EMPIRICAL TESTING OF A CGE TRADE MODEL WITH AND WITHOUT GRAVITY ON CHINESE DATA

DOCTORAL THESIS

A thesis submitted for the degree of Doctor of Philosophy

Author: Gang Chen

Supervisor: Prof. Patrick Minford

Co-Supervisor: Dr. Yongdeng Xu

Department of Economics

Cardiff University

July 24, 2022

Acknowledgements

Throughout my PhD candidature at Cardiff University, I have received a tremendous amount of support and would like to devote a few paragraphs to expressing my gratitude to those who have contributed to my ability to submit today.

First and foremost, I would like to thank my primary supervisor Prof. Patrick Minford for providing me with the funding to undertake this PhD study. I am grateful for his patience and kindness, which is crucial for me who haven't been with my family for over two years and was suffering loneliness during this pandemic. Beside that, his dedication and passion for research have always inspired me throughout my PhD study.

I would like to thank My second supervisor Dr. Yongdeng Xu, who is a expert at coding. He always helped me address advanced programming problems with great patience. I have been constantly amazed by his genius way of processing data.

My PhD colleagues and friends have been essential to my candidature. Without valuable discussion with my colleagues Dr. Peiying Tian, Dr. Yue Gai and Dr. Zhiting Wu, and without the companionship of Baicheng Yang, Yuanwei Zhang, Jingxian Yang, I am not sure if i could able to complete.

Most importantly, I thank my parents for their unconditional trust and support.

Contents

1 Background and Motivation **2**

1.1 Research Questions and Contribution 11

1.2 Outline 12

2 Literature Review **14**

2.1 Gravity Model of Trade 15

2.1.1 The Theoretical 15

2.1.2 The Empirical Works on China Based on Gravity Model . 18

2.2 Classical Trade Model 22

2.2.1 The Theoretical 22

2.2.2 The Empirical Works on China Based on Classical Model . 24

2.3 Indirect Inference 28

3 Model Set-up **34**

3.1 Introduction 34

3.2 The rival classical and gravity models of trade 35

3.2.1 The modelling of product differentiation in the two models 38

3.3 The Set-up of CGE model 41

3.3.1 Summary of Variables 41

3.3.2 The Model of Production 41

3.3.3 The Model of Consumption 43

3.3.4 The model of trade 45

3.3.5 The Full Model 47

3.3.6 The statistical nature of the CGE model 56

3.4 The Application of Indirect Inference Method 58

3.4.1 Why we use Indirect Inference? 58
3.4.2 The Auxiliary Model 58
3.4.3 Indirect Inference Wald Test 62
3.5 Power of the Test 63

4 Data 65
4.1 Source of Data 65
4.2 Descriptive Analysis 66
4.2.1 Unit Root Test 78

5 Testing Results 80
5.1 Testing Process 80
5.1.1 Model Residuals and Innovations 83
5.2 Test Results for Part-of-model test 86
5.2.1 The IRFs: how the models work 89
5.2.2 Impulse Response Functions 91

6 Policy Implication and Conclusion 97
6.1 Policy Implication 97
6.2 Which model should be used? 97
6.3 Conclusion 98
6.4 Limitations and Further Research 99

7 Appendix 109
7.1 Test Results for UK version 109
7.1.1 Impulse Response Functions (UK) 112
7.2 Summary of Test Results 115

List of Figures

1.1 China's import and export trade volume from 1980 to 2020 4

1.2 China's trade data and tariffs 6

1.3 Time-Space Compression: Technology Shrinks Our World 7

1.4 One (land) belt one (maritime) road 9

3.1 The CGE model 42

3.2 Indirect inference method 59

3.3 Variables used in the Auxiliary 60

4.1 China's agricultural output 1987-2018 66

4.2 China's manufacturing output 1987-2018 67

4.3 China's service output 1987-2018 68

4.4 China's low-skilled labour & high skilled labour supply 1987-2018 69

4.5 China's land supply 1987-2018 70

4.6 Low-skilled & skilled labour real wage 1987-2018 71

4.7 Return on land 1987-2018 72

4.8 Price levels 1987-2018 73

4.9 Trade shares 1987-2018 74

4.10 Capital 1987-2018 75

4.11 Return on capital 1987-2018 76

4.12 Real effective exchange rate 1987-2018 77

5.1 Model residuals 84

5.2 Model innovations (gravity (NTT) model for Part-of-model test of US version) 85

5.3 Model innovations (classical model for Part-of-model test of US version) 85
5.4 Actual and average of simulated data for China 88

7.1 Actual and average of simulated data for China 111
7.2 Auxiliary of UK version 116
7.3 Model residual (classical model for Part-of-model test of UK version) 117
7.4 Model innovations (gravity (NTT) model for Part-of-model test of UK version) 118
7.5 Model innovations (classical model for Part-of-model test of UK version) 119

List of Tables

1.1 China's export commodity structure from 1980 to 2010 (proportion %) . . . 5
1.2 Increasing mileage of transportation routes(1950—2008) (10,000 km) 8

3.1 Summary of Variables . . . 41
3.2 Stationary Test by ADF test . . . 61
3.3 Power of the test . . . 64

4.1 ADF Tests on data . . . 78
4.2 Data description . . . 79

5.1 ADF Tests on model residuals . . . 80
5.2 Estimated coefficients for the error process . . . 83
5.3 Coefficients of VAR(1) model . . . 86
5.4 Cointegration test for the variables in the VAR(1) model . . . 87
5.5 Indirect Inference test results for the China . . . 88
5.6 Effects of 10% tariff on food and manufacturing for China . . . 92

7.1 Cointegration test for the variables in the auxiliary model . . . 111
7.2 II Wald test results when equations 1)-4) are used, with w/h . . . 112
7.3 Summary of Test Results . . . 115
7.4 Summary of Welfare Costs . . . 115
7.5 Summary of RXR Effects . . . 115

Abstract

This thesis has set up two rival Computable General Equilibrium (CGE) trade models by incorporating the theories of classical model and gravity model, where the gravity model is in fact based on New Trade Theory (NTT). Afterwards, this thesis tests those two rival trade models by indirect inference method and the results show that gravity (NTT) model is rejected, whereas classical trade model passes, which suggests classical trade model is the more appropriate model to be used to evaluate China's trade policies. Also, in order to verify the validity of my testing method, this thesis conducts an experiment to examine the power of the test by Monte Carlo experiment and the experiment shows that this test has considerable ability to reject the false model. Furthermore, this thesis examined the tariffs effects and the results shows the classical model sacrifices more welfare than gravity (NTT) model does if we rise the tariffs. This is mainly because the gravity (NTT) model benefits from the term of trade gains through the movements of real exchange rate, whereas the real exchange rate does not move under the framework of classical trade model, so there are no term of trade gains for classical trade model if the tariffs are raised. To sum up, this thesis concludes that Chinese government should use classical models to measure and formulate trade policies and the trade policy formulated should be based on free trade.

Chapter 1

Background and Motivation

> [1] *"Today, we stand on the verge of an unprecedented ability to liberate global trade for the benefit of our whole planet with technological advances dissolving away the barriers of time and distance. It is potentially the beginning of what I might call 'post geography trading world' where we are much less restricted in having to find partners who are physically close to us."*
>
> (Liam Fox, 2016)

Since the reform and opening up, China's economy has expanded significantly. China's gross domestic product (GDP) has been increasing at an annual nominal growth rate of 14.5 percent on average from 1978 to 2017. The average annual actual growth rate is 9.3% after subtracting the 4.8 percent average annual inflation rate. The average annual growth rate in constant prices is 9.5 percent, with the economy doubling every eight years on average, and all three indicators have been among the greatest in the world over the last 40 years.

In terms of worldwide rankings, China's overall economic production amounted for just 1.8 percent of the global economy in 1978, putting it in eleventh place. Then China surpassed Germany to take third place in the world in 2007. After that China surpassed Japan to become the world's second largest economy in 2010. In terms of purchasing power parity, China's GDP actually surpassed

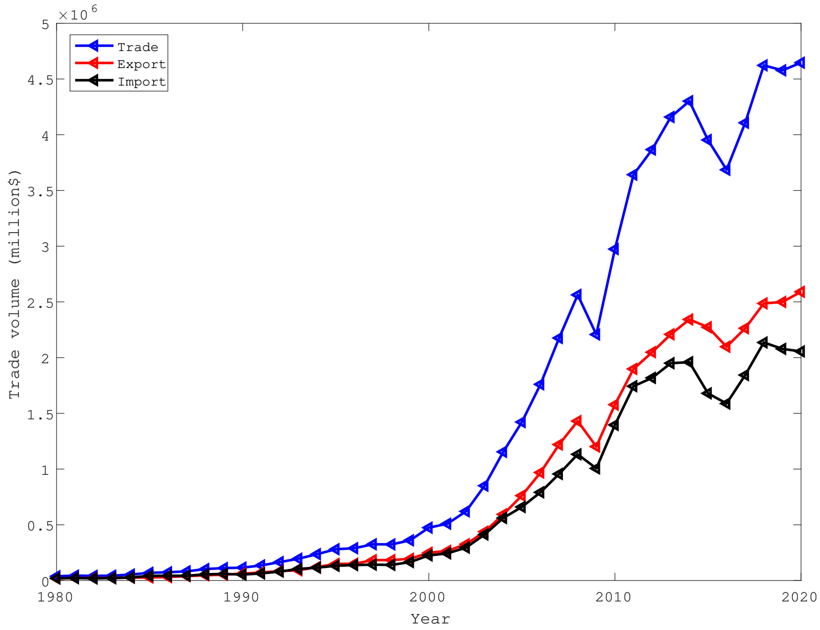
[1] This speech was delivered by International Trade Secretary Liam Fox at the Manchester Town Hall on 29 September 2016. The Keynote Speech is available at https://www.liamfox.co.uk/news/dr-liam-fox-mp-keynote-speech

that of the United States in 2014, making it the world's largest economy. As a result, China's GDP reached 12.3 trillion US dollars in 2017, accounting for nearly 15% of world total economic output, up 13 percentage points from 1978. Also China's contribution to global economic development has surpassed 30% in recent years, and China is gradually becoming a source of power for global economic growth. In terms of per capita GDP, China had a per capita GDP of 156 dollars in 1978, and a per capita gross national income of only 200 dollars. At the time, China was a typical low-income country in the world, as well as one of the poorest. China's per capita GDP increased to $8,640 US dollars in 2017. After accounting for price changes, it has grown by 22.8 times since 1978, with an average annual real growth rate of 8.5 percent. China's per capita gross national income in 2016 was US$8,250, more than the average for upper-middle-income nations, and it rose to 95th place out of 217 countries ranked by the World Bank. The results of China's remarkable economic development make us very interested in the causes of China's economic success, which gives us even more motivation to study China's economic policies. This thesis mainly focuses on China's trade policies.

With the advancement of technology, especially the development of the Information Technology, our entire world is becoming more and more closely connected. The same is true in China, especially, since China's reform and opening up in 1978, the development of international trade has become one of the key factors for China's sustained and rapid economic growth. As Figure 1.1 shown that In 1980, China's total import and export volume was only 38140 million dollar and the China's total trade accounts for less than one percent of world trade at that time. However, China's total trade reached 4646257.39 million dollar in 2020, which is over 121 times higher than the total trade in 1980. Also, the total export reached 2590645.56 million dollar in 2020, which accounts for 13.2% of world total export and it makes China become the world's largest exporter of goods. China is the only country that has achieved 2 trillion US dollar in exports of goods.

Not only the trade volume has undergone tremendous changes, but the structure of China's import and export commodities have also changed. In the 1980s,

Figure 1.1: China's import and export trade volume from 1980 to 2020



Source: National Bureau of Statistics of China

the commodity trade structure of China has started to change from primary goods to manufactured goods. The proportion of exports of high-tech products such as electronics and information technology continues to expand since 2000. As the Table 1.1 shown that the proportion of primary products have been significantly decreased from 50.3% to 5.2% between 1980 and 2010. To the contrary, the proportion of manufactured products have been sharply increased from 49.7% to 94.8% between 1980 and 2010. This marked change in the structure of export commodities mainly originated from the changes in China's factor endowments. For instance, due to foreign investment and technology transfer, China's agriculture productivity has increased rapidly, which force large amount of cheap unskilled labour moved to manufacturing. According to the theory of comparative advantage, China naturally tends to produce more industrial products rather than primary products due to the increased agriculture productivity. After that, as the endowment of labor costs continue to rise, China's industrial structure has been continuous upgrading. Especially, with the increase of the Chinese government expenditures on education, the proportion of China's skilled labor has been increasing rapidly after 2000. Also, China's per capita income has also grown rapidly with it. Those changes in endowment have further caused the labor force to shift to the service industry. China's service trade has entered a new stage of development and the scale has expanded rapidly because of the changing of endowment. Service trade in tourism, transportation, construction, communications, insurance, finance, computer and information services have been increasing rapidly especially in recent years. Specially, China's service trade volume has quadrupled from 72 billion US dollar to 362 billion US dollar.

Table 1.1: China's export commodity structure from 1980 to 2010 (proportion %)

Year	1980	1990	2000	2010
Total Trade	100.0	100.0	100.0	100.0
Primary Products	50.3	25.6	10.2	5.2
Manufactured Products	49.7	74.4	89.8	94.8
Mechanical & Electrical Products	7.7	17.9	42.3	59.2

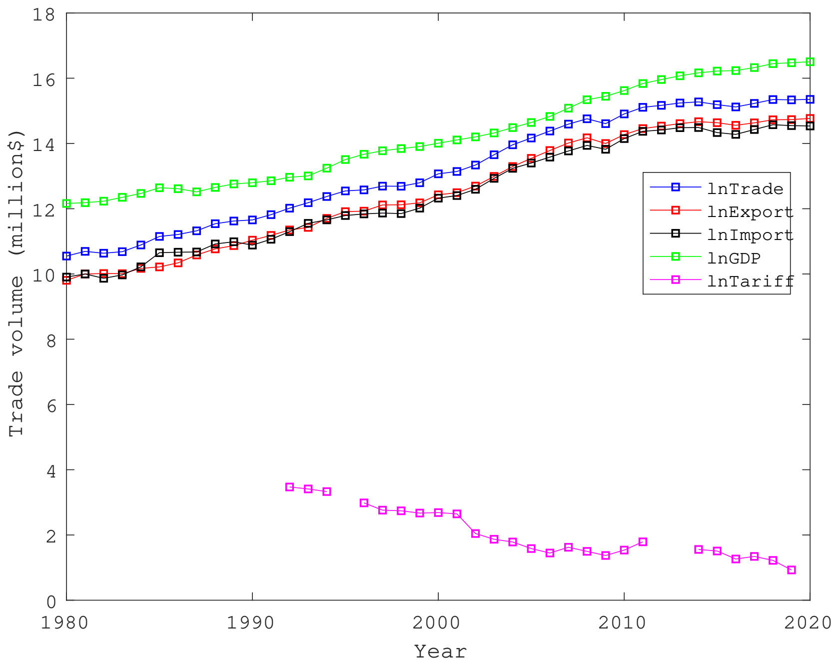
Source: China Customs Statistics Yearbook

China has formed a comprehensive and diversified trade commodity structure. After the reform and opening up, China began to make continuous efforts to establish trade relations with other countries. Trading partners have rapidly grown to 231 countries. Since 2000, China has made efforts to open up markets in emerging countries and developing countries. From 2005 to 2010, the proportion of China's trade in goods with ASEAN increased from 9.2% to 9.8%, and the proportion of trade with other BRICS countries increased 2% within 5 years. Also, the proportion of China's trade volume with Latin America and Africa increased 2.7% and 1.5% respectively from 2005 to 2010.

These achievements are due to China's reform and opening-up policies and World Trade Organization (WTO) accessions. Since China joined the World Trade Organization in 2001, China has continuously reduced tariffs and cut non-tariff measures. The overall level of tariffs on imported goods in China has reduced tariffs significantly with 5.4% down within 5 years. By 2005, it took only five years for China to reduce tariffs to compliance with WTO standards in accordance with the agreement.

According to Minford & Xu (2018), the trade is greatly determined by the demand from neighbours under the theoretical framework of the gravity (NTT) model, which suggests that the policy implication of gravity (NTT) model is reducing trade barriers with neighbours - so more trade with neighbours, but do not reduce or even raise the tariffs with distant markets - so less trade with distant markets.

Figure 1.2: China's trade data and tariffs



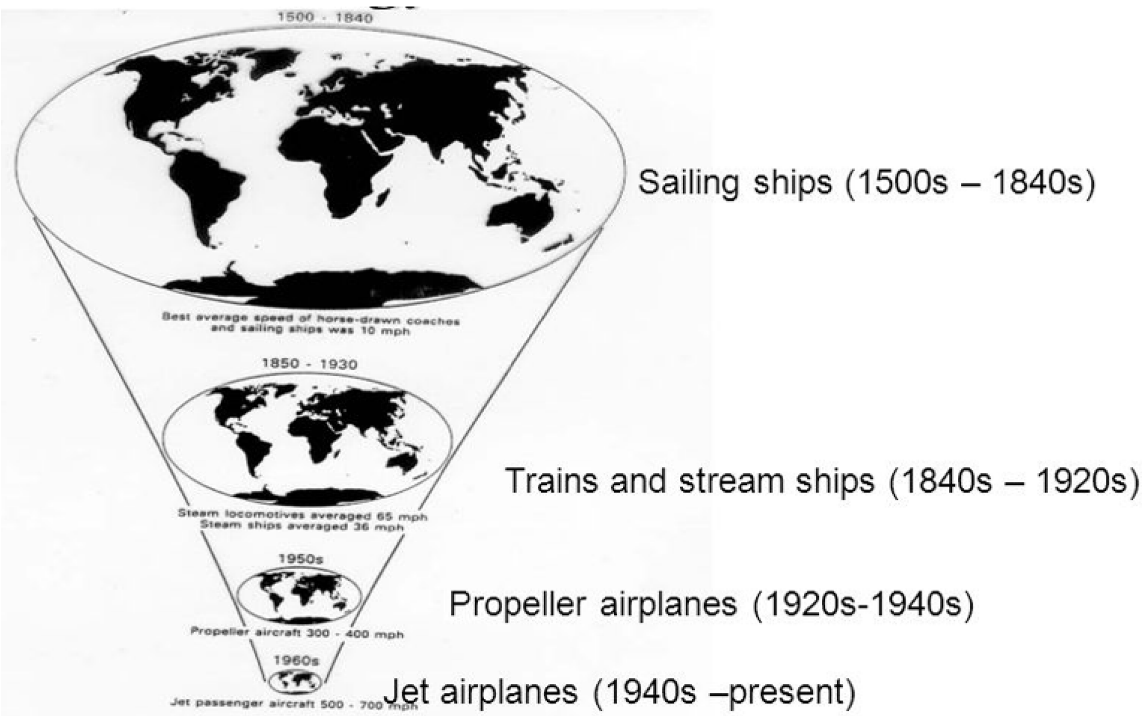
Source: World Bank and National Bureau of Statistics

However, the welfare would be higher with free trade rather than trade protectionism under the theoretical framework of the classical trade model so the policy implement of classical trade model is lower the tariffs regardless of distance, which is quite different with gravity model that only lower tariffs with neighbours but raise the tariffs with distant market.

The Figure 1.2 shows that since China opened up from 1980, the GDP and trade volume have been increasing rapidly along with the gradual reduction of tariffs, which indicates that the policy of reducing tariffs and free trade promote economic development significantly. Under this circumstance, the classical trade model seems to be more fit to be used to evaluate China's trade policies instead of gravity model but we still need to test them.

Also, the reason why the trade volume is negative correlated with distance and positive correlated with size of markets that is both of them are linked to transport cost since distance is proportional to transportation costs and the size of the market is inversely proportional to unit transport costs. so the transport cost is vital to the gravity model. According to Venables (2006), rising in trade with neighbours is associated with rising international transport costs, which indicates the higher cost of transport, the stronger gravity of the trade would be and vice versa. The worldwide trade would be more and more with the development of transport technology since the distance becomes less and less vital to transport costs. According to Smelser et al. (2001), the transport costs contains both the costs of time and money, the trade only occurs when the benefits derived from transports exceed transport costs. Due to the development of technology, the cost of transportation is constant falling in both time and money cost.

Figure 1.3: Time-Space Compression: Technology Shrinks Our World



Source: Harvey (1989) The condition of post-modernity an enquiry into the origins of cultural change. pp.241

As the Figure 1.3 shown, time cost of transportation has been significantly reduced as the development of technology. Cairncross (1995) radically argues that as the information revolution, the distance is dead, the world will shrink, so the distance will no longer limit human activity. The world will become more integrated and eventually countries will have no borders. Couclelis (1996) argues that the distance is not dead but its influence is waning. Lendle et al. (2016) investigate the impact of distance on e-commerce such as eBay, and they found that the impact of distance on e-commerce is 65% smaller than that of other types of trade. They explain that this is due to the reduction of search costs. The world has been entered the age of Cyberspace after 1990, the information can be delivered in seconds. The technology dramatically reduces the search cost, which is the main reason that the impact of distance is much less in e-commerce and information services. This is even more significant in China. According to CNNIC (2021), China had 989 million Internet users, and the Internet penetration rate reached 70.4% by December 2020. Furthermore, China has been the world's largest online retail market since 2013 with 782 million online shopping users. Moreover, the Chinese government is also pushing forward with e-payment services, which reduce barriers for e-commerce significantly. The number of online payment users in China had reached 854 million, up 86.36 million from March 2020 by December 2020. This provides an important foundation for the development of e-commerce.

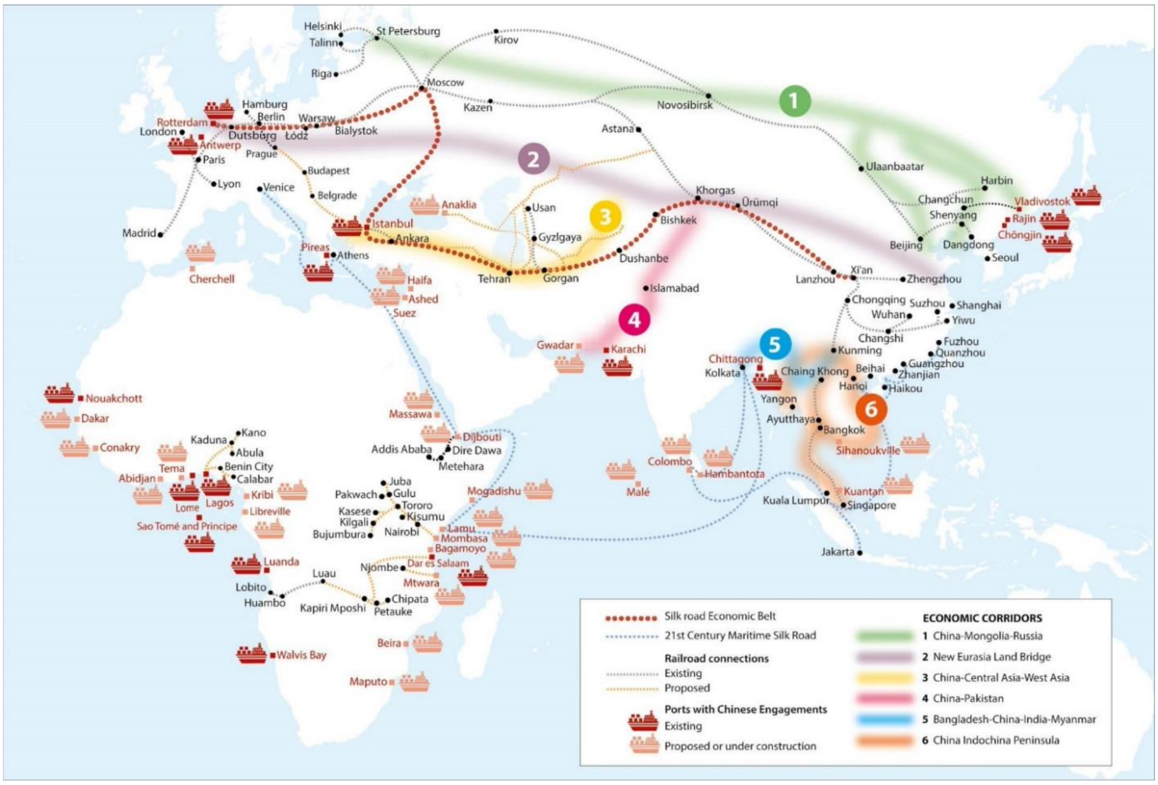
Not only is the infrastructure for e-commerce developing rapidly, so is China's transportation infrastructure. According to Zhang et al. (2009), since the Chinese economic reform in 1979, China has invested in and built transportation infrastructure on a large scale. By the end of 2008, the total mileage of China's transportation lines had reached 3,991,000 square kilometers, which is an increase of 32.79 times from the 118,100 square kilometers in 1949. This has greatly improved the internal transportation environment and reduced transportation costs within China.

Table 1.2: Increasing mileage of transportation routes(1950—2008) (10,000 km)

Year	Railway	Highway	Water Transportation	Air Route
1950	2.22	9.96	7.36	1.13
1952	2.29	12.67	9.50	1.31
1978	5.17	89.02	13.60	14.89
Growth Rate %				
1950-1978	233	894	185	1318
1978-2008	154	419	90	1653

As the Table 1.2 shown, the mileage of internal transportation routes has been increasing dramatically since 1950 in China, especially the air route had been increased by 16 times between 1978 and 2008. This growth rate is not only dramatic compared with China own self, but also very impressive compared with other countries. As Lawrence et al. (2019) stated, China has built 25,000 km of high-speed railway, which is more than all other countries combined in the last decade.

Figure 1.4: One (land) belt one (maritime) road



Source: OECD research from multiple sources, including: HKTDC, MERICS, Belt and Road Center, Foreign Policy, The Diplomat, Silk Routes, State Council Information Office of the People's Republic of China, WWF Hong Kong (China).

China not only reduces internal transportation costs, but also helps to build transportation networks with other countries. According to OECD (2018), China has invested millions of dollars in infrastructure for promoting belt and road initiative (BRI), 480.3 billion had been invested in the BRI-participating economics between 2005 and 2017, 32% of the infrastructure investment had been used to construct transport and 56% of the investment had been used to build power stations. As the Figure 1.4 shown China has been largely investing in international transport, which can significantly improve the efficiency of transportation and reduce the international transportation costs. Transport cost constraints in international trade will become less and less important for China. This situation actually shakes the foundation of the gravity model that links to high transportation cost with distant market, which naturally force them to trade more with neighbors but trade less with distant market.

China's export commodity structure has been changed a lot since 1978. Specifically, the types of China's export commodities have been changed from primary goods to manufacturing goods and high tech products since 1980. The proportion of exports of high tech products such as electronics and information technology continues to expand especially after 2000. This phenomenon comes from changes in China's internal factor endowments rather than changes in external demand. With the rising in China's productivity and the increase in labor costs, China has to upgrade its industry and eliminate low-end manufacturing. The average annual wages in China has been continuous increasing dramatically, the average yearly wage was 1459 CNY in 1987 and it increased to 82413 CNY in 2018, which is over 56 times higher than the wage in 1987. So it is not possible for China to keep its low-end manufacturing competitive all the time. It is clear that this export structure changes are due to the change from supply side instead of demand side. Under this circumstance, we may be able to speculate which model is more suitable for studying China's trade policy since the structure of trade exports mainly depends on the country's factor endowments. As we know the trade is not affected by external demand under the framework of the classical trade model. On the contrary, trade structure is mainly driven by demand under the framework of the gravity model since the country is facing smaller market due to the nature of gravity model that more trade with neighbors but trade less with distant market.

China not only is investing hardly in order to reduce the transportation cost but also working hard to reduce non-tariff management. For example, China is very ambitious to promote Renminbi internationalization, which can provide a convenient and stable international monetary environment for the trade with rest of world. It also can reduce the risk and cost for the trade partners with China. According to PBC (2021), in the first quarter of 2021, the RMB ranked fifth among the official foreign exchange reserve currencies of the IMF, accounting for 2.5% of global foreign exchange reserves, up 1.4% from 2016 when the RMB was added to the SDR basket. By the end of June 2021, the total amount of domestic RMB held by overseas entities with 40% year-on-year increase reached 1.61 trillion US dollar. This was also announced in the report that, in the next stage, the central bank will further keep improving the policy support system and infrastructure arrangements for the cross-border use of RMB, promoting the opening of financial markets, developing the offshore RMB market, and creating a more convenient environment for people to use RMB.

In conclusion, China's rapid development is inseparable from international trade, so we should be more careful in choosing the appropriate model to study China's trade policy. From the background of China, it seems that the classical trade model is more suitable for China rather than the gravity model, but we still need to test them to verify our conjecture. This thesis sets up two rival Computable General Equilibrium (CGE) models of world trade, one based on classical theories of comparative advantage, the other based on recent gravity theories, this thesis tests those two types trade models by indirect inference method to see which model is more suitable for China to analyze China's trade policy.

1.1 Research Questions and Contribution

International trade is one of the main reasons behind China's rapid development, so it is crucial to find the proper model to investigate China's trade policy. There are mainly two types of trade models in academia so far, one is the gravity model, which has been the workhorse model of international trade recently, when Tinbergen (1962) firstly attempted to use the gravity model to analyse the bilateral trade flow and he found that the bilateral trade scale between two countries is directly proportional to their economic aggregate and inversely proportional to the distance between those two countries. The other one is the classical trade model, which was firstly proposed by Ricardo (1817) and further developed by Heckscher (1919), Ohlin (1935), Stolper & Samuelson (1941) and Rybczynski

(1955). Clearly the classical trade model is much older than the gravity trade model however we cannot judge a model simply by the "age" of it. gravity model of trade is not developed based on classical trade model, so gravity trade models are not updated version of classical models and they are completely different trade models as they are based on different assumptions. Therefore, when choosing which model to be used to measure trade policy, we should test which model's assumptions are more in line with the country's national conditions.

The contribution of the thesis is no one has done this kind of test before and it is necessary to test the model before use it to evaluate the trade policy since there is identification problem that, although there are substantial empirical evidences to support the gravity model of trade, the classical trade model also can get similar empirical results. Interesting thing is this situation also happens in physics, the theory of gravity was developed by Newton (1687) and the relativity theory was proposed by Einstein (1922) both can explain the physical phenomena happens on the earth very accurately. Similarly, although gravity model has been empirically succeed, classical trade models too can generate trade data in line with these regressions, but in a different way. So there is an identification problem. It is necessary that we have to test those two models before we use them to evaluate trade policies. This is actually a very reasonable suspicion that whether we should use the gravity model to evaluate the China's trade policy based on the country background because the reason why China has been developed so fast in the last 40 years is because of the reform and opening up and the massive free trade with the world rather than the trade protectionism, which is the main policy implications of gravity model of trade that is more trade with neighbours but less trade with distant markets.

1.2 Outline

This thesis contains of seven chapters in total, the second chapter provides a theoretical and empirical works about China of classical model and gravity model. Also, it introduces a key method, indirect inference method, that we used to test these two rival models.

The third chapter is the methodology part, it introduces the set-up of the classical model and gravity (NTT) model, explains where these models come from and what is the difference between them. Also, the indirect inference method is explained in detail in this chapter. In additional, we perform the power of test in order to ensure that our indirect inference wald test has sufficient enough power to reject the false model, so this indirect inference method is reliable.

The fourth chapter introduces the source of data and shows descriptive analysis of data. We discuss the data the data about their units, trend and explain the reason behind the structural breaks.

The fifth chapter first shows the testing process that how our test be performed: step 1 check the stationarity of out data; step 2 re-estimate error process; step 3 get simulated data and put them into auxiliary model; step 4 compare the simulated data and actual data by using indirect inference wald test. After that we show the impulse response functions with 10% Tariffs on food and manufacturing, and 1% Productivity shocks to see how our model works.

Finally, the last chapter concludes this thesis by summarizing findings from our testing results, policy implications, limitations and suggestions for further research.

Chapter 2

Literature Review

There are many literature reviews on classical trade models and gravity models. A large number of studies of the former appeared before the 1960s, whereas the latter appeared in the 1960s and has been in a dominant position ever since in the field of international trade recently. Although the gravity model of trade is very popular recently and quite successful in empirical analysis, it has no theoretical foundation support when this model was first proposed[1]. Isard & Peck (1954) and Beckerman (1956) relied on their intuition to found the empirical evidences that the closer the distance between countries, the larger the scale of trade flows between them. On the contrary, the classical trade model was first proposed based on the theory of Ricardo (1817). According to Anderson & Van Wincoop (2003), although the gravity model has a lot of supporters and is very empirically successful, the gravity model of trade has no theoretical foundation, which could lead to two main important problems, that are, empirical estimation results could be biased due to omitted variables, secondly we cannot conduct comparative statics exercises under the framework of standard gravity equation. Although it potentially has those two drawbacks, unfortunately it still has not been tested and compared with classical trade model to see which model has better performance so far[2]. This thesis first sets up the classical trade model and gravity model of trade by using computable general equilibrium model (CGE), then tests them

[1] It was not until Anderson (1979) established the Armington model in 1979 that he provided a theoretical foundation for the gravity relationship for the first time.

[2] Except Minford & Xu (2018) set up two rival CGE models of trade and tested the classical trade model and gravity model for the first time ever based on UK data.

by indirect inference method based on China's data. Thus, in this chapter, we mainly focus on three categories of literature that are gravity model of trade, classical model and indirect inference method.

2.1 Gravity Model of Trade

2.1.1 The Theoretical

The name of "gravity model" was first used in physics, which was proposed by Newton (1687) to describe the force of attraction between two objects, which is proportional to their mass and inversely proportional to the square of the distance between them. Based on this theory of physics, Isard & Peck (1954) first introduced it to economics relied on their intuition and found the empirical evidences that the closer the distance between countries, the larger the scale of trade flows between them. So named it the gravity model of trade. But the model did not get much attention until Tinbergen (1962) introduced it formally into international trade and it quickly gained considerable empirical supports. Since then, a large number of empirical studies on international trade have been conducted and the results show that gravity model of trade has described the flow of international trade fairly well in a world wild range. For those reasons, the gravity model of trade has gradually become the most robust empirical finding and the benchmark model in international trade research after decades of development.

Initially, the gravity equation is a purely empirical formula that is inspired by the form of Newton's law of gravity, which suggests the trade volume between two counties is positively correlated with their economic aggregates and is inversely correlated with distance. Specifically, the trade flow between two countries equals the multiplication of the GDP of the two countries divided by the distance between them.

$$T_{A,B} \propto \frac{(GDP_A)^{\alpha} \times (GDP_B)^{\beta}}{(Distance_{AB})^{\gamma}} \tag{2.1}$$

In this general version of gravity equation, the α, β and γ are the elasticities of the total trade bilateral volume to GDP and distance respectively. According to Baier

& Bergstrand (2009), those two variables are essentially linked to the trade costs, that is, the longer distances, the higher total transaction cost. Also, the higher GDP means higher demand, so transportation costs per unit of merchandise will fall. Under this context, since the distance only is one of the measurements of transaction costs, so it also can be essentially written as a more general expression by replacing the distance with transactions cost.

$$T_{A,B} \propto \frac{(GDP_A)^{\alpha} \times (GDP_B)^{\beta}}{(Transaction_{AB})^{\gamma}} \tag{2.2}$$

When α, β and $\gamma \approx 1$[3], it is standard gravity equation, which has been constantly and surprisingly robust over different countries and contexts for a long time. Although the linear connection (α, $\beta \approx 1$) between logarithmic economic size and trade flow is very likely and well examined in a variety of theoretical settings, there are no credible research about the whether the role of logarithmic distance is linear $\gamma \approx 1$ as well, until Chaney (2018) explained this for the first time. From this perspective, we can see the gravity model of trade relies on intuition very much since it was first formulated in 1960s and those core details of this gravity model of trade had not been fully explained until 2018, while the gravity model of trade has been wildly used for over 50 years.

Many excellent economists did try to get the gravity model from the micro-theoretical foundation. Armington (1969) proposed a hypothesis that no country produces exactly identical goods, which implicitly suggests that no two countries are exactly the same. This hypothesis provides a precondition for the theoretical basis of the gravity model. Anderson (1979) was the first economist formed the theoretical foundation of gravity model of trade by combining Armington model and Constant Elasticity of Substitution (CES) preferences[4], which provide a good tool to measure the differentiated goods from countries in different geographical locations.

$$X_{ij} = \alpha_{ij}\tau_{ij}^{1-\theta} \times \frac{Y_i}{\Pi_i^{1-\theta}} \times \frac{Y_j}{P_j^{1-\theta}} \tag{2.3}$$

[3]The γ equals 2 in Newton's law of universal gravitation, which is actually in contrast to gravity model of trade.

[4]Interesting thing is Anderson (1979) did use Cobb-Douglass preferences in the body of his paper, but he writes that "there is little point in the exercise" and put the CES preferences in the appendix. Nevertheless, this article became famous because of the Armington model with CES preferences.

where X_{ij} represents exports from i to j. Y is country's income. Π and P are country's price index. This equation first explained the country's income actually plays a role in gravity model of trade.

Since then, the new trade theory (NTT) has been established in the 1980s (Ethier 1982, Krugman 1984, 1986, Brander & Spencer 1985, Eaton & Grossman 1986, Grossman & Horn 1988, Grossman & Helpman 1993). In general, the new trade theory models aim to solve the limitations of traditional trade theory by embracing a broader range of factors and dealing with certain trade realities in a more complicated and sophisticated way. In fact, this thesis is going to test the specification of the gravity model is based on New Trade Theory (NTT).

Bergstrand (1985), the one of notable economists following Anderson, who gave microeconomics foundation for gravity model of trade. He realized although many economists had found the empirical evidences about intra-industry trade in bilateral trade. There are still no unified theoretical framework for those studies. For example, started from Balassa (1966), Balassa & Bauwens (1987) further developed the intra-industry trade theory and found the empirical relationship that the share of intra-industry trade flow is correlated with level of income, country size, trade orientation, income equality and so on. Bergstrand (1985, 1990) set up a theoretical model of monopolistic competition to test the empirical relationships of intra-industry trade by further developing the theoretical framework[5]. After completing the derivation of the theoretical model, he used empirical analysis to verify the correctness of the theoretical model. The results show that the theoretical model about intra-industry trade is reliable and the empirical results reveal the negative relationships between income inequality and intra-industry trade. Melitz (2003) developed a heterogeneous firms model to examine the effects of intra-industry trade on international trade.

Chaney (2008) further revised the Krugman (1980) model by considering heterogeneous firms instead of the model with identical firms. Deardorff (1998) also derived a similar gravity model by using the Heckscher–Ohlin theory. Furthermore, Eaton & Kortum (2002) developed a general equilibrium version of gravity

[5]The theoretical framework of intra-industry trade was developed by Dixit & Norman (1980), Helpman (1981, 1987),Krugman (1979, 1980, 1981), Helpman & Krugman (1985), Markusen (1986).

model by incorporating a multi-country Ricardian trade model. The structure equations that he derived is linked to the comparative advantage, which is the driving force of trade. Then he also applied the geographic barriers, which can restrict trade activities. Anderson & Van Wincoop (2003) resolved the border puzzle by considering the trade friction, they believe the trade is not only depends on trade costs but also that multilateral trade resistance plays an important role.

One of the drawbacks of the "tradition" version gravity model is that it only considers bilateral trade resistance between countries i and j, which does not fit the reality, whereas multilateral trade resistance is closer to reality. For instance, trade between France and Italy is determined by how expensive it is for either to trade with the other in comparison to the expenses of trading with other nations. Assuming that France and a third country trade partner, such as UK, reduce the trade cost at this time, then even if the trade resistance between France and Italy remains unchanged, the trade share between France and Italy will eventually be taken by the United Kingdom (Adam et al. 2007). So multilateral trade resistance is indeed needed to be introduced. Anderson & Van Wincoop (2003) set up the new version of gravity (NTT) model by adding substitutability between trade with a country's different partners.

2.1.2 The Empirical Works on China Based on Gravity Model

Gravity model of trade has been wisely used in many countries for a long time, especially in US and EU. However, China has always been the special case because of its political system and the degree of openness. China's degree of openness to the world was very low before the reform and opening up. Until China joined the WTO in 2001, China's trade volume increased rapidly, then trade issues became the main focus of research in China. So there are relatively limited empirical works of trade about China.

Roberts (2004) investigated the impact of China-ASEAN Free Trade Area (CAFTA) and found that the gravity model can explain trade flows within CAFTA well in terms of goodness of fit. Also he argues that the benefit for less-developed countries such as Cambodia, Laos, Myanmar and Viernam to join CAFTA depends on how much those relatively more developed countries such as Singapore, Malaysia, Thailand and China are willing compromise. Additional, this study shows in terms of the potential trade creation that may arise from the integration, the model suggested a rather insignificant effect. Although trade diversion effects were not explicitly modelled, the resultant unitary elasticity on the cost of trade distance variable offers a solid indicator of CAFTA's little effect on world trade via trade diversion.

Greenaway et al. (2008) applies the gravity model to investigate how China's export growth from 1990 to 2003 displaced other Asian countries' exports to the third market and they find the displacement effect does exist, and the effect is even greater on developed countries. Similarly, China's economic development has also increased China's imports from developed countries, especially Japan and South Korea, which shows China has successfully taken over some manufacturing industries from developed countries by taking advantage of its factor endowment.

Bussière & Schnatz (2009) use a gravity model-based benchmark to assess China's global trade integration and they found that China's international trade is well-integrated in world markets in terms of economic size, location and other relevant factors. Moreover, they use trade intensity measurement to evaluate integration of China in world markets and the results show that China is already extremely well integrated into global markets. However, compared to their trade intensity with other Asian nations, the United States and Australia's trade connections with China do not appear to be particularly strong.

Yang & Martinez-Zarzoso (2014) uses a proper gravity model to investigate whether the ASEAN–China Free Trade Agreement (ACFTA) can promote the trade and the results show that indeed the agreement can increase trade significantly. These trade organizations can reduce internal tariffs within the organization in order to promoting China's foreign trade. This also explains why China has been actively seeking to join various trade organizations.

There are many trade frictions, the culture distance is one of the important influencing factors. For China, cultural difference with other countries is huge, because China is the only nation with a five-thousand-year continuous history, which unfortunately is an important factor hindering the development of trade.

Lien et al. (2012) studied the impact of China's cultural exports on China's trade. They use the Confucius Institute effects as a tool to measure the link between cultural exports and trade. The results show that there is a significant positive effect on developing countries but relatively smaller effects on developed countries. It also shows that China is sparing no effort to integrate into the globalization of trade from all aspects.

Liu et al. (2020) evaluated the cultural distance and institutional distance effects on China's trade relationship with the Belt and Road ($B\&R$) countries by using gravity model. The results are threefold, 1) the cultural distance and institutional distance effects are indeed exist and it actually hinders the China's trade with $B\&R$) countries; 2) the cultural distance has larger effects than the institutional distance on the China's trade with $B\&R$) countries; 3) the announcement of BRI did reduce the influence of the cultural distance on China's trade with $B\&R$) countries, but it increased the influence of institutional distance.

Caporale et al. (2015) use the gravity model and incorporate unobserved heterogeneity, that is so called fixed effect vector decomposition (FEVD) technique and the results show that the trade structure and trade volume are significantly related in China. Specifically, the trading structure has been changed from Resource-based products and Labor-intensive products to technology-intensive products. This paper actually reveals one of the characteristics of gravity model that is the development of international trade induce foreign indirect investment, which can ultimately boost productivity.

Rasoulinezhad & Wei (2017) first empirical attempt to investigate bilateral trade trends between China and 13 OPEC member countries using a panel-gravity trade model from 1998 to 2014. According to their observations, the gravity equation appears to fit the data pretty well. Using the Fixed effects, Random effects, and FMOLS approaches, they confirm the existence of long-term relationships between bilateral trade flows and the main components of the gravity model such as GDP, income (GDP per capita), the difference in income, exchange rate, openness level, distance, and WTO membership. Also, the estimation findings suggest that the trade pattern between China and OPEC member nations is explained by differences in factor endowments such as energy resources and technology, which actually fits the Heckscher-Ohlin theory.

Irshad et al. (2017) use a gravity model to investigate China's trade pattern with OPEC member nations throughout the period 1990-2016 in their paper. The results of the estimation show that the gravity equation fits the data well. China was the world's largest oil importer, importing over 73% of its oil from OPEC member countries. Indeed, energy is the most traded commodity and the primary driver of trade volume growth between China and OPEC member countries during the previous two decades. We have established that China's bilateral trade with OPEC members has a favorable influence on GDP, GDP per capita, and trade openness in both China and OPEC's WTO members. While having a negative impact on trading cost. Their also found that bilateral exchange rate depreciation has a detrimental impact on China's bilateral trade with OPEC.

Jie & Zhihong (2020) investigate the trade creation effect of the China-Asean free trade area by using the gravity model of trade. In their paper, 23 trade countries from North America, South America, Asia, Europe, and Oceania were chosen. In order to make an empirical examination of the China-Asean free trade area, they build the gravity model. The results show that the rise of trade flow will be aided by an increase in GDP in trading countries. Second, while CAFTA will enhance trade volume, the effect will be minor. Furthermore, geographical distance has a detrimental influence on trade flow growth. Differentiated cooperation is required to facilitate the development of the China-Asean free trade area. It must engage in sub-regional cooperation through CAFTA and encourage trade cooperation under the One Belt, One Road initiative.

Emikönel (2022) examine trade between China and 97 countries that play a significant role in China's bilateral trade from 2008 to 2019. According to their empirical findings, a growth in the GDP of the countries involved in trade increases the volume of trade between China and 97 countries, as well as China's exports. Similarly, an increase in GDP is seen to improve trade between China and ASEAN, APEC, and OPEC. It demonstrates that the distance-trade relationship has a detrimental impact on international trade. Regardless of distance, the presence of land borders between nations involved in trade has been shown to have a favorable impact on trade.

2.2 Classical Trade Model

2.2.1 The Theoretical

The theoretical of classical trade model started from Smith (1776), who first put forward the theory of absolute advantage in his book. He believes that there are absolute cost differences between countries in the production of products, and this difference is the reason for the beginning of international trade. Specifically, if country A's cost of producing a certain product is lower than country B, then country A has an absolute advantage over country B, so country A can export goods to country B. He believes that every country should carry out an international division of labor in accordance with this theory. This theory successfully explained part of the reason why international trade started, but he could not explain those countries that do not have absolute advantages but still can have bilateral trade with other countries.

Ricardo (1817) first solved the defects of Adam Smith's absolute advantage theory and put forward the theory of comparative advantage. Specifically, a country should produce the products that have comparative advantages rather than absolute advantages compared with other countries. Each country should focus on producing the products what they relatively good at and this mainly depends on the labour productivity of the country. In this comparative advantage theory, he assumes perfect competition and trade is balanced, that is, total imports equal total exports. Under this circumstance, the technology determines labor productivity, which decides the cost of production. So technology actually determine a country's comparative advantage, which ultimately affects the trade flow. The theory of comparative advantage makes the theory of absolute advantage more general and precisely explains the reason why international trade started.

Dornbusch et al. (1977) incorporate the Ricardian trade theory and set up the trade model with continuum of goods. The Dornbusch-Fischer-Samuelson (DFS) model is considered to be the most standard economic model of comparative advantage theory. In this model, when trade starts, the price of all commodities will not rise, represent Household's welfare will ultimately be improved.

Heckscher (1919) and Ohlin (1935) developed the comparative advantages model by assuming the technology is identical across countries. In this case, the comparative advantages are dependent on factor endowment of the country such as skilled labour, unskilled labour, capital, land supply and so on. In this theory, those differences on factor endowment determines the trade flow instead of technology.

Stolper & Samuelson (1941) argue that an increase in the price of one commodity will lead to an increase in the price of the factor that is used more in this commodity, while the price of another factor will relatively decrease. Given that assumption, all countries tend to export the commodity that make extensive use of the country's relatively abundant factor, which is actually the main idea of Heckscher-Ohlin Model.

Rybczynski (1955) assumes that the relative price of a commodity remains unchanged, and an increase in one factor will lead to an increase in the output of products that use that factor intensively, while the output of another commodity will decrease.

The main defect of Heckscher-Ohlin Model is that it is limited by two factor endowments and two countries. Vanek (1968) first develops the 2 $\times$ 2 Heckscher-Ohlin Model to be n $\times$ n. In terms of the factors used to produce goods, each country ends up exporting its factor endowment, which is more abundant than the world's.

Krugman (1979, 1980) model is the core of the new trade theory. It has two main different assumptions with Neoclassical Model of Trade that he abandons the assumption of perfect competition and constant returns to scale. He developed a new trade theory based on the research from Dixit & Stiglitz (1977) about monopolistic competition and product diversity. Krugman believes that differences in relative prices or cost are not necessary for trade to occur. Even when consumer preferences, technology and resource endowments are exactly the same, economies of scale will directly benefit trade participants.

As the computing power of computers increases, trade models tend to be more sophisticated and complex. In the 21st century, the trade model with corporate heterogeneity has become popular. Eaton & Kortum (2002) incorporate the idea of Ricardian trade with continuum of goods and heterogeneous company into trade model. The emergence of this model is called the revival of the Ricardo model.

2.2.2 The Empirical Works on China Based on Classical Model

Due to political system and other historical reasons, China's foreign trade development is quite late. China's international trade barely started in 1979 and began to grow rapidly after it joined the WTO in 2001. When researchers started to study China's trade, the classical trade model was no longer popular at that time. Therefore, there are not many literatures that use classical trade model to study China's trade.

With the rapid rise of China, there are more and more supporters of the China Threat Theory. Under the framework of the two countries' trade theory, the welfare of the country decreases as the technology of the trading partners is more similar (Hicks 1953, Dornbusch et al. 1977, Samuelson 2004, Ju & Yang 2009). However, di Giovanni et al. (2014) measure the impact of China's entry into global trade on the world economy with respect to technological change by using a quantitative Ricardian-Heckscher-Ohlin model and the results are very counter-conjecture that China's economic integration will increases the welfare of the world if China's productivity growth is unbalanced. This is because China's existing comparative advantage pattern is common around the world, thus unbalanced productivity growth strategy makes Chinese products more differentiated than the world average. Additionally, the welfare of Asian countries will increase even more, but those countries dominated by textile and clothing industries actually will experience small welfare losses. Furthermore, If China's production is more differentiated rather than developed in all sectors, the world's welfare will increase even more.

Bao et al. (2013) incorporate the Heckscher–Ohlin (H-O) and New Economic Geography (NEG) into the trade model and investigate the distribution of industrial activity in China and they find that China's industrial distribution has generally shifted to coastal cities since 1998. Also, the results show the theory of classical model with supply of factors play an important role in China since the main reason behind this phenomenon is the distribution of factor endowments such as infrastructure, policy support and capital[6] are very unequal. So industry is gradually shifting to the coastal areas during that period.

Wu (2007) uses an extended Heckscher–Ohlin model to investigate exports from different regions of China. The results show that coastal areas are doing better than other areas in term of export performance. Infrastructure, government spending and so on all have affected the performance of exports in different regions significantly. This finding also shows the distribution of factor endowments are quite different within different a regions of China. Specifically, the coastal areas have relative more endowments of immobile factors such as more labour in coastal areas than other areas given the same acreage of land. This actually reveals the main idea of Heckscher–Ohlin model that factor endowments determines the cost of production, so more abundant factor endowments, the greater the comparative advantage and ultimately boosts exports.

Pham (2008) uses Heckscher–Ohlin model and investigates the phenomenon of across-product specialization in USA, the results show that this phenomenon is highly related with China since China produces a large amount of labor-intensive products and those products are largely imported by USA. This finding shows China's trade is mainly driven by its factor endowments that is relatively adequate low skilled labour compared with USA.

Lederman et al. (2008) investigate how the rise of China and India in global markets is influencing trade specialization trends in Latin American economies. They create a measure of Revealed Comparative Advantage, which is based on the Ricardian comparative advantage concept, by combining 3-digit ISIC sector, country, and year. Both imports and exports are accounted for in this Revealed Comparative Advantage. The empirical studies look into the relationship between Latin American's Revealed Comparative Advantages and the two Asian economies China and India. According to econometric estimations, Latin American's specialization pattern has been moving in the opposite way of China and India's trade specialization pattern, with the exception of Mexico. Labor-intensive

[6]Although capital is mobile, the policy support can induce the capital flow to coastal cities easily (Fleisher et al. 2010)

sectors of Latin American's including both unskilled and skilled are likely to have been severely impacted by China and India's expanding presence in global markets, but natural resource and scientific knowledge intensive sectors are likely to have profited from their rise since 1990.

Similarly, Lu (2010) explains why trade between China and the United States began and shows the reason it is much easier to use the Heckscher–Ohlin model to explain the trade between US and China. The comparative advantage is the most important reason that can drive the trade since the country like China have to make use of their advantage of factor endowment such as labour-abundant in order to export products to developed countries. Because of the fact that the US is willing to buy Chinese goods mainly because of the low labor cost in China, so the goods made in China are good and cheap. For these reasons, distance and GDP are relative less important.

Marshall (2011) shows that in spite of significant differences in factor productivity, the increase of China's exports in recent years is consistent with the Heckscher–Ohlin–Vanek prediction of the factor content of trade based on global differences in factor endowments. Although China's capital is more productive than the US capital, a comparison of input–output data of 33 different countries from the Organisation for Economic Co-Operation and Development in the year 2000 reveals that China's labor productivity compared to the US is the lowest in the sample. This further highlights the value of a factor-specific productivity adjustment as compared to the factor-neutral productivity adjustment that is often used in the Heckscher–Ohlin–Vanek literature. As shown for China, the use of value-added data to evaluate factor utilization aids in correcting for differences in factor quality and productivity across sectors that are not detected. The low average worker productivity in China is a result of the economy's unequal structure, with most jobs still concentrated in the outdated agricultural and service industries and just 11% in the more advanced, export-focused manufacturing sector.

Wood & Mayer (2011) assess the effects of China's globalization on the sectoral structures of other countries, particularly developing countries, and in particular on the balance between labor-intensive manufacturing and primary production, which is important for overall economic progress, income distribution, and employment. They used Heckscher–Ohlin trade theory to describe China's opening as a shift in effective global average factor endowments that changed the relative endowments and so the comparative advantage of all other countries. They found that China's openness reduced the share of labor-intensive manufacturing in total manufacturing and primary production in other countries by 1 to 3.5 percentage points, and the associated export share by 1.5 to 5 percentage points. The bigger values in these ranges are more likely to represent upper limits than the smaller ones are lower limits. These are typical outcomes. China's trade liberalization is likely to have had a greater impact on nations whose products are similar to those manufactured in China, as well as on smaller and more open countries in terms of output. China's influence on these shares was also greater in countries that generate significant amounts of both labor-intensive manufacturing and basic goods, as opposed to those that are highly specialized in only one of these areas. However, China's influence was very minor, other elements frequently dominated. Despite China's enormous size and remarkable growth, their estimates suggest that its openness had little impact on the broad sectoral structures of other countries, and they believe can not think of any realistic way to make this influence look substantially greater. The impact is not insignificant, and it must have been considerably greater in some countries and more narrowly defined sectors than average, but their estimations show that the prevalent perception of China's rise as a danger to economic development and fairness in the rest of the developing world is overblown.

Ito et al. (2017) argue that one of the most characteristic elements of globalization has been the dispersion of production chains across borders since the 1980s. Nonetheless, many scholars are merely scratching the surface of its implications for trade theory and policy. They argue that value-added trade should be more closely aligned with comparative advantage theories than gross trade, since value-added flows capture where production factors, such as skilled and unskilled labor, are employed throughout the global value chain. They provide empirical evidence that Heckscher–Ohlin theory accurately predicts manufacturing trade in value-added terms, much better than it does for gross shipping flows. While countries export across a wide variety of industries, which provide more value-added in ways that make intense use of their abundant factor.

Yan et al. (2020) argues that recent research has focused on global value networks and trade-embodied carbon emissions, but it has yet to explain how shifts in locations within global value chains impact the emissions embodied in a given economy's trade. Carbon emissions are a byproducts of production operations that employ fossil-fuel-based energy; Carbon emissions may be used as an ideal indicator of a country's carbon endowment, which are closely linked to environmental regulations. To explain the flow patterns of trade-embodied emissions in a global-value-chain framework, they builds an expanded environmental Heckscher-Ohlin-Vanek model by using carbon emissions as a measure of carbon endowments. This research also looks at the influence of a specific economy's emissions embedded in trade as a result of a shift in global value chain. They found that a Heckscher-Ohlin-Vanek model can be employed to describe China's and its trading partners' carbon-flow patterns. Economy locked in the middle-to-high levels of their global value chains, especially those with relatively substantial carbon endowments, have lower or even negative net carbon outflows, whereas economies locked at the two extremities of similar global value chains have larger net carbon outflows. These economies should impose tougher environmental rules, optimize their energy structures, and increase their energy efficiency to lower their net emissions embodied in trade. Moving up or down along global value chains to stay near to either end of the production chain is another effective approach to avoid the carbon-lock-in effect.

2.3 Indirect Inference

This thesis uses indirect inference method to test the Computable General Equilibrium model. This useful method was first proposed by Smith Jr (1993). Around the same time Gourieroux et al. (1993) gave this method a name "indirect inference" and they present this method based on a "incorrect criterion" that is auxiliary model, which does not give a direct consistent estimator of the research interest. They examined the method and the result shows that this method is powerful enough and the indirect inference method can be applied in various fields such as microeconometrics, macroeconometrics and finance. In additional, they believe the approaches outlined in the study need only that the model be capable of simulation; hence, they should be applicable to models whose complexity precludes a direct inference.

Genton & Ronchetti (2003) point out that they believe the indirect inference method is a useful tool for testing complex model, however they also argue that the robustness of the auxiliary model should be taken into account to get more reliable results. This method does not require the auxiliary model completely true. Consequently, the auxiliary model can be unreliable as a result of this flexible criterion. This is the reason we introduce the power of the test in the next chapter, which can ensure this method has adequate reliability.

Dridi & Renault (2000) create a semi-parametric version of indirect inference (II) in this study, which they refer to as semi-parametric indirect inference (SII). They offer a brand-new idea of partial entanglement that places a focus on pseudo true values of interest. The primary distinction between this idea of encompassing and the earlier one is that certain parts of the pseudo-true value of interest linked to the structural parameters really correspond to real unknown values. Due to the misspecifications in the structural model employed as a simulator, this helps they to develop a theory of robust estimate. Asymptotic probability distributions for our SII estimators are also provided, along with Wald Encompassing Tests (WET) and recommendations for the usage of Hausman type tests on the assumptions required to ensure the consistency of the SII estimators. They also provide examples based on semi-parametric stochastic volatility models to explain the theory.

Keane & Smith (2003) create a useful simulation-based technique for estimating dynamic discrete choice models. The approach draws on the concepts of indirect inference and can handle lagged dependent variables, serially correlated errors, unobserved variables, and many other choices. Since the objective surface of discrete choice models is a step function, gradient-based optimization techniques cannot be used to accomplish indirect inference in these models. This study demonstrates how to smooth the goal surface to get around this problem.

The crucial concept is to employ a smoothed function of the latent utilities as the auxiliary model's dependent variable. Consistency is ensured when the smoothing value approaches 0 since this function provides the discrete option suggested by the latent utilities. In order to ensure that the estimate has the same limiting distribution as the indirect inference estimator and that gradient-based optimization techniques may converge more easily, they set requirements on the smoothing. When the auxiliary model is sufficiently rich, a series of Monte Carlo trials demonstrate that the technique is quick, reliable, and almost as effective as maximum likelihood.

According to Garcia et al. (2011), the stable distribution is especially helpful for modeling processes that often occur in financial series and have heavy-tailed and skewed distributions. Its estimate does, however, provide a number of difficulties, which they addressed in this study. They proposed an indirect inference estimation method that is well suited to such features since a stable distribution's density function lacks a closed form yet a stable series is simple to mimic. They demonstrated in a Monte Carlo simulation that the approach worked well and was more efficient than competing methods. They employed a variation of the indirect inference technique known as restricted indirect inference to enhance the qualities of the estimator in limited samples as the stability parameter's value approaches two. They also demonstrated that the skewness and kurtosis found in daily returns with jumps may be accurately captured using their new method for estimating stable distributions. Indirect inference offers specification tests for the matched qualities, in this case the unconditional distribution, as a byproduct, even though we do not discuss testing in this study. One may picture a set of diagnostic instruments. For instance, independent evaluations of the stability model's capacity to capture the four important properties of the data are made possible by the binding function's capability to be interpreted parameter by parameter. By combining our skewed-t auxiliary parameters with McCulloch quantile-based functions, one can also run an omnibus test to provide an automated over-identification test.

Monfardini (1998) provide two indirect inference estimators based on the selection of an autoregressive auxiliary model and an ARMA auxiliary model, respectively, as a tool for the estimation of stochastic volatility models. These options enable the construction of the best indirect inference estimators while also making it simple to estimate the auxiliary parameters. Some Monte Carlo experiments' findings show that indirect inference estimators function effectively in limited sample settings, while being less effective than Bayes and Simulated EM techniques.

Gouriéroux et al. (2010) argue that in short time span panels, bias in the estimation of the parameters of dynamic panel models by conventional methods such as ML is typically not negligible, and conventional GMM approaches run into bias and variance problems when the autoregressive coefficient is close to unity, as it frequently is in practical work. Here, they offer a method for bias reduction that uses indirect inference to calibrate the bias function and very slightly increases variance. Simulations demonstrate that the method works very well in both the linear dynamic panel model with and without an unintentional trend. They demonstrate how the method itself may be used to several different panel types with minimal modification and is extremely universal. Recent research by Hahn & Newey (2004) showed how to utilize the jackknife method to lessen the bias in ML estimation for nonlinear panel models. They think indirect inference may be used in similar ways in nonlinear panel models. The methodology may be utilized in the same way with different base estimation techniques, even though the current contribution only uses indirect inference in relation to the ML estimator. The indirect inference strategy is computationally more demanding than other techniques since it uses a simulation-based estimating technique. The base estimator used here has a minimal variance, therefore the indirect inference estimator only requires a few simulated pathways to exhibit strong finite sample qualities. As a result, the indirect inference procedure's computing cost is not particularly high and its advantages from a limited sample are sufficiently large to justify the extra work.

Meenagh et al. (2019) review recent results in indirect inference applications to DSGE models and demonstrate that researchers should customize the power of their test to the model under inquiry in order to strike a compromise between high power and finding a robust model; this will require focusing on a restricted number of key variables, which depends on whose behaviour they should focus. In addition, current research demonstrates that it makes little difference whether those irrelevant variables are included or not. In addition, they demonstrated how indirect inference may be used to test part of model and the results show that there is minimal to no power loss in comparison to employing the full model. They also have shown how indirect inference tests may be used to examine both the exact and weak identification of DSGE models, despite the fact that identification does not seem to be a significant issue in practice. Furthermore, they have shown that likelihood ratio tests also have poor power in predicting tests conducted outside the sample.

According to Le et al. (2016), the main difference between the direct inference and the indirect inference method is that the direct inference test asks how well the model predicts current data, while the indirect inference test asks how closely the model replicates the features of the auxiliary model estimated from the data. They compared the Indirect Inference and Direct Inference Methods. They particularly focus on the Likelihood Ratio as a representative of direct inference. They choose to compare the distributions of the Wald statistic and likelihood ratio tests for a test of certain data characteristics by using Monte Carlo simulations to address these questions. The test findings indicate that the indirect inference Wald test is much more powerful than the direct inference LR test.

Minford & Xu (2018) investigate the empirical data pertaining to whether or not the Classical model or the Gravity model governs UK trade. They used yearly data from 1965 to 2015 using the Indirect Inference method, which has a tremendous amount of power in the application. The Gravity model differs from the Classical model in two ways: it assumes imperfect competition in global markets and that the overall trade share has a positive effect on productivity. The results show that the Classical model passed our primary test with relatively easily, as did the Gravity model, albeit with a lower level of probability; however, when the test's power was increased to include the maximum number of data features to be matched, the gravity model was rejected while the classical model survived. Finally, they show Monte Carlo power function indicates that even in the weakest test, relatively modest parameter mistakes will always result in rejection.

Chapter 3

Model Set-up

3.1 Introduction

With the development of the computer, the power of the computer to process data has been improved significantly, which provides the foundation for the development of the CGE model. The advantage of the CGE model is that it can provide a rigorous and theoretically consistent framework for studying trade policy. This model can reliable simulations, which help us better understand the impact of policy changes on the economy and trade. The CGE model is one of the most popular quantitative analysis techniques in trade. It relies heavily on computer simulations and it can figure out what will happen to the current economy if we change a specific trade policy at a certain point in time. In the CGE model, general equilibrium is assumed. This assumption gives the CGE model a characteristic, that is, the mutual dependence and influence between economic variables, so every change in the variable will cause other variables in the economy to change accordingly.

Burfisher (2021) states that the CGE model is a very useful tool to help us better understand the impact of economic policies, so this model is very popular in the government. Specifically, the CGE models are often used for global climate change, the spread of human diseases, the international transfer of labor and trade policies. The CGE model is a highly comprehensive model because it describes the entire economy based on the utility maximization of firms and consumers. This model can depict the interaction of each of the different components of an economy. Given the above, it is easy to understand that such a model requires a huge database and complex model code. Therefore, such the CGE model needs powerful computer and complete databases to support it, where these obstacles are no longer a big problem for us now since the power of computer and the availability of database are good enough for us to conduct the CGE models.

With the continuous integration of the global economy, there is an increasing demand for quantitative analysis of global economic policies. So Hertel (1997) established the GTAP project in 1992, which is the largest and most influential of the CGE models. The project provides many the CGE modeling researchers with free global databases, standard modeling frameworks, and software training, which helps Researchers for the CGE models greatly reduce the cost of access.

The CGE model is a comparative static model so there are no dynamic inside, which means the endogenous variables would be affected by the exogenous shocks instantly. For example, the prices can react to shocks without lag. Similarly, market clearing condition can be reached instantaneously. The reason why this thesis uses the comparative static CGE model is that it is too complicated to build up a large dynamic model to describe the whole economy and there are no such powerful computer can do the calculation for those thousands of equations. So this thesis uses this relatively simple but still complicated enough the CGE model to implement the tests and the feature of comparative static the CGE model can help us exclude the dynamic effects and focuses more on the main research objections. Also, since the parameters are constant across regime change, in other words they are policy invariant, so the CGE model satisfies the famous Lucas' critique (Lucas 1976).

3.2 The rival classical and gravity models of trade

The Gravity model of trade has been dominant in the study of international trade recently (Shepherd et al. 2013). Although the gravity model of trade empirically succeed in explaining trade flows, this model did not have a convincing theoretical basis until Bergstrand (1985) put forward a world trade model under the framework of general equilibrium, which adopts characteristics of gravity model. This thesis also puts forward a general equilibrium world trade model by making certain assumptions, including the gravity (NTT) model is mainly driven by forces of demand and this demand originates from neighbouring countries and other countries adjusted by distance due to transport costs and border costs; substitutability between products is quite limited, which means competition is likely to be imperfect, so prices set up as a mark-up on costs and the prices are relatively stable. The demand is linked with productivity directly in this model, as once demand has determined trade, the production needs to meet this demand, which has led to foreign direct investment (FDI) and innovative technology entering the production sector, those will eventually boost productivity. To sum up, demand is the key of gravity (NTT) model since supply is largely driven by the forces of demand.

This thesis sets up the general equilibrium models by adopting assumptions summarised by gravity modellers. According to Breinlich et al. (2016), these general equilibrium models mainly have four primitive assumptions. As those gravity modellers stated in the Conceptual Framework section : "1) Dixit-Stiglitz preferences; 2) one factor of production; 3) linear cost functions; 4) perfect or monopolistic competition. There are also three macro-level restrictions are shared including: 1) trade is balanced, excess supply goes to rest of world in the classical model, whereas in the gravity (NTT) model, there is a real devaluation adjusting mark-ups in all sectors, via real exchange rate, forcing export demand to be equal to import demand, so this assumption fits both models' nature and does not create a methodological bias against the gravity (NTT) model for China; 2) aggregate profits are a constant share of aggregate revenues; 3) the import demand system exhibits constant elasticity of substitution (CES). Although these assumptions are extremely restrictive and relatively unrealistic, those restrictive assumptions do fit some of the most important trade models, including the CGE model by Armington (1969); the new trade theory model by Krugman (1980); the Ricardian model with geographic barriers by Eaton & Kortum (2002) and the Melitz (2003) model of heterogeneous firms, which make those assumptions are practical relevant." Output is given as fixed supplies of each product in this model and there is very limited substitutability between products in demand.

These assumptions explain how to set up a gravity general equilibrium model. As previously explained, demand is the key of gravity (NTT) model, production is driven by demand. The principal transmission route that can be used to establish the gravity equations is the consumer demand system. With linear cost functions, supply-side forces are limited to one factor of production. Unlike intermediate commodities that can be exported to the retail market, there is still no structural model of consumers at the retail level.Factor markets, with demand functions from producers and supply functions from households and endowments, are also not fully represented. The gravity equations are a reduced form model that can describe the behaviour of endogenous variables such as trade, GDP, and traded prices, but they are not a structural model of consumer demand. This thesis will solve the full general equilibrium model to see if it can accurately predict the behaviour of these endogenous variables.

There are two main key features are needed in order to create a gravity version of a full CGE model:

(1) substitutability between products is quite limited. It is this feature that makes geography so dominant, since once demanded a product is difficult to dislodge; similarly, selling into distant markets is hard because it has to be broken into by large price cuts. Competition is likely to be imperfect, with prices set up as a mark-up on costs; however this thesis still set perfect competition as the default in the retail sector in both models as mark-up goes to zero.

(2) trade itself boosts productivity automatically. The demand is linked with productivity directly in this model, as once demand has determined trade, the production needs to meet this demand, which has led to foreign direct investment (FDI) and innovative technology entering the production sector, those will eventually boost productivity. So productivity is determined by the exogenous variable that is trade in gravity (NTT) model. However, in the classical model the exogenous variables that can determine productivity are countries' factor supplies and policies such as Chinese economic reform. It is clear that these two models have completely different identification for the determination of productivity so it is a usefully aspect to help us distinguish and identify the gravity CGE version model from the classical CGE version model.

The rival model of gravity (NTT) model is the classical model, which developed by Ricardo (1817), Heckscher (1919), Ohlin (1935), Stolper & Samuelson (1941) and Rybczynski (1955). The key difference between the classical model and the gravity (NTT) model is that the classical model is centered on factors. According to classical trade models, they produce goods in which factor endowments are abundant. On the contrary, the production is driven by demand in the gravity (NTT) model. These assumptions of classical model can be summarized as follows: high competition across world markets; same world prices subject to transport costs and trade barriers; prices equal average costs due to free entry market; capital is mobile; there are three immobile factors, that are unskilled labour, skilled labour and land; output in each sectors is determined by supply factors and productivity. If more domestic goods are produced than home demands, those goods will be exported, and imported if deficit. The retail sector will be added into the model in order to resolve the problem of this model that it cannot allocate demand to imports and home goods and exports to different foreign markets. This also reveals the key difference between classical model and gravity (NTT) model that the causal structures are completely opposite. The core structure of trade is determined by supply in the classical model, and demand adjusts to match it. In the gravity (NTT) model, on the other hand, demand determines the structure of trade and compels supply to meet it.

3.2.1 The modelling of product differentiation in the two models

Product heterogeneity can be distinguished based on product type and origin. Anderson (1979) first provides a good characterization of trade flows between many countries by combining Armington (1969) and Constant Elasticity of Substitution (CES) preferences. This thesis follows the Armington (1969) model with CES preference to describe the demand system that depends on two levels: one is product type and the other is origin of products respectively. This thesis uses the elasticity of substitution to distinguish these two levels of product differentiation. Demand for intermediate products can be established by type, and then demand for their various origins can be calculated, with market-clearing for origin achieved by their origin relative price and the real exchange rate of the origin country: market-clearing implies that Output equals Aggregate Demand for Output(AD) plus Real Exchange Rate(RXR) times Export(X) minus Import(M). Hence if GDP equals AD, as imposed in the CGE model, then this becomes RXR*X=M, so RXR moves to solve for current account equilibrium, which reveals the nature of imperfect substitutability in the gravity (NTT) model, in other words the elasticity of substitution across origins is finite.

In the classical model, the elasticity of substitution across origins is infinite, which means substitutability between products is perfect. Thus products are exported to wherever there is demand for them. In this sense, the classical model does have an effect of "gravity" on trade since demand does affect the trade. As a result, classical modellers never considered the Tinbergen equations to be a source of empirical problems in their models. The models, in effect, represent a sort of perfect trade-diversion. This is why we need test both of trade models, even though the gravity model has been empirically succeed recently, Classical trade models too can generate trade data in line with these regressions, but in a different way.

This thesis does not use a two-layered system of demand for intermediate products. This is because if there are number of i types of goods and number of j geographic origins, the number of demand equations would be $i * j$, which could very well creates thousands demand equations and each equation with its own error term. Thus the power of our test would be reduced since this CGE model contains such a large amount of variability. As a result, this thesis adds retail demand as an extra 'layer' between final and intermediate goods, which is in line with the reality. Another advantage is that this setting allows the gravity (NTT) model and the classical model share the same intermediate produce CGE model, under the default assumption of perfect competition [1]. This thesis adds geographic origins into the retail level. All intermediate products get branded at the retail level. In major markets we assume this branding is by geographical origin. However in the classical model this thesis assumes products in the one

[1] Although in theory, the gravity (NTT) model should be imperfectly competitive, which means the price of goods is equal to cost plus mark up, it makes no practical difference to assume perfect competition where the mark-up simply goes to zero and so we make perfect competition our default assumption

major market namely rest of world (ROW) market is branding in an origin-free way. In this case these unsold products can be sold in ROW market with origin-free way, thus these products are under perfect substitution with other origins, which is one of the characteristics of the classical trade model. However in the gravity (NTT) model the ROW retail market demand is still branded by origin, which means imperfect substitutability by origin across all markets for the gravity (NTT) model. Thus in the gravity (NTT) model the real exchange rate can move to adjust prices according to demand due to the imperfect substitutability between products' geographic origins in order to achieve current account equilibrium. Whereas in the classical model the ROW markets act to absorb excess supplies at world prices because of perfect substitutability of origin.

There are two layers of firms selling products into associated markets. The first layer firms are selling intermediate goods with perfect competition, however the second layer firms are selling branded, differentiated, products to consumers. This thesis will explain this process in detail in the next section.

3.3 The Set-up of CGE model

3.3.1 Summary of Variables

We defined all variables used in this thesis firstly.

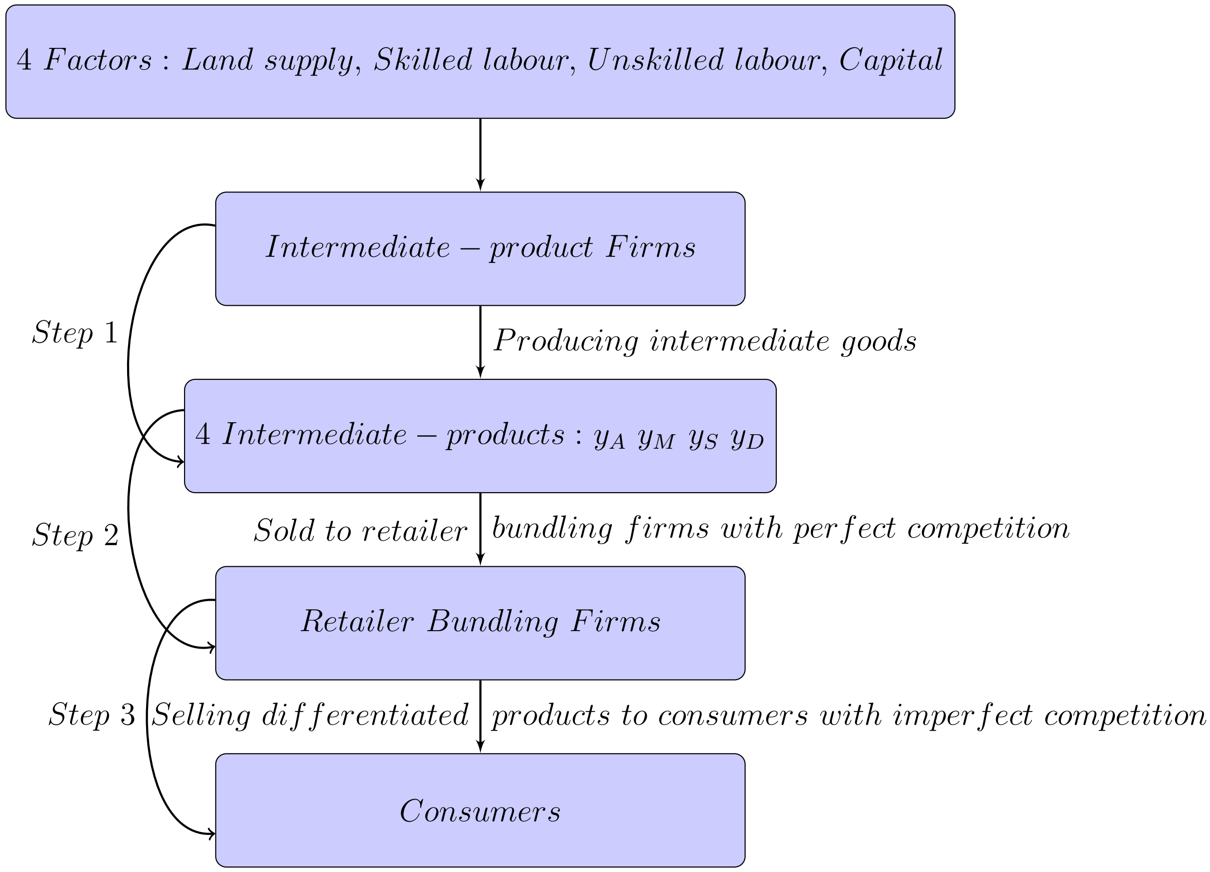
Table 3.1: Summary of Variables

Notation	Definition
p	Price
y	Output(GDP)
N	Unskilled labour
H	Skilled labour
L	Land
K	Capital (physical)
w	Wages of unskilled labour
h	Wages of skilled labour
r	Real rate of return on physical capital
E	Expenditure
l	Rent on land
b	Rate of unemployment benefit(equals one)
POP	Working population
Suffixes	Definition
G	Government expenditure/GDP
A	Agriculture
M	Manufacturing
S	Services
ROW	Rest of World

3.3.2 The Model of Production

This thesis follows the one Minford et al. (1997) developed for assessing the effects of globalisation on the world economy. Firstly, we set up the basic version of CGE model by 4 types of products: agriculture, manufacture, service and domestic goods; 4 factors of production: land supply, skilled labour, unskilled labour and capital; and 4 country blocs: China, EU, US and rest of world. Afterwards, we incorporate the different characteristics of gravity (NTT) model and classical model into the base model, then we get the gravity version of a CGE model and the classical CGE model, we will explain the set-up in detail later. As is shown in Figure 3.1 that there are three steps to set up the basic version of CGE model.

Figure 3.1: The CGE model



In the Step 1, firstly, all four types of factor endowments, that are land supply, skilled labour, unskilled labour and capital (mobile), go into intermediate-product firms as input and those intermediate-product firms produce four types of intermediate goods, which include agriculture, manufacture, service and non-tradable goods. This model follows the set-up of Heckscher-Ohlin-Samuelson and uses the Cobb-douglas technology for production functions. So we do the profit maximising problem in each sector with respect to the Cob-Douglas technology.

$$\Pi = p * y - w * N - h * H - r * K \tag{3.1}$$

Given the Cob-Douglas technology:

$$y = A * (N^{\alpha}) * (H^{\beta}) * K^{1-\alpha-\beta-\gamma} \tag{3.2}$$

$$N = \frac{\alpha * p * y}{w} \tag{3.3}$$

$$H = \frac{\beta * p * y}{h} \tag{3.4}$$

$$K = \frac{(1 - \alpha - \beta - \gamma) * p * y}{r} \tag{3.5}$$

In the Step 2, those four intermediate goods become cost of retailer bundling firms and as this thesis mentioned before the gravity (NTT) model and the classical model share the same intermediate produce CGE model, under the default assumption of perfect competition. So we are minimising cost function in this step two.

$$C(w, r, l, h, y, \pi) = y * \theta * w^{\alpha} * h^{\beta} * l^{\gamma} * r^{1-\alpha-\beta-\gamma} * \pi^{-1} \tag{3.6}$$

Because all intermediate products are all sold to retailer bundling firms with perfect competition, price in each sector equals to the marginal cost:

$$p = w^{\alpha} * h^{\beta} * l^{\gamma} * r^{1-\alpha-\beta-\gamma} * \pi^{-1} \tag{3.7}$$

3.3.3 The Model of Consumption

The consumers buy retail goods differentiated by branding, so in the Step 3 the substitutability is imperfect. Specifically, in the Step 3 the cost for retailer bundling firms are the same and these final products are sold with imperfect competition. Here we use this famous Armington (1969) set-up and incorporate Constant Elasticity of Substitution (CES) preferences as Anderson (1979) did in the appendix of his paper. The export price equals marginal cost times a mark-up. The reasons we prefer the CES preferences are threefold. 1) they are homothetic; 2) they are less restrictions comparing with Cobb-Douglas function; 3) they are extremely tractable[2].

Distributor's costs are identical and all supply to the retail market at mrginal cost times a mark-up reflecting the identical elasticity of demand. Demand for each brand is determined by an Armington cascade model in each country. Thus

[2]Although many trade economists like this CES preferences, they do not really believe the true preferences are CES. They just simply use those CES preferences for convenient (Allen & Arkolakis 2014).

consumers have a disaggregated utility function, C , over country brands as follows:

$$MaxC_J = \left(\sum v_i * C_i^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{3.8}$$

Maximising this subject to total consumption demand:

$$s.t.C_J = \sum p_i * C_i$$

Create the Lagrangian:

$$L = \sum \left\{ v_i C_i^{\left(\frac{\sigma-1}{\sigma}\right)^{\frac{\sigma}{\sigma-1}}} + \lambda \left(C_J - \sum p_i C_i \right) \right\} \tag{3.9}$$

Then the first order condition $\frac{\partial L}{\partial C_i}$ yields this:

$$C_i = C_J \left(\frac{\lambda p_i}{v_i}\right)^{-\sigma} \tag{3.10}$$

From the Lagrangian, we can get $\frac{\delta L}{\delta C_J} = \lambda$. Since the constraint $L = C_J$ must be satisfied, so $\frac{\delta L}{\delta C_J} = 1$. hence $\lambda = 1$.

Finally we get this equation 3.11, which reads the ith demand curve:

$$C_i = v_i^{\sigma} * p_i^{-\sigma} * C_J \tag{3.11}$$

where J is the main product category, which includes all the intermediate goods. C_J is the amount demanded of the main product according to the model's Cobb-Douglas demand function. CGE models assume general equilibrium, so total demand equals total output of each country. $p_i = \mu * MC * P_J$, is the relative price of the country product dependent on the country's relative distance and tariff rate. $\mu = \frac{\sigma}{\sigma-1}$ being the mark-up. P_J the product's price to the country from the world market, is set equal to world prices adjusted for the general MFN tariff rate and transport cost from the world market in the country. MC is normalised at unity.

The expression of mark up is derived from the profit maximisation problem under monopolistic competition.

$$Max \sum (p_i * C_i - MC * C_i) \tag{3.12}$$

$$s.t.C_i = v_i^{\sigma} * p_i^{-\sigma} * C_J$$

Create the Lagrangian:

$$L = \sum \left\{ (p_i * C_i - MC * C_i) + \mu \left(v_i^{\sigma} * p_i^{-\sigma} * C_J - C_i \right) \right\} \tag{3.13}$$

Then the first order condition $\frac{\partial L}{\partial C_i}$ yields this

$$p_i = \mu + MC \tag{3.14}$$

The equation 3.14 shows that prices set up as a mark-up on marginal costs.

The demand functions above are specified for the China, the EU and US where we have data on differential tariffs by country. In the Rest of the World (ROW) we assume that MFN tariffs hold and distances from the three other blocs are all the same. Thus in effect the ROW can act as a residual market that can absorb all the products are not demanded by China, EU and US.

So far we have finished the basic set-up of CGE model without considering the trade part. Because the characteristics of the trade structures are different under the different framework of gravity (NTT) model and classical trade model.

3.3.4 The model of trade

Classical Trade Model

Under the framework of classical trade model, the trade shares only depend on the domestic output regardless the demand from others. The ROW retail brands not by origin, so buys from anywhere. Thus ROW in the classical trade model acts to absorb all the goods are not demanded by China, EU and US.
China's demand for imports from trade bloc i, where i = EU, US and ROW

$$ln(M_i) = a_i + b_i * ln(E_T) + em_i \tag{3.15}$$

Trade bloc i demand for China exports, where i = EU, US

$$ln(X_i) = c_i + d_i * ln(E_i) + ex_i \tag{3.16}$$

Exports to ROW: residual supply of China's traded output.

$$X_{ROW} = y_T - E_T - (X_{US} + X_{EU} - M_{US} - M_{EU} - M_{ROW}) \tag{3.17}$$

Gravity (NTT) model

Under the framework of gravity (NTT) model, because of the characteristics of gravity that tend to trade more with neighbours, they are facing smaller markets than classical model, so in this case the real exchange rate does largely affect the size of trade shares. The role of Rest of World here is different from the classical model that they does not act to absorb the residual supply of China's outputs anymore because all countries including ROW brand by origin. In gravity (NTT) model, the real exchange rate takes over the role and moves to adjust the foreign prices and solve for current account equilibrium. In this model, distance is a constant in the model; and for China (the only model being tested) RXR is a multilateral real exchange rate.

With imperfect competition, the real exchange rate, RXR affects trade. So the trade share bloc: China's demand for import from trade bloc, where E_T stands for China's demand of tradable goods, i = EU, US, ROW.

$$ln(M_i/E_T) = \psi * ln(RXR) + e_{M,i} \tag{3.18}$$

Trade bloc i demand for China exports, where i = EU, US. E_i stands bloc i's demand for China exports.

$$ln(X_i/E_i) = -\psi * ln(RXR) + e_{X,i} \tag{3.19}$$

The movement of real exchange rate solves the current account equilibrium[3].

$$\sum_i (M_i) = RXR * \sum_i (X_i) \tag{3.20}$$

Another special feature of gravity (NTT) model, that is ,there is a link from trade intensity to productivity since the demand determines the production and foreign direct investment will flow into producing countries, ultimately leading to accelerate productivity (Breinlich et al. 2016)[4]. We do not include FDI in this models; it is assumed that K moves around countries to satisfy demand. So we assume total size of trade that is export plus import, which attracts flows of foreign direct investment and ultimately boosts productivity: $T = \frac{TotalTrade}{E_{China}} = \frac{E_T}{E_{China}} * \frac{M_{EU}}{E_T} + \frac{E_T}{E_{China}} * \frac{M_{US}}{E_T} + \frac{E_T}{E_{China}} * \frac{M_{ROW}}{E_T} + \frac{E_{EU}}{E_{China}} * \frac{X_{EU}}{E_{EU}} + \frac{E_{US}}{E_{China}} * \frac{X_{US}}{E_{US}} + \frac{E_{ROW}}{E_{China}} * \frac{X_{ROW}}{E_{ROW}}$ The productivity terms can be written as:

$$\Delta ln(\pi_{i,t}) = c_{i,t} + v_i * \Delta T + \epsilon_{i,t} \tag{3.21}$$

$$where : i = M, S, A, D$$

3.3.5 The Full Model

Our model follows the one created by Minford et al. (1997) for measuring the impacts of globalisation on the global economy, so parameters for our model are calibrated from this paper. This model performed well empirically in explaining the trade trends of the period 1970–1990; it identified a group of major causal "shocks" during this period and provided a good fit to the period's prominent features, such as terms of trade, production shares, sectoral trade balances, relative wage movements, and employment/unemployment trends.

The model incorporates the fundamental assumptions of the Heckscher-Ohlin-Samuelson framework. Production functions are supposed to be Cobb-Douglas

[3]It shows one of the characteristics of gravity (NTT) model that all countries including ROW brand by origin.

[4]The trade also can influence the productivity in classical model as well but the channel is not that direct as gravity (NTT) model is since in gravity (NTT) model FDI has plenty of incentive to flow into producing country due to the volume of trade, whereas in the classical model productivity is determined by countries' factor supplies and policies(Eaton & Kortum 2002).

and identical across countries. Since factor shares are expected to be constant, we were able to calibrate the model using precise China's data. Non-traded and three traded sectors including agricultural, manufacturing and service sectors. There are three immobile factors of production: unskilled labor, skilled labor, and land. Capital is mobile.

The world is divided into four blocs: China, EU (UK is not included), US, ROW (rest of world). In our model here, focusing on the China, we treat world prices and other countries' consumption as exogenous processes initially, but since China is big country, so we endogenize the world prices and GDPs by VAR. The reason that EU, US and ROW are not handled structurally is because it would make our model too complicated and generate too many equations that our computer do not have enough power to solve them. This is also the reason we call our test as "Part of model test".

Model Specification

Model listing-Classical Model

Equations for all prices

$$p_M = w^{0.52234} * h^{0.14366} * l^{0.035} * (p_M * r)^{0.299} * {\pi_M}^{-1} \tag{3.22}$$

$$p_S = w^{0.21168} * h^{0.51832} * l^{0.033} * (p_M * r)^{0.237} * {\pi_S}^{-1} \tag{3.23}$$

$$p_A = w^{0.147} * h^{0.132} * l^{0.079} * (p_M * r)^{0.642} * {\pi_A}^{-1} \tag{3.24}$$

$$p_D = w^{0.38024} * h^{0.168} * l^{0.113} * (p_M * r)^{0.331} * {\pi_D}^{-1} \tag{3.25}$$

p_M, p_S and p_A have been used to solve for w, h and l respectively. Then we can take a logarithm of these prices equations both side then rearrange them to get equations for ln(w), ln(h) and ln(l):

$$ln(w) = \frac{1}{0.52234} * [ln(p_M * \pi_M) - 0.14366 * ln(h) - 0.035 * ln(l) - 0.299 * ln(p_M * r)] \tag{3.26}$$

$$ln(h) = \frac{1}{0.51832} * [ln(p_S * \pi_S) - 0.21168 * ln(w) - 0.033 * ln(l) - 0.237 * ln(p_M * r)] \tag{3.27}$$

$$ln(l) = \frac{1}{0.079} * [ln(p_A * \pi_A) - 0.147 * ln(w) - 0.132 * ln(h) - 0.642 * ln(p_M * r)] \quad (3.28)$$

$\pi_M, \pi_S, \pi_A, \pi_D$, are exogenous productivity error processes.

Equations of factor demands

$$N = w^{-1} * (0.147 * p_A * y_A + 0.52234 * p_M * y_M + 0.21168 * p_S * y_S + 0.38024 * p_D * y_D) * e_M \quad (3.29)$$

$$H = h^{-1} * (0.132 * p_A * y_A + 0.14366 * p_M * y_M + 0.51832 * p_S * y_S + 0.168 * p_D * y_D) * e_S \quad (3.30)$$

$$L = l^{-1} * (0.079 * p_A * y_A + 0.035 * p_M * y_M + 0.033 * p_S * y_S + 0.113 * p_D * y_D) * e_A \quad (3.31)$$

$$K = k^{-1} * (0.642 * p_A * y_A + 0.299 * p_M * y_M + 0.237 * p_S * y_S + 0.331 * p_D * y_D) * e_K \quad (3.32)$$

$$y_M = \frac{1}{0.52234 * p_M} * [N * w * e_M - 0.38024 * p_D * y_D - 0.21168 * p_S * y_S - 0.147 * p_A * y_A] \quad (3.33)$$

$$y_S = \frac{1}{0.51832 * p_M} * [H * h * e_S - 0.168 * p_D * y_D - 0.14366 * p_M * y_M - 0.132 * p_A * y_A] \quad (3.34)$$

e_M, e_S, e_A, e_K are factor demand error processes. y_A follows exogenous process.

Equations for factor supplies

$$N = e_N * (w/b)^{0.1} * POP^{0.5} * G^{0.5} \quad (3.35)$$

where b is unemployment benefit and we assume there are no unemployment benefit in China, so b=1. G stands for government spending on education, more government spending on education, then less low-skilled labour supply. POP stands for working population.

$$H = e_H * (h/w)^{0.1} * G^{0.5} \quad (3.36)$$

where e_M and e_H are error processes. h/w stands for income gap between skilled labour and low-skilled labour, if this gap widens, supply of skilled labour will increase. G stands for government spending on education, more government spending on education, then more skilled labour supply. These equations are simple labour supply equations: unskilled labour supply depends on the unskilled wage/benefit ratio as well as a population elasticity. Skilled labour depends on the ratio of skilled to unskilled wages as well as also an elasticity to government spending which is partly devoted to raising skills. Note that other driving elements are in the error term.

$$L = l^{-1} * (0.079 * p_A * y_A + 0.035 * p_M * y_M + 0.033 * p_S * y_S + 0.113 * p_D * y_D) * e_A \quad (3.37)$$

We treat primary sector output (agriculture mainly) as politically controlled and essentially fixed exogenously because of interventionist planning systems. The supply of land is adjusted (via planning and other controls) to enforce this output requirement but otherwise to satisfy land demands from other sectors. L is supplied equal to demand.

Equation for domestic output

$$y_D = 0.5 * E \quad (3.38)$$

We assume half of expenditure is from domestic output, so put 0.5 as the coefficient of total expenditure.

Equation for output

$$y = y_D + y_M + y_S + y_A \quad (3.39)$$

Total output equals the sum of manufacturing output, agricultural output, service output and domestic output.

Equation for equilibrium condition

$$E = y \quad (3.40)$$

Total expenditure equals total output.

Equation for demand of tradable goods

$$E_T = E - y_D \quad (3.41)$$

Total demand of tradeable goods equals total output minus domestic output.

Equation for demand for goods in manufacturing sector

$$E_M = E_T - E_S - E_A \tag{3.42}$$

Equation for demand for goods in service sector

$$E_S = 0.9 * E_T - 3.1017e + 03 - 12 * (p_S - p_T) \tag{3.43}$$

This equation is estimated by China's data.

Equation for demand for goods in agriculture sector

$$E_A = 0.05 * E_T - 695.6911 - 5 * (p_A - p_T) \tag{3.44}$$

This equation is estimated by China's data.

Equation for consumer price index

$$p = p_M * \frac{E_M^{base}}{E^{base}} + p_S * \frac{E_S^{base}}{E^{base}} + p_A * \frac{E_A^{base}}{E^{base}} + p_D * \frac{E_T^{base}}{E^{base}} \tag{3.45}$$

Equations for world prices

$$p_{it} = \alpha_{it} + \beta_{it} p_{A\,t-1} + \gamma_{it} p_{M\,t-1} + \sigma_{it} p_{S\,t-1} + \delta_{it} y_{US\,t-1} + \Phi_{it} y_{EU\,t-1} + \phi_{it} y_{ROW\,t-1} + \eta_{it} \tag{3.46}$$

where i=A, M, S; j=US, EU, ROW; We endogenize the world prices of US, EU and ROW by VAR since China is a big country, so the outputs and prices can have a major effect world prices and outputs.

$$p_M = {p_M}^{world} * (1 + T_M) \tag{3.47}$$

$$p_S = {p_S}^{world} * (1 + T_S) \tag{3.48}$$

$$p_A = {p_A}^{world} * (1 + T_A) \tag{3.49}$$

T_M,T_S,T_A, are simply the tariff+non-tariff+transport cost real barriers to trade between the target country (US, EU) and world markets. As we do not have time-series data on these, they are all set to unity; what this implies is that all these effects are absorbed into the model's error terms. The exchange rate simply changes all prices in proportion in sterling, leaving them unchanged in dollars. So effectively all the prices in this model are in dollars relative to world manufacturing prices in dollars- the numeraire. World prices, ${p_M}^{world}$,${p_S}^{world}$,${p_A}^{world}$ are exogenous processes.

$$p_T = p_M * \frac{E_M}{E_T} + p_S * \frac{E_S}{E_T} + p_A * \frac{E_A}{E_T} \tag{3.50}$$

Error process

The error process follows AR(1) process.

$$ln(\pi_{i,t}) = c_{1i} + \rho_{1i} ln(\pi_{i,t-1}) + \phi_{1i,t} + \varepsilon_{i,t} \tag{3.51}$$

$i = M, S, A, D$

$$ln(e_{i,t}) = c_{2i} + \rho_{2i} ln(\pi_{i,t-1}) + \eta_{i,t} \tag{3.52}$$

$i = M, S, A, N, H, K$

Trade share bloc

China import demand for trade bloc i, where i=EU,US,ROW; Trade bloc i demand for China exports, where i=EU,US; Export to ROW:residual supply of China traded output.

China import demand for trade bloc i, where $i = EU, US, ROW$

$$ln(M_i) = a_i + b_i * ln(E_T) + em_i \tag{3.53}$$

Trade bloc i demand for China exports, where $i = EU, US$

$$ln(X_i) = c_i + d_i * ln(E_i) + ex_i \tag{3.54}$$

Exports to ROW: residual supply of China traded output.

$$X_{ROW} = y_T - E_T - (X_{US} + X_{EU} - M_{US} - M_{EU} - M_{ROW}) \quad (3.55)$$

$em_i andex_i$ are trade share error process. We estimate $a_i, b_i, c_i, d_i$by OLS.

Gravity (NTT) model Variant

Since this is CGE model, which is comparatively static model and this model requires current account balance, so **China import demand for trade bloc** i becomes

$$ln(\frac{M_i}{E_T}) = cm_i + \psi * RXR + em_i \quad (3.56)$$

Trade bloc i **demand for China exports** becomes

$$ln(\frac{X_i}{E_T}) = cx_i + \psi * RXR + ex_i \quad (3.57)$$

Where RXR moves to solve for **current account equilibrium** in the equation

$$X_{ROW} + X_{US} + X_{EU} = RXR * (M_{ROW} + M_{US} + M_{EU}) \quad (3.58)$$

The em_i and ex_i are exogenous error processes. We estimate cm_i and cx_i by OLS and bootstrap the trade share data ($\frac{M_i}{E_T}$ and $\frac{X_i}{GDP_i}$) from above equations; we set the elasticities of demand to the real exchange rate at (import) $\phi = 2$, (export) $\phi = -2$.

To embody the gravity (NTT) model idea that trade affects productivity via intensifying links with foreign firms, including FDI, we now also rewrite the productivity terms as a function of total trade, $T, \pi_M, \pi_S, \pi_A, \pi_D$ are now no longer purely exogenous productivity error processes but now each contain a term in T, defined as follows:

$$TotalTrade = M_{EU} + M_{US} + M_{ROW} + X_{EU} + X_{US} + X_{ROW} \quad (3.59)$$

$$T = \frac{TotalTrade}{E_{China}} \quad (3.60)$$

The productivity terms are then written as:

$$\Delta ln(\pi_{i,t}) = c_{1,t} + \upsilon_i \Delta T + \varepsilon_{i,t} \tag{3.61}$$

$i = M, S, A, D$

Solving the Trade Model

Step 1 Given the exogenous world price (p_M, p_S, p_A) and the productivity errors ($ln(\pi_M)$, $ln(\pi_S)$, $ln(\pi_A)$) solve for w, h, l from Equation 3.26, Equation 3.27, Equation 3.28 and rearrange them in matrix form as:

$$\begin{pmatrix} 0.52234 & 0.14366 & 0.035 \\ 0.21168 & 0.51832 & 0.033 \\ 0.147 & 0.132 & 0.079 \end{pmatrix} \begin{pmatrix} ln(w) \\ ln(h) \\ ln(l) \end{pmatrix} =$$

$$\begin{pmatrix} 1 & 0 & 0 & -0.299 \\ 0 & 1 & 0 & -0.237 \\ 0 & 0 & 0 & -0.642 \end{pmatrix} \times \begin{pmatrix} ln(pM) \\ ln(pS) \\ ln(pA) \\ ln(pM*r) \end{pmatrix} + \begin{pmatrix} ln(\pi_M) \\ ln(\pi_S) \\ ln(\pi_A) \end{pmatrix}$$

So

$$\begin{pmatrix} ln(w) \\ ln(h) \\ ln(l) \end{pmatrix} = \begin{pmatrix} 0.52234 & 0.14366 & 0.035 \\ 0.21168 & 0.51832 & 0.033 \\ 0.147 & 0.132 & 0.079 \end{pmatrix}^{-1}$$

$$\times \left[\begin{pmatrix} 1 & 0 & 0 & -0.299 \\ 0 & 1 & 0 & -0.237 \\ 0 & 0 & 0 & -0.642 \end{pmatrix} \begin{pmatrix} ln(pM) \\ ln(pS) \\ ln(pA) \\ ln(pM*r) \end{pmatrix} + \begin{pmatrix} ln(\pi_M) \\ ln(\pi_S) \\ ln(\pi_A) \end{pmatrix} \right]$$

Step 2 Given POP, G, w, b, h, w and the factor supply errors (eN , eH), solve for labour supply N and H.

$$N = e_N * (w/b)^{0.1} * POP^{0.5} * G^{0.5} \tag{3.62}$$

$$H = e_H * (h/w)^{0.1} * G^{0.5} \tag{3.63}$$

Step 3 Given the world price (pM, pS, pA, pD), agriculture output (yA), factor supply (N, H), factor cost (w, h) and the factor demand error errors (eM, eS, eA), solve for yM, yS, yD from Equation 3.29, Equation 3.30 and Equation 3.39.

$$y_M = (\frac{1}{0.52234 * p_M})*(N*w*e_M - 0.38024*p_D*y_D - 0.21168*p_S*y_S - 0.147*p_A*y_A) \tag{3.64}$$

$$y_S = (\frac{1}{0.51832 * p_S}) * (H * h * e_S - 0.168 * p_D * y_D - 0.14366 * p_M * y_M - 0.132 * p_A * y_A) \quad (3.65)$$

$$y_D = y_M + y_S + y_A \quad (3.66)$$

From Equation 3.30, Equation 3.31 and Equation 3.40 we get:

$$\begin{pmatrix} N * w * e_M \\ H * h * e_S \end{pmatrix} =$$

$$\begin{pmatrix} 0.52234p_M + 0.38024p_D & 0.21168p_S + 0.38024p_D & 0.147p_A + 0.38024p_D \\ 0.14366p_M + 0.168p_D & 0.51832p_S + 0.168p_D & 0.132p_A + 0.168p_D \end{pmatrix} \begin{pmatrix} y_M \\ y_S \\ y_A \end{pmatrix}$$

So $$\begin{pmatrix} y_M \\ y_S \end{pmatrix} = \begin{pmatrix} 0.52234p_M + 0.38024p_D & 0.21168p_S + 0.38024p_D \\ 0.14366p_M + 0.168p_D & 0.51832p_S + 0.168p_D \end{pmatrix}^{-1} \times \begin{pmatrix} N * w * e_M - (0.147p_A + 0.38024p_D) * y_A \\ H * h * e_S - (0.132p_A + 0.168p_D) * y_A \end{pmatrix}$$

Solve for E_t and other endogenous variables in the model

$$E_t = y_M + y_S + y_A \quad (3.67)$$

3.3.6 The statistical nature of the CGE model

To be precise, the CGE model asserts a set of equilibrium (cointegrating) relationships between trade variables which implies the nature of the exogenous and error processes. The reduced form relationships (i.e. between the solved-out variables and also with the exogenous ones) are cointegrating relationships, which we explain when we will describe the auxiliary model in later.

We have set up the CGE trade models as equilibrium relationships and so cointegrated, where A is the cointegrating matrix, x is the vector of endogenous variables, z is the vector of non-stationary exogenous variables, such as productivity and u is the vector of other shocks:

$Ax_t = Bz_t + u_t$

z is a nonstationary I(1) process, defining the changing equlibrium trend. The other shock vector , u, must be stationary under the true model. For simplicity we model it as AR(1), so that $u_t = Pu_{t-1} + \eta_t$ where P has the AR coefficients for each error along its diagonal. Notice that the shock includes the whole current deviation of x from its equilibrium value, $A^{-1}Bz_t$, including the 'dynamic' effects in response to the shocks due to adjustment costs and expectations. It is the gradual disappearance of these effects that creates the autocorrelation. The reduced form of this model is a VARX(1), as we can show using the ABCD method of Villaverde et al:

$x_t - A^{-1}Bz_t = A^{-1}u_t = A^{-1}Pu_{t-1} + A^{-1}\eta_t = A^{-1}P(Ax_{t-1} - Bz_{t-1}) + A^{-1}\eta_t =$
$A^{-1}PA(A^{-1}Ax_{t-1} - A^{-1}Bz_{t-1}) + v_t$
$= \Lambda(x_{t-1} - A^{-1}Bz_{t-1}) + v_t$

where $\Lambda = A^{-1}PA$. Thus x can be written either as a VARX, with z as its exogenous driving vector, X, or as a VECM, where the lagged deviation from its equilibrium acts on it, pushing it towards equilibrium. The VECM we write as

$\Delta x_t = \Delta(A^{-1}Bz_{t-1}) + v_t - (I - \Lambda)(x_{t-1} - A^{-1}Bz_{t-1}) + v_t$

indicating that x changes with the change its equilibrium value as well as adjusting in response to its lagged deviation from equilibrium.

We can also note that the elements of x will be cointegrated in a variety of reduced form relationships with each other and with z, owing to their common trends in z. These relationships we treat as the auxiliary model.

3.4 The Application of Indirect Inference Method

The figure 3.2 shows the procedure that how indirect inference produce method works. Both actual data and simulated data are used separately as input for the same auxiliary model in order to get different coefficients of auxiliary model based on simulated data and actual data. Then we measure the difference of those coefficients by Wald statistic to see whether our model fits the data well.

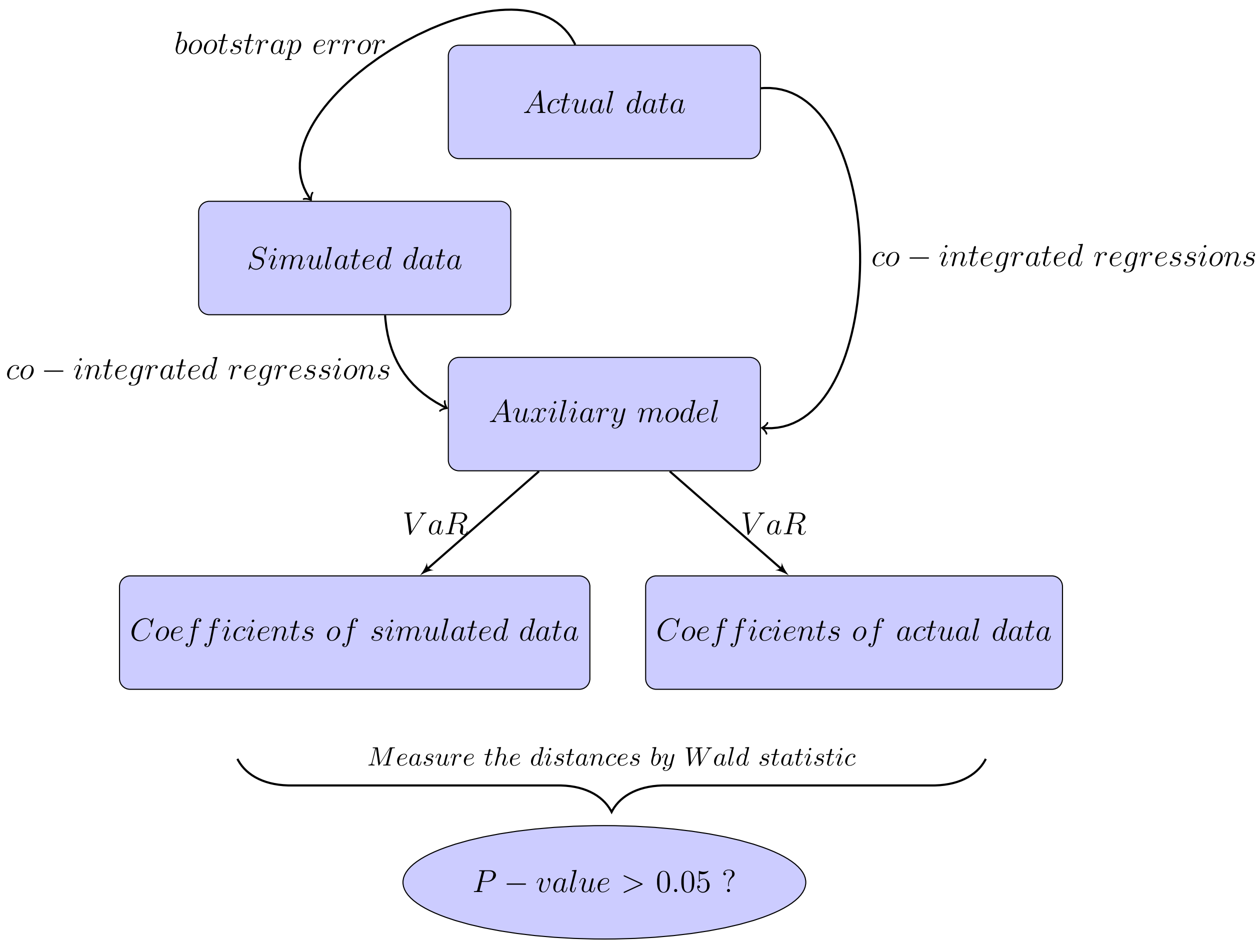
3.4.1 Why we use Indirect Inference?

This model of China, even with world prices etc exogenised, has important cross—equation restrictions, notably between price-cost equations and output equations (factor market-clearing). So it is a complex CGE model, with high nonlinearity. Minford and XuMinford & Xu (2018) show that the power of indirect inference is high for such a model, using the UK model in their case. Also the indirect inference is developed and verified by Minford et al. (2009), Le et al. (2011) and Calvet & Czellar (2015). Although there are two other alternative methods that are Bayesian estimation and Maximum likelihood. The reason that this thesis does not use Bayesian estimation is because it is highly rely on the priors, so this method can be easily biased by the poor parametric distribution of priors (Arellano & Bonhomme 2009). Gravity trade model has been dominant recently and this kind of situation would highly affect the priors, which could lead our testing results biased if we still use Bayesian estimation to test those two rival models. According to Le et al. (2016), the Maximum likelihood estimation (direct inference) produces high estimation bias in small sample size and the power of the test is quite limited in small sample size. This thesis only uses the annual data from 1987 to 2018, so it is quite small sample size. So indirect Inference is justified. Under this circumstance the indirect inference method is best choice for this thesis.

3.4.2 The Auxiliary Model

In indirect inference, the facts regarding the behaviour of the data are estimated separately from the model being tested; this estimated model of the data is re-

Figure 3.2: Indirect inference method



ferred to as the "auxiliary model" and it is created to capture the key relationships in the data that the modellers need to match with their theory-based structural model under test. The test taking process is quite simple to understand. We start by estimating the auxiliary model, which captures the feature found in the data during the sample period we are working with. The same auxiliary model is then estimated on each of these parallel history samples. Next, we simulate the model repeatedly to generate parallel histories of this sample period. Finally, the many estimated auxiliary relationships provide us with their "joint distribution". The probability that this model produced the actual feature we discovered in the data may be found from this joint distribution. To put it very loosely, we construct the world in accordance with the model, and then we inquire as to how probable the real world we see would be in accordance with that model. We normally set a cut-off probability of 5%, so if the likelihood is low, we reject the model.

This graph only gives a general idea about how the indirect inference method works, and I will introduce the operation mechanism of our test step by step later. Before that we have to set up the auxiliary model firstly, which is used to capture the characteristics of the country facts.

The dependent variables in the auxiliary model we will use in our test are the trade shares and the output share: $TS_{EU} = \frac{M_{EU}+X_{EU}}{GDP_{China}}$, $TS_{US} = \frac{M_{US}+X_{US}}{GDP_{China}}$, $TS_{ROW} = \frac{M_{ROW}+X_{ROW}}{GDP_{China}}$, $OS_{China} = \frac{y_M}{y_S}$.
The auxiliary model equations are:

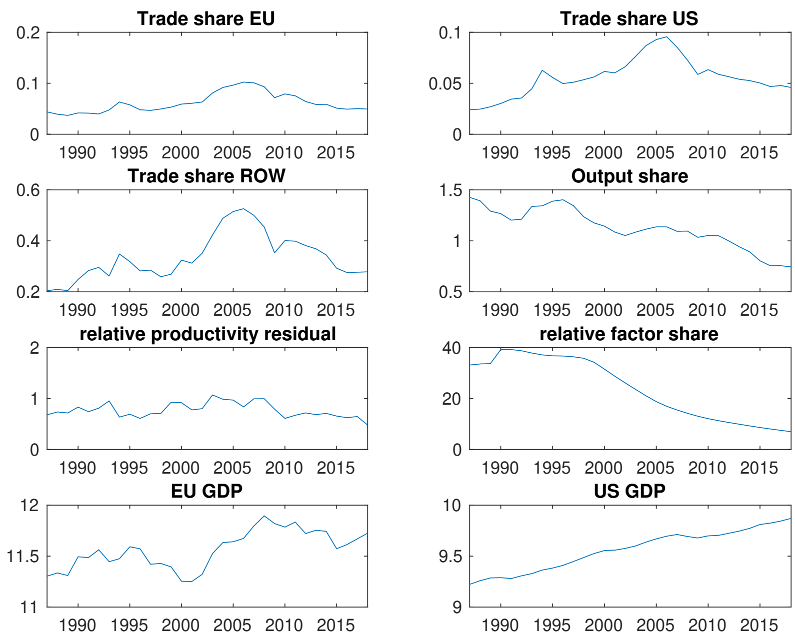
$$TS_{EU} = \alpha_{EU} + \alpha_{11}\frac{\pi_M}{\pi_S} + \alpha_{12}\frac{N}{H} + \alpha_{13}ln(GDP_{EU}) + \alpha_{14}ln(GDP_{US}) + \alpha_{15}\frac{w}{h} + \varepsilon_1 \tag{3.68}$$

$$TS_{US} = \alpha_{US} + \alpha_{21}\frac{\pi_M}{\pi_S} + \alpha_{22}\frac{N}{H} + \alpha_{23}ln(GDP_{EU}) + \alpha_{24}ln(GDP_{US}) + \alpha_{25}\frac{w}{h} + \varepsilon_2 \tag{3.69}$$

$$TS_{ROW} = \alpha_{ROW} + \alpha_{31}\frac{\pi_M}{\pi_S} + \alpha_{32}\frac{N}{H} + \alpha_{33}ln(GDP_{EU}) + \alpha_{34}ln(GDP_{US}) + \alpha_{35}\frac{w}{h} + \varepsilon_3 \tag{3.70}$$

$$OS_{China} = \alpha_{China} + \alpha_{41}\frac{\pi_M}{\pi_S} + \alpha_{42}\frac{N}{H} + \alpha_{43}ln(GDP_{EU}) + \alpha_{44}ln(GDP_{US}) + \alpha_{45}\frac{w}{h} + \varepsilon_4 \tag{3.71}$$

Figure 3.3: Variables used in the Auxiliary



From the figure 3.3, we can see all the trade shares reached the peak around 2005, this is because the definition of trade share is total trade volume divided by total China's output. Because China's GDP grew rapidly after 2005, which was faster than the trade growth rate of these countries, which led to a decline in trade share from around 2005.

The output share is the ratio of manufacturing output and service output, it is clear that the output share has downward trend. This reveals the process of industrial upgrading in China.

The relative productivity residual is defined as the ratio of manufacturing sector's productivity and service sector's productivity. It fluctuates between 0 and 1, which indicates the service sector's productivity is slightly higher than manufacturing sector's productivity.

The relative factor share is defined as the ratio of low skilled-labour's wage and skilled-labour's wage. From the graph, we can see the overall trend of relative factor share is downward, which shows the income gap between low skilled labour and skilled labour is very high but the it is decreasing.

Table 3.2: Stationary Test by ADF test

Variables	Stationary	Non-stationary
TS_{EU}		✓
TS_{US}		✓
TS_{ROW}		✓
OS_{China}		✓
$\frac{\pi_M}{\pi_S}$		✓
$\frac{N}{H}$		✓
$\frac{w}{h}$		✓
$log(E_{EU})$		✓
$log(E_{US})$		✓
Residuals		
ε_1	✓	
ε_2	✓	
ε_3	✓	
ε_4	✓	

From the Table 3.2, it is clear that those variables are all non-stationary. However the residuals: $\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4$ in the reduced form are stationary, which means those regressions should be co-integrated therefore. Although the auxiliary model does not require to be the perfect to describe the data "facts", we still want to it be close enough to the "facts", so our testing can have good enough power to reject the false model. So we assess the power of the test in the next section, and from the Table 3.3 the result shows indeed our test has good enough power to reject the false model.

3.4.3 Indirect Inference Wald Test

Indirect inference methods can be incorporated with many types of statistics. In this thesis, i use the Wald statistic, so it is called Indirect inference Wald (IIW) test. The whole process is shown in Figure 3.2.

Firstly, i put all the actual data into the structural models, which is shown in the section of "The full model", we can get all the structural shocks. Then i bootstrap 5000 times all those shocks in order to get the simulated data.

Secondly, we input the simulated data and the actual data into the auxiliary model respectively to get two groups of estimated coefficients, one is for the simulated data, the other one is for the actual data.

Thirdly, we can use the Wald statistic to see whether the simulated data fits the "facts" or not.

This paper uses a Wald statistic based on difference between a_T and $\overline{a_S(\theta_0)}$, where a_T stands for the estimates of the data descriptors derived from actual data and $\overline{a_S(\theta_0)}$ stands for the mean of their distribution based on the simulated data. Then i can compute the Wald statistic:

$$WS = \left(a_T - \overline{a_S(\theta_0)}\right)' V\left(a_S(\theta_0)\right)^{-1}\left(a_T - \overline{a_S(\theta_0)}\right) \tag{3.72}$$

Where $V\left(a_S(\theta_0)\right)^{-1}$ can be used to measure the distance between the actual data descriptors and mean of their distribution based on the simulated data and the $V\left(a_S(\theta_0)\right)^{-1}$ is the inverse of the variance-covariance matrix of the distribution of simulated estimates α_S, the θ_0 is the vector of parameters of the trade model on the null hypothesis that it is true.

Then this paper transforms the Wald Statistic to t-statistic by the Mahalanobis Distance based on the same joint distribution, normalised as a t-statistics:

$$T = \left(\frac{\sqrt{2WS_A} - \sqrt{2k-1}}{\sqrt{2WS_i^{95th}} - \sqrt{2k-1}}\right) \times 1.648 \tag{3.73}$$

Where WS_A is the Wald statistic based on the actual data, WS^{95th} is the Wald statistic based on the 95% of the simulated data. This t-statistic can be easily transformed to p-value, which can give us a more familiar indicator of how close the model is to the actual data. If the p-value less than 0.05, it suggests we do not reject the model at 95% confidence interval.

3.5 Power of the Test

Although indirect inference is the best choice for this thesis in theory, the assessment of power of the test is still needed. Especially, although we do not require the auxiliary model must be correctly specified, there is no guarantee whether this model has adequate reliability. The power of the test follows the one Le et al. (2016) developed a Monte Carlo experiment to compare the performance of the direct inference and indirect inference. The detailed steps of the Monte Carlo experiment are as follows:

Step 1. Generate samples from true model We used all regressions in the auxiliary model to do the Monte Carlo experiment and treat our classical model as true model. Then we generate 1000 samples from this true classical model.

Step 2. Falsify true model The rejection rate w2l l naturally rise as the model gets further and further away from the truth, but here what we want to learn through the Monte Carlo experiment is how fast this rejection rate rising as the false rate increasing. We assume the rejection rate is 5% when the model is true then we falsify all the parameters by x% alternately odd and even.

Monte Carlo experiment shows our test has substantial but not excessive power[5] to examine those two models. As the experiment results are shown in Table 3.3, the rejection rate increases steeply as the percentage misspecified over 5% and if the has 15% false rate, it can be almost totally rejected by this indirect inference method with 90.25% chance under 95% confidence interval, which can

[5] We do not hope the test power to be too strong, otherwise even models that are very close to true will be rejected

be considering as quite good power of this testing method. So this thesis can conclude that this test does have sufficient enough power to reject the false model.

Table 3.3: Power of the test

Percent of incorrectly specified	Rate of rejection by indirect inference
True	5%
1%	5.95%
3%	7.6%
5%	11.95%
7%	23.25%
10%	45.1%
15%	90.25%
20%	99.65%

Chapter 4

Data

4.1 Source of Data

All data are annual data from 1987 to 2018. The sources of the China's data are as follows:

1) Output by sector: Agriculture, Industry, Service, Nontraded - source is: **National Bureau of Statistics**.

2) Export and import data (manufacturing and service)- source is: **State Administration of Foreign Exchange**.

3) Export and import data (agriculture)-source is: **National Bureau of Statistics**.

4) Goods price index: Agriculture, Industry, Service - source is: **National Bureau of Statistics**.

5) Working population - source is: **National Bureau of Statistics**.

6) Land supply and Return on land (Housing price) - source is: **National Bureau of Statistics**.

7) Gross capital formation (%GDP) and Real effective exchange rate index - source is: **World bank**.

8) China Average Yearly Wages - source is: **Trading economics**.

9) Skilled labour and unskilled labour - source is: **National Bureau of Statistics**.

10) Earnings of skilled workers: Ratio of skilled earning to unskilled earnings (Decile9/Decile5) Source: **World inequality**.

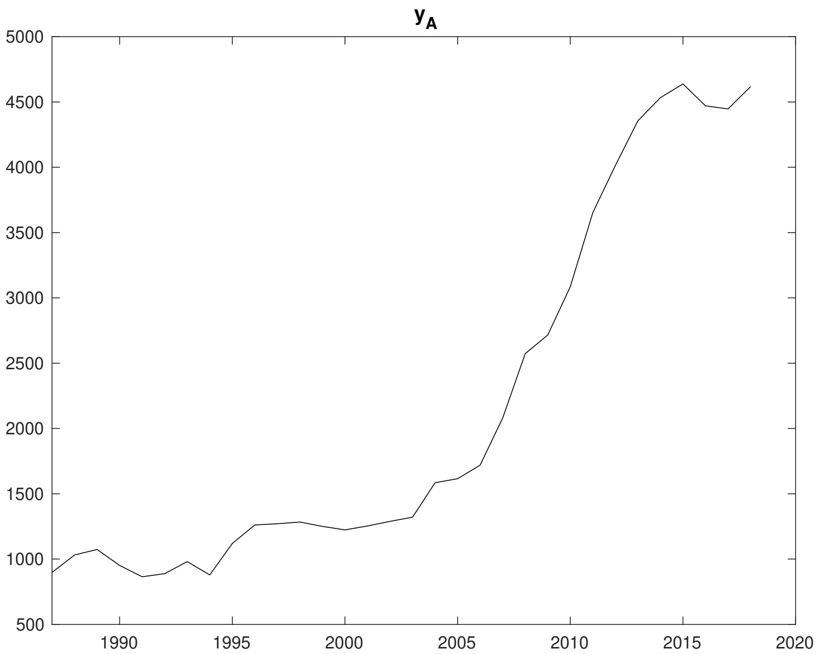
11) Import and export by area - source is: **International Monetary Fund**.

12) Return on capital (Deposit interest rate) - source is: **World Bank**.

4.2 Descriptive Analysis

In this section, we show all the 15 data have been used in this thesis. All the data are real data by excluding price level. Also, The unit of these outputs are in millions of US dollars.

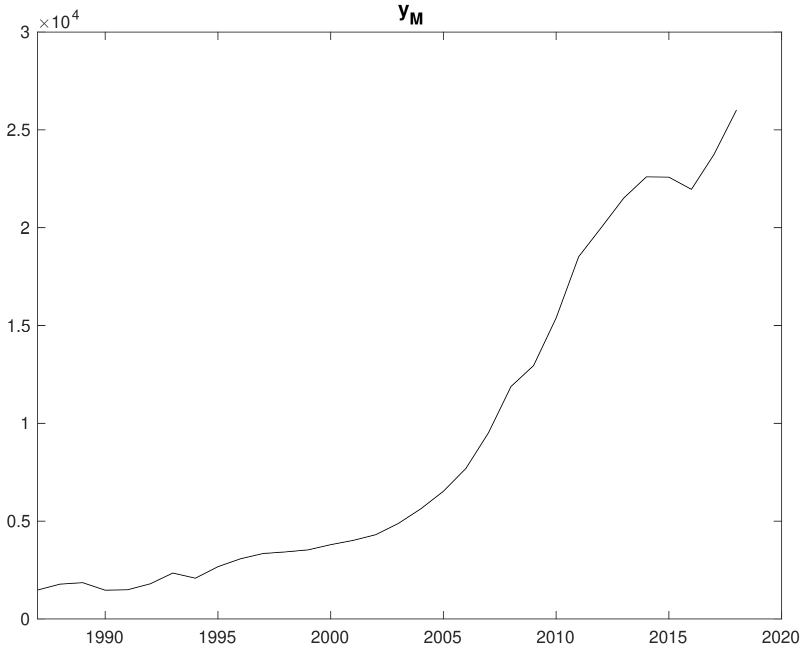
Figure 4.1: China's agricultural output 1987-2018



From the figure we can see the y_A, which stands for China's agricultural output from 1987 to 2018, was quite stable before 2000 and it started to increase dramatically after 2005 but this upward trend was broken in 2015.

The reason why it started to rise rapidly after 2000 is because China joined the WTO in 2001, and the introduction of foreign advanced production technology and tools led to an increase in productivity. At the same time, due to the increase in foreign trade demand, it stimulated people's enthusiasm for production. There are mainly four reasons why China's agricultural output broke the upward trend in 2015. First, the most direct reason is the reduction of agricultural production caused by natural disasters in the country. The second is to speed up the urbanization led to the decrease of the agricultural area in China. The third is due to the industrial upgrading, labor force transferring to industry and services. Although industrial upgrading and workforce reductions preceded 2015, productivity gains made up for these reductions. However, the agricultural productivity level may tends to limit in 2015, consequently technology can no longer increase productivity faster than labor and land are lost.

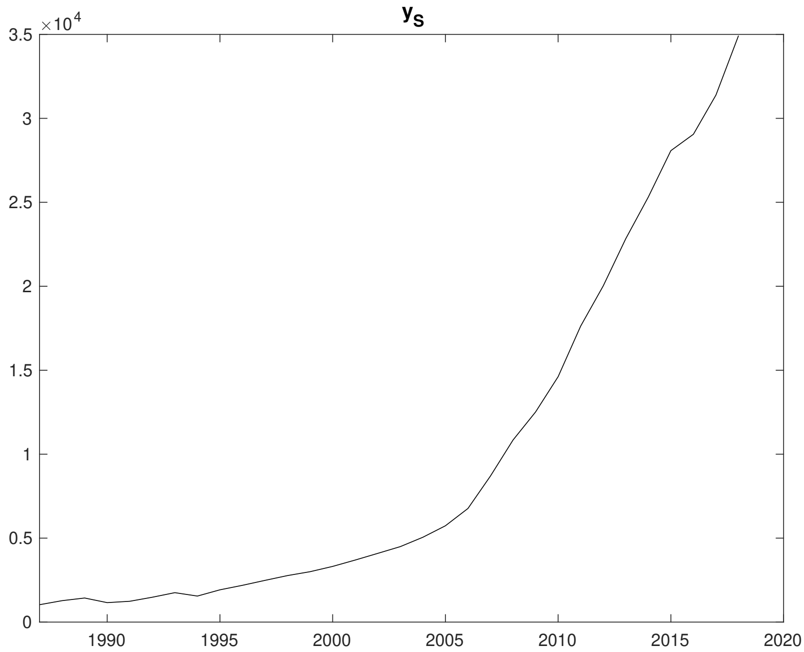
Figure 4.2: China's manufacturing output 1987-2018



From the figure we can see the y_M, which stands for China's manufacturing output from 1987 to 2018, was quite stable before 2000 and it started to increase dramatically after 2000 but this upward trend was broken around 2015 and it just stopped for a moment in 2015 and then continued to rise.

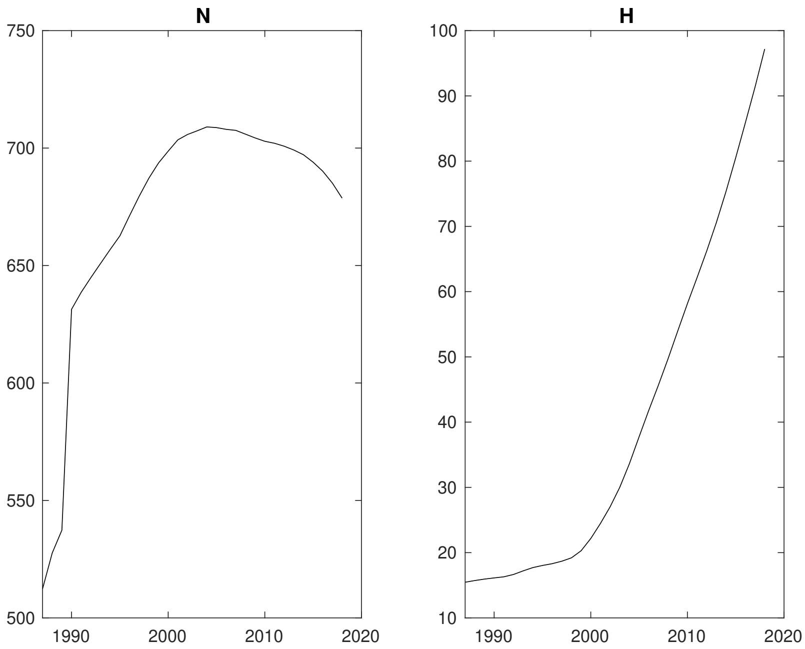
The reason why the manufacturing output started to rise rapidly after 2000 is quite similar with agricultural output. After China joined the WTO in 2001, a large amount of capital,labor and other factors entered the manufacturing sector, resulting in a significant increase in manufacturing output. In 2015, production costs rose due to rising raw material prices, and industrial output declined briefly due to lower foreign demand. After 2015, driven by Chinese real estate, industrial production began to recover and rose rapidly.

Figure 4.3: China's service output 1987-2018



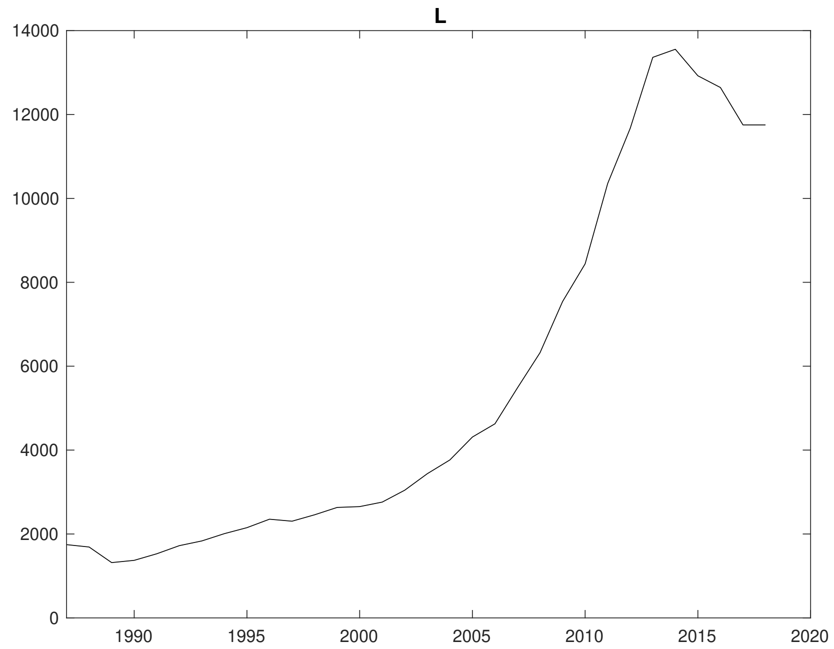
From the figure we can see the y_S, which stands for China's service output from 1987 to 2018, was increasing gradually before 2005 and it started to increase dramatically after 2006 continuously. This is mainly because the year of 2006 is the final deadline for China to open up banking, trade, express delivery, hotel and tourism services as promised by China's accession to the WTO. Since then, Chinese service enterprises in these fields must comply with international rules and face the strong competition brought about by the entry of foreign capital. Also, with the development of China's education and the acceleration of urbanization, it has continuously provided more skilled labor for the service industry.

Figure 4.4: China's low-skilled labour & high skilled labour supply 1987-2018



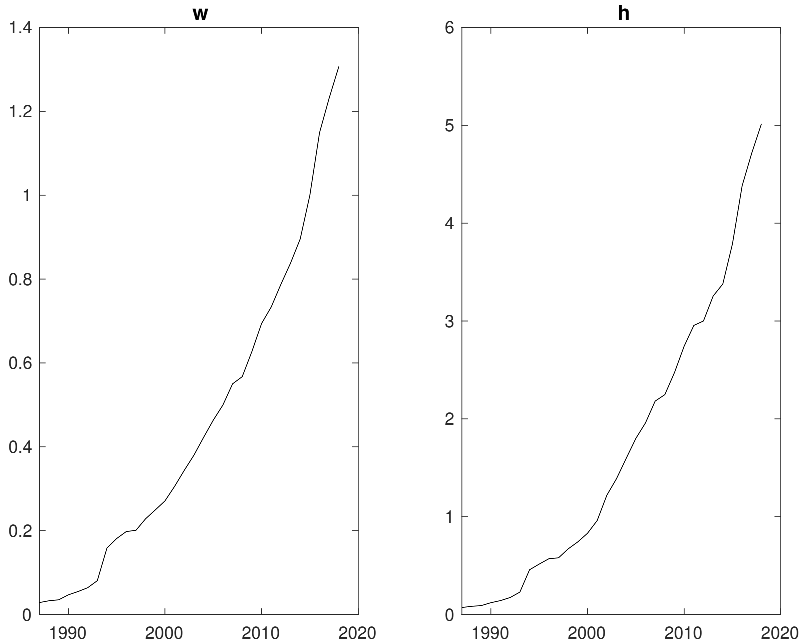
N stands for low-skilled labour supply and H stands for skilled labour supply, the unit of data is millions. This thesis defines those who go to college as the skilled labour, but those who do not go to college as the low-skilled labour. From this figure we can see that low-skilled labour increased dramatically before 2000, this is mainly because of the Cultural Revolution, many people are unable to enter the school and be educated during that period, whereas population increased dramatically, by the time they reach adulthood, they automatically become low-skilled labour. The supply of low-skilled labour tends to be stable after 2000 and began to decline after 2005, this is because more people can start to get education after 1990, as a result we can see the high skilled labour increases dramatically after 2000, these people have a greater chance of becoming a highly skilled labour and they do have big motivation to become skilled labour as China is constantly upgrading its industry, so the demand for skilled labour is growing rapidly.

Figure 4.5: China's land supply 1987-2018



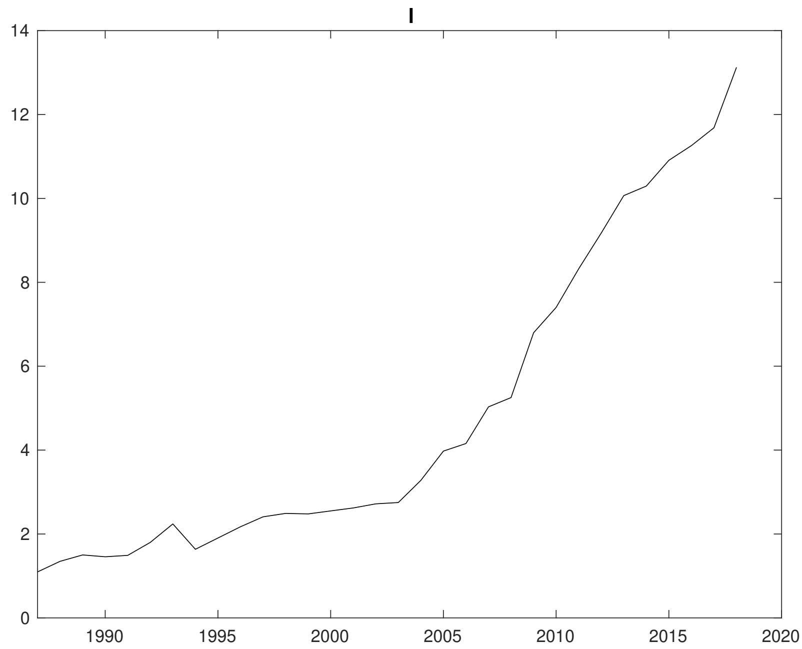
L stands for land supply, it peaked around 2014. As we stated before, China treats primary sector output as politically controlled and essentially fixed exogenously because of the highly interventionist planning system. The supply of land is adjusted via planning and other controls to adjust to this output requirement; in other words the supply of land is demand determined. Also, as we can see the trend of land supply is quite similar with the trend of agricultural output, this is because agricultural production is very dependent on the supply of land.

Figure 4.6: Low-skilled & skilled labour real wage 1987-2018



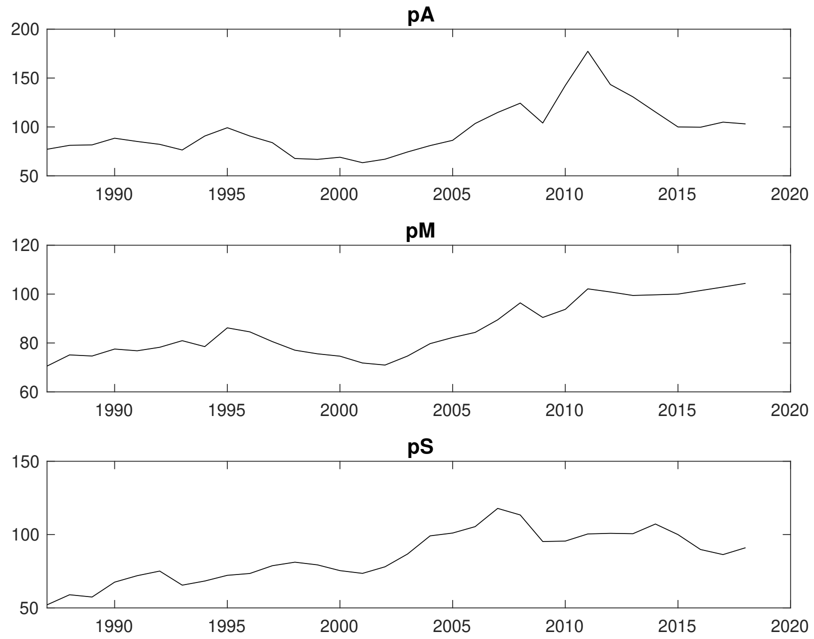
w stands for low-skilled labour real wage, we use indexed China average yearly wages to represent it, the real wage in the base year 2015 is 1. Because skilled labour real wages are not available so we use ratio of skilled earning to unskilled earnings to estimate real wages of skilled labour h. As we can see both real wages w and h are increasing sharply and h is naturally higher than w all the time.

Figure 4.7: Return on land 1987-2018



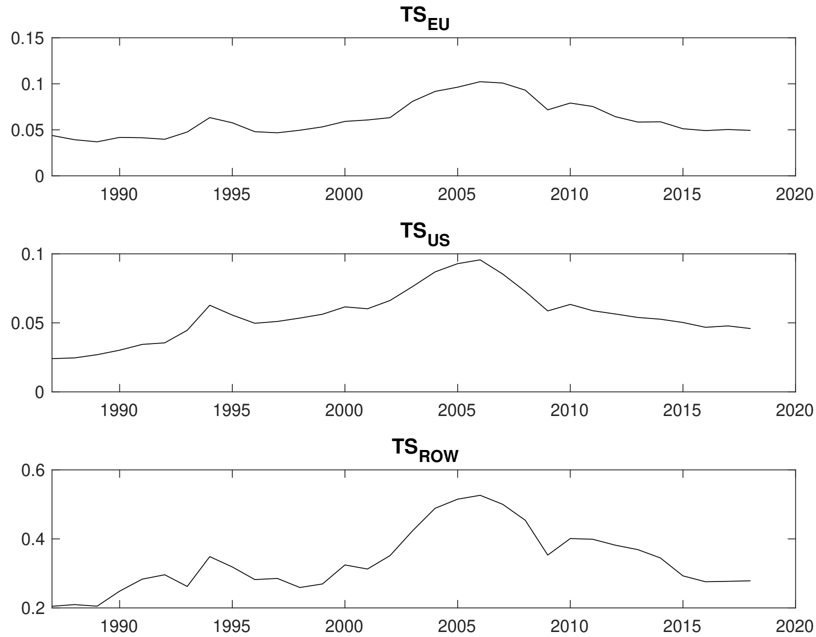
I represents return on land, we use real housing price to represent return on land in this thesis. From the graph, we can see the real housing price was quite stable before 2005 then started to increase very sharply. It is clear that the house price growth slowed from 2012 to 2015 then it started growing fast again from 2016. This also confirms what has been said above, the manufacturing output began to recover after 2015, driven by real estate.

Figure 4.8: Price levels 1987-2018



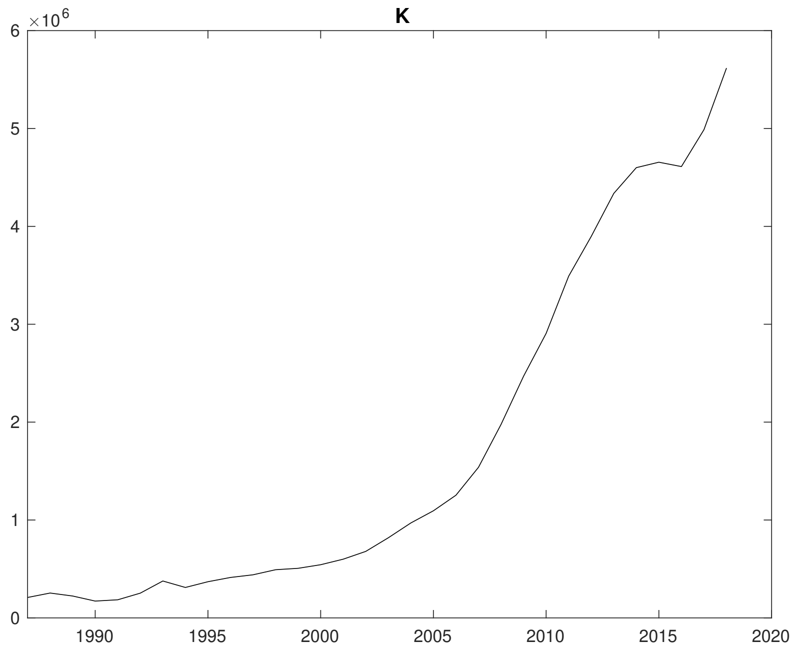
p_M,p_S,p_A are price level indexations for manufacture, service and agriculture respectively, all of the price levels are 100 in the base year 2015. From the figure 4.8, we can see prices of manufacture, service have been increased a lot compared to 1987. Agricultural prices have been very flat and stable until 2008, when they started to get out of control a little bit, suddenly and quickly rose, peaked in 2011, and then began to gradually decline. This is mainly because of the financial crisis in 2008, in response to the financial crisis, the Chinese government implemented a monetary easing policy of RMB 4 trillion to stimulate the economy. Then when the economy stabilized in 2011, the Chinese government began to intervene in the prices of agricultural products to alleviate people's livelihood problems. The price level of manufacture mainly presents an upward trend from 2002, apart from the 2008 financial crisis. The price level of service reached the peak around 2007 and started to decline gradually after the financial crisis.

Figure 4.9: Trade shares 1987-2018



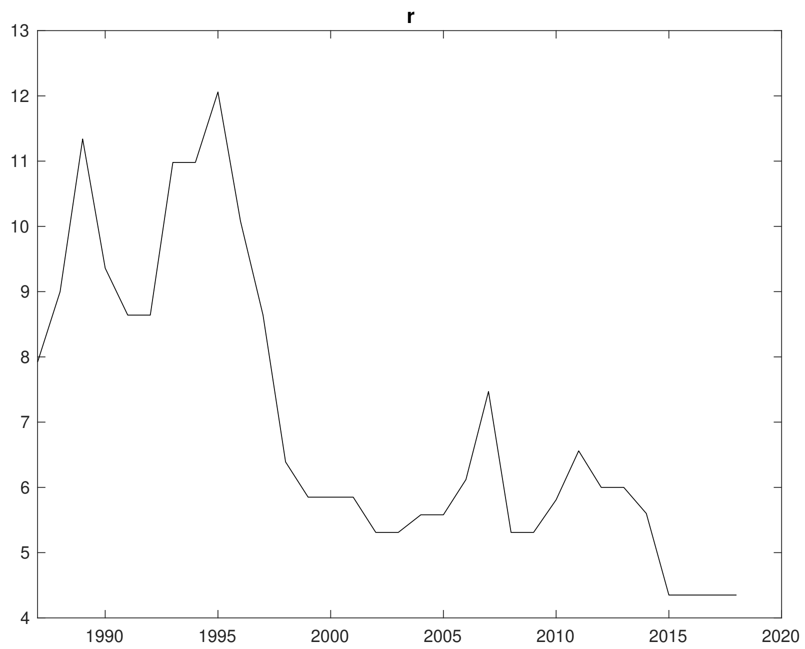
The trade shares are defined as total trade (imports+export) divided by China's total output. All of trade shares with EU, US and rest of world reached the peak around 2008, this is mainly because China's economy heavily rely on trade before 2008, however demand in the international market has shrunk sharply, resulting in a significant drop in China's foreign trade volume during the financial crisis, then China's economy turned to rely more on domestic market rather than international trade.

Figure 4.10: Capital 1987-2018



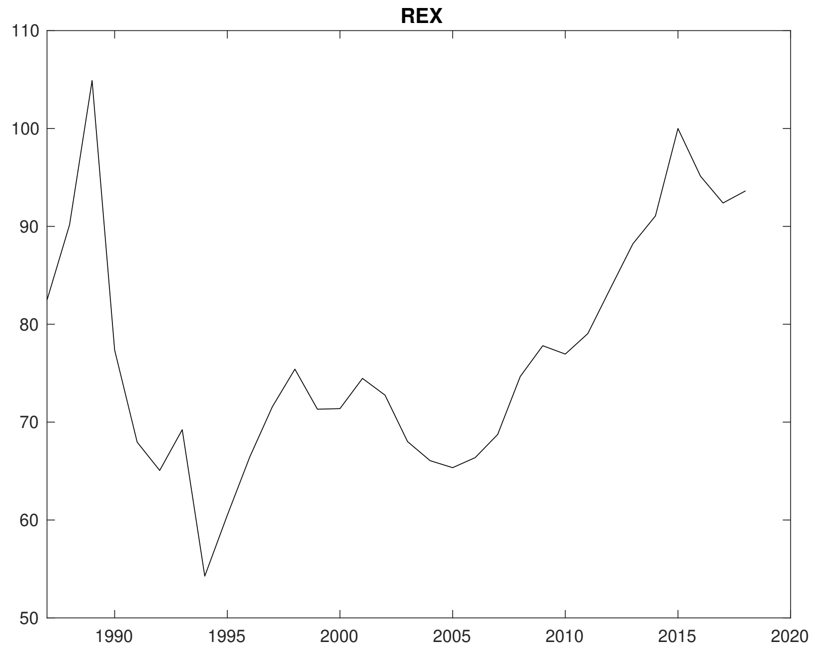
From the figure we can see the K, which stands for capital from 1987 to 2018, was increasing gradually before 2005 and it started to increase sharply after 2006 continuously since China joined WTO, apart from it slowed down a while around 2015 then rose sparely again after 2016.

Figure 4.11: Return on capital 1987-2018



r represents return on capital, we use deposit interest rate as return on capital. From the figure 4.11, we can see the return on capital, the volatility is high and the overall trend is downward. Why is the overall trend declining? First, the marginal rate of return on capital has been declining. Second, economic development is driven by consumption and needs to release liquidity. Therefore, the government has to try to reduce interest rates to stimulate consumption in order to boost economy.

Figure 4.12: Real effective exchange rate 1987-2018



In this thesis, we use real effective exchange rate index to represent real exchange rate. From this graph, we can see the real exchange rate has great fluctuation. It reached the peak in 1989 then it dropped suddenly and rapidly to the lowest point in 1994. After that, the real effective exchange rate increased fast between 1994 and 1999. Then it fell again in volatility until 2005. The reason why it fluctuates so violently is because China carried out exchange rate reform during that period, and before 2005, China had not formed a good exchange rate mechanism. China improved the system for determining the RMB exchange rate on July 21, 2005. The RMB exchange rate is no longer fixed to a single U.S. dollar; instead, it selects several major currencies to form a currency basket and calculates changes to the RMB multilateral exchange rate index with reference to the currency basket. Implement a managed floating exchange rate system based on the supply and demand of the market and adjusted relative to a basket of currencies. As a result, the real effective exchange rate increased gradually after 2005, this increase is due to the popularity of Chinese goods. The real effective exchange rate reached the limitation in 2015 as the Chinese export decreasing after 2015.

4.2.1 Unit Root Test

Table 4.1: ADF Tests on data

Variables	Stationary	Non-stationary	ADF statistic(p-value)
y_M		✓	0.92251
y_S		✓	0.92251
y_A		✓	0.85268
N		✓	0.31085
H		✓	0.99581
L		✓	0.72723
w		✓	0.99967
h		✓	0.99748
l		✓	0.99165
p_M		✓	0.78794
p_S		✓	0.76989
p_A		✓	0.65697
RXR		✓	0.57152
k		✓	0.98156
r		✓	0.27325
TS_{ROW}		✓	0.93174
TS_{US}		✓	0.94768
TS_{EU}		✓	0.96189

From this unit root test, it is clear that all data we used in this thesis are non-stationary.

Table 4.2: Data description

Variables	Mean	STD	MAX	MIN	Median
y_M	9183.6	8370.3	26020	1468.5	4593.2
y_S	9761.9	10531	34925	1035.7	4294.2
y_A	2154.4	1394.7	4638	864.52	1304.8
N	6.7196e+08	5.2712e+07	7.09e+08	5.1237e+08	6.9382e+08
H	3.9977e+07	2.6176e+07	9.718e+07	1.5465e+07	2.8515e+07
L	5.4851e+05	4.3438e+05	1.3556e+06	1.3179e+05	3.2408e+05
w	0.45717	0.37518	1.3069	0.028759	0.36204
h	1.6987	1.4893	5.0157	0.072868	1.3046
l	4.8558	3.7408	13.125	1.0962	2.7342
p_M	85.486	11.144	104.4	70.539	81.585
p_S	84.986	16.944	117.86	52.072	83.762
p_A	96.117	25.941	177.4	63.4	89.577
RXR	76.949	12.12	104.89	54.267	74.563
k	1.7266e+06	1.7886e+06	5.6177e+06	1.717e+05	7.4886e+05
r	7.0294	2.2613	12.06	4.35	6
TS_{ROW}	0.061373	0.019165	0.10228	0.036921	0.057994
TS_{US}	0.055652	0.018506	0.095624	0.024048	0.054765
TS_{EU}	0.33561	0.089664	0.52625	0.2046	0.31562

From this table, we can see the mean values of outputs are quite far away from median values. The mean value of low-skilled labour (N) is very closed to the median value. Service sector has the biggest gap between maximum and minimum in outputs, which indicates the China's service sector has grown the fastest over the past 32 years. The maximum value of skilled labour supply is more 6 times higher than the minimum value, whereas the low-skilled labour does not have that much difference. Both low-skilled wage and skilled wage increases significantly, with 45 times and 68 times differences respectively. The agricultural price level is the most volatile price level with the highest standard deviation among price levels.

Chapter 5

Testing Results

5.1 Testing Process

Firstly, we extract the structural errors $\pi_{i,t}$, $e_{i,t}$, $em_{i,t}$, $ex_{i,t}$ from the structural models we listed in the section of "The full model". Then we test the stationarity of the errors by ADF test.

Table 5.1: ADF Tests on model residuals

Variables	Stationary	Non-stationary
$ln(\pi_M)$		✓
$ln(\pi_S)$		✓
$ln(\pi_A)$		✓
$ln(\pi_d)$		✓
$ln(e_M)$		✓
$ln(e_S)$		✓
$ln(e_A)$		✓
$ln(e_K)$		✓
$ln(e_N)$		✓
$ln(e_H)$		✓
em_{US}	✓	
em_{EU}	✓	
em_{ROW}	✓	
ex_{US}	✓	
ex_{EU}	✓	
ex_{ROW}	✓	

Classical trade model

Secondly, this paper derives the simulated data. For the classical trade model, as this thesis states in the section of "Model Setup", the trade is driven by the factor endowments instead of demands from others, so the trade, which represents demand, does not affect the outputs and productivity. From the Table 5.1, we can see all the $\pi_{i,t}$, $e_{i,t}$ are all non-stationary, so we use first difference method in order to make them stationary before we re-estimate error process.

$$\Delta ln(\pi_{i,t}) = c_{1,t} + \rho_{1,i}\Delta ln(\pi_{i,t-1}) + \varepsilon_{i,t} \tag{5.1}$$

Where i=M, S, A, d

$$\Delta ln(e_{i,t}) = c_{2,t} + \rho_{2,i}\Delta ln(e_{i,t-1}) + \eta_{i,t} \tag{5.2}$$

Where i=M, S, A, K, N, H

This paper estimate the AR(1) process and bootstrap the $\pi_{i,t}$ and e_i, t. After that, we can substitute them into the structural models we listed in the full model section to solve the all endogenous variables. So we get the simulated data.

Based on the ADF test shown in Table 5.1, we can assume the trade share errors are following an AR(1) process:

$$em_{i,t} = c_{1,i} + \rho_{1,i}em_{i,t-1} + \varepsilon_{mi,t} \tag{5.3}$$

Where i=US, EU, ROW

$$ex_{i,t} = c_{2,i} + \rho_{2,i}ex_{i,t-1} + \varepsilon_{xi,t} \tag{5.4}$$

Where i=US, EU

This paper estimates the AR(1) process above and draw the bootstrapped trade share data from trade share equations in classical trade model.

Gravity (NTT) model

For the gravity (NTT) model, as this thesis states in the model setup section, the trade affect the productivity directly as the FDI would flow into the producing country. This paper assumes $v_i = 2$, which means 1% rise in the total trade share in GDP would lead to 2% rise in productivity for each sector.

$$\Delta ln(\pi_{i,t}) = c_{1,t} + v_{1,i}\Delta T + \varepsilon_{i,t} \tag{5.5}$$

Where i=M, S, A

$$\Delta ln(e_{i,t}) = c_{2,t} + \rho_{2,i}\Delta ln(e_{i,t-1}) + \eta_{i,t} \tag{5.6}$$

Where i=M, S, A, K, N, H

Based on the ADF test shown in Table 5.1, we can assume the trade share errors are following an AR(1) process:

$$em_{i,t} = c_{1,i} + \rho_{1,i}em_{i,t-1} + \varepsilon_{mi,t} \tag{5.7}$$

Where i=US, EU, ROW

$$ex_{i,t} = c_{2,i} + \rho_{2,i}ex_{i,t-1} + \varepsilon_{xi,t} \tag{5.8}$$

Where i=US, EU

This paper estimates the AR(1) process above and draw the bootstrapped trade share data from trade share equations in gravity (NTT) model.

Table 5.2: Estimated coefficients for the error process

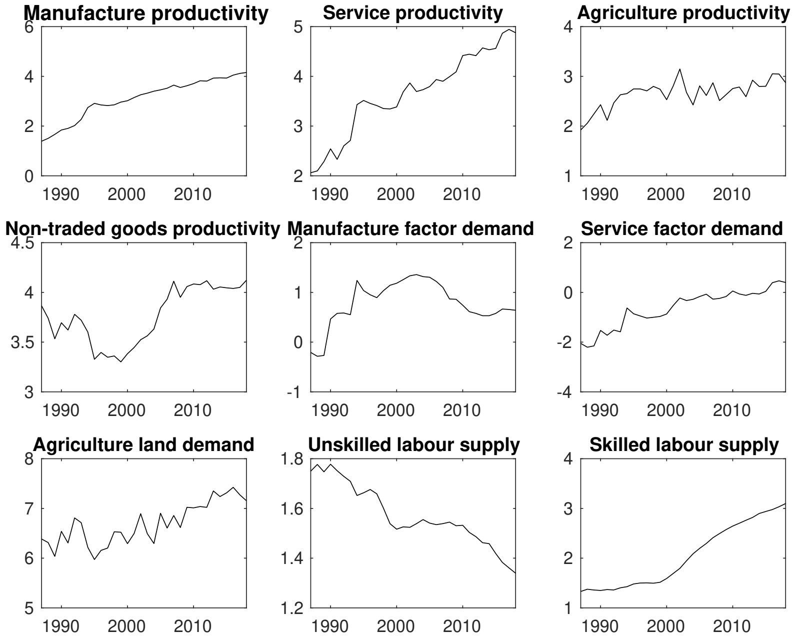
	Classical trade model		Gravity model		
Estimates	ρ	c	ρ	c	v
$\Delta ln(\pi_M)$	0.232904475	0.066104502		0.058079105	2
$\Delta ln(\pi_S)$	-0.082093105	0.108749006		0.06620441	2
$\Delta ln(\pi_A)$	-0.462143715	0.038601567		0.000933386	2
$\Delta ln(\pi_d)$	-0.065232837	0.011434679	-0.063702671	0.007919346	
$\Delta ln(e_M)$	0.016820259	0.028557812	0.017896521	0.025494612	
$\Delta ln(e_S)$	-0.170404062	0.108474169	0.010678145	0.083418302	
$\Delta ln(e_A)$	-0.33591248	0.029694098	-0.330503235	0.032023378	
$\Delta ln(e_K)$	0.052366174	-0.027274325	0.034244532	-0.022495404	
$\Delta ln(e_N)$	0.07005461	-0.013436989	0.132774676	-0.011413546	
$\Delta ln(e_H)$	0.794604332	0.011670616	0.777508535	0.013874751	
em_{US}	0.738053649	-0.003248286	0.701129748	-0.000174711	
em_{EU}	0.404312885	0.021377263	0.723030253	-0.008452609	
em_{ROW}	0.814287061	0.007175305	0.725784359	-0.00285725	
ex_{US}	0.899360129	-0.005819217	0.899360129	-0.005819217	
ex_{EU}	0.845064446	0.037562677	0.845064446	0.037562677	
ex_{ROW}			0.753539995	-0.003859963	

Appendix shows the residuals for the classical model (Figure 5.1) and the model innovations (classical model Figure 5.2 and gravity (NTT) model Figure 5.3).

5.1.1 Model Residuals and Innovations

In this section, we show the model residual and innovations. The model residuals are the same for both classical model and gravity (NTT) model. These residuals are extracted from the structure models we showed before. These residuals are the keys of our model when we simulate our data.

Figure 5.1: Model residuals



From the figure, we can see all residuals are fluctuating and from the previous ADF test, we know all those residuals are non-stationary. So we have to take first difference in order to make them stationary. Then we can re-estimate those error processes by using VAR. After that, we can get the residuals of this VAR, which are defined them as innovations.

Figure 5.2: Model innovations (gravity (NTT) model for Part-of-model test of US version)

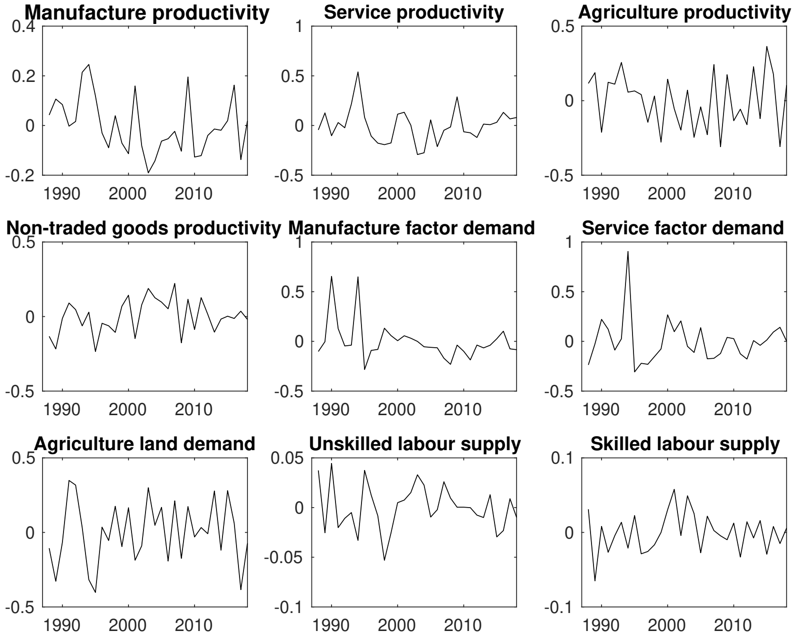
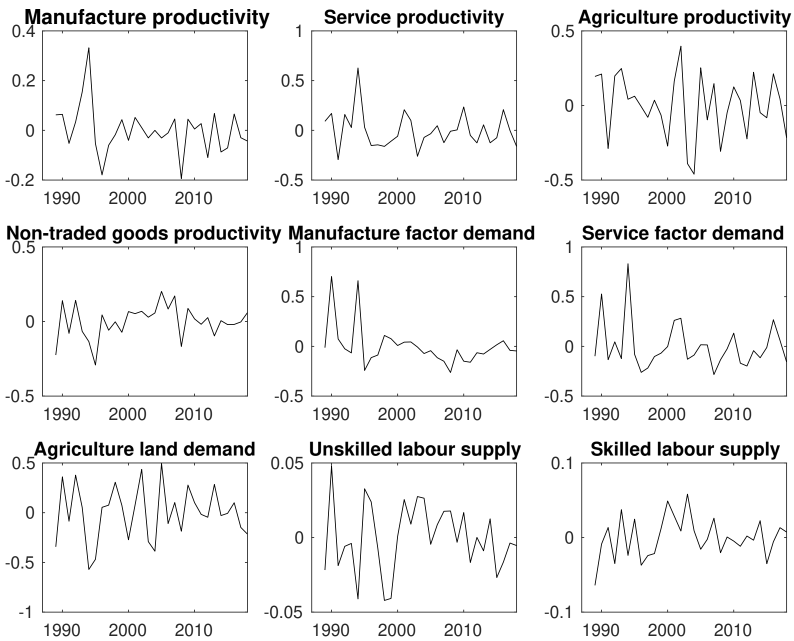


Figure 5.3: Model innovations (classical model for Part-of-model test of US version)



The innovations are different in classical model and gravity (NTT) model.

This is because in the gravity model the productivity is determined by trade volume, whereas it is not in the classical model. So the re-estimate error process is slightly different between them.

From those two graphs, we can see innovations are fluctuating over time, since the innovations are by construction white noise.

5.2 Test Results for Part-of-model test

In this part-of-model test, the world prices and other exogenous variables are simulated from a reduced form VAR model. We do it because China is a big country so the outputs and prices can have a major effect world prices and outputs. Therefore, this thesis uses a reduced form VAR model to endogenize the world prices and outputs of US, EU and ROW. The VAR model is shown in equation 5.9 and equation 5.10

$$p_{it} = \alpha_{it} + \beta_{it} p_{A t-1} + \gamma_{it} p_{M t-1} + \sigma_{it} p_{S t-1} + \delta_{it} y_{US t-1} + \Phi_{it} y_{EU t-1} + \phi_{it} y_{ROW t-1} + \eta_{it} \tag{5.9}$$

where

$$i = A, M, S$$

$$y_{jt} = \alpha_{jt} + \beta_{jt} p_{A t-1} + \gamma_{jt} p_{M t-1} + \sigma_{jt} p_{S t-1} + \delta_{jt} y_{US t-1} + \Phi_{jt} y_{EU t-1} + \phi_{jt} y_{ROW t-1} + \eta_{jt} \tag{5.10}$$

where

$$j = US, EU, ROW$$

Table 5.3: Coefficients of VAR(1) model

	$p_{A,t-1}$	$p_{M,t-1}$	$p_{S,t-1}$	$y_{US,t-1}$	$y_{EU,t-1}$	$y_{ROW,t-1}$
$p_{A,t}$	0.8366	-1.0710	-0.9976	0.0093	0.0011	-0.0001
$p_{M,t}$	0.0876	0.7185	-0.1428	0.0024	0.0001	-5.09E-05
$p_{S,t}$	0.3013	-0.3193	0.6566	0.0061	8.51E-05	-0.0002
$y_{US,t}$	-5.8143	9.1905	-5.1242	0.9938	-0.0002	0.0015
$y_{EU,t}$	322.1173	-334.0904	-82.0339	7.0475	0.8502	-0.1975
$y_{ROW,t}$	451.3837	-1743.0142	-1426.0567	18.0512	1.2767	0.6016

Table 5.4: Cointegration test for the variables in the VAR(1) model

ADF test	Stationary	Trend Stationary	Non-stationary
p_A			✓
p_M			✓
p_S			✓
y_{US}			✓
y_{US}			✓
y_{EU}			✓
y_{ROW}			✓
Residuals			
η_A	✓		
η_S	✓		
η_M	✓		
η_{US}	✓		
η_{EU}	✓		
η_{ROW}	✓		

From the Table 5.4 we can see all the variables are non-stationary, however residuals are stationary, so we can conclude the Equation 5.9 and Equation 5.10 are both co-integrated.

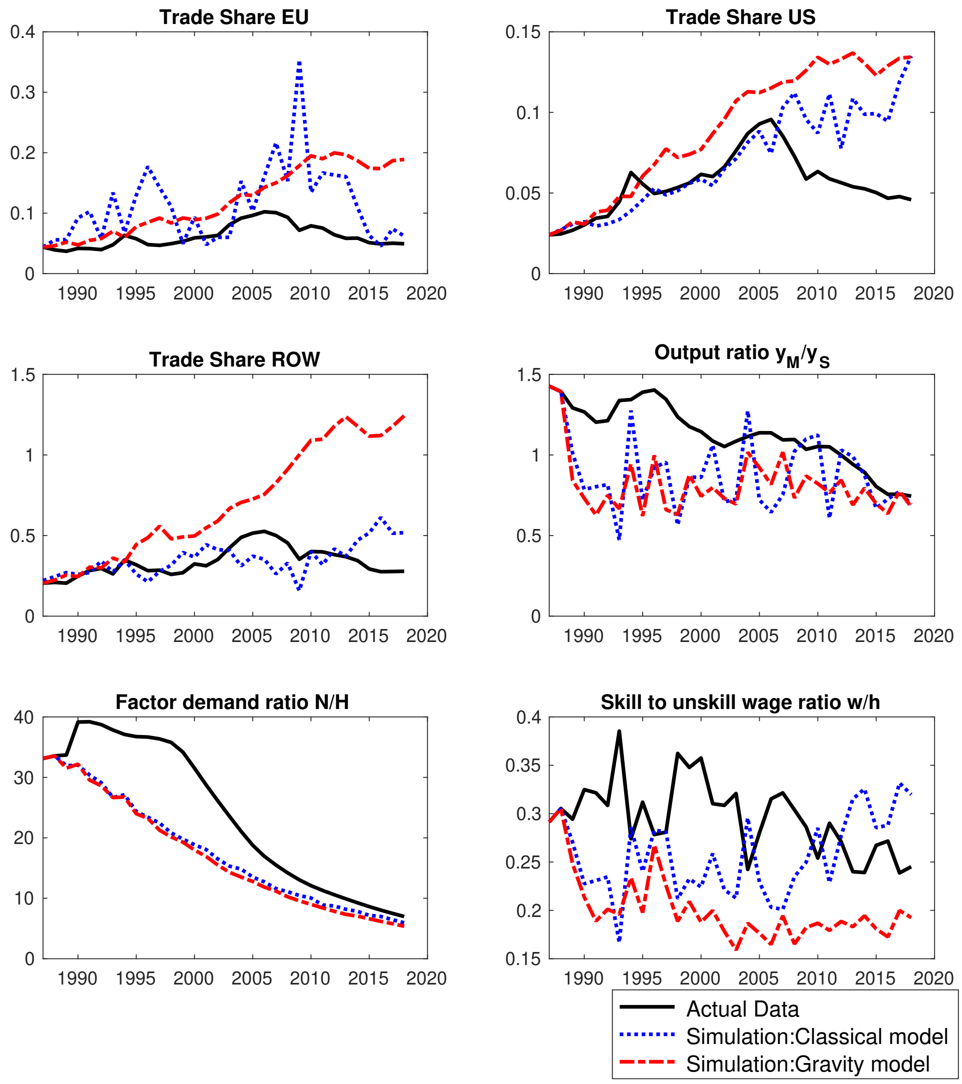
As the Figure 5.4 shown, the simulations of classical model performs fit the actual data better than the simulations of gravity (NTT) model, which suggest the classical model performs better than gravity (NTT) model under the framework of this CGE trade model. The charts are an attempt to see just where the gravity (NTT) model fails to match the data behaviour. They reveal that it crucially gets the trade data behaviour wrong. The classical model does not; hence in general it matches. In fact the classical model IS accepted on the Wald test whereas the gravity model is strongly rejected. The charts are simply shown to give some hints on what might be going on with the simulations to generate these results. Of course the Wald test is not at all decided by average simulated behaviour vs actual data behaviour; it is decided by the joint match of simulated variable cointegrating relationships vs those for the data. What we see in the graphs is that the gravity model crucially fails to match trade data behaviour, while the classical model matches it to a fair degree. Since for much of the other data both models have a similar match, this tells us that the classical model will match the data correlation with trade of different variables while the gravity model will not. This implies that the gravity model fails largely because it fails to match trade movements. As the Table 5.5 shown, the classical trade model passes with p-value equals 0.1052, whereas the gravity trade model is rejected with p-value equals 0.0344. The testing results show the gravity trade model does not fit the China's data, so we should use the classical trade model rather than the gravity trade model when we measure and formulate China's trade policy.

Table 5.5: Indirect Inference test results for the China

	Equations in auxiliary model in full	P-value
Classical trade model	eq1,eq2,eq3,eq4	0.1052
Gravity trade model (ψ=0.6)	eq1,eq2,eq3,eq4	0.0344*

*P-value with * indicates a rejection of the model at 5% significance level.*

Figure 5.4: Actual and average of simulated data for China



The conclusion from this is that the classical model fits the China trade facts and passes, while the gravity (NTT) model is rejected. This result suggests that we should use the classical model to assess the China trade facts instead of the gravity (NTT) model that has been the dominant trade model recently.

This thesis next investigates two weaker version of the gravity (NTT) model by excluding productivity effect of trade and raising substitutability.

	Equations in auxiliary model	P-value
Classical trade model	1),2),3),4)	0.1052
gravity (NTT) model($\psi = 0.6$) with no dT	1),2),3),4)	0.0413*
Weak gravity (NTT) model ($\psi = 2.0$)with DT	1),2),3),4)	0.0738

*P-value with * indicates a rejection of the model at 5% significance level.*

The results show that the weaker version of the gravity (NTT) model, without the productivity effect of trade, is getting better but still is rejected as the p-value rises from 0.0344 to 0.0413. Furthermore, we get another weaker version of the gravity (NTT) model by raising ψ from 0.6 to 2.0 and the productivity effect of trade is included. The result shows that the a weaker gravity (NTT) model with high substitutability ($\psi = 2.0$) passes the test with p-value equals 0.0738. This actually reveals how these two characteristics of gravity (NTT) model, that are the productivity effect of trade and limited substitutability, reduce the probability of trade models to pass our test.

5.2.1 The IRFs: how the models work

The workings of the Classical model

The model works through three sets of equations:

1. Price=marginal cost
2. Factor market clearing
3. Market clearing of the non-traded sector

Under 1, since world prices are exogenous, these equations for traded goods and services solve for the prices of immobile home factors, skilled and unskilled labour and land. The solutions give factor prices rising in the prices of the traded sector intensive in them: thus wages of unskilled rise as the manufactures world price rises. If productivity at home and abroad are the same. They yield factor price equalisation. Finally, the price of non-traded goods equals the costs given by these factor prices.

Under 2, demands for immobile home factors must equal their supply which is largely exogenous but may respond somewhat to factor price. These market-clearing equations are solved for the output of each traded sector. The solutions give the output of a trade sector rising in the price of the factor in which it is intensive, because as it rises the factor supply rises and also other sectors use it less, making more available for the intensive sector. In the model as specified, the output of the primary (agriculture and mining) sector is exogenised as set politically by planning, since this is a virtually universal practice, owing to the political sensitivity of this sector. This implies that in the model unskilled wages largely determine manufactured output while skilled wages largely determine services output. The land market clears at the land price set under 1, by demands for land rising to equal the supply of land. Hence land prices also determine traded sectors' output, given that the non-traded sector output share of GDP will be set under 3 below. We have 3 equations, with primary output and the GDP share of non-traded set elsewhere, in output of manufactures and services and in total GDP. Thus total GDP output rises to absorb the supply of land.

Finally under 3, the non-traded sector demand must equal its supply at the relative price of non-traded vs traded goods. Since this relative price is set under 1 above, this is brought about by the change in the share of non-traded output in GDP, becoming equal to its share in demand as set by GDP and relative prices. So for example if the price of land rises, this will raise the relative price of non-traded goods which are intensive in land relative to average traded goods; hence this will lower the production of non-traded goods relative to GDP.

How does the gravity model differ?

All the above also occurs in the gravity model. The difference is that in the gravity model the country demands and supplies of traded output must be equal; as the tariffs diminish imports from abroad, this is achieved by a real appreciation: RXR rises, giving a terms of trade gain.

Application to an IRF- the tariff shock

Now let us apply this to the IRF for the 10% tariff on manufactures and agriculture. This directly raises the home prices of these two sectors, which via 1 raises the factor prices of unskilled labour and land in which they are intensive respectively, and lowers the wage of skilled labour. Via 2 services output, intensive in skilled labour, contracts, while manufactures output expands. Non-traded prices, intensive in land, rise, causing the non-traded output share of GDP to fall. Equilibrium in the land market requires GDP to fall. This gives a welfare loss from the tariffs.

Under the gravity model the rise in RXR offsets this welfare loss to some extent.

5.2.2 Impulse Response Functions

10% Tariffs on food and manufacturing

In this section, this thesis first raises tariff on food and manufacturing by 10% to see how the economy reacts differently under the gravity trade model and classical trade model. From the Table 5.6 we can see the movement directions of both model are the same but not to the same extent. Specifically, the total output of China is reduced by 4.3167% and 5.0564% under the framework of gravity (NTT) model and classical trade model respectively, which suggests that if we raise tariffs under the theory of the classical trade model, more output will be sacrificed.

Similarly, this thesis calculates the welfare[1] and the results show that the total welfare of China is reduced by 4.4% and 8.1% under the framework of gravity trade model and classical trade model respectively. It also indicates that more welfare will be sacrificed if we raise the tariffs under the guidance of classical trade theory.

In additional, the table 5.6 shows that the imposition of a 10 percent tariff on food and manufactures increases manufacturing by more than 50 percent and

[1]Note on welfare measure: Welfare loss from the tariff is computed as: [Welfare percent =% output loss/GDP + consumer surplus lost - Terms of Trade gain.] Where the Term of Trade gain is percent fall in RXR $\times$ import share of GDP, the consumer surplus loss is percent rise in CPI $\times$ 0.5.

reduces agricultural output by 50 percent in both. This illustrates the high non-linearity of these models due to the cross-equation restrictions in the Heckscher-Ohlin-Samuelson model set-up for one country. As noted above even for one country this is a complex CGE model.

Table 5.6: Effects of 10% tariff on food and manufacturing for China

Variables	Base Run	10% tariff on p_A and p_M		% Changes	
		Gravity	Classical	Gravity	Classical
y	131120	125460	124490	-4.3167	-5.0564
y_A	4620	4620	4620	0.00	0.00
y_M	26020	40850	40200	56.9946	54.4965
y_S	34920	17260	17420	-50.5727	-50.1145
y_D	64460	62730	62240	-4.3167	-5.0641
E_A	1110	970	950	-12.6126	-14.4144
E_M	15080	14940	14910	-0.9284	-1.1273
E_S	49370	46820	46380	-5.1651	-6.0563
w	130.6859	154.9312	149.7413	18.5523	14.5811
h	501.5669	456.6338	443.2067	-8.9585	-11.6356
l	113.5687	225.0442	166.9573	98.1569	47.0100
N	678.68	690.3289	687.9808	1.7164	1.3704
H	97.18	94.6477	94.6877	-2.6058	-2.5646
L	117.5247	65.9792	84.7111	-43.8594	-27.9207
K	56.1775	57.3851	55.2562	2.1496	-1.6400
p	1.02	1.1172	1.0836	9.5294	6.2353
p_A	0.9876	1.0863	1.0863	10.00	10.00
p_M	1	1.1	1.1	10.00	10.00
p_S	0.872	0.872	0.872	0.00	0.00
p_D	1.1367	1.331	1.2639	17.0933	11.1903
RXR	93.6283	116.7607	93.6283	24.7066	0.00
RXR Welfare		0.0978			
Welfare				-4.4	-8.1

1% Productivity shocks

In this section, we show the Impulse Response Functions, which are driven by the 1% productivity shocks. Our purpose of doing this is to show how our model reacts the shocks.

$\varepsilon_{\pi_j},\ j = M, S, A, d$ denote productivity shocks in manufacturing sector, service sector, agriculture sector, and non-tradable sector.

	Base run	1% ε_{π_M}		1% ε_{π_S}		1% ε_{π_A}		1% ε_{π_d}	
		Gravity	Classical	Gravity	Classical	Gravity	Classical	Gravity	Classical
TS_{EU}	0.049346	-0.3841%	-0.5054%	-0.5240%	-0.5464%	0.7159%	0.8576%	-0.2346%	-0.2928%
TS_{US}	0.04585	-0.3841%	-0.6160%	-0.5240%	-0.6660%	0.7159%	1.0453%	-0.2346%	-0.3569%
TS_{ROW}	0.27849	-0.3841%	-0.4527%	-0.5240%	-0.4894%	0.7159%	0.7682%	-0.2346%	-0.2623%
$\ln \pi_M$	0.90114	1.1664%	1.1664%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%
$\ln \pi_S$	1.4629	0.0000%	0.0000%	0.6381%	0.6883%	0.0000%	0.0000%	0.0000%	0.0000%
$\ln \pi_A$	1.4119	0.0000%	0.0000%	0.0000%	0.0000%	0.8302%	0.7385%	0.0000%	0.0000%
$\ln \pi_d$	1.0339	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.9689%	1.0222%
$y(GDP)$	131120	0.7726%	0.8431%	1.0563%	0.9121%	-1.4166%	-1.3989%	0.4709%	0.4868%
y_A	4617.5	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
y_M	26020	9.3462%	9.0390%	-6.4450%	-6.2074%	-2.9646%	-2.9020%	0.9586%	0.9816%
y_S	34925	-5.6032%	-5.2370%	6.8801%	6.4266%	-0.4463%	-0.4601%	0.1687%	0.1814%
y_D	65562	0.7726%	0.8431%	1.0563%	0.9121%	-1.4166%	-1.3989%	0.4709%	0.4868%
E_A	1114.6	2.2723%	2.4797%	3.1069%	2.6827%	-4.1664%	-4.1143%	1.3850%	1.4316%
E_M	15079	0.1680%	0.1833%	0.2296%	0.1983%	-0.3080%	-0.3041%	0.1024%	0.1058%
E_S	49368	0.9234%	1.0077%	1.2626%	1.0902%	-1.6931%	-1.6720%	0.5628%	0.5818%
w	1.3069	2.3552%	2.3552%	-0.4272%	-0.4272%	-0.8489%	-0.8489%	0.0000%	0.0000%
h	5.0157	-0.7524%	-0.7524%	2.3245%	2.3245%	-0.6233%	-0.6233%	0.0000%	0.0000%
l	13.125	-3.0230%	-3.0230%	-2.9971%	-2.9971%	16.5200%	16.5200%	0.0000%	0.0000%
N	678.68	0.2331%	0.2331%	-0.0428%	-0.0428%	-0.0852%	-0.0852%	0.0000%	0.0000%
H	97.18	-0.3078%	-0.3078%	0.2730%	0.2730%	0.0227%	0.0227%	0.0000%	0.0000%
L	11752	4.3861%	4.4293%	3.8562%	3.7772%	-14.5040%	-14.5010%	-0.3091%	-0.3038%
K	56177	1.4885%	1.5076%	0.3630%	0.3558%	-0.6668%	-0.6716%	-0.0880%	-0.0874%
RXR	93.63	-0.6393%		-0.8719%		1.1960%		-0.3907%	

From this table, we can see if we increase 1% productivity shocks in manufacturing sector. All of trade shares decrease but no more than -1%. This is because if we increase 1% productivity in manufacturing sector, the manufacturing output will increase and total output will increase as well. The total export to EU, US and ROW increase less than total output, as a result the all trade shares decrease. Same thing happens in service sector and non-trade goods sector. The only special case is in the agricultural sector. From the table we can see if we increase 1% productivity shocks in agricultural sector, all trade shares will decrease. This is because even if we increase 1% productivity shocks in agricultural sector, the agricultural output does not change because We treat agricultural sector output as politically controlled and essentially fixed exogenously because of interventionist planning systems. The supply of land is adjusted (via planning and other controls) to enforce this output requirement. As we can see in the table, the land supply decreased about 14%, this is because of the 1% productivity shocks in agricultural sector, so demand for land is decreased and it forces the return on land increases, which actually hurts other industries. As a result the total output decreased, which leads to the Trade shares increase.

Also, if we increase 1% productivity shocks in manufacturing sector, the low skilled labour wage increase, whereas skilled labour wage decrease. This is sensible since most manufacturing sector are labour intensive, if we increase 1% productivity shocks in manufacturing sector, the output will be higher then workers' incomes will naturally rise. Reduced output in the service sector due to crowding out, which leads to lower earnings for skilled labour. Ultimately, employment of high-skilled and low-skilled workers changes with income. Similarly, if we increase 1% service shocks in service sector, the low skilled labour wage decrease, whereas skilled labour wage increase. Also, the number of skilled workers increase, whereas the number of low skilled workers decrease. The special case is the 1% agricultural productivity shocks. As we stated above, if we increase agricultural productivity shocks, it will hurt the whole economy, so both high skilled and low skilled labour's wage decrease. However, from the table, we can see it seems this shock hurts less on service as the output of service sector decrease less than manufacturing sector. This is probably because the service sector rely less on land supply. This may explain the reason why skilled labour supply increase a bit in this case, because this sector is relatively better.

Moreover, the demand reacts quite different, if we increase 1% agricultural productivity shocks. For the shocks of manufacturing and service, all demands for agricultural, manufacturing and service goods increase. But they are all decreased, if we increase 1% agricultural productivity shocks. This mainly because the total output decreases and labour's wages decrease but return on land (housing price) increases. As a result, of course all of the demand will decrease.

Chapter 6

Policy Implication and Conclusion

6.1 Policy Implication

The main reason for the different welfare costs of the classical model and gravity (NTT) model is that the welfare of gravity (NTT) model is largely affected by the term of trade gains. As i state in the Model Setup section, the movement of real exchange rate solves the current account equilibrium, so once we rise the tariffs, the gravity (NTT) model would be benefited from the term of trade gains by targeting the geographic origin of trade. Whereas classical model has no benefits from the term of trade since the exporter country can sell the products to the Rest of World, so the real exchange rate does not move to solve the current account equilibrium, therefore the term of trade does not react if we rise the tariffs.

The main point of this thesis has emerged, that is, if we use the classical trade model as a tool to study China's trade policy, it will give us a policy suggestion led by the idea of free trade. Whereas, if we use the gravity (NTT) model as a tool to study China's trade policy, it will eventually lead China's trade policy towards trade protectionism.

6.2 Which model should be used?

Since different trade models have diametrically opposite policy recommendations, we must be very cautious when choosing which trade model to use to research and formulate trade policies. As the Table 8.3 shown, the classical model fits the

Chinese data very well but the gravity (NTT) model is completely rejected by our test. Therefore, the classical trade model is the more appropriate model to study Chinese policy rather than gravity (NTT) model.

The policy suggestion of the classical model is free trade, while the gravity (NTT) model is trade protectionism. Base on the results of my thesis, although the U.S. has been launching a trade war against China over the years, China still should continue to try best to communicate and cooperate with every country in the world, continue to open up the market, reduce trade controls and formulate more liberalized trade policies. Because the Sino-US trade war is detrimental to the common interests of both parties and is unsustainable.

6.3 Conclusion

This thesis has set up two rival Computable General Equilibrium trade models by incorporating the theories of classical model and gravity (NTT) model. Afterwards, this thesis tests those two rival trade models by indirect inference method and the results show that gravity (NTT) model is rejected, whereas classical trade model passes, which suggests classical trade model is the more appropriate model to be used to evaluate China's trade policies. In order to verify the validity of my testing method, this thesis conducts an experiment to examine the power of the test by Monte Carlo experiment. The experiment shows that this test has considerable ability to reject the false model. Furthermore, this thesis examined the tariffs effects and the results shows the classical model sacrifices more welfare than gravity (NTT) model does if we rise the tariffs. This actually shows the main different policy implications between those two rival models. Specifically, the classical model gives a policy suggestion led by the idea of free trade, whereas the gravity (NTT) model will eventually lead trade policy towards trade protectionism. As noted above, the classical model 'fits the data' in the sense used here that it is not rejected in its ability to match the data behaviour, while the gravity model does not 'fit the data' in this sense. The point being made here is that the ability in the gravity model to improve the terms of trade creates an element tending to increase protection. We agree that overall protection could still be damaging.

Based on the test results of this thesis, China should use classical trade model to study trade policies and formulate more trade policies centered on free trade, where making more free trade policies is exactly what China is currently planning as China is building more free trade zones.

6.4 Limitations and Further Research

There are some limitations of this study, which may lead to errors in our results. These limitations are mainly from data. First of all, the data is quite short, we only have 32 years of annual data. Although our indirect inference method has the best performance to deal with small sample size, more data will make our results more reliable. Secondly, the data sources are inconsistent. Some of data are from Chinese office website and these data are in RMB, such as outputs, return on land and so on, so we have to convert them into dollars by using exchange rate. This behavior may produce some data errors. Also, the data inconsistency occurs in export and import data by sectors. The National Bureau of Statistics only provides us import and export data for agriculture. In this case, we have to collect import and export data for manufacturing and service from State Administration of Foreign Exchange. Due to different statistical calibers, this may also lead to errors in our data. Thirdly, China's data lack credibility. The reliability of China's data has not been high, which has also attracted the attention of Premier Li Keqiang. In 2017, he signed the State Council's decree and announced the "Regulations for the Implementation of the Statistics Law of the People's Republic of China", which will take effect on August 1, 2017. This may suggest that the credibility of data was quite low before 2017 and our data range is between 1987 and 2018. Lastly, the parameters for our model are based on Minford et al. (1997), although this model works well in many study, this work is quite old and may not fit China's facts since China is quite different country as it has different economic and political systems. In the future, we may try to estimate those parameters based on China's data.

Bibliography

Adam, C., Cobham, D. et al. (2007), Modelling multilateral trade resistance in a gravity model with exchange rate regimes, *in* 'Centre for Dynamic Macroeconomic Analysis Conference Papers', Citeseer.

Allen, T. & Arkolakis, C. (2014), 'Lecture 1: The Armington Model'.

Anderson, J. E. (1979), 'A theoretical foundation for the gravity equation', *The American Economic Review* **69**(1), 106–116.

Anderson, J. E. & Van Wincoop, E. (2003), 'Gravity with gravitas: A solution to the border puzzle', *American Economic Review* **93**(1), 170–192.

Arellano, M. & Bonhomme, S. (2009), 'Robust priors in nonlinear panel data models', *Econometrica* **77**(2), 489–536.

Armington, P. S. (1969), 'A theory of demand for products distinguished by place of production', *Staff Papers* **16**(1), 159–178.

Baier, S. L. & Bergstrand, J. H. (2009), 'Bonus vetus OLS: A simple method for approximating international trade-cost effects using the gravity equation', *Journal of International Economics* **77**(1), 77–85.

Balassa, B. (1966), 'Tariff reductions and trade in manufacturers among the industrial countries', *The American Economic Review* **56**(3), 466–473.

Balassa, B. & Bauwens, L. (1987), 'Intra-industry specialisation in a multi-country and multi-industry framework', *The Economic Journal* **97**(388), 923–939.

Bao, C., Chen, Z. & Wu, J. (2013), 'Chinese manufacturing on the move: Factor supply or market access?', *China Economic Review* **26**, 170–181.

Beckerman, W. (1956), 'Distance and the pattern of intra-European trade', *The Review of Economics and Statistics* pp. 31–40.

Bergstrand, J. H. (1985), 'The gravity equation in international trade: some microeconomic foundations and empirical evidence', *The Review of Economics and Statistics* pp. 474–481.

Bergstrand, J. H. (1990), 'The Heckscher-Ohlin-Samuelson model, the Linder hypothesis and the determinants of bilateral intra-industry trade', *The Economic Journal* **100**(403), 1216–1229.

Brander, J. A. & Spencer, B. J. (1985), 'Export subsidies and international market share rivalry', *Journal of International Economics* **18**(1-2), 83–100.

Breinlich, H., Dhingra, S., Ottaviano, G., Sampson, T., Van Reenen, J. & Wadsworth, J. (2016), 'Brexit 2016: Policy analysis from the Centre for Economic Performance', *CEP, LSE* **2016**.

Burfisher, M. E. (2021), *Introduction to computable general equilibrium models*, Cambridge University Press.

Bussière, M. & Schnatz, B. (2009), 'Evaluating China's integration in world trade with a gravity model based benchmark', *Open Economies Review* **20**(1), 85–111.

Cairncross, F. (1995), 'The death of distance: a survey of telecommunications', *The Economist* **30**(9), 5–6.

Calvet, L. E. & Czellar, V. (2015), 'Through the looking glass: Indirect inference via simple equilibria', *Journal of Econometrics* **185**(2), 343–358.

Caporale, G. M., Sova, A. & Sova, R. (2015), 'Trade flows and trade specialisation: The case of China', *China Economic Review* **34**, 261–273.

Chaney, T. (2008), 'Distorted gravity: The intensive and extensive margins of international trade', *American Economic Review* **98**(4), 1707–21.

Chaney, T. (2018), 'The gravity equation in international trade: An explanation', *Journal of Political Economy* **126**(1), 150–177.

CNNIC (2021), 'Statistical report on Internet Development in China'.
URL: *http://www.cac.gov.cn*

Couclelis, H. (1996), 'The death of distance'.
URL: *https://journals.sagepub.com/doi/pdf/10.1068/b230387*

Deardorff, A. (1998), Determinants of bilateral trade: Does Gravity Work in a Neoclassical World?, *in* 'The Regionalization of the World Economy', National Bureau of Economic Research, Inc, pp. 7–32.
URL: *https://EconPapers.repec.org/RePEc:nbr:nberch:7818*

di Giovanni, J., Levchenko, A. A. & Zhang, J. (2014), 'The Global Welfare Impact of China: Trade Integration and Technological Change', *American Economic Journal: Macroeconomics* **6**(3), 153–83.
URL: *https://www.aeaweb.org/articles?id=10.1257/mac.6.3.153*

Dixit, A. K. & Stiglitz, J. E. (1977), 'Monopolistic competition and optimum product diversity', *The American economic review* **67**(3), 297–308.

Dixit, A. & Norman, V. (1980), *Theory of international trade: A dual, general equilibrium approach*, Cambridge University Press.

Dornbusch, R., Fischer, S. & Samuelson, P. A. (1977), 'Comparative advantage, trade, and payments in a Ricardian model with a continuum of goods', *The American Economic Review* **67**(5), 823–839.

Dridi, R. & Renault, E. (2000), 'Semi-parametric indirect inference', *LSE STICERD Research Paper No. EM392* .

Durlauf, S. & Blume, L. E. (2016), *The new Palgrave dictionary of economics*, Springer.

Eaton, J. & Grossman, G. M. (1986), 'Optimal trade and industrial policy under oligopoly', *The Quarterly Journal of Economics* **101**(2), 383–406.

Eaton, J. & Kortum, S. (2002), 'Technology, geography, and trade', *Econometrica* **70**(5), 1741–1779.
URL: *http://www.jstor.org/stable/3082019*

Einstein, A. (1922), The general theory of relativity, *in* 'The Meaning of Relativity', Springer, pp. 54–75.

Emikönel, M. (2022), 'The impact of international organizations on Chinese trade as the determiner of trade: the gravity model approach', *The Chinese Economy* **55**(1), 26–40.

Ethier, W. J. (1982), 'National and international returns to scale in the modern theory of international trade', *The American Economic Review* **72**(3), 389–405.

Fleisher, B., Li, H. & Zhao, M. Q. (2010), 'Human capital, economic growth, and regional inequality in China', *Journal of Development Economics* **92**(2), 215–231.

Garcia, R., Renault, E. & Veredas, D. (2011), 'Estimation of stable distributions by indirect inference', *Journal of Econometrics* **161**(2), 325–337.

Genton, M. G. & Ronchetti, E. (2003), 'Robust indirect inference', *Journal of the American Statistical Association* **98**(461), 67–76.

Gourieroux, C., Monfort, A. & Renault, E. (1993), 'Indirect inference', *Journal of Applied Econometrics* **8**(S1), S85–S118.

Gouriéroux, C., Phillips, P. C. & Yu, J. (2010), 'Indirect inference for dynamic panel models', *Journal of Econometrics* **157**(1), 68–77.

Greenaway, D., Mahabir, A. & Milner, C. (2008), 'Has China displaced other Asian countries' exports?', *China Economic Review* **19**(2), 152–169.

Grossman, G. M. & Helpman, E. (1993), *Innovation and growth in the global economy*, MIT Press.

Grossman, G. M. & Horn, H. (1988), 'Infant-industry protection reconsidered: the case of informational barriers to entry', *The Quarterly Journal of Economics* **103**(4), 767–787.

Hahn, J. & Newey, W. (2004), 'Jackknife and analytical bias reduction for nonlinear panel models', *Econometrica* **72**(4), 1295–1319.

Harvey, D. (1989), 'The condition of postmodernity an enquiry into the origins of cultural change'.

Heckscher, E. F. (1919), *The effect of foreign trade on the distribution of income*.

Helpman, E. (1981), 'International trade in the presence of product differentiation, economies of scale and monopolistic competition: A Chamberlin-Heckscher-Ohlin approach', *Journal of International Economics* **11**(3), 305–340.

Helpman, E. (1987), 'Imperfect competition and international trade: Evidence from fourteen industrial countries', *Journal of the Japanese and International Economies* **1**(1), 62–81.

Helpman, E. & Krugman, P. R. (1985), *Market structure and foreign trade: Increasing returns, imperfect competition, and the international economy*, MIT Press.

Hertel, T. W. (1997), *Global trade analysis: Modeling and applications*, Cambridge University Press.

Hicks, J. R. (1953), 'An inaugural lecture', *Oxford Economic Papers* **5**(2), 117–135.

Irshad, M. S., Xin, Q., Shahriar, S. & Arshad, H. (2017), 'A panel data analysis of China's trade pattern with OPEC members: Gravity model approach', *Asian Economic and Financial Review* **8**(1), 103–116.

Isard, W. & Peck, M. J. (1954), 'Location theory and international and interregional trade theory', *The Quarterly Journal of Economics* pp. 97–114.

Ito, T., Rotunno, L. & Vézina, P.-L. (2017), 'Heckscher–Ohlin: Evidence from virtual trade in value added', *Review of International Economics* **25**(3), 427–446.

Jie, H. & Zhihong, T. (2020), 'The effect of trade creation in China-Asean free trade area based on the gravity model', *Journal of Intelligent & Fuzzy Systems* **38**(6), 7061–7065.

Ju, J. & Yang, X. (2009), 'Hicks theorem: Effects of technological improvement in the Ricardian model', *International Review of Economics & Finance* **18**(2), 239–247.

Keane, M. & Smith, A. A. (2003), 'Generalized indirect inference for discrete choice models', *Yale University* .

Krugman, P. (1980), 'Scale economies, product differentiation, and the pattern of trade', *The American Economic Review* **70**(5), 950–959.

Krugman, P. (1984), 'Import protection as export promotion: International competition in the presence of oligopoly and economies of scale', *Monopolistic Competition and International Trade* pp. 180–93.

Krugman, P. R. (1979), 'Increasing returns, monopolistic competition, and international trade', *Journal of International Economics* **9**(4), 469–479.

Krugman, P. R. (1981), 'Intraindustry specialization and the gains from trade', *Journal of Political Economy* **89**(5), 959–973.

Krugman, P. R. (1986), *Strategic trade policy and the new international economics*, MIT Press.

Lawrence, M., Bullock, R. & Liu, Z. (2019), *China's High-Speed Rail Development. International Development in Focus.*
URL: *https://openknowledge.worldbank.org/handle/10986/31801*

Le, V. P. M., Meenagh, D., Minford, P. & Wickens, M. (2011), 'How much nominal rigidity is there in the US economy? Testing a New Keynesian DSGE Model using indirect inference', *Journal of Economic Dynamics and Control* **35**(12), 2078–2104.

Le, V. P. M., Meenagh, D., Minford, P., Wickens, M. & Xu, Y. (2016), 'Testing macro models by indirect inference: a survey for users', *Open Economies Review* **27**(1), 1–38.

Lederman, D., Olarreaga, M. & Rubiano, E. (2008), 'Trade specialization in Latin America: the impact of China and India', *Review of World Economics* **144**(2), 248–271.

Lendle, A., Olarreaga, M., Schropp, S. & Vézina, P.-L. (2016), 'There goes gravity: eBay and the death of distance', *The Economic Journal* **126**(591), 406–441.

Lien, D., Oh, C. H. & Selmier, W. T. (2012), 'Confucius institute effects on China's trade and FDI: Isn't it delightful when folks afar study Hanyu?', *International Review of Economics & Finance* **21**(1), 147–155.

Liu, A., Lu, C. & Wang, Z. (2020), 'The roles of cultural and institutional distance in international trade: Evidence from China's trade with the Belt and Road countries', *China Economic Review* **61**, 101234.

Lu, D. (2010), 'Exceptional exporter performance? evidence from Chinese manufacturing firms', *manuscript, University of Chicago* .

Lucas, R. E. (1976), 'Econometric policy evaluation: A critique', *Carnegie-Rochester Conference Series on Public Policy* **1**, 19–46.
URL: *https://www.sciencedirect.com/science/article/pii/S0167223176800036*

Markusen, J. R. (1986), 'Explaining the volume of trade: an eclectic approach', *The American Economic Review* pp. 1002–1011.

Marshall, K. G. (2011), 'The factor content of Chinese trade', *The Journal of International Trade & Economic Development* **20**(6), 769–787.

Meenagh, D., Minford, P., Wickens, M. & Xu, Y. (2019), 'Testing DSGE models by indirect inference: a survey of recent findings', *Open Economies Review* **30**(3), 593–620.

Melitz, M. J. (2003), 'The impact of trade on intra-industry reallocations and aggregate industry productivity', *Econometrica* **71**(6), 1695–1725.

Minford, P., Riley, J. & Nowell, E. (1997), 'Trade, technology and labour markets in the world economy, 1970–90: a computable general equilibrium analysis', *The Journal of Development Studies* **34**(2), 1–34.

Minford, P., Theodoridis, K. & Meenagh, D. (2009), 'Testing a model of the UK by the method of indirect inference', *Open Economies Review* **20**(2), 265–291.

Minford, P. & Xu, Y. (2018), ‘Classical or Gravity? Which trade model best matches the UK facts?’, *Open Economies Review* **29**(3), 579–611.

Monfardini, C. (1998), ‘Estimating stochastic volatility models through indirect inference’, *The Econometrics Journal* **1**(1), 113–128.

Newton, I. (1687), *Philosophiae naturalis principia mathematica*, Vol. 2, typis A. et JM Duncan.

OECD (2018), *The Belt and Road Initiative in the global trade, investment and finance landscape*.
URL: *https://www.oecd.org/finance/Chinas-Belt-and-Road-Initiative-in-the-global-trade-investment-and-finance-landscape.pdf*

Ohlin, B. (1935), *Interregional and international trade*, Harvard University Press, Cambridge.

PBC (2021), ‘Renminbi Internationalization Report 2021’.

Pham, C. S. (2008), ‘Product specialization in international trade: A further investigation’, *Journal of International Economics* **75**(1), 214–218.

Rasoulinezhad, E. & Wei, W. (2017), ‘China’s trade with OPEC member countries: A panel-gravity model approach’, *The Chinese Economy* **50**(5), 339–355.

Ricardo, D. (1817), *Principles of political economy and taxation*, G. Bell and sons.

Roberts, B. (2004), ‘A gravity study of the proposed China-Asean free trade area’, *The International Trade Journal* **18**(4), 335–353.

Rybczynski, T. M. (1955), ‘Factor endowment and relative commodity prices’, *Economica* **22**(88), 336–341.

Samuelson, P. A. (2004), ‘Where Ricardo and Mill rebut and confirm arguments of mainstream economists supporting globalization’, *Journal of Economic Perspectives* **18**(3), 135–146.

Shepherd, B. et al. (2013), ‘The gravity model of international trade: A user guide’.

Smelser, N. J., Baltes, P. B. et al. (2001), *International encyclopedia of the social & behavioral sciences*, Vol. 11, Elsevier Amsterdam.

Smith, A. (1776), *The wealth of nations [1776]*, Vol. 11937, na.

Smith Jr, A. A. (1993), 'Estimating nonlinear time-series models using simulated vector autoregressions', *Journal of Applied Econometrics* **8**(S1), S63–S84.

Stolper, W. F. & Samuelson, P. A. (1941), 'Protection and real wages', *The Review of Economic Studies* **9**(1), 58–73.

Tinbergen, J. (1962), 'Shaping the world economy; suggestions for an international economic policy'.

Vanek, J. (1968), 'The factor proportions theory: The n—factor case', *Kyklos* **21**(4), 749–756.

Venables, A. J. (2006), *Shifts in economic geography and their causes*, number 767, Centre for Economic Performance, London School of Economics and Political . . . .

Wood, A. & Mayer, J. (2011), 'Has China de-industrialised other developing countries?', *Review of World Economics* **147**(2), 325–350.

Wu, Y. (2007), 'Export performance in China's regional economies', *Applied Economics* **39**(10), 1283–1293.

Yan, Y., Wang, R., Zheng, X. & Zhao, Z. (2020), 'Carbon endowment and trade-embodied carbon emissions in global value chains: evidence from China', *Applied Energy* **277**, 115592.

Yang, S. & Martinez-Zarzoso, I. (2014), 'A panel data analysis of trade creation and trade diversion effects: The case of ASEAN–China Free Trade Area', *China Economic Review* **29**, 138–151.

Zhang, W., Wang, J. et al. (2009), '60 years of new China: development and change of transportation', *Economic Geography* **29**(11).

Chapter 7

Appendix

7.1 Test Results for UK version

In this section, we replace the US data by UK data. Specifically, the trade share with US becomes trade share with UK and we use GDP_{UK} instead of GDP_{US} in the new Auxiliary Model, also the Rest of World changes accordingly. This is the original work of this study. Initially, we treat UK as one of country blocs and put US into the rest of world. This issue was first raised by Dr Ezgi Kaya, it is quite weird that we treat a small country as a country bloc but put a big country (US) into rest of world. Although we think it will not affect our results, we still treat US as a country bloc and put UK into rest of world, and the UK was not part of the EU, so the UK is not double-counted. I put the UK version here is for comparison, which might answer the question for indirect inference method that does the choice of auxiliary model affect the result?

In the case of China, we need to simulate all other countries' GDPs and also world prices because plainly China, as another large continental economy, has a major effect on them. Here therefore to test China we simulate the China model as the part of the world model to be tested, and we simulate the other country variables required to solve this part via a reduced form VAR model. The VAR model is shown in Equation 7.1 and Equation 7.2.

$$p_{it} = \alpha_{it} + \beta_{it} p_{At-1} + \gamma_{it} p_{Mt-1} + \sigma_{it} p_{St-1} + \delta_{it} y_{UKt-1} + \Phi_{it} y_{EUt-1} + \phi_{it} y_{ROWt-1} + \eta_{it} \tag{7.1}$$

where

$$i = A, M, S$$

$$y_{jt} = \alpha_{jt} + \beta_{jt} p_{At-1} + \gamma_{jt} p_{Mt-1} + \sigma_{jt} p_{St-1} + \delta_{jt} y_{UKt-1} + \Phi_{jt} y_{EUt-1} + \phi_{jt} y_{ROWt-1} + \eta_{jt} \tag{7.2}$$

where

$$j = UK, EU, ROW$$

The variables in the auxiliary model are: $TS_{EU} = \frac{M_{EU}+X_{EU}}{GDP_{China}}, TS_{UK} = \frac{M_{UK}+X_{UK}}{GDP_{China}}$, $TS_{ROW} = \frac{M_{ROW}+X_{ROW}}{GDP_{China}}, OS_{China} = \frac{y_M}{y_S}$, which we put on the left hand side for convenience; and on the right hand side we have the relative productivity residual of manufacturing/services, $\frac{\pi_M}{\pi_S}$; the relative factor share, skilled/unskilled labour, $\frac{H}{N}$; the wage of unskilled relative to skilled workers, $\frac{w}{h}$; and EU, GDP and UK GDP.

The auxiliary model equations are potentially:

$$\begin{aligned}
TS_{EU} &= \gamma_1 + a_{11}\frac{\pi_M}{\pi_S} + a_{12}\frac{N}{H} + a_{13}\log(GDP_{EU}) + a_{14}\log(GDP_{UK}) + a_{15}\frac{w}{h} + \varepsilon_1 && 1) \\
TS_{UK} &= \gamma_2 + a_{21}\frac{\pi_M}{\pi_S} + a_{22}\frac{N}{H} + a_{23}\log(GDP_{EU}) + a_{24}\log(GDP_{UK}) + a_{25}\frac{w}{h} + \varepsilon_2 && 2) \\
OS_{China} &= \gamma_3 + a_{31}\frac{\pi_M}{\pi_S} + a_{32}\frac{N}{H} + a_{33}\log(GDP_{EU}) + a_{34}\log(GDP_{UK}) + a_{35}\frac{w}{h} + \varepsilon_3 && 3) \\
TS_{ROW} &= \gamma_4 + a_{41}\frac{\pi_M}{\pi_S} + a_{42}\frac{N}{H} + a_{43}\log(GDP_{EU}) + a_{44}\log(GDP_{UK}) + +a_{45}\frac{w}{h} + \varepsilon_4 && 4)
\end{aligned}$$

We will use these equations in full in our analysis, as discussed in earlier cases.

These variables, endogenous and exogenous, will not be stationary. However the residuals in the reduced form are stationary, as the Table 7.1 shown. So these Auxiliary model equations should be co-integrated therefore

Figure 7.1: Actual and average of simulated data for China

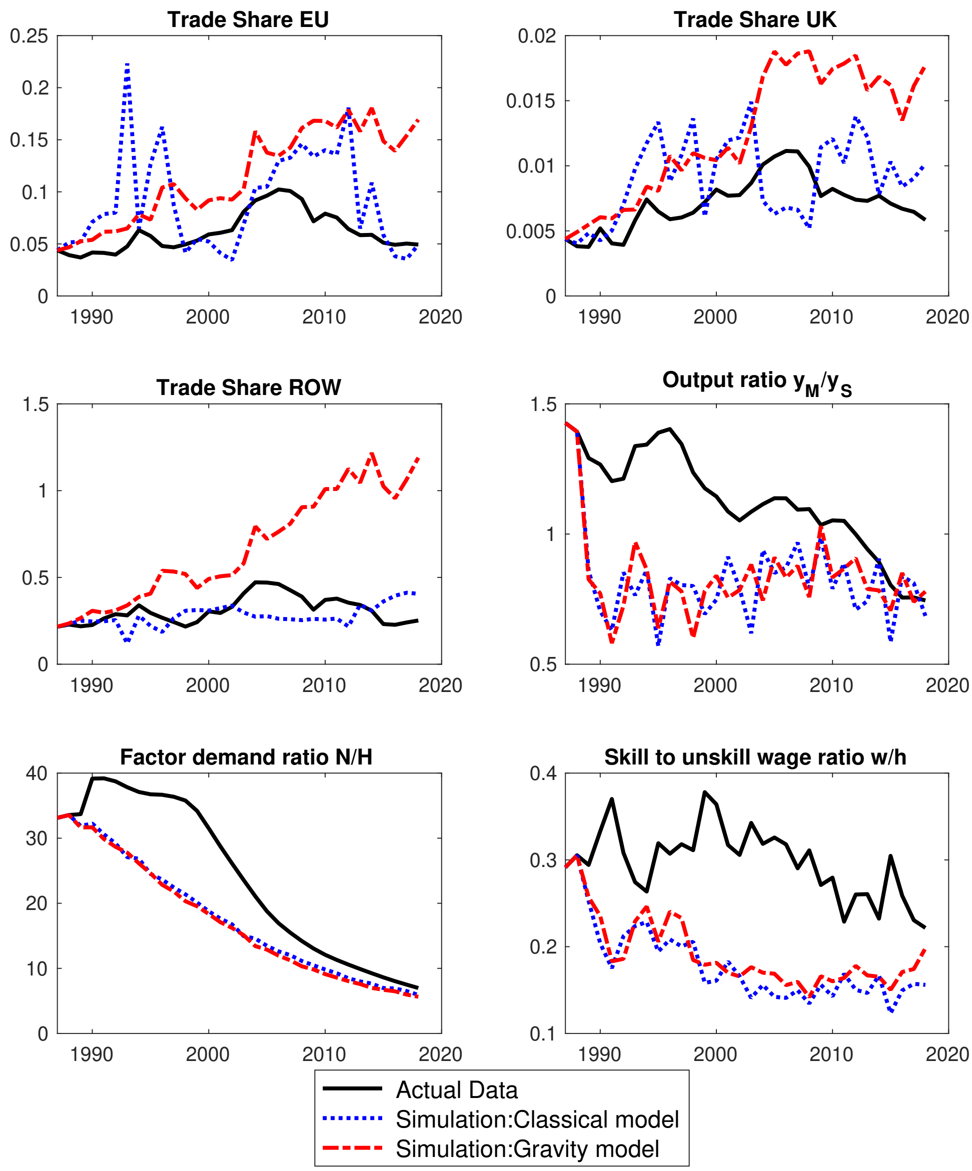


Table 7.1: Cointegration test for the variables in the auxiliary model

ADF test	Stationary	Trend stationary	Nonstationary
TS_{EU}			$\surd$
TS_{UK}			$\surd$
TS_{ROW}			$\surd$
OS_{China}			$\surd$
π_M/π_S			$\surd$
N/H			$\surd$
w/h			$\surd$
$\log(E_{EU})$			$\surd$
$\log(E_{UK})$			$\surd$
Residuals			
ε_1	$\surd$		
ε_2	$\surd$		
ε_3	$\surd$		
ε_4	$\surd$		

The test in which we use all four equations 1)-4) is shown below:

Table 7.2: II Wald test results when equations 1)-4) are used, with w/h

	Equations in auxiliary model-in full	P-value
Classical trade model	1),2),3),4)	0.076
gravity (NTT) model ($\psi = 0.6$)	1),2),3),4)	0.046*

*P-value with * indicates a rejection of the model at 5% significance level.*

The conclusion from this is that the classical model fits the China trade facts and passes, while the gravity (NTT) model is rejected.

This thesis next investigate whether a weaker version of the gravity (NTT) model, without the productivity effect of trade and so simply with imperfect competition in intermediate goods, can pass the test. It turns out the gravity (NTT) model without productivity effect of trade is rejected with p-value equals 0.0054 and this thesis also finds that a weaker gravity (NTT) model with high substitutability ($\psi = 2.0$) passes the test with p-value equals 0.056.

	Equations in auxiliary model	P-value
Classical trade model	1),2),3),4)	0.076
gravity (NTT) model($\psi = 0.6$) with no dT	1),2),3),4)	0.0054*
Weak gravity (NTT) model ($\psi = 2.0$)with DT	1),2),3),4)	0.056

*P-value with * indicates a rejection of the model at 5% significance level.*

7.1.1 Impulse Response Functions (UK)

What is of interest is to compare a policy change, here i show the 10% tariff effects[1] on food and manufacturing and i calculate the welfare loss[2] if we change the policy. It can be seen that there is not much difference but that the gravity effect on welfare is worse because the terms of trade are worsened (an appreciation of the exchange rate) by the tariff in this case.

[1] The base run is based on year 2010 data.

[2] Note on welfare measure: Welfare loss from the tariff is computed as: [Welfare percent =% output loss/GDP + consumer surplus lost - Terms of Trade gain.] Where the Term of Trade gain is percent fall in RXR × import share of GDP, the consumer surplus loss is percent rise in CPI × 0.5.

10% Tariff on food and manufacturing

Table 11: Effects of 10% tariff on food and manufacturing

	Base Run	10% tariff on food and manufacs		(% change)	
		Gravity	Classical	Gravity	Classical
$y(GDP)$	120188.54	118065.22	118002.96	-1.77	-1.82
yA	8865.48	8865.48	8865.48	0.00	0.00
y_M	43552.69	55587.28	55546.87	27.63	27.54
y_S	26977.08	13539.85	13539.13	-49.8098	-49.8125
y_D	40793.28	40072.61	40051.47	-1.77	-1.82
E_A	1507.89	1437.16	1435.10	-4.69	-4.83
E_M	17398.14	17328.61	17326.55	-0.40	-0.41
E_S	60489.23	59226.85	59189.83	-2.09	-2.15
w	1.927	2.209	2.207	14.64	14.58
h	4.343	3.840	3.838	-11.60	-11.64
l	11.40	16.72	16.76	46.76	47.03
N	678.68	688.02	687.98	1.38	1.37
H	97.180	94.687	94.688	-2.57	-2.56
L	11098.97	8174.39	8154.89	-26.35	-26.53
K	50982.02	50566.42	50540.32	-0.82	-0.87
$p(cpi)$	1.10353	1.14711	1.14708	3.9494	3.9460
p_A	1.201691	1.321860	1.321860	10.00	10.00
p_M	1	1.1	1.1	10.00	10.00
p_S	1.103	1.103	1.103	0.00	0.00
p_D	1.15	1.28	1.27	11.20	11.19
RXR	89.12	97.43	89.12	9.32	0.00
Welfare				-1.9599	-3.793

Next, i show those two types of Impulse Response Functions, the first one is driven by the 1% productivity shocks and the other one is driven by 1% trade demand shock. My purpose of doing this is to show how our model reacts the shocks.

1% Productivity shocks

$\varepsilon_{\pi_j},\ j = M, S, A, d$ denote productivity shocks in manufacturing sector, service sector, agricultural sector, and non-tradable sector.

	Base run	1% ε_{π_M}		1% ε_{π_S}		1% ε_{π_A}		1% ε_{π_d}	
		Gravity	Classical	Gravity	Classical	Gravity	Classical	Gravity	Classical
TS_{EU}	0.0493	6.48%	1.45%	6.17%	1.95%	5.68%	2.97%	6.14%	2.04%
TS_{UK}	0.0058	10.22%	0.74%	9.43%	1.35%	8.02%	2.56%	9.35%	1.45%
TS_{ROW}	0.2785	4.45%	1.83%	4.40%	2.28%	4.41%	3.20%	4.40%	2.36%
$\ln \pi_M$	1.0782	1.17%	0.98%	0.21%	0.00%	0.27%	0.00%	0.25%	0.00%
$\ln \pi_S$	1.2303	0.17%	0.00%	1.06%	0.87%	0.24%	0.00%	0.22%	0.00%
$\ln \pi_A$	1.2426	0.00%	0.00%	0.00%	0.00%	0.86%	0.86%	0.00%	0.00%
$\ln \pi_d$	0.9701	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.92%	0.92%
$y(GDP)$	120188.54	1.31%	0.96%	0.49%	0.11%	-1.07%	-1.55%	0.40%	-0.04%
y_A	8865.48	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
y_M	43552.69	14.34%	13.75%	4.94%	4.35%	6.32%	5.55%	8.87%	8.15%
y_S	26977.08	-3.01%	-3.19%	8.64%	8.41%	1.88%	1.61%	2.49%	2.24%
y_D	40793.28	-7.45%	-7.77%	-8.20%	-8.54%	-9.63%	-10.06%	-8.28%	-8.68%
E_A	1507.89	19.09%	18.00%	16.55%	15.38%	11.72%	10.24%	16.28%	14.93%
E_M	17398.14	1.41%	1.33%	1.22%	1.14%	0.87%	0.76%	1.20%	1.10%
E_S	60489.23	7.76%	7.31%	6.73%	6.25%	4.76%	4.16%	6.62%	6.07%
w	1.927	2.74	2.36%	-0.02%	-0.43%	-0.32%	-0.85%	0.48%	0.00%
h	4.343	-0.45%	-0.75%	2.67%	2.32%	-0.20%	-0.62%	0.39%	0.00%
l	11.40	-4.20%	-3.02%	-4.27%	-3.00%	14.56%	16.52%	-1.52%	0.00%
N	678.68	0.27%	0.23%	0.00%	0.04%	-0.03%	-0.09%	0.05%	0.00%
H	97.180	-0.31%	-0.31%	0.27%	0.27%	0.01%	0.02%	-0.01%	0.00%
L	11098.97	1.73%	0.13%	0.79%	-0.92%	-16.30%	-18.12%	-2.65%	-4.56%
K	50982.02	0.76%	0.42%	-0.41%	-0.77%	-1.18%	-1.64%	-0.67%	-1.09%
RXR	89.12	-26.98%		-23.95%		-17.75%		23.62%	

7.2 Summary of Test Results

Table 7.3: Summary of Test Results

Types of Tests	P-value	
	Classical Model	gravity (NTT) model
US version of Part-of-model Test	0.1052	0.0344*
UK version of Part-of-model Test	0.076	0.046*

*P-value with * indicates a rejection of the model at 5% significance level.*

The valuable information is from this results is it seems the even we change the Auxiliary Model by replacing some reasonable variables, it does not affect the test results too much. While there are still some differences, these differences may be due to the different country blocs instead of the auxiliary model. It actually shows one of the characteristics of the Indirect Inference Method that is, as Durlauf & Blume (2016) stated that when we choose the auxiliary model, it actually need not be correctly specified.

Table 7.4: Summary of Welfare Costs

Types of Tests	Welfare Costs	
	Classical Model	gravity (NTT) model
US version of Part-of-model Test	-8.1%	-4.4%
UK version of Part-of-model Test	-3.793%	-1.9599%

From the Table 7.5, we can see that in both of cases, the classical model will sacrifice more welfare in order to rise the tariffs, which gives us a policy suggestion that we should not rise the tariffs if the classical trade model fits the country's data well.

Table 7.5: Summary of RXR Effects

Types of Tests	RXR effects in Gravity Model
US version of Part-of-model Test	4.7313139%
UK version of Part-of-model Test	1.78478%

Figure 7.2: Auxiliary of UK version

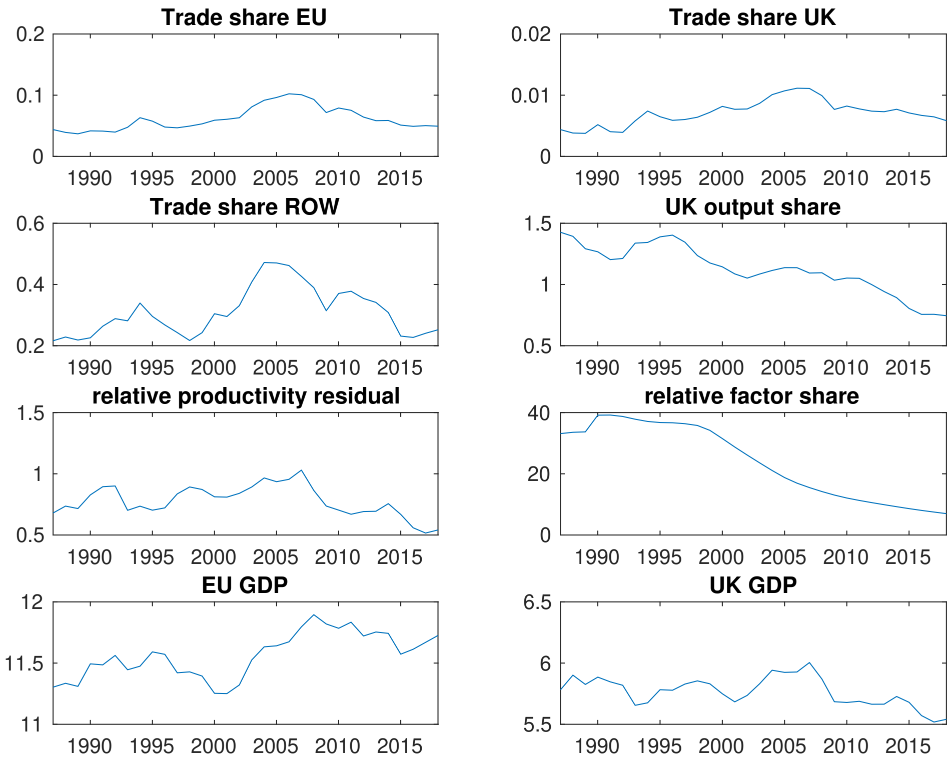


Figure 7.3: Model residual (classical model for Part-of-model test of UK version)

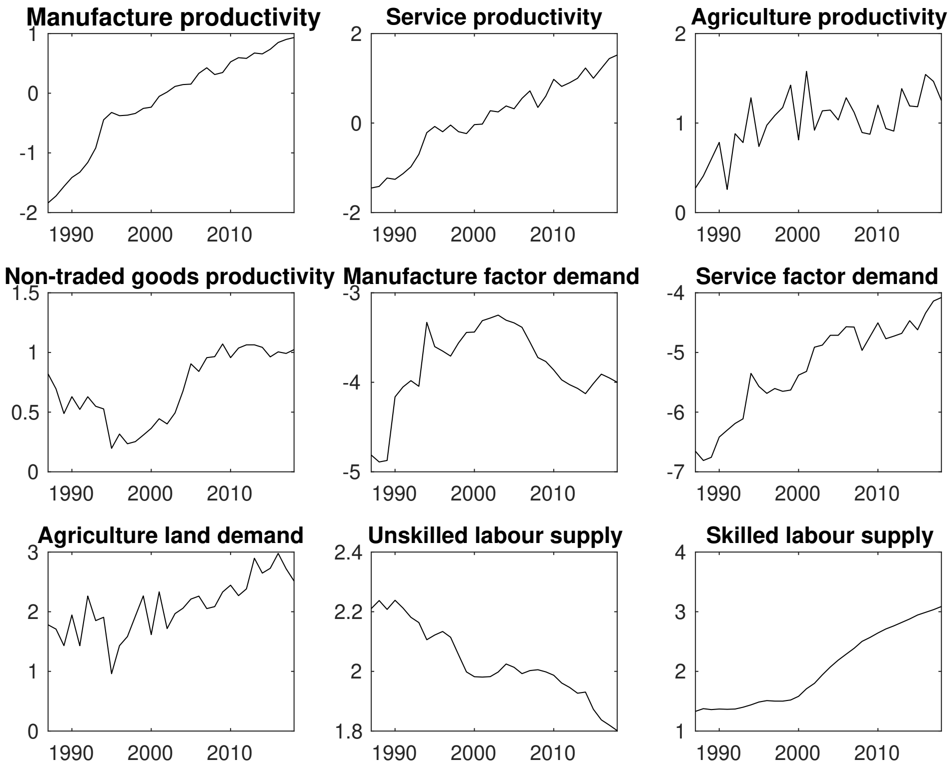


Figure 7.4: Model innovations (gravity (NTT) model for Part-of-model test of UK version)

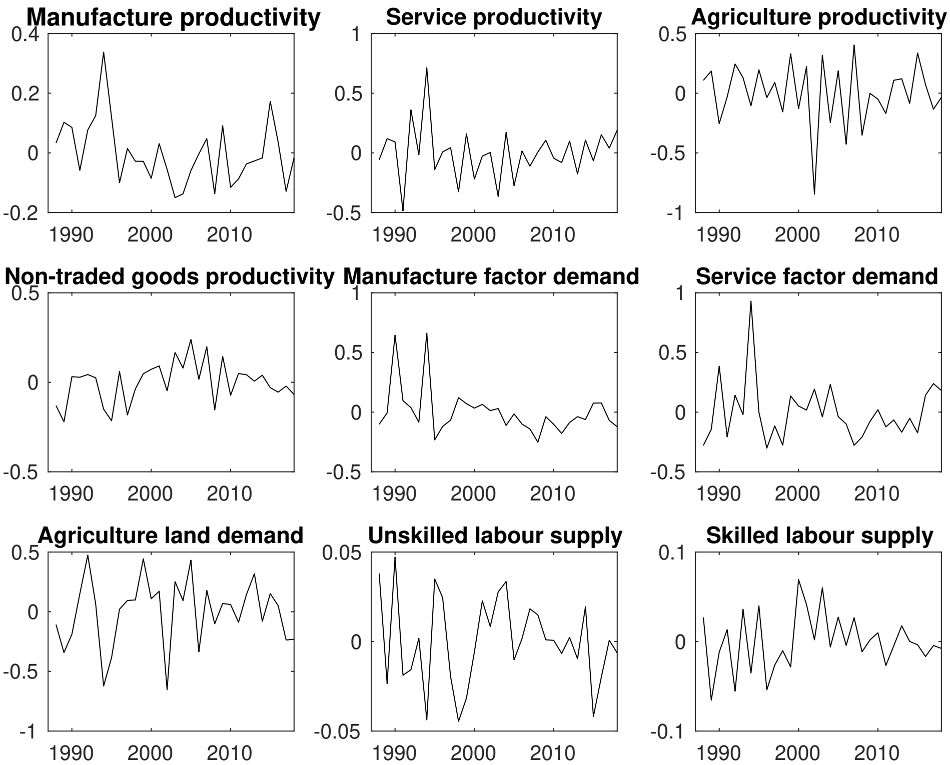


Figure 7.5: Model innovations (classical model for Part-of-model test of UK version)