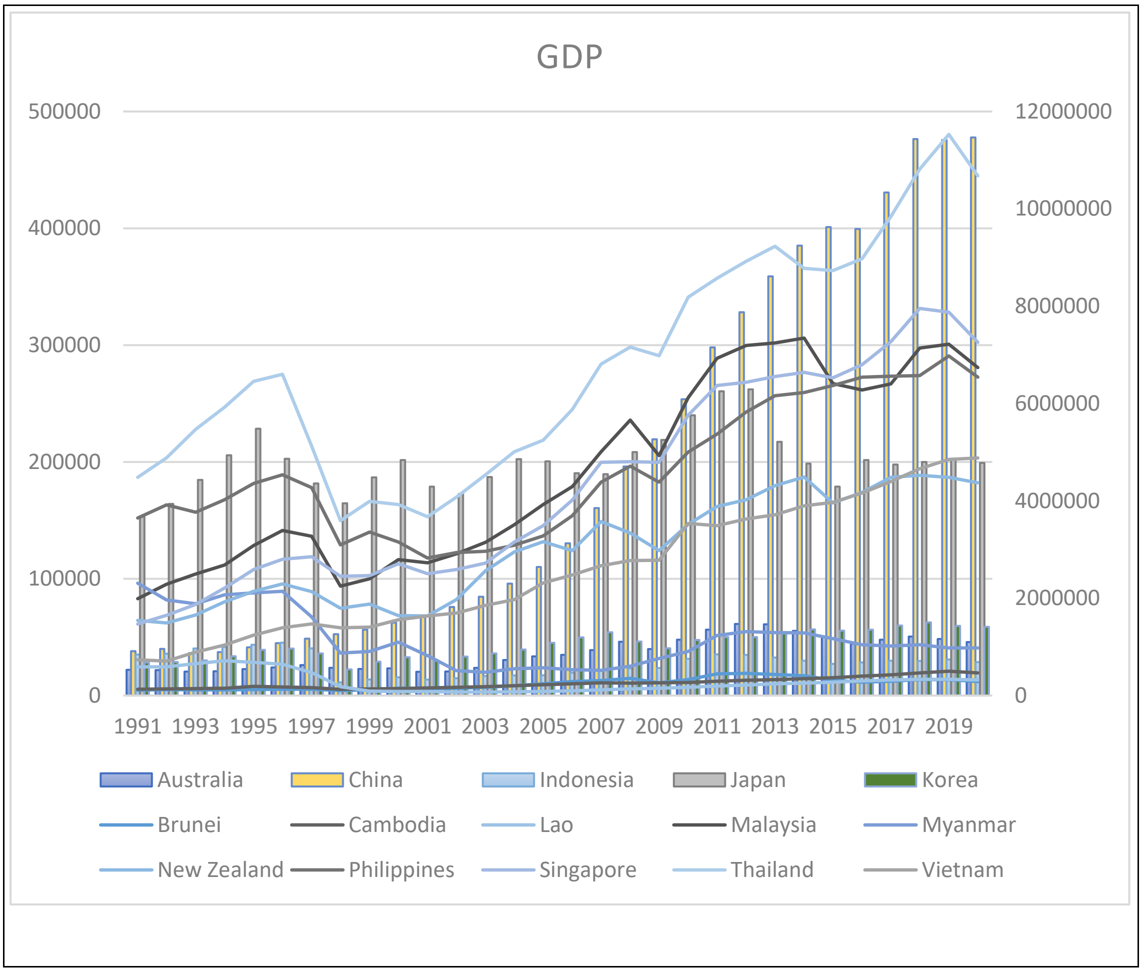
year	Myanmar			New Zealand			Philippines		
	Total X	Total M	(X+M/GDP)%	Total X	Total M	(X+M/GDP)%	Total X	Total M	(X+M/GDP)%
1991	23717.06	48061.39	75%	14469.04	12648.50	42%	25945.77	37974.37	42%
1992	25234.51	38606.80	78%	13979.50	13726.81	45%	26550.60	39332.38	40%
1993	24203.92	35846.69	76%	15438.15	14223.19	43%	28505.22	44633.28	47%
1994	21204.90	34709.02	65%	17340.23	17277.37	43%	30805.26	51667.95	49%
1995	21589.06	42204.12	73%	19085.49	19246.66	43%	37282.83	60704.49	54%
1996	18337.57	41507.10	67%	19590.86	20135.86	42%	41042.74	63608.06	55%
1997	13529.72	34199.21	71%	18893.43	19615.58	43%	47709.72	73991.94	68%
1998	8982.84	18606.77	76%	15294.09	16734.64	43%	51059.58	51105.45	79%
1999	9283.93	16842.61	69%	16337.41	19154.81	45%	57968.78	50236.20	77%
2000	25672.35	22709.80	106%	16549.10	18120.51	51%	60039.82	54187.09	87%
2001	26456.52	11075.74	110%	17057.67	16916.42	50%	47946.77	49299.35	83%
2002	16663.30	7318.76	112%	17485.13	18608.10	44%	51115.42	51431.82	84%
2003	11989.33	5657.05	89%	19775.91	22379.41	39%	51423.40	53231.65	85%
2004	12718.49	5956.51	81%	24088.27	27346.75	42%	53724.41	59626.12	88%
2005	13087.57	5752.26	79%	25014.18	30033.20	42%	52396.20	60268.75	83%
2006	12727.95	4830.96	79%	24950.30	29310.88	44%	56617.53	62096.78	77%
2007	9656.85	4807.32	67%	29321.54	33428.25	42%	59097.37	65008.81	68%
2008	8640.64	4865.73	54%	31909.77	35729.55	49%	53086.57	65355.21	60%
2009	8101.45	4092.70	38%	25489.84	26230.96	42%	40713.24	47616.41	48%
2010	7893.66	4945.03	34%	31349.09	30681.95	42%	51431.67	60192.97	54%
2011	7757.74	8253.50	31%	36049.81	35299.89	44%	45877.31	63177.59	49%
2012	8514.83	7463.04	29%	35433.69	36510.76	43%	48189.16	62922.22	46%
2013	10164.91	10774.80	39%	37229.63	37296.70	42%	48768.13	61454.14	43%
2014	9654.47	13850.88	44%	38858.44	39305.75	42%	53882.20	61903.13	45%
2015	8839.87	13148.82	45%	31822.04	33860.42	40%	50802.70	63544.25	43%
2016	8558.77	11363.66	46%	31001.78	33379.10	37%	48021.46	78225.66	46%
2017	9597.31	13309.99	54%	34508.47	36193.99	38%	52497.77	77229.09	47%
2018	10808.85	12521.52	54%	35749.01	38617.70	39%	53262.29	86043.77	51%
2019	10769.22	11057.18	53%	35056.18	36946.30	39%	54682.64	93169.25	51%
2020	8782.24	9076.49	44%	33411.83	32018.19	36%	47906.18	67653.41	42%

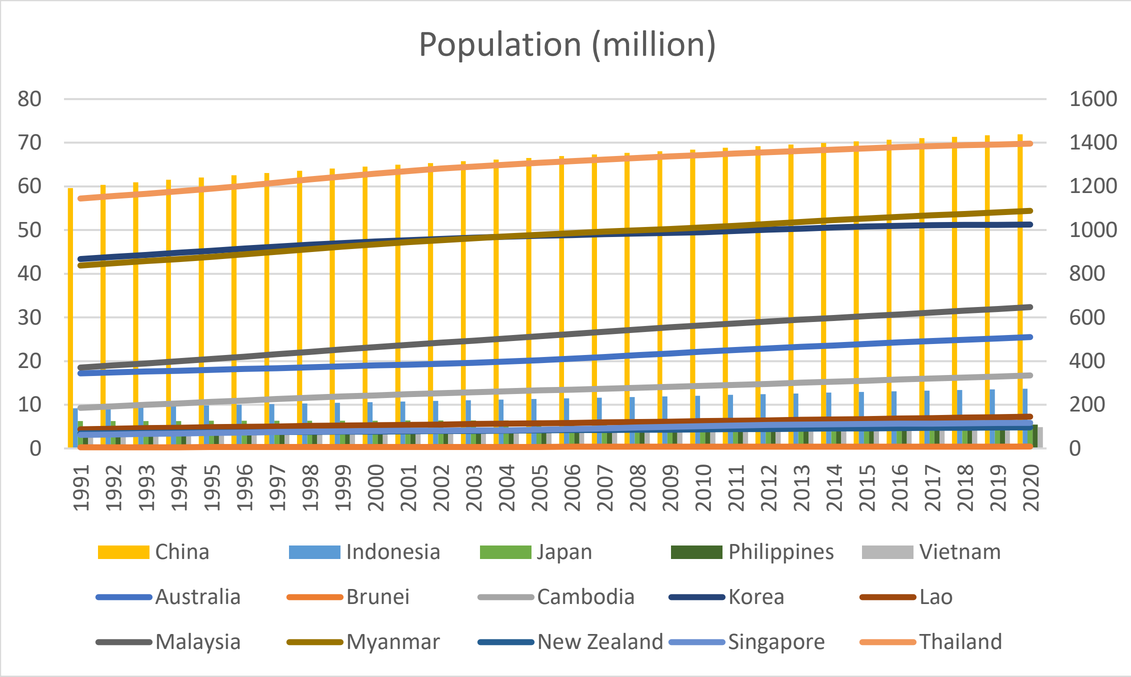
year	Singapore			Thailand			Vietnam		
	Total X	Total M	(X+M/GDP)%	Total X	Total M	(X+M/GDP)%	Total X	Total M	(X+M/GDP)%
1991	79720.45	89218.00	276%	54861.53	72161.50	68%	6953.43	7887.35	49%
1992	83562.41	95022.69	260%	59248.64	74275.84	66%	8720.84	9048.35	60%
1993	95344.85	109895.82	263%	65932.43	81622.69	65%	8395.17	11035.35	52%
1994	120950.41	128132.92	271%	77582.58	92672.00	69%	10727.92	15415.56	61%
1995	145052.69	152664.89	276%	93268.76	122537.40	80%	13991.90	20810.08	67%
1996	151511.68	158983.68	266%	84813.12	112589.67	72%	17579.12	26587.11	76%
1997	148818.12	157359.77	258%	83112.96	90273.52	81%	21650.08	27107.55	80%
1998	130787.49	120908.44	247%	72956.44	57560.98	87%	19806.08	24068.26	76%
1999	136523.32	132144.81	262%	76821.26	66128.02	86%	23589.82	24000.08	81%
2000	162027.24	158021.10	284%	89153.89	80053.71	104%	30115.83	32536.47	97%
2001	141578.18	134830.97	265%	82829.84	78942.17	106%	31394.23	33872.60	96%
2002	146093.54	135900.34	261%	86976.56	81760.45	99%	33611.83	39717.49	104%
2003	185813.42	158248.73	304%	99670.41	94089.64	103%	39272.79	49218.71	115%
2004	226887.29	197188.61	323%	116189.66	114003.44	110%	47962.22	57806.33	129%
2005	260990.26	227621.82	336%	127250.55	136469.96	121%	54332.78	61386.23	120%
2006	306488.77	268920.30	344%	144130.49	144179.00	118%	62015.31	69785.54	128%
2007	330011.12	290429.00	311%	166122.36	152559.13	112%	69766.71	90055.42	144%
2008	350044.80	330738.92	340%	180070.83	183421.86	122%	73178.89	94065.16	145%
2009	277722.15	252880.60	266%	156833.81	139109.46	102%	62811.70	76389.31	120%
2010	352308.74	310800.62	277%	193359.32	185120.62	111%	70249.10	83364.78	104%
2011	389627.23	347038.39	278%	212123.23	220686.58	121%	78688.86	87985.30	115%
2012	372219.79	344549.86	267%	212603.41	234203.07	120%	85958.15	86227.94	114%
2013	365764.20	330764.37	255%	205387.34	228393.20	113%	93287.52	93660.35	121%
2014	360086.13	321792.83	246%	201798.93	204673.07	111%	101585.54	98904.89	123%
2015	310433.60	262319.39	211%	190935.72	182874.96	103%	110869.23	121041.54	140%
2016	293733.97	250533.59	192%	193360.54	176482.24	99%	118552.31	124440.52	140%
2017	323178.06	285801.29	201%	211997.36	201018.74	101%	138998.38	146474.33	156%
2018	363000.48	325975.28	208%	222819.83	221722.62	99%	150388.02	146188.85	153%
2019	341489.55	313973.23	200%	216632.01	210940.86	89%	158628.42	152285.73	154%
2020	252092.92	228858.95	159%	204132.52	184397.53	87%	164275.82	153323.11	156%

Source: Results of authors own calculations

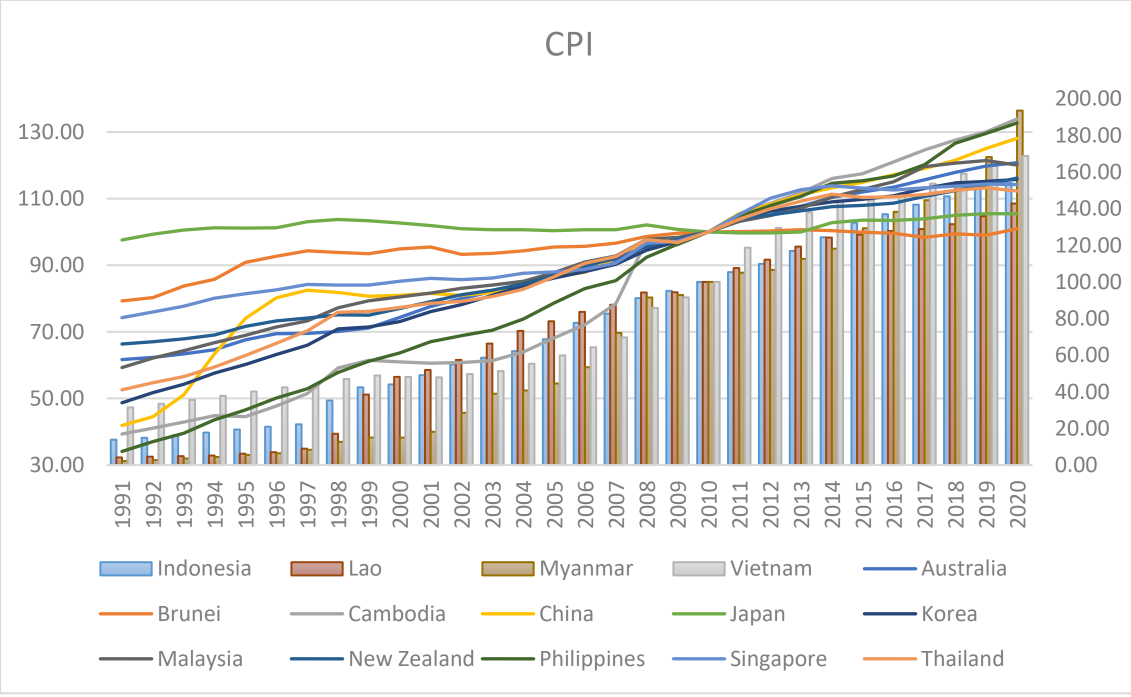
APPENDIX C

Figure C.1 shows dynamic magnitudes of some relevant macroeconomic indicators for RCEP countries during the analysis period. Note: measurements for cluster are given on the right side of the graphs; measurements for lines are given on the left side.





Population (million)
80
70
60
50
40
30
20
10
0
1600
1400
1200
1000
800
600
400
200
0
1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020
China
Indonesia
Japan
Philippines
Vietnam
Australia
Brunei
Cambodia
Korea
Lao
Malaysia
Myanmar
New Zealand
Singapore
Thailand



CPI
130.00
110.00
90.00
70.00
50.00
30.00
200.00
180.00
160.00
140.00
120.00
100.00
80.00
60.00
40.00
20.00
0.00
1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020
Indonesia
Lao
Myanmar
Vietnam
Australia
Brunei
Cambodia
China
Japan
Korea
Malaysia
New Zealand
Philippines
Singapore
Thailand

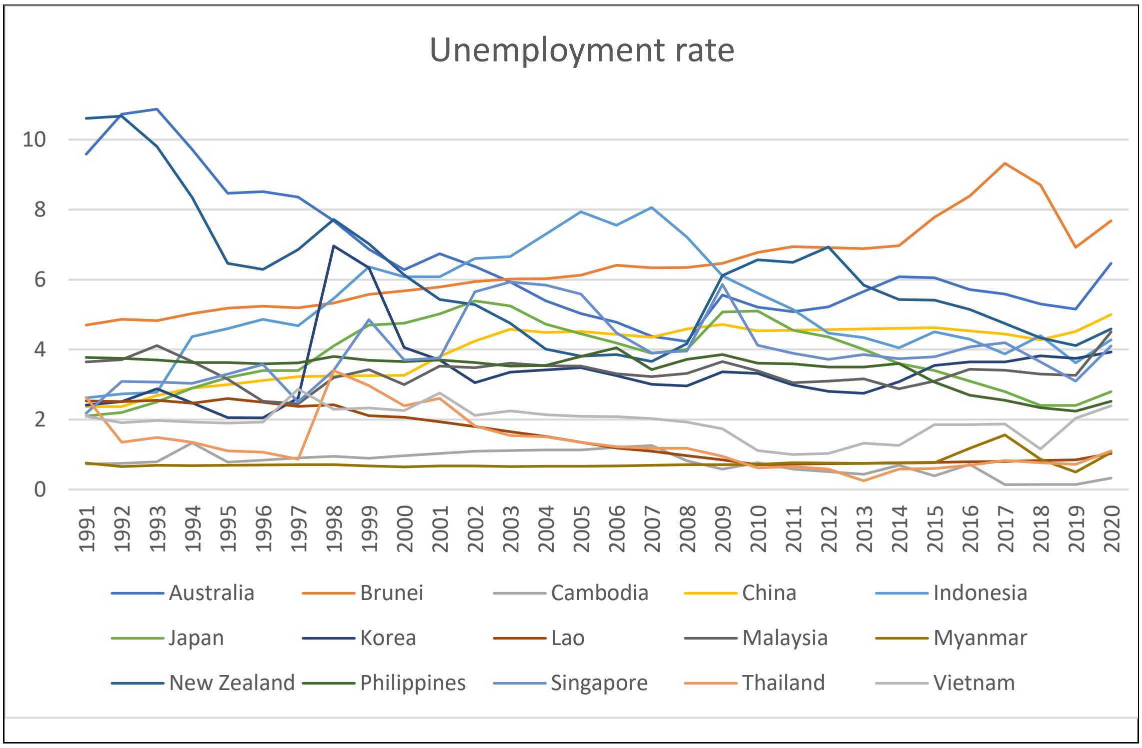


Figure C. 1

Macroeconomic indicators for RCEP countries

Source: Author's own graphical illustrations

APPENDIX D

In order to simulate the analysis in this thesis or recreate similar analysis using data for different sets of countries, the Stata17 commands that are used to carry out the analysis are presented below, in a stepwise chain. Note: lines starting with a star symbol (*) indicate that it is a line of code.

1) The "`import excel`" command can be used to import data from an Excel sheet to Stata. After the command the directory of the Excel sheet on the computer should entered in quotation marks. For example:

```
*import excel "C:\Users\P.B\Desktop\Thesis Revision\Her ulke icin ayri ayri
LN\Australia LN.xlsx"
```

Data can also be imported by going to the menu File>Import>Excel Spreadsheet.

2) After importing the data, its panel structure should be defined and declared to the program. The "`xtset`" command can be used to do so. After the command, the panel ID and time variables should be declared. For example:

```
*xtset impid year
```

In data used for the analysis in this thesis, the variable *impid* (importer ID) is used as the panel ID variable, in order to distinguish between different trading partners. For example, Thailand and Vietnam's importer ID is 14 and 15 respectively. The *year* variable contains values from 1991 to 2020 which represents the years of trade with each trading partner.

3) After setting up and declaring the panel structure of the data. A fixed effects regression can now be performed. The "`xtreg, fe`" command can be used to do so. For example:

```
*xtreg exprts expgdp impgdp exppop imppop twrdist, fe
```

The terms between "`xtreg`" and "`,`" are the variables in the analysis. The first term following the "`xtreg`" command represents the dependent variable (exports); the rest are the independent variables. The "`fe`" term at the end of the command line stands for fixed effects. When conducting a random effects regression, this term will be replaced with "re". After entering the command, results of the fixed effects model will automatically be presented on the screen.

To ensure that the fixed effects regression model is the appropriate model to use rather than the random effects model, a Hausman test needs to be performed on the data. The Hausman test can only be performed once a random effects regression has also been conducted. Therefore, a random effects regression needs to be made and the "xtreg, re" command can be used to do so. For example:

```
*xtreg exprts expgdp impgdp exppop imppop twrdist, re
```

However, it is necessary to store the results of both, fixed effects and random effects models in the memory, so a Hausman test can be later performed based on those results. The "estimate store" command is used to store the results in the memory. For example:

```
*estimate store fe
```

The "fe" in the end of the command stands for fixed effects, to indicate the results that needs to be stored. To simplify, in order to estimate and also store the results of both fixed and random effects regressions, the commands need to be entered in the following sequence:

```
*xtreg exprts expgdp impgdp exppop imppop twrdist, fe
*estimate store fe
*xtreg exprts expgdp impgdp exppop imppop twrdist, re
*estimate store re
```

4) After performing both fixed and random effects regressions and also storing their results, the Hausman test can now be performed using the command:

```
*Hausman fe re
```

Depending on the results of the Hausman test the appropriate model for the analysis can be determined; however, a rule of thumb is that if prob>chi2 = x<0.05 then the alternative hypothesis cannot be rejected and the null hypothesis can be rejected which claims that the random effects model is the appropriate model. To simplify, if prob>chi2 = x<0.05, then we proceed with the fixed effects model.

APPENDIX E

Fixed effects gravity model regression outputs for 15 RCEP countries in the analysis, generated using Stata17 statistical software.

Australia

```
. xtreg exprts expgdp impgdp exppop imppop twrdist, fe

Fixed-effects (within) regression               Number of obs     =        344
Group variable: impid                           Number of groups  =         14

R-squared:                                      Obs per group:
     Within  = 0.7062                                         min =         19
     Between = 0.0287                                         avg =       24.6
     Overall = 0.0197                                         max =         28

                                                F(5,325)          =     156.24
corr(u_i, Xb) = -0.8440                         Prob > F          =     0.0000

------------------------------------------------------------------------------
      exprts | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      expgdp |   .8693897    .122696     7.09   0.000     .6280111    1.110768
      impgdp |   .0729522   .0634952     1.15   0.251    -.0519612    .1978656
      exppop |   2.022192   .4856344     4.16   0.000     1.066808    2.977576
      imppop |  -2.027483    .343567    -5.90   0.000    -2.703379   -1.351587
     twrdist |   .5992059   .0470948    12.72   0.000     .5065568     .691855
       _cons |    -9.1084    3.93448    -2.32   0.021    -16.84866   -1.368137
-------------+----------------------------------------------------------------
     sigma_u |   4.712733
     sigma_e |  .37017961
         rho |  .99386792   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(13, 325) = 47.24                   Prob > F = 0.0000
```

Brunei

```
. xtreg exprts expgdp impgdp exppop imppop twrdist, fe

Fixed-effects (within) regression               Number of obs     =        309
Group variable: impid                           Number of groups  =         14

R-squared:                                      Obs per group:
     Within  = 0.6547                                         min =         15
     Between = 0.8966                                         avg =       22.1
     Overall = 0.8228                                         max =         27

                                                F(5,290)          =     109.97
corr(u_i, Xb) = -0.1480                         Prob > F          =     0.0000

------------------------------------------------------------------------------
      exprts | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      expgdp |   1.379922   .3189782     4.33   0.000     .7521159    2.007727
      impgdp |   .1485079   .2300277     0.65   0.519    -.3042276    .6012434
      exppop |   .1326514   1.340143     0.10   0.921    -2.504988    2.770291
      imppop |  -.6679064    1.28705    -0.52   0.604     -3.20105    1.865237
     twrdist |   1.000499   .0516272    19.38   0.000     .8988877    1.102111
       _cons |  -16.06196   13.72747    -1.17   0.243    -43.08007    10.95615
-------------+----------------------------------------------------------------
     sigma_u |  1.2808636
     sigma_e |  1.1962298
         rho |  .53412674   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(13, 290) = 13.21                    Prob > F = 0.0000
```

Cambodia

```
. xtreg exprts expgdp impgdp exppop imppop twrdist, fe

Fixed-effects (within) regression               Number of obs     =        281
Group variable: impid                           Number of groups  =         14

R-squared:                                      Obs per group:
     Within  = 0.7225                                         min =         17
     Between = 0.0000                                         avg =       20.1
     Overall = 0.0430                                         max =         23

                                                F(5,262)          =     136.42
corr(u_i, Xb) = -0.6856                         Prob > F          =     0.0000

------------------------------------------------------------------------------
      exprts | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      expgdp |   1.421804   .7084083     2.01   0.046     .0269057    2.816702
      impgdp |  -.8065908   .2132657    -3.78   0.000    -1.226524   -.3866578
      exppop |   5.115117   2.561096     2.00   0.047     .0721648    10.15807
      imppop |  -1.333338   1.172977    -1.14   0.257       -3.643    .9763239
     twrdist |   .8866577   .0622488    14.24   0.000      .764086    1.009229
       _cons |  -62.78955    27.2804    -2.30   0.022    -116.5063   -9.072811
-------------+----------------------------------------------------------------
     sigma_u |  3.5466633
     sigma_e |  .79308498
         rho |  .95237787   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(13, 262) = 26.39                    Prob > F = 0.0000
```

China

```
. xtreg exprts expgdp impgdp exppop imppop twrdist, fe

Fixed-effects (within) regression               Number of obs     =        344
Group variable: impid                           Number of groups  =         14

R-squared:                                      Obs per group:
     Within  = 0.9241                                         min =         20
     Between = 0.7526                                         avg =       24.6
     Overall = 0.7738                                         max =         28

                                                F(5,325)          =     791.35
corr(u_i, Xb) = -0.6512                         Prob > F          =     0.0000

------------------------------------------------------------------------------
      exprts | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      expgdp |   1.021706   .1099921     9.29   0.000       .80532    1.238093
      impgdp |  -.0266249   .0788723    -0.34   0.736    -.1817895    .1285397
      exppop |   .4756719   1.896849     0.25   0.802    -3.255981    4.207325
      imppop |   1.019306   .3825699     2.66   0.008     .2666801    1.771932
     twrdist |    .586645   .0566953    10.35   0.000      .475109     .698181
       _cons |  -38.22264   36.02894    -1.06   0.290     -109.102    32.65674
-------------+----------------------------------------------------------------
     sigma_u |   1.290989
     sigma_e |  .36052296
         rho |  .92765519   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(13, 325) = 63.09                    Prob > F = 0.0000
```

Indonesia

```
. xtreg exprts expgdp impgdp exppop imppop twrdist, fe

Fixed-effects (within) regression               Number of obs     =        342
Group variable: impid                           Number of groups  =         14

R-squared:                                      Obs per group:
     Within  = 0.4542                                         min =         18
     Between = 0.8895                                         avg =       24.4
     Overall = 0.8723                                         max =         29

                                                F(5,323)          =      53.76
corr(u_i, Xb) = 0.6287                          Prob > F          =     0.0000

------------------------------------------------------------------------------
      exprts | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      expgdp |   .6604591   .0563431    11.72   0.000     .5496134    .7713048
      impgdp |  -.0271069    .060259    -0.45   0.653    -.1456566    .0914428
      exppop |  -1.763915   .3947074    -4.47   0.000    -2.540437   -.9873931
      imppop |   .2515783   .3532014     0.71   0.477    -.4432874    .9464441
     twrdist |   .5127122   .0449278    11.41   0.000      .424324    .6011003
       _cons |   29.44138   4.301982     6.84   0.000     20.97794    37.90482
-------------+----------------------------------------------------------------
     sigma_u |   1.055618
     sigma_e |  .33864127
         rho |  .90669061   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(13, 323) = 80.63                    Prob > F = 0.0000
```

Japan

```
. xtreg exprts expgdp impgdp exppop imppop twrdist, fe

Fixed-effects (within) regression               Number of obs     =        346
Group variable: impid                           Number of groups  =         14

R-squared:                                      Obs per group:
     Within  = 0.7267                                         min =         17
     Between = 0.7446                                         avg =       24.7
     Overall = 0.7301                                         max =         29

                                                F(5,327)          =     173.90
corr(u_i, Xb) = -0.8623                         Prob > F          =     0.0000

------------------------------------------------------------------------------
      exprts | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      expgdp |   .8687231   .1891175     4.59   0.000     .4966826    1.240764
      impgdp |   .2731904   .0552392     4.95   0.000     .1645212    .3818595
      exppop |   18.41538   2.970707     6.20   0.000     12.57127    24.25949
      imppop |   1.302518   .2153202     6.05   0.000     .8789303    1.726106
     twrdist |   .7256258   .0514143    14.11   0.000     .6244813    .8267702
       _cons |  -382.4099   52.72145    -7.25   0.000     -486.126   -278.6939
-------------+----------------------------------------------------------------
     sigma_u |  2.2986929
     sigma_e |  .33125828
         rho |  .97965559   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(13, 327) = 95.32                   Prob > F = 0.0000
```

South Korea

```
. xtreg exprts expgdp impgdp exppop imppop twrdist, fe

Fixed-effects (within) regression               Number of obs     =        334
Group variable: impid                           Number of groups  =         14

R-squared:                                      Obs per group:
     Within  = 0.8659                                         min =         17
     Between = 0.9161                                         avg =       23.9
     Overall = 0.9071                                         max =         28

                                                F(5,315)          =     406.65
corr(u_i, Xb) = -0.2437                         Prob > F          =     0.0000

------------------------------------------------------------------------------
      exprts | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      expgdp |   .7156389   .1205534     5.94   0.000     .4784472    .9528306
      impgdp |    .119505   .0623904     1.92   0.056    -.0032497    .2422596
      exppop |   4.361595   .8418038     5.18   0.000     2.705327    6.017864
      imppop |   .3328042   .2980767     1.12   0.265    -.2536688    .9192772
     twrdist |   .8654737   .0432408    20.02   0.000     .7803963    .9505511
       _cons |  -91.05827   10.42453    -8.74   0.000    -111.5688   -70.54776
-------------+----------------------------------------------------------------
     sigma_u |  .66591118
     sigma_e |  .27926533
         rho |  .85043131   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(13, 315) = 105.47                  Prob > F = 0.0000
```

Laos

```
. xtreg exprts expgdp impgdp exppop imppop twrdist, fe

Fixed-effects (within) regression               Number of obs     =        269
Group variable: impid                           Number of groups  =         14

R-squared:                                      Obs per group:
     Within  = 0.6619                                         min =          5
     Between = 0.8065                                         avg =       19.2
     Overall = 0.7093                                         max =         29

                                                F(5,250)          =      97.87
corr(u_i, Xb) = -0.6767                         Prob > F          =     0.0000

------------------------------------------------------------------------------
      exprts | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      expgdp |   1.444225   .0932968    15.48   0.000     1.260477    1.627973
      impgdp |   .2706809   .2263991     1.20   0.233    -.1752117    .7165736
      exppop |   .3479759   1.035162     0.34   0.737    -1.690774    2.386725
      imppop |   .8118185   1.121722     0.72   0.470    -1.397412    3.021049
     twrdist |    1.00528   .0810023    12.41   0.000     .8457465    1.164814
       _cons |  -51.24465    11.8009    -4.34   0.000    -74.48651   -28.00279
-------------+----------------------------------------------------------------
     sigma_u |  2.2682216
     sigma_e |  .93921659
         rho |  .85363628   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(13, 250) = 10.54                    Prob > F = 0.0000
```

Malaysia

```
. xtreg exprts expgdp impgdp exppop imppop twrdist, fe

Fixed-effects (within) regression               Number of obs     =        344
Group variable: impid                           Number of groups  =         14

R-squared:                                      Obs per group:
     Within  = 0.8446                                         min =         17
     Between = 0.8989                                         avg =       24.6
     Overall = 0.8939                                         max =         27

                                                F(5,325)          =     353.34
corr(u_i, Xb) = 0.3357                          Prob > F          =     0.0000

------------------------------------------------------------------------------
      exprts | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      expgdp |   .8829137   .1127584     7.83   0.000     .6610852    1.104742
      impgdp |  -.2368025   .0486594    -4.87   0.000    -.3325298   -.1410753
      exppop |   .8646439    .343049     2.52   0.012      .189767    1.539521
      imppop |   .0528894    .324223     0.16   0.871    -.5849514    .6907301
     twrdist |   .8407265   .0436441    19.26   0.000     .7548659    .9265871
       _cons |  -17.61846   3.321546    -5.30   0.000     -24.1529   -11.08402
-------------+----------------------------------------------------------------
     sigma_u |  .76284482
     sigma_e |  .30985793
         rho |  .85837781   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(13, 325) = 115.81                   Prob > F = 0.0000
```

Myanmar

```
. xtreg exprts expgdp impgdp exppop imppop twrdist, fe

Fixed-effects (within) regression               Number of obs     =        238
Group variable: impid                           Number of groups  =         14

R-squared:                                      Obs per group:
     Within  = 0.5713                                         min =          8
     Between = 0.0139                                         avg =       17.0
     Overall = 0.0060                                         max =         20

                                                F(5,219)          =      58.36
corr(u_i, Xb) = -0.7425                         Prob > F          =     0.0000

------------------------------------------------------------------------------
      exprts | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      expgdp |   .3965762   .1423732     2.79   0.006     .1159792    .6771731
      impgdp |  -.8950321   .2188754    -4.09   0.000    -1.326404   -.4636603
      exppop |  -1.020178    2.01696    -0.51   0.614    -4.995314    2.954959
      imppop |  -1.865696   1.039168    -1.80   0.074    -3.913745    .1823543
     twrdist |   .9357158   .0588113    15.91   0.000     .8198072    1.051624
       _cons |   74.77855   24.90258     3.00   0.003     25.69917    123.8579
-------------+----------------------------------------------------------------
     sigma_u |  5.2920899
     sigma_e |  .59451446
         rho |  .98753697   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(13, 219) = 61.91                   Prob > F = 0.0000
```

New Zealand

```
. xtreg exprts expgdp impgdp exppop imppop twrdist, fe

Fixed-effects (within) regression               Number of obs     =        339
Group variable: impid                           Number of groups  =         14

R-squared:                                      Obs per group:
     Within  = 0.6708                                         min =         19
     Between = 0.6569                                         avg =       24.2
     Overall = 0.6409                                         max =         27

                                                F(5,320)          =     130.43
corr(u_i, Xb) = 0.3981                          Prob > F          =     0.0000

------------------------------------------------------------------------------
      exprts | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      expgdp |   .6850374   .2163981     3.17   0.002     .2592947     1.11078
      impgdp |   .0530909   .0753415     0.70   0.482    -.0951363    .2013182
      exppop |   1.074286   1.004984     1.07   0.286    -.9029244    3.051497
      imppop |  -.3889511   .4776555    -0.81   0.416    -1.328693    .5507906
     twrdist |   .5845015   .0370684    15.77   0.000     .5115729    .6574301
       _cons |  -14.65383   7.613251    -1.92   0.055    -29.63218     .324519
-------------+----------------------------------------------------------------
     sigma_u |  1.8958146
     sigma_e |  .46337416
         rho |  .94362686   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(13, 320) = 42.51                   Prob > F = 0.0000
```

Philippines

```
. xtreg exprts expgdp impgdp exppop imppop twrdist, fe

Fixed-effects (within) regression               Number of obs     =        336
Group variable: impid                           Number of groups  =         14

R-squared:                                      Obs per group:
     Within  = 0.5701                                         min =         15
     Between = 0.8525                                         avg =       24.0
     Overall = 0.8080                                         max =         29

                                                F(5,317)          =      84.09
corr(u_i, Xb) = 0.4903                          Prob > F          =     0.0000

------------------------------------------------------------------------------
      exprts | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      expgdp |  -.5331157   .1507962    -3.54   0.000    -.8298035   -.2364279
      impgdp |  -.1993043   .0963697    -2.07   0.039    -.3889093   -.0096993
      exppop |   2.278499   .4439152     5.13   0.000     1.405107    3.151892
      imppop |   .5018293   .5316256     0.94   0.346     -.544131     1.54779
     twrdist |   .5277875   .0451889    11.68   0.000     .4388794    .6166955
       _cons |  -15.95012   4.624702    -3.45   0.001    -25.04911   -6.851129
-------------+----------------------------------------------------------------
     sigma_u |   1.431537
     sigma_e |  .50726754
         rho |  .88844261   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(13, 317) = 60.63                    Prob > F = 0.0000
```

Singapore

```
. xtreg exprts expgdp impgdp exppop imppop twrdist, fe

Fixed-effects (within) regression               Number of obs     =        334
Group variable: impid                           Number of groups  =         14

R-squared:                                      Obs per group:
     Within  = 0.8061                                         min =         13
     Between = 0.0498                                         avg =       23.9
     Overall = 0.1007                                         max =         27

                                                F(5,315)          =     261.91
corr(u_i, Xb) = -0.5312                         Prob > F          =     0.0000

------------------------------------------------------------------------------
      exprts | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      expgdp |   1.319697   .1804437     7.31   0.000     .9646698    1.674724
      impgdp |   .0210016   .0565398     0.37   0.711    -.0902418    .1322451
      exppop |  -.2324537   .4777846    -0.49   0.627    -1.172506    .7075987
      imppop |  -.9778453   .3364267    -2.91   0.004    -1.639773   -.3159178
     twrdist |   .8108995   .0489636    16.56   0.000     .7145624    .9072365
       _cons |   1.236693   4.086804     0.30   0.762     -6.80419    9.277577
-------------+----------------------------------------------------------------
     sigma_u |  2.1235982
     sigma_e |   .2996557
         rho |  .98047739   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(13, 315) = 109.79                   Prob > F = 0.0000
```

Thailand

```
. xtreg exprts expgdp impgdp exppop imppop twrdist, fe

Fixed-effects (within) regression               Number of obs     =        345
Group variable: impid                           Number of groups  =         14

R-squared:                                      Obs per group:
     Within  = 0.8828                                         min =         20
     Between = 0.0169                                         avg =       24.6
     Overall = 0.1894                                         max =         27

                                                F(5,326)          =     491.04
corr(u_i, Xb) = -0.3581                         Prob > F          =     0.0000

------------------------------------------------------------------------------
      exprts | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      expgdp |   .6811834   .0812616     8.38   0.000     .5213202    .8410467
      impgdp |  -.1074515   .0481046    -2.23   0.026    -.2020861   -.0128169
      exppop |    8.63128   .7177145    12.03   0.000     7.219344    10.04322
      imppop |  -.4351795   .3289017    -1.32   0.187    -1.082217    .2118582
     twrdist |   .7168776   .0363933    19.70   0.000     .6452823    .7884729
       _cons |  -147.2643    8.32018   -17.70   0.000    -163.6323   -130.8962
-------------+----------------------------------------------------------------
     sigma_u |  1.5002401
     sigma_e |  .31680509
         rho |  .95731101   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(13, 326) = 89.82                   Prob > F = 0.0000
```

Vietnam

```
. xtreg exprts expgdp impgdp exppop imppop twrdist, fe

Fixed-effects (within) regression               Number of obs     =        331
Group variable: impid                           Number of groups  =         14

R-squared:                                      Obs per group:
     Within  = 0.7881                                         min =         15
     Between = 0.7255                                         avg =       23.6
     Overall = 0.7249                                         max =         28

                                                F(5,312)          =     232.05
corr(u_i, Xb) = -0.0518                         Prob > F          =     0.0000

------------------------------------------------------------------------------
      exprts | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      expgdp |     1.3733   .5163272     2.66   0.008     .3573763    2.389224
      impgdp |  -.7811042   .1051378    -7.43   0.000    -.9879729   -.5742354
      exppop |   3.740758   3.130827     1.19   0.233    -2.419445    9.900962
      imppop |   .7904612   .6984765     1.13   0.259    -.5838587    2.164781
     twrdist |   .8650223   .0543264    15.92   0.000     .7581298    .9719148
       _cons |  -82.96443   43.33518    -1.91   0.056    -168.2306    2.301707
-------------+----------------------------------------------------------------
     sigma_u |  1.0488675
     sigma_e |  .68151457
         rho |  .70314043   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(13, 312) = 38.16                   Prob > F = 0.0000
```