THE CAUSAL RELATIONSHIP BETWEEN GDP, POPULATION GROWTH, TRADE AND CO2 EMISSIONS IN CHINA

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DECLARATION

We hereby declare that:

(1) This undergraduate research project is the end result of our own and that due acknowledgement has been given in the reference to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this research project has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Equal contribution has been made by each group member in completing the research project.

(4) The word count of this research paper is 10,231.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
AR	Autoregressive
ARDL	Autoregressive-Distributed Lag
CO2	Carbon Dioxide
ECT	Error Correction Term
EKC	Environment Kuznets Curve
ER1	Economic Rebalancing Policy
ER2	Domestic Demand Expansion Policy
FDI	Foreign Direct Investment
GDP	Gross Domestic Products
IOA	Input-Output Analysis
JJ	Johansen-Juselius
NAFTA	North American Free Trade Agreement
OLS	Ordinary Least Square
PP	Phillip-Perron
S2S	Simple Two Step
SDA	Structural Decomposition Analysis
SIC	Schwarz Information Criterion
SOEs	State Owned Enterprises
UNPF	United Nations Population Fund
US	United States
VAR	Vector Autoregressive
VECM	Vector Error Correction Model

LIST OF APPENDICES

ABSTRACT

The aim of this study is to identify the causal relationship among the variable which is gross domestic product (GDP), population growth, trade and CO2 emission in China. The main reason we choose China as our research object is that the air quality in China is the worst among the worldwide. The duration that we used in this research is 52 year that is from 1960 to 2011. In this research we conduct Augmented Dickey-Fuller (ADF) test, and Phillips-Perron (PP) unit root tests to examine the stationary of the data. Moreover, Johansen methodology, Granger causality test and Vector Error Correction Model (VECM) are conducted. The main finding in this study is that all independent variables are not Granger cause the CO2 emissions in China.

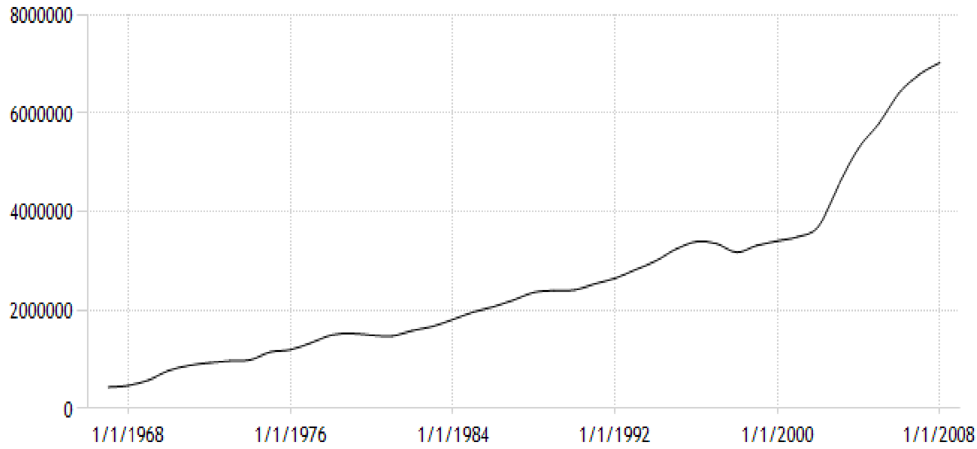
CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

In this new globalization economy, emissions of CO_2 (Carbon Dioxide) gaseous are greatly concerned by every government in the world since earlier in the 1980s. The increase of the CO_2 emissions is a major threat to the global climate change to the extent that either developing countries or developed countries have to consider its impacts. Given that developing countries generally have less productive technologies and restriction on the environment degrading activities, an increased in manufacturing activities represent developing countries are undertaking the developed countries on the aspect of environmental degradation.

Due to the reason that China is the largest country in the world and it is under an exclusively substantial development, it then claimed to be the world largest CO_2 emissions country. The rapid growth brings China great benefits but at the expenses of massive environmental degradation and used up large amount of energy. The graph in next page shows the emissions of CO_2 growth in China from year 1968 to 2008. In 1980, China had emitted total of 1460 million tones CO_2. The figure had increased to 6499 million tons in 2007. Most recent in 2013, the figure has reached 10,330 million tons. Therefore in this paper, we aimed to investigate the emissions of CO_2 gaseous which is determined by gross domestic product (GDP), population growth and trade in China.

Figure 1.1: Graph of China's CO2 Emissions (Kilotons)



Source: World Bank Group

1.1 Research Background

When sunlight strikes the earth, it will convert into heat waves and these waves will be reflected to the space. However, CO2 absorbs heat waves because these wave lengths are longer than sun lights. Therefore, it stops the heat from being reflected into the space. This is called "greenhouse effect". Internationally the emissions of CO2 are calculated in tones.

In 2007, CO2 emissions embodied in China's net exports accounted for about 1176 million metric tons which is almost 22% of China's CO2 emissions. Most of China's export-embodied CO2 is associated with productions of machineries and equipments instead of the energy intensive products such as aluminums and steels. On the other side, according to Ren et.al (2014), they have analyzed carbon emissions embodied in China's international trade during 2000–2010. They also numerically examine the main factors influencing carbon emissions and conclude that China's growing trade surplus causes the rapidly growing CO2 emissions. From 2005 until 2010, China's trade surplus increased from $102 billion to $181.76 billion with CO2 emissions increased from estimately 2130 million tons to 2821 million tons. In 2010, China is responsible for about 20 percent energy demand. Therefore, a large portion of the

CO2 emissions in China is embodied in goods produced for exports and consumed by other countries. Some researchers have studied the carbon emissions embodied in China's trade. For example, Shui and Harriss (2006) suggest that by producing exports for United States (US) consumers, China has resulted in about 7% to 14% of its CO2 emissions.

According to Choi et.al (2010), in the early stage of economic development, a small portion of excess income is typically allocated for environmental problems. Therefore, the industrialization process is likely to brings some environmental problems at this stage. When GDP increases and reach a certain level, the pollution level started to decrease typically. These two effect since the early stage of economic development until the booming GDP will cause the relationship between GDP and the level of pollution to become an inverted U-shaped curve. Kuznets (1955) said this refers to the environmental Kuznets curve (EKC). Recently, a number of studies have proved the effect of economic growth on environmental consequences. In addition, the greenhouse effect phenomenon has also been a hot topic among researchers these days.

The major source of environmental problems which is emissions of CO2 accounts for the largest portion of greenhouse gas. Therefore, it is meaningful to determine the causal relationships between environmental pollution, emissions of CO2 and economic growth. Liu et. al (2014) proves that a higher population density would have an effect on the environment depends on the type of pollutants. Higher population density increased wastewater discharge but decreased solid waste productions in China and its three regions.

1.2 Problem Statement

As our global average temperature is getting higher, the issues of CO2 emissions need to be considered and examine properly so that the "greenhouse effect" will not be worsening with time pass and affecting our next generation negatively. Furthermore the emissions of CO2 also will indirectly harm the countries in term of economics as when the situation goes from worse to worst. A great expenses need to be covered by governments to compensate nations' health problem by then, taking responsibility on natural disaster caused by "greenhouse effect" and etc.

There are many more side effect where emissions of CO2 will bring. However, this paper proposed that GDP, population growth and trade have significant relationship with the emissions of CO2 in China. Besides, our studies also planned to examine both long run and short run dynamic relationship between all these independent variables with emissions of CO2 in China. Generally, the economic activities in China will be influenced if the CO2 emissions is not under good control by the government.

1.3 Research Objectives

1.3.1 General Objectives

This paper attempts to identify and investigate the amounts and factors of CO2 being emmited into the China's atmosphere so that appropriate policies can be implemented. The ultimate goals is to achieve a situation where negatives externalities cost can be offset by the economic benefits gained from the CO2 emitted activities such as producing machines, providing public transport services and etc. Besides, it can be a useful information for CO2 emissions related corporations. This is because they can take these negative externalities into their cost account to show their concerned toward the society. With the product price increment they are willing and able to produce less.

As a result, there are less emissions of CO2 into the atmosphere. With the result in our research, the probability of future losses are able to reduce in the next generation. Our paper will also study the relationship between GDP, population growth and trade, and emissions of CO2 based on time-series data.

1.3.2 Specific Objectives

This paper is investigating on:

i.) To examine the causal relationship between emissions of CO2 and each of the independent variables chosen such as GDP, population growth and trade in China.

ii.) To understanding the causal relationship between each of the separate independent variables and the emissions of CO2.

iii.) To examine the relationship between the dependent and all the independent variables in short run and long run.

1.4 Research Questions

i.) Are quaterly time-series data of CO2 emissions be significantly illustrated the independent variables which are GDP, population growth and trade in a rapid developing country of China?

ii.) Are all the factors chosen significant in both long run and short run?

iii.) Is our model free from economic problems?

iv.) Do the factors chosen have bilateral relationship with each other?

v.) Is the relationship among the variables is of useful toward for the government to have a better policy to rule the country?

1.5 Significance of the Study

In this study, we examine the causal relationship between dependent variable (CO2 emissions) and independent variables (GDP, population growth and trade) in China by using quarterly data from year 1960 to 2011.We also investigate the long run relationship among these variables. This is to enhance the knowledge related to this field in order for the Chinese government to make relevant decision in the future.

Besides, we found out that there are a few number of previous researchers' studies able to support our finding which is there is no causal relationship between dependent and independent variables by using the Granger causality test. Moreover, this paper also shows there is existence a long-run or co-integration relationship among these variables chosen by applying the Johansen methodology.

In conclusion, to the best of knowledge and to fill up the gap of knowledge related to the emissions of CO2 in China due to lack of researches in this field, our study aimed to help the Chinese government to understand on how and to what extent this four variable chosen affect the emissions of CO2. This is to help the Chinese government to promote economic efficiency by making sound policy in the future.

1.6 Chapter Layout

The chapter layout of this paper is arranged in the following sequences in which literature review in Chapter 2 that related to our studies. The methodology of our study has detailed shown in Chapter 3, following by Chapter 4 which are stating about the data analysis. Lastly, discussion, conclusion and policies implication are shown in the last chapter.

1.7 Conclusion

Generally in Chapter 1, our study is talking about the major effects of the three factors that cause the emissions of CO2. This study briefly explains the background of CO2 emissions in China in order to help the Chinese government has a better understanding towards China's emissions of CO2. This paper has also illustrated the motives of testing the causal relationship between all the independent variables (GDP, population growth and trade) and CO2 emissions.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

Previous chapter has shown our research background, problem statement, general and specific objectives and significance of our study about the CO2 emissions in China. Before carrying out the empirical analysis, we have to review the previous researchers' studies that are related to the macroeconomic variables and CO2 emissions. Hence, this chapter has reviewed many journals which related to this topic. We have carried out the previous journals and articles as our review to the best of our knowledge and we found out there are limited literature studies consistent to our finding in this study.

We will investigate the relationship between the independent variable (GDP, population growth and trade) that we have chosen and CO2 emissions. The relationship between each variable is being studied neither in term of long run and short run (or causal) relationship. In this chapter, the methods used by various researchers to conduct their studies as well as major finding will be discussed and explained.

We have reviewed EKC hypothesis in this chapter. EKC hypothesis is a common theoretical tool which has been widely used by many researchers to test the relationship between environment and macroeconomic variables. The relationship between environment pollution and economic growth shows an inverted U-curve (Arrow, 1995; Cole, 1997; De Bruyn, et al., 2002).

2.1 GDP and CO2 Emissions

According to the EKC hypothesis theory, most of the researchers concerned about the relationship between GDP and CO2 emissions to confirm the effectiveness of the EKC hypothesis. Saboori (2012) chose Malaysia as his research to indicate the study by exploiting the co-integration test of the EKC hypothesis to test the relationship between GDP and CO2 emissions. They tested the EKC hypothesis by using the ARDL methodology from the period of 1980 until 2009 by using annual data. The empirical results also showed the relationship between GDP and CO2 emissions in the long run as CO2 emissions are the dependent variable.

According to previous researchers, an inverted U-shape curve has been studies between GDP and CO2 emissions and hence supporting the EKC hypothesis which focused on China (Song, 2008; Jalil & Mahmud, 2009; Zhang & Cheng, 2009). Narayan (2010) also examined the EKC hypothesis by using the Pedroni panel co-integration and the estimation tests for 43 developing countries in the long run. The result shows that there is a relationship between GDP and CO2 emissions in long run. Besides, Wang (2011) proved the relationship between GDP and CO2 emissions is inversed to the EKC hypothesis in the China. As a result, the empirical analysis shows and supports the co-integrated relationship between GDP and CO2 emissions in the long run.

Managi (2006) mentioned that GDP and reduction of environmental degradation are compatible in accordance to the EKC hypothesis. He also said that an inverted relationship between GDP and CO2 emissions is empirical associated with smaller levels of pollution after some thresh-old income point. EKC hypothesis stated that environment pollution increase initially when the industry is being developed by a country and decrease until a certain level of economic progress. Hence, there will be an inverted U-shape relationship between GDP and CO2 emissions. Over the past decade, the study also indicated the effect and relationship between CO2 emissions and GDP which they appear in an inverted U-shape or monotonically decreasing form (Hettige, Lucas, & Wheeler, 1992).

Previous researchers have carried out a positive and negative relationship of non-linear and linear term of GDP with CO2 emissions by carring the presence of EKC. According to the researchers, Saidi and Hammami (2014) argued the impact of GDP on CO2 emissions by using simultaneous equation model with panel data for 58 countries from period 1990 to 2012. The result showed that GDP has negative impact on CO2 emissions. Besides, other study also investigated the causal relationship between GDP and CO2 emissions from the period of 1960 to 1990 by using a cross-country panel data set over 88 countries (Coondoo & Dinda, 2002). The result does not provide much evidence for the current of a general causal relationship between GDP and CO2 emissions. Based on co-integration analysis Chebbi (2009), he mentioned there is a negative long run relationship between GDP and CO2 emissions.

Fodha and Zaghdoud (2010) examined the EKC literature studied the existence of a statistically significant correlation between the level of GDP and environment degradation which implies a unidirectional causal relationship. Narayan and Popp (2012) tested the EKC hypothesis from the period of 1980 to 2004 for 43 countries which have been developed. They investigated the EKC hypothesis according to short run and long run income elasticity towards the CO2 emissions and they found out it is evident to reduce the CO2 emissions for a country as its income has increased if using the long run income elasticity. From the study of Solarin (2014), he also argued that CO2 emissions increase with lower income countries but decline with the higher income countries. Richmond and Kaufmann (2006) argued that the relationship between GDP and CO2 emissions has no significant effect.

However, the previous empirical results do not always confirm to this EKC hypothesis due to a high level for country's income does not necessarily ensure the larger efforts to contain the CO2 emissions (Pao & Tsai, 2010). By using the Engle-Granger co-integration approach, Lise and Montfort (2007) rejected the EKC hypothesis during the period 1970 to 2002. Ang (2008) found a positive link between GDP and CO2 emissions. The other researchers, Fodha and Zaghdoud (2010) carried the existence relationship between GDP and CO2 emissions in the long run; showing that there is monotonically increasing the linear model and has positive effect between GDP and CO2 emissions. Haliciogly (2009) found that GDP has a positive long run and short run impact to CO2 emissions in the newly industrialized countries.

Some of the researchers argued that the studies could not find the proven about the effect of GDP on CO_2 emissions. Although the EKC hypothesis assumes the inverted U-shape relationship between CO_2 emissions and GDP, researchers proved that U-shape curve and N-shape curve shows the normality of EKC hypothesis while some found that EKC hypothesis is not appropriated. (Lise, 2006; Halicioglu, 2009) Lise (2006) also argued that EKC hypothesis has rejected the linear relationship between GDP and CO_2 emissions. The other researchers, Van Monfort (2006) and Akbostanci (2009) also refused the EKC hypothesis from the year of 1970 to 2002 by using panel data techniques and Engle-Granger co-integration method in Turkey. Their study shows the N-shape relationship between GDP and CO_2 emissions but does not determine the existence hypothesis.

Other than that, major findings from researches show positive significant bi-directional relationship between GDP and CO_2 emissions by using the data of time series from 1960 to 2008 and employing the Fully Modified Ordinary Least Square (OLS) co-integration approach in the long run (Saboori, Sapri & Baba, 2014). Besides, Shafik (2014) mentioned that GDP has a positive relationship with CO_2 emissions when he examined the relationship between GDP and wide range of environment indicators. The other researchers, Menyan and Wolde Rufael (2010) for South Africa also reported a positive and statistically significant relationship between GDP and CO_2 emissions.

Yet, Narayan (2010) mentioned that inverted U-shape EKC hypothesis only occurred in the Middle East and South Asian panel which imply that CO_2 emissions have declined when the income increase. Hence, there is only negative relationship between income variables and CO_2 emissions in the South Africa and Turkey significantly. As a result, it implies that the GDP has significantly declined the CO_2 emissions in the panel which supports the EKC hypothesis.

According to previous researchers, a secondary relationship between GDP and CO2 emissions has been found in a sample period by supporting the EKC hypothesis. The causality effect shows that there is only one way causality between GDP and CO2 emissions, implying GDP is Granger cause to the CO2 emissions in the long run (Farhani, Chaibi, & Rault, 2014).

Besides, Apergis and Payne (2010) found that GDP is Granger cause to CO2 emissions. The causality analysis shows the bidirectional causality between GDP and CO2 emissions. They also used the time series and the annually data to investigate the EKC hypothesis in Malaysia but the present study do not show strongly to it. The causality test shows unidirectional relationship between GDP and CO2 emissions.

Moreover, previous researchers stated that not only GDP Granger cause to CO2 emissions but also CO2 emissions Granger cause to GDP (Azlina, Law & Mustapha, 2014). They found that GDP and CO2 emissions are co-integrated and the causality test shows there is a one way relationship between GDP and CO2 emissions. Besides, the result of the Granger causality test also shows unidirectional causality relationship between CO2 emissions and GDP within the vector error correction model (VECM).

In additional, many researchers also indicated that CO2 emissions are Granger cause to GDP by using the panel data (Dinda & Coondoo, 2006). However, they argued that the GDP might be increase if the CO2 emissions are unidirectional causality to GDP. Besides, Soytas (2007) also stated that the Granger causality test between GDP and CO2 emissions in the United States shows a unidirectional causality relationship. Therefore, they concluded that GDP may not be a solving method to CO2 emissions problem.

2.2 Population Growth and CO2 Emissions

The major factor that contributes the environment problem in China is demographic factors. The evidence from UNPF (United Nations Population Fund) demonstrated the impacts of population growth were accounted for 40% to 60% of the CO2 emissions. (UNPF, 2009) Due to the rapid expansion of population in China, it increases the burden of housing, transportation, water and electricity supplies, education and health electricity, and thus, it lead to increase the CO2 emissions in China.

Previous researchers argued that the human activities on the environment can be divided into two lines of research. Firstly, researchers studied the relationship between the demographic changes and CO2 emissions at different level of scale with various methods and results. All of the factors which influencing the pattern of the CO2 emissions are demographic changes such as changes in population size, urbanisation and the age composition of households (O'Neill BC, Liddle , Jiang, Smith, Pachauri, & Dalton.). By using the time series data, the researchers conducted that the data has produced much greater variance in population elasticity estimations (Poumanyvong & Kaneko, 2006; Wang, Yin, Zhang & Li, 2012; Liddle, 2011; Cole & Neumayer, 2004).

Some researchers studied that the higher level of CO2 emissions has be produced when population increased. Cole and Neumayer (2004) found the CO2 emissions increase as population in a country increase. Poumanyyong and Kaneko (2006) also concluded that there is positive relationship between population growth and CO2 emissions. Many researchers stated that population growth is one of the main issue which it increases the CO2 emissions in Beijing and Guang Dong area.

Besides, the effect of age structure and household size on CO2 emissions has attracted generally concerns among the demographic factors. Some of the researchers found that working-age population with age around 15 to 64 years old has negative impact in developed countries while it has positive impact in developing countries (Fan et al. 2006). Moreover, Cole and Neumayer (2004) also found a negative correlation between household size and CO2 emissions in both develop and developing countries.

Urban population growth is one of the factors that affect the energy consumption in China. Therefore, it may lead to the CO_2 emissions increase as the energy consumption increase in the country. Due to the high population, human activities can cause the economics of scale which can reduce the energy use and associated CO_2 emissions. Previous researchers argued that the higher the urban population may reduce the CO_2 emissions by reducing the energy used in a country (Glaeser & Kahn, 2010; Kamal-Chaoui & Robert, 2009; Newman & Kenworthy, 1989).

However, the impact of changes in industrial composition, technological advance and institutional reformed by urban population growth in CO_2 emissions has been ignored. It is because the higher the population, the higher the CO_2 emissions has been produced as the natural resource based r heavy industries are outstanding. Hence, China has adopted the clean technology which it may closely relate to the manufacturing's plants ownership status (Zheng & Kahn, 2013). The researchers mention that China state owned enterprises (SOEs) manager are concerned about the political officials and may have fewer incentives to reduce the CO_2 emissions under the target of the profit.

According to Henderson (2003), he has identified a non-monotonous impact of urban population growth on economic development and suggested a range of value for optimal primacy level below which it bring up the urban population growth rather than prevent the economic growth. Other researchers also mentioned that population growth is one of the key factors which affecting the CO_2 emissions in China. They investigated how the population growth on economic activities which they influence the CO_2 emissions strengthen by using the China's provincial level data.

Moreover, based on previous researchers, Knapp and Mookerjee (1996) also examined the relationship between population growth and CO_2 emissions by using Granger Causality test and annual data from the year 1880 to 1989. The empirical result shows that there is no long run co-integrating relationship between population growth and CO_2 emissions. However, the causality test examines that there is short run dynamic relationship among them. Besides, the causality result also suggest that population growth is Granger Cause to the CO_2 emissions with 83.81% significantly. In other words, the regression estimation of the model shows the elasticity of CO_2

emissions to population growth at significant level 5.5% from 1978 to 2008 based on their study.

2.3 Trade and CO2 Emissions

China is the large trade nation and CO2 emissions emitter. Therefore, North South trade model has been developed by Copeland (1994) and Taylor (1997) to test the relationship between international trade and environment pollution. The result showed that the developed countries' environment has been improved by using the free trade method while it deteriorates the environment of developing countries.

China has a global trade surplus with United Stated country. However, the environmental has influenced the trade such as depletion of the resources and destruction of the environment. Most of the slow end and energy intensive exports caused the CO2 emissions increase in China (Lin & Sun, 2010). They evaluated CO2 emissions of imports and exports in China show that power generation dedicated those most to the countries' CO2 emissions. Weber and Matthews (2007) stated that the CO2 emission in trade include US and its seven large business partners. They found that the result shows the net imports of CO2 which increase sharply from 1997 to 2004.

Previous researches used multiplicative clauses of openness degree and income to determine CO2 emissions in their study. They found that national trade has negative effect on the environment. (Copeland & Taylor, 2001) Cole (2004) argued that the EKC model found the openness in trade and trade in goods produced by industry affect the CO2 emissions in the developed countries. However, he realizes that it is only small relative effect to other determinants of CO2 emissions.

There are few studies following the methodology of Ang and Liu (2007) and Halicioglu (2009) to examine the relationship between trade liberalization and environment pollution in China and India (Kankesu, Reetu & Liu, 2012). Previous researchers also focused on the empirical analysis of testing the global trade implicit CO2 emissions (Lin & Sun, 2010)

Grossman and Krueger (1991) establish the theoretical framework analysing environment effect of foreign trade. In the study of North American Free Trade Agreement (NAFTA), they measured the effect of trade on CO_2 emissions into different types of effects such as scale, structure and technology effect. By the way they found that economic growth is the main factor of the trade to influence the environment.

Many researchers like to use input-output analysis (IOA) to examine the relationship between global trade and CO_2 emissions. Recent empirical studies used the input-output analyses to examine the relationship between open trade and CO_2 emissions in China. Researchers mentioned that increasing the trade openness has result in more CO_2 emissions (Weber, 2008; Yan & Yang, 2010). Besides, the elements analysis of CO_2 emissions could produce useful information of the observed changing in CO_2 emissions and also in-depth understanding. The input-output model was built by structural decomposition analysis (SDA) and developed to analyse the changes in the CO_2 emissions at productivity level. Cheng and Lin (2001) argued that the factors which affected CO_2 emissions changes during 1984 to 1994 in Taiwan's petrochemical industries examined the related contribution of the factors to CO_2 emissions changes in the industries.

Other researchers, Copeland and Taylor (2004) examined that China is a wide country with the positive relationship between economic and environment regulations, for example, the regional and national CO_2 emissions may be affected by the interval trade. In other word, they argued that a changing of pollution-intensive industry from regions with stringent regulation to regions with weaker regulations is caused by reducing the barriers of trade.

Shui and Harriss (2006) indicated that CO_2 emissions increase the manufacturing's comparative advantage because there is less economic stimulus measurement for reducing the previous CO_2 emissions. Therefore, the positive relationship between CO_2 emissions and comparative advantage should be considered such as US–China trade. The regressions analysis shows that there is a not perfect correlation but significant relationship between CO_2 emissions and trade in the both countries.

Industries in China have much more carbon-intensity than Japanese counter parts. It shows a negative correlation but significant relationship between the comparative advantages of trade in China to Japan. However, some of the researchers found that there is no significant relationship between CO2 emissions and trade openness. (Jalil & Mahmud, 2009). They showed that India country only have focused on composition effect, technique effect and decomposing scale.

According to Naranpanawa (2011), he argued that trade openness is Granger cause to CO2 emissions in the short run. Besides, the trade openness was found to be statistically at significant level 10% in the Granger causality result. However, he could find any relationship between trade openness and CO2 emissions in the long run from causality test. As a result, Granger causality test shows that there is unidirectional causality between CO2 emissions and trade openness in the short run. In other words, CO2 emissions would be boosted by increasing in trade openness in the short run.

In the other hand, Halicioglu (2009) mentioned that it is evident to establish the relationship between trade openness and CO2 emissions in the long run in Sri Lanka, which has been happening for the last two decades. However, the result shows that there is no significant relation contributed to the CO2 emissions.

2.4 Conclusion

Based on previous literature reviews, all the evidence provided was strong to confirm the direction of this study. The effects are proven to have either causality or not causality relationship toward the dependent variables and independent variables. The significant of the objective of this research is going to be confirmed through the following chapter. Therefore, we are going to conduct the empirical analysis to test whether our findings whether can match with the result of previous journals. The methodology used will be elaborated in Chapter 3.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter is regarding the research methodology, which consists of research design, data collection methodology used is inappropriate in the study, result obtained could be misleading. The methodologies discussed in this chapter will be put to further usage in the upcoming chapters but for now, only explanation regarding the nature of the tests will be discussed. The following test will be discussed in order.

a) The augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests
b) The Johansen methodology
c) Vector Error Correction Model (VECM)
d) Granger causality test

3.1 Research Design

In this study, quantitative research was used to meet our study objective. Quantitative methods are particularly useful when researchers seek to study large scale patterns of behavior as they can be measured and quantified. A Research design can be defined as a detailed outline of how an investigation will take place. The research design will typically include how data is to be collected, what method to used, how the method will be implement and the intended means for analyzing data collection. The main purpose of carrying out a research is to explain the phenomenon. This research paper aims to identify the relationship between CO2 emission and gross domestic product (GDP), CO2 emission and trade, and CO2 emission and population in China during 1960 to 2011. Data is collected and analyzed using mathematical methods but in order to do so, data collected have to be in numerical form.

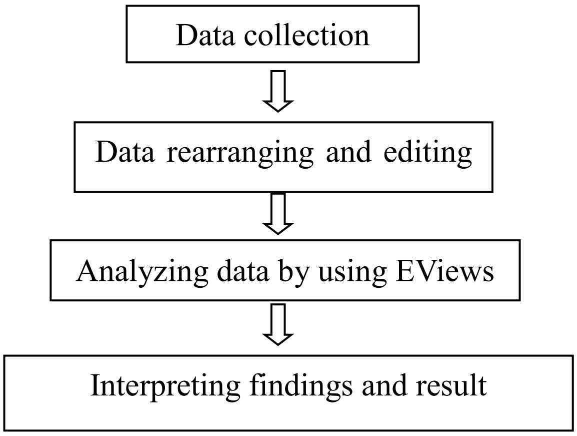
3.2 Data Collection Methods

Secondary data were used to carry out this research. In order to determine whether the macroeconomic variables have impact on CO2 emissions in China, data regarding CO2 emissions, GDP, population growth and trade were obtained from World Bank Data. We used quarterly time series data to conduct this study, which stretches from 1960 to 2011, a period of 52 years (208 observations). The two main reasons that we use secondary data are to save time and reduce the cost of researching. Current researchers also do not need to spend much time to obtain the data by themselves because the data were already collected, published for free and is available from many sources.

3.3 Data Processing

A few steps are involved in data processing. Firstly, researchers will obtain the data which needed from all available sources. After obtaining the data, researchers rearrange and edit the data before running an empirical analysis and interpreting the finding subjected to the research objectives.

Figure 3.1: Steps of Data Processing



3.4 Data Description

Table 3.1: Description of Data in Tabular Form

Variable	Unit	Source
Carbon Dioxide emissions (CO_2)	Metric ton per capital	World Data Bank
Gross domestic product (GDP)	Current (US$)	World Data Bank
Trade (TRD)	(% of GDP)	World Data Bank
Population growth (POP)	Annual %	World Data Bank

3.4.1 CO2 Emissions

CO2 emissions in the model use the measurement of metric ton per capital.

3.4.2 GDP

GDP is measure by current (US$). GDP at buyer's prices is the amount of gross value added by all local producers in the economy plus any product taxes and minus any subsidies not included in the value of the goods. Dollar figures for GDP are changed from domestic currencies using a year authorized exchange rates. For a few countries where the authorized exchange rate does not reflect the rate effectively useful to real foreign exchange transactions, an alternative exchange factor is used.

3.4.3 Population Growth

Population growth is calculated in annual percentage. Population growth (annual %) is the exponential rate of growth of midyear population from year t-1 to t, expressed as a percentage.

3.4.4 Trade

Trade is measured in percentage of GDP. The trade consists of net exports where exports minus imports of China.

3.5 Model Specification

The initial model with dependent variable (CO2 emissions) and independent variables (GDP, population growth and trade) is specified as follow.

$$CO2 = f\,(GDP, POP, TRD) \tag{1}$$

$$CO2_t = \beta_0 + \beta_1 GDP_t + \beta_2 POP_t + \beta_3 TRD_t + \varepsilon_t \tag{2}$$

CO2 = CO2 emissions

GDP = Gross domestic products

POP = Population growth

TRD = Trade

β_0 = Intercept

ε = Error term

$_t$ = time trend

The variables are then transformed into logarithmic form in order to reduce the skewness of data and make the result more interpretable.

$$LNCO2_t = \beta_0 + \beta_1 LNGDP_t + \beta_2 LNPOP_t + \beta_3 LNTRD_t + m_t$$

LNCO2 = Natural log of CO2 emissions

LNGDP = Natural log of gross domestic product

LNPOP = Natural log of population growth

LNTRD = Natural log of trade

β_0 = Intercept

m = Random error term

$_t$ = time trend

3.6 Methodology

3.6.1 The Unit Root Test

In this study, the unit root test can be performed to determine whether the data is stationary or non-stationary trend. The data with stationary time series have constant mean and variance over a time period while the data with non-stationary time series will inconstant mean and variance over the time. Non-stationary time series do not have a long run mean which the series return. Moreover, the variance is needy over time and goes to infinity as sample period approach infinity. According to Granger and Newbold (1974), the estimated regression result will be spurious if there is existing random walk between the dependent and independent variable. It could cause econometric problem where the normality assumption of hypothesis testing such as T-statistics to become useless and invalid. So, we use Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) unit root test to double check for the stationary of our model.

3.6.1.1 The Augmented Dickey-Fuller (ADF) Unit Root Test

ADF is used to recognize the problem of having a unit root in the model. ADF test is a parametric test which assumes that a model is normally distributed and there is a need to increase the lag length in order to eliminate the impact of serial correlation (Phillips & Xiao, 1998). The parametric test for stationary, ADF test has null hypothesis (H_o) and alternative hypothesis (H_1) where H_o depicts that there is unit root (non-stationary) and H_1 means there is no unit root (stationary). To conduct these tests, two ways can be used to choose an appropriate lag length which is Schwarz Information Criterion (SIC) and Akaike Information Criterion (AIC). According to Ayalew, Babu, and Rao (2012), a main advantage of SIC is that for a wide range of statistical problem, it is order consistent; when the sample size grows to infinity, the probability of choosing the accurate model converges to unity. This leads to more parsimonious models. Identical to the AIC, the lower the value of SIC, the better the model the model will be. The difference between AIC and SIC is that AIC is designed to choose model which can forecast better and is less concerned with having too many parameters which can cause overestimation of right lag length and choose not consistent proper lag length.

3.6.1.2 The Phillips-Perron (PP) Unit Root Test

PP test is one of the tests for unit root test. The serial correlation in the error term will be minimized by using non parametric method without add lagged difference of error terms like ADF Test. This quality giving PP test a plus over ADF Test which allows researchers need not to recognize a suitable lag length for the unit roots checking.

ADF and PP unit root tests have similar asymptotic distribution but just different by the way of dealing with serial correlation in the regression. Nevertheless, there is condemnation on PP test that PP test is performing less well compared to ADF However, ADF test has its own limitation. AR order in ADF test is very important. If we wrongly specified the AR order in ADF test, the test will be misused. In contrast, if we over-specified AR order, ADF test's power will suffer. Even though these problems can be prohibited in the PP test, the PP test will be less powerful than ADF test if we can properly specify AR order. Since we use Eviews 6.0 software to run ADF test which can straight give the proper AR order of the variables in the test, we should prioritized the result of ADF test over PP test due to its strength. After taking a few of consideration, we decided to use both ADF and PP test to examine for the presence of unit root in our research in order to ensure the accuracy of the test by double checking and compare the result from ADF test and PP test

.

ADF test and PP test distribute the same null hypothesis which is there is a unit root or the time series variable is non-stationary while the other hypothesis is there is no unit root in the time series variable. We will reject the null hypothesis if the p-value is smaller than 10%, 5% and 1%, otherwise we do not reject the null hypothesis.

3.6.2 The Johansen Methodology

Johansen-Juselius co-integration test is conducted to find out an accessible long run equilibrium relationship between the selected variables. The test suggests that time series variables cannot move far away from one another if there is a stationary long run relationship between the integrated variables. This method is based on the vector autoregressive (VAR) models and permits the testing of hypothesis as regards the equilibrium relationship between the variables (Abubakar & Abudllahi, 2013). The co-integration test also helps decrease the spurious rejection frequency. On the other hand, the spurious refusal recurrence stays extensive and seems to increment with the quantity of variable in the framework, even in the wake of applying such detail test (Hjalmarsson & Osterholm, 2007).

Another co-integration test is known as the Engle-Granger (EG) approach. Johansen Juselius is a much better approach compared to EG approach. This is because researchers are more likely to apply the results of Johansen-Juselius on the asymptotic distribution of the likelihood ratio test. These distributions are given in terms of a multivariate Brownian motion process (Johansen and Juselius, 1990). In contrast, EG approach can only take account up to two variables in the model. Moreover, most of the researchers carry out this test by using Trace and Maximum Eigen value test in order to examine the co-integration of the model. If the null hypothesis is rejected, there exists a co-integration relationship. Gonzalo (1994) concluded that the Johansen's approach performs better when the errors are not normally distributed, or when the dynamic of the vector error correction model (VECM) are unknown and additional lags are included in VECM.

3.6.3 Vector Error Correction Model (VECM)

VECM offers a possibility to apply VAR model to coordinated multivariate time arrangement. In the course readings they name a few issues in applying VECM offers a plausibility to apply VAR to coordinated a VAR to incorporated time arrangement, the most essential of which is the alleged spurious regression (t-statistics are greatly significant and R^2 is high albeit there is no connection between the variables).

According to L¨utkepohl & Kr¨atzig (2005) VEC modeling is a regulated strategy, where every assignment is linked to a special panel. When a model has been evaluated, the diagnostic tests as well as the stability study, structural study and forecasting use the outcome from the evaluation. On the off chance that adjustments in the model determination are made by the client, these outcomes are eliminated and the model must be estimated. As it were, just results identified with one model at once are kept in the framework. Consequently, there ought to be no perplexity with respect to the model setup while experiencing the investigation.

There are different estimation procedures available for estimating a model of the type (1), depending on the precise model specification. If there are no zero restrictions on the matrices and there are no exogenous variables, that is, a reduced form model is specified without exogenous variables and where each equation has the same right-hand side variables, then the Johansen reduced rank (RR) estimation procedure (Johansen (1995)) and a simple two step (S2S) method was started by Ahn and Reinsel (1990) or L¨utkepohl and Kr¨atzig (2004) can be applied.

3.6.4 Granger Causality Test

Granger (1969) built up a similarly straightforward test that characterized causality as a variable Y is said to Granger cause X, if X can be anticipated with more prominent precision by utilizing past estimations of variable Y as opposed to not utilizing such past values, every single other term stay unaltered. When variable X Granger causes variable Y, then changes in X should precede changes in Y. The concept of Granger Causality test is defined in terms of predictability and exploits the direction of the flow of time to achieve a causal ordering of associated variables. Since it does not rely on the specification of an econometric model, it is particularly suited for empirical model building strategies as suggested by Sims (1980).

As indicated by Foresti (2007), there are three distinctive sort of circumstances in which a Granger-causality test can be connected. Initial, a basic Granger-causality test between two variables and their lags. Second, a VAR system, for this situation the Granger cause variable Y and variable Y does not Granger cause variable X. More or less, one variable (Xt) is said to Granger cause another variable (Yt) if the lags estimations of Xt can figure Yt and the other way around.

3.7 Conclusion

This chapter provides discussion of data collection, data processing, data description and also the methodologies to be used in the following chapter. The methodologies discussed are made up of unit root test, co-integration test, and error correction model. These tests can be used in order to find out the impact of gross domestic product, trade and population growth onto co2 emission. The following chapter is data analysis, where results from the mentioned test will be presented and interpreted clearly.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

The empirical results from several tests conducted will be discussed in this chapter. Firstly, the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests are carried out to see whether the all of the variables chosen such as CO2 emissions, GDP, population growth and trade, are stationary. After that, the co-integrating relationship between variables can be identified through the trace test and maximum eigenvalue from Johansen methodology. Lastly, Vector Error Correction Model (VECM) is applied in order to continue the Granger causality test. We use this test to check the existence of causal relationship between the dependent and independent variables.

4.1 The Unit Root Test

Stationary of variables is important to ensure us avoid from spurious regression chosen. Therefore, a comparison is made between the t-statistic and critical value from both ADF and PP tests.

H_0: *$\delta = 0$ (There is a unit root.)*

H_1: *$\delta < 0$ (There is no unit root.)*

4.1.1 The Augmented Dickey-Fuller (ADF) Test

Table 4.1: Stationary of Variables in the ADF Unit Root Test

Variables	The augmented Dickey-Fuller (ADF) test	
	Level Form with Trend and Intercept	1st Difference with Intercept
CO2 emissions	-3.229289**	-4.925074*
GDP	0.565632	-4.610294*
Population growth	-2.351915	-5.121263*
Trade	-2.319787	-3.989655*

Source: EViews 6

Note:
* and ** represent significance level of 5% and 10% respectively.

According to Table 4.1, all variables are not stationary at level form with trend and intercept at 5 percent of significance level. Therefore, null hypothesis is not rejected which mean that the variables have a unit root. After that, all of these variables go to first differencing with intercept and result demonstrated that there is no unit root (stationary) for them at all significance level, which is 1%, 5% and 10% respectively. Then, we will go to the alternative for unit root test, the Phillip-Perron (PP) test.

4.1.2 The Phillips-Perron (PP) Test

Table 4.2: Stationary of Variables in the PP Unit Root Test

Variables	The Phillips-Perron (PP) test	
	Level Form with Trend and Intercept	**1st Difference with Intercept**
CO2 emissions	-4.862037*	-4.782760*
GDP	-0.920345	-6.525951*
Population growth	-4.306829*	-6.130086*
Trade	-2.816696	-6.202480*

Source: EViews 6

Note:
* and ** represent significance level of 5% and 10% respectively.

From the PP test result above we can see that all variables are stationary at first differencing with intercept at significant level 5%. However, the dependent variable (CO2 emissions) and one of the independent variables (population growth) at level form with trend and intercept are also stationary at the same significant level. Previous researchers, Davidson and MacKinnon (2004), showed that the ADF test is perform better in finite sample than PP test. Therefore, we will choose ADF test to continue the Johansen methodology.

4.2 The Johansen Methodology

The Johansen Methodology is utilized to check the presence of long run or co-integration relationship among the variables. Firstly, we carried out the VAR lag order selection criteria (Table 4.3) to choose the optimal lag length based on AIC and SIC due to this test is very sensitive to the lag length selection. Previous researcher, Schorfheide (2005), suggest that the SIC is more accurate. Therefore, 2 lag lengths are selected and used to conduct the Johansen methodology.

Table 4.3: The VAR Lag Order Selection Criteria

Lag	Akaike Information Criterion (AIC)	Schwartz Information Criterion (SIC)
0	0.482888	0.549317
1	-17.99556	-17.66341
2	-20.57831	-19.98045*
3	-20.48797	-19.62438
4	-20.36446	-19.23515
5	-20.87502	-19.47999
6	-21.37214	-19.71140
7	-21.25885	-19.33239
8	-21.15765	-18.96548
9	-21.76645	-19.30855
10	-22.44221*	-19.71859

Source: EViews 6

Note:

* represent lag order selected by the criterion.

Table 4.4: The Johansen Co-integration Test

Hypothesized No. of CE(s)	Trace Statistic	Max-Eigen Statistic	5% Critical Value	
			Trace	Maximum Eigenvalue
r = 0	75.18367	54.71373	47.85613	27.58434
r ≤ 1	20.46994	14.27953	29.79707	21.13162
r ≤ 2	6.190413	3.889376	15.49471	14.26460
r ≤ 3	2.301037	2.301037	3.841466	3.841466

Source: EViews 6

Note:
r represents the number of co-integrating vectors.

H_0: There is no long run relationship between the variables (The variables are not co-integrated).

H_1: There is a long run relationship between the variables (The variables are co-integrated).

Based on Table 4.4, the null hypothesis is rejected when the co-integrating vector is 0 because both trace and Max-Eigen statistics is larger than their 5% of critical value. This indicates that there is presence of co-integrating relationships among the variables. With co-integrating relationship means that CO2 emissions, GDP, population growth and trade are moving together in the long run.

4.3 Vector Error Correction Model (VECM)

In the wake of confirming that there is exist of one co-integrating relationship among the variables, hence we decided to use the VECM to continue Granger causality test. The model with ECT (Error Correction Term) has been predicted as follow.

Model specification:

$$DLNCO2 = 0.002382 - 0.000277ECT_{t-1} + 0.625529DLNCO2_{t-1} + 0.167132DLNCO2_{t-2} + 0.000997DLNGDP_{t-1} - 0.003181DLNGDP_{t-2} + 0.003412DLNPOP_{t-1} + 0.015576DLNPOP_{t-2} + 0.005037DLNTRD_{t-1} + 0.009843DLNTRD_{t-2} + \varepsilon_t$$

Where,

DLNCO2 = First difference of natural log of CO2 emissions in China (metric tons per capita)

DLNGDP = First difference of natural log of GDP in China (current USD)

DLNPOP = First difference of natural log of population growth in China (annual %)

DLNTRD = First difference of natural log of trade in China (% of GDP)

ECT = Error Correction Term

ε_t = Error term

Note:

The lag length for all variables in the VECM is based on the minimum SIC.

ECT is the main concern in VECM because it used to captures the short run or dynamic adjustment of variables towards the long run equilibrium. The ECT above with a negative sign and significant at confidence level 5% demonstrates that there is 0.0277% of adjustment among the variables for each quarter to achieve the long run relationship. This shows that the VECM has very slow speed of adjustment which is 3611 quarters or 903 years are needed to have a completely adjustment.

4.4 Granger Causality Test

Conducted of the Granger causality test is to define whether the two time series variables are presence a causal relationship between each other. Stationary data has been utilized in this test because of the VECM requirement.

Table 4.5: The Pairwise Granger Causality Test

Granger Cause	Probability (P-value)
LNGDP → LNCO2	0.9929
LNCO2 → LNGDP	0.2206
LNPOP → LNCO2	0.8319
LNCO2 → LNPOP	0.9856
LNTRD → LNCO2	0.3582
LNCO2 → LNTRD	0.6539

Source: EViews 6

Note:

The narrows denote the direction of Granger causality, as LNGDP Granger causes LNCO2, LNPOP Granger causes LNCO2, and LNTRD Granger causes LNCO2.

4.4.1 Gross Domestic Products (GDP)

H_0: GDP does not Granger causes CO2 emissions.

H_1: GDP does Granger causes CO2 emissions.

According to Table 4.5, GDP do not Granger causes the CO2 emissions due to the P-value of 0.9929 is larger than significance level 5%. Thus, the null hypothesis is not rejected and demonstrates there is no causal relationship from GDP to CO2 emissions in China. This finding is same to the research result of Ozturk and Acaravci (2010) which demonstrate that there is no causal evidence from GDP to CO2 emissions in Turkey.

4.4.2 Population Growth (POP)

H_0: POP does not Granger causes CO2 emissions.

H_1: POP does Granger causes CO2 emissions.

Table 4.5 has shown that there is also no causal relationship between POP and CO2 emissions at 5% of confidence level with a P-value 0.8319. Hence, the null hypothesis is not rejected. Previous researchers Beguma, Sohaga, Abdullaha, Jaafar (2015) found that population growth have no causality relationship to CO2 emissions. This is similar with our finding.

4.4.3 Trade (TRD)

H_0: TRD does not Granger causes CO2 emissions.

H_1: TRD does Granger causes CO2 emissions.

Trade does not Granger causes towards the CO2 emissions in China at significance level 5% too. Previous studies that done by Zaman (2012) also unable to find out the causality relationship among these two variables.

4.5 Conclusion

We are using unit root tests, lag length selection criteria, co-integration test and VECM before carry out the main test in this chapter, which is Granger causality test. The next chapter will be concluded with policy implications, limitations and recommendations to further improve the CO2 emissions problem in China.

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATIONS

5.0 Introduction

From our research, this chapter focuses on summary of statistical analyses, major findings and policies implication for CO_2 emissions in China. Moreover, some limitations arise in this research paper will be highlighted and recommendations will be provided for future research.

5.1 Summary of Statistical Analysis

The unit root test is carried out to test the stationary of variables chosen. Therefore, augmented Dickey-Fuller and Phillips-Perron tests are conducted to make the variables stationary. After conduct the testing, the result obtained is that all the variables (CO_2 emissions, GDP, population growth and trade) are not stationary in level form at significance level 5%. But, they become stationary at first difference at same significance level.

Since all the variables follow $I(1)$, therefore we proceed further to conduct the co-integration testing to identify whether the model have long run relationship effect. The empirical result shows that it has a long run equilibrium relationship between CO_2 emissions, GDP, population growth and trade. Hence, we used VECM rather than VAR model which is used for short run effect.

Continue the testing, Granger causality test is conducted to find out whether the short run relationship between the variables is in unidirectional or bidirectional causal. From the Granger causality test result, we found that it does not causal relationship between CO2 emissions and GDP, population growth and trade at significance level 1%, 5% and 10% respectively.

5.2 Discussion of Major Findings

There are some tests applied in our study such as the unit root test, Johansen methodology, VECM and Granger causality test. We conducted ADF test is to identify whether there is an existence of unit root in the variables (CO2 emissions, GDP, population growth and trade). Besides, the Johansen methodology was used to determine the co-integration relationship among these variables and result showed that the variables are co-integrated or moving together in the long run. Therefore, VECM was built and the speed of adjustment was identified with ECT. The ECT value of 0.000277 which indicated that CO2 emissions in China are adjusted 0.0277% every quarter and they need to use 3611 quarters or 903 years to fully recover the CO2 emissions problem. We advise China to take an earlier action before the CO2 emissions problem become serious.

The Granger causality test is our main test and it was utilized to examine causal relationship between two variables. According to the causality test result, all independent variables are found that does not Granger cause the CO2 emissions in China. Our Granger causality results are difference from the majority studies done by previous researchers as mentioned in literature review section. Most of their results showed that there is a causal relationship from the independent variables (GDP, population growth and trade) to the CO2 emissions.

Therefore, the problem that we are facing in this research is limited empirical studies that able to provide the reason why our macroeconomic variables are not Granger causes CO2 emissions. We will discuss this problem in the limitation part later.

5.3 Policies Implication

Due to the CO2 emissions problem need some times to overcome, so we are more concerned about the methods that can be applied by China's government to reduce the CO2 emissions. Based on our study, there are some important policies implications attained from our finding.

Firstly, we would discuss about the policies implication on trade side. Policymakers should implement the incentive-based approaches in order to reduce the CO2 emissions at a lower cost. Under a tax on energy-intensive exports, the either fee for each ton of CO2 emissions or CO2 contained in fossil fuels would be levy by policymakers. The tax would also stimulate entities to reduce the CO2 emissions if the cost of doing so was less than the cost of paying the tax. Hence, policymakers should place the tax above the cost of reducing CO2 emissions even the total amount of CO2 would be uncertain and emitted in each year. Tariffs also should be imposed by policymakers based on the carbon content embodied in trade in order to prevent carbon leakage and support the domestic producers' competitiveness. Government of China should cut down the tax rebates and increase the export tariffs to limit the export of energy-intensive products in order to reduce the CO2 emissions. The tariffs are measured by the Comprehensive Energy-saving Reduction Program Work Notice of China in China's Twelfth FYP (The State Council of China, 2011). Based on the Twelfth FYP, policymakers are encouraged to adjust the economic structures in order to reduce the credit on heavy industries and encourage the domestic consumptions in China. Policymakers should also develop an economic rebalancing policy (ER1) plus the effect of combining it with domestic demand expansion policy (ER2) in order to rebalance the economic under the policies in China. The implementation of economic rebalancing target can be achieved by imposing endogenous taxes or subsidies on all sectors. In other words, policies that made by policymakers would be the important methods to stimulated domestic consumptions under the trade.

The policymakers in China are also suggested to concern about the economic growth on CO2 emissions. They are encouraged to take care of the clean surroundings and impose the policies about environmental friendly technologies in energy productions areas to reduce the CO2 emissions and increase the GDP. It is very important for China to invest more on energy projects in order to achieve the full energy potential. Therefore, the research and investment on clean energy should be proceeded to control the CO2 emissions. The factors which will increase the exhaust of industrial pollutants should be considered by policymakers in order to realize the sustainable development of population, resources and environment in China.

Other than trade and economic growth sides, policymakers also need to concern about the China population on CO2 emissions. The narrowing of the household size and higher income led to increase the per capita consumptions and higher carbon intensive in their lifestyles. Policymakers are encouraged to promote the adoption of high efficiency and energy saving of large household appliances due to advocate the green consumptions and sustainable lifestyles. Moreover, the key factor which policymakers should put effort is to optimize the population structure. They should also control the floating population in China in order to ease the urban surplus. Besides, policymakers are not encouraged to reduce the impacts of CO2 emissions by preventing the economic activities in the urban area. The best method to reduce the CO2 emissions are to engage with varieties of economic instruments related with the industrial composition change. For instant, shutting down heavily polluted industries and nudging the industrial structures in the urban area can be avoided by trying the clean industries or services industries to reduce CO2 emissions per unit of economic activities. The policymakers are also encouraged to promote and adopt better techniques such as use of renewable energy for environment management to reduce the CO2 emissions for large urban population. Besides, promoting ownership reform and increasing non-SOE share also is an option to push urban area close to “green environment performance”.

5.4 Limitations of the Study

Similar with previous researches, our studies also face some difficulties or limitations throughout the whole process. Data constraint is one of the major limitations in this paper. As we know, China is a developing country so that there is still having some sets of data not yet full such as the energy consumption data. Therefore we cannot include the energy consumption as one of the independent variables into the model as how we planned to at first. Thus, the model may lack of small amount of information to explain the dependent variable emissions of CO2. Furthermore, there are categories of energy used data that are similar to the energy consumption data. Description of these two terms is ambiguous where we could not decide which one can best describe the dependent variables of CO2 emissions in China. Overall, we do not choose energy consumption as our independent variable in this research. In addition, there is also a limitation on the data due to the lack of monthly data of CO2 emissions as the data is only collected for quarterly. This makes us hardly to determine whether to use monthly data or quarterly data of CO2 emission is the best for the model.

Moreover, this research only investigates in China. The information and result discuss in this paper only describe the situation in China and applicable in the case of China when the Chinese government or investors wish to make use of the data. Due to the different production ability, political rules and regulation, culture and other factors, other Asia countries such as Malaysia, Korea, Japan, Indonesia and Brunei are only encouraged to revise on our finding where necessary where it could not helped to make best policy decision. Besides, due to the econometric problem we have faced after number of times the foreign direct investment (FDI) data in China has been run, we decided to drop this variable from our independent variables too.

This study also concerns on one main point which is testing on the causal relationship between each independent variable that affects the emissions of CO2 in the short run. Perhaps there are some more significant independent variables has not been considered. It might cause the final result lose of accuracy and probably existence of bias at the end.

5.5 Recommendations for Future Research

Based on our study, we encourage the future researchers to solve several econometric problems before deciding which independent variable to include into the model. The main purpose for doing so is to make sure the result is reliable and accurate in their studies. In addition, we are also using time-series data in this paper. However there are some disadvantages by using the time-series data. Therefore, whichever researchers who want to study this related topic is encouraged to use other form of data in order to avoid the econometric problem such as panel data.

Moreover, future researchers are also encouraged using different frequency set of the data such as semi-quarterly or monthly to examine the consistency of the findings so that they can increase the reliability of the study. Future researchers are encouraged to examine the relationship of the causal relationship variable with the emissions of CO2 in other sectors such as financial sector as the financial sector is a growing sector which may describe the emissions of CO2 in China. The result may be more significant when more and more sectors to be considered.

5.6 Conclusion

As a conclusion, we have investigated the Johansen methodology and Granger Causality test to test the relationship among all the variables in this paper. The result shows that GDP, population growth and trade has co-integration (long run) relationship but has no causality (short run) relationship with CO2 emissions in China. Moreover, some limitations and recommendations are also discussed in this paper. Finally we are very glad that this paper also has met our primary objective in which to examine the causal relationship between GDP, population growth and trade in China towards CO2 emissions.

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APPENDICES

Appendix 1: The ADF Unit Root Test on CO2 Emissions

(a) Level Form with Trend and Intercept

Null Hypothesis: LNCO2 has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 5 (Automatic based on SIC, MAXLAG=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.229289	0.0817
Test critical values:	1% level	-4.004132	
	5% level	-3.432226	
	10% level	-3.139858	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LNCO2)

Method: Least Squares

Date: 08/01/15 Time: 20:03

Sample (adjusted): 1961Q3 2011Q4

Included observations: 202 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNCO2(-1)	-0.025278	0.007828	-3.229289	0.0015
D(LNCO2(-1))	0.665183	0.066651	9.980077	0.0000
D(LNCO2(-2))	0.203244	0.075012	2.709505	0.0073
D(LNCO2(-3))	0.069911	0.076336	0.915840	0.3609
D(LNCO2(-4))	-0.463556	0.075160	-6.167600	0.0000
D(LNCO2(-5))	0.299146	0.063897	4.681716	0.0000

C	-0.012750	0.004942	-2.580009	0.0106
@TREND(1960Q1)	0.000290	8.83E-05	3.279530	0.0012

R-squared	0.674455	Mean dependent var	0.010323
Adjusted R-squared	0.662708	S.D. dependent var	0.023936
S.E. of regression	0.013901	Akaike info criterion	-5.674906
Sum squared resid	0.037488	Schwarz criterion	-5.543885
Log likelihood	581.1655	Hannan-Quinn criter.	-5.621895
F-statistic	57.41767	Durbin-Watson stat	2.019369
Prob(F-statistic)	0.000000		

(b) First Difference with Intercept

Null Hypothesis: D(LNCO2) has a unit root

Exogenous: Constant

Lag Length: 4 (Automatic based on SIC, MAXLAG=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.925074	0.0000
Test critical values:	1% level	-3.462737	
	5% level	-2.875680	
	10% level	-2.574385	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LNCO2,2)

Method: Least Squares

Date: 08/01/15 Time: 20:04

Sample (adjusted): 1961Q3 2011Q4

Included observations: 202 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNCO2(-1))	-0.226156	0.045919	-4.925074	0.0000
D(LNCO2(-1),2)	-0.080606	0.065106	-1.238083	0.2172
D(LNCO2(-2),2)	0.123063	0.064972	1.894099	0.0597
D(LNCO2(-3),2)	0.181906	0.065305	2.785502	0.0059
D(LNCO2(-4),2)	-0.299076	0.064671	-4.624600	0.0000
C	0.002777	0.001084	2.562949	0.0111

R-squared	0.318595	Mean dependent var	0.000522
Adjusted R-squared	0.301213	S.D. dependent var	0.016997
S.E. of regression	0.014208	Akaike info criterion	-5.640717
Sum squared resid	0.039568	Schwarz criterion	-5.542452
Log likelihood	575.7124	Hannan-Quinn criter.	-5.600959
F-statistic	18.32824	Durbin-Watson stat	2.018279
Prob(F-statistic)	0.000000		

Appendix 2: The ADF Unit Root Test on GDP

(a) Level Form with Trend and Intercept

Null Hypothesis: LNGDP has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 13 (Automatic based on SIC, MAXLAG=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.565632	0.9994
Test critical values:	1% level	-4.006059	
	5% level	-3.433156	
	10% level	-3.140406	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LNGDP)

Method: Least Squares

Date: 08/02/15 Time: 01:49

Sample (adjusted): 1963Q3 2011Q4

Included observations: 194 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNGDP(-1)	0.003432	0.006068	0.565632	0.5724
D(LNGDP(-1))	0.707207	0.073456	9.627613	0.0000
D(LNGDP(-2))	0.198565	0.085411	2.324810	0.0212
D(LNGDP(-3))	0.058188	0.086712	0.671049	0.5031
D(LNGDP(-4))	-0.992904	0.087001	-11.41258	0.0000
D(LNGDP(-5))	0.707934	0.109544	6.462571	0.0000
D(LNGDP(-6))	0.141624	0.111490	1.270286	0.2056
D(LNGDP(-7))	0.035066	0.111961	0.313203	0.7545
D(LNGDP(-8))	-0.669112	0.111629	-5.994085	0.0000

D(LNGDP(-9))	0.463559	0.109476	4.234347	0.0000
D(LNGDP(-10))	0.030069	0.087481	0.343717	0.7315
D(LNGDP(-11))	0.014984	0.087457	0.171332	0.8642
D(LNGDP(-12))	-0.405667	0.087210	-4.651621	0.0000
D(LNGDP(-13))	0.245193	0.073238	3.347914	0.0010
C	-0.078201	0.145844	-0.536199	0.5925
@TREND(1960Q1)	-1.36E-05	0.000132	-0.102828	0.9182

R-squared	0.676342	Mean dependent var	0.026199
Adjusted R-squared	0.649067	S.D. dependent var	0.029001
S.E. of regression	0.017180	Akaike info criterion	-5.211263
Sum squared resid	0.052537	Schwarz criterion	-4.941749
Log likelihood	521.4925	Hannan-Quinn criter.	-5.102129
F-statistic	24.79752	Durbin-Watson stat	1.966215
Prob(F-statistic)	0.000000		

(b) First Difference with Intercept

Null Hypothesis: D(LNGDP) has a unit root

Exogenous: Constant

Lag Length: 4 (Automatic based on SIC, MAXLAG=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.610294	0.0002
Test critical values:	1% level	-3.462737	
	5% level	-2.875680	
	10% level	-2.574385	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LNGDP,2)

Method: Least Squares

Date: 08/01/15   Time: 20:06

Sample (adjusted): 1961Q3 2011Q4

Included observations: 202 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNGDP(-1))	-0.281764	0.061116	-4.610294	0.0000
D(LNGDP(-1),2)	-0.013957	0.063013	-0.221498	0.8249
D(LNGDP(-2),2)	0.135057	0.062575	2.158328	0.0321
D(LNGDP(-3),2)	0.179274	0.062742	2.857301	0.0047
D(LNGDP(-4),2)	-0.470612	0.061247	-7.683882	0.0000
C	0.007410	0.001952	3.795452	0.0002

R-squared	0.488862	Mean dependent var	0.000365
Adjusted R-squared	0.475823	S.D. dependent var	0.025639
S.E. of regression	0.018562	Akaike info criterion	-5.106112
Sum squared resid	0.067534	Schwarz criterion	-5.007847
Log likelihood	521.7173	Hannan-Quinn criter.	-5.066354
F-statistic	37.49161	Durbin-Watson stat	2.053601
Prob(F-statistic)	0.000000		

Appendix 3: The ADF Unit Root Test on Population Growth

(a) Level Form with Trend and Intercept

Null Hypothesis: LNPOP has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 9 (Automatic based on SIC, MAXLAG=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.351915	0.4037
Test critical values:	1% level	-4.005076	
	5% level	-3.432682	
	10% level	-3.140127	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LNPOP)

Method: Least Squares

Date: 08/01/15 Time: 20:07

Sample (adjusted): 1962Q3 2011Q4

Included observations: 198 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNPOP(-1)	-0.016854	0.007166	-2.351915	0.0197
D(LNPOP(-1))	0.690749	0.057022	12.11369	0.0000
D(LNPOP(-2))	0.002953	0.015407	0.191661	0.8482
D(LNPOP(-3))	-0.023994	0.011065	-2.168538	0.0314
D(LNPOP(-4))	0.104816	0.009251	11.33055	0.0000
D(LNPOP(-5))	-0.083469	0.010920	-7.643836	0.0000
D(LNPOP(-6))	0.003367	0.009109	0.369634	0.7121
D(LNPOP(-7))	0.038784	0.008924	4.346114	0.0000

D(LNPOP(-8))	-0.140977	0.008956	-15.74057	0.0000
D(LNPOP(-9))	0.097184	0.009556	10.17020	0.0000
C	0.025959	0.011434	2.270397	0.0243
@TREND(1960Q1)	-5.84E-05	2.61E-05	-2.238496	0.0264

R-squared	0.921453	Mean dependent var	-0.000257
Adjusted R-squared	0.916808	S.D. dependent var	0.022588
S.E. of regression	0.006515	Akaike info criterion	-7.170690
Sum squared resid	0.007895	Schwarz criterion	-6.971401
Log likelihood	721.8983	Hannan-Quinn criter.	-7.090024
F-statistic	198.3658	Durbin-Watson stat	2.295605
Prob(F-statistic)	0.000000		

(b) First Difference with Intercept

Null Hypothesis: D(LNPOP) has a unit root

Exogenous: Constant

Lag Length: 9 (Automatic based on SIC, MAXLAG=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.121263	0.0000
Test critical values:	1% level	-3.463576	
	5% level	-2.876047	
	10% level	-2.574581	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNPOP,2)
Method: Least Squares
Date: 08/01/15 Time: 20:07
Sample (adjusted): 1962Q4 2011Q4
Included observations: 197 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNPOP(-1))	-0.243580	0.047563	-5.121263	0.0000
D(LNPOP(-1),2)	-0.197113	0.066016	-2.985841	0.0032
D(LNPOP(-2),2)	0.028542	0.025527	1.118130	0.2650
D(LNPOP(-3),2)	-0.012730	0.016250	-0.783348	0.4344
D(LNPOP(-4),2)	0.080595	0.012636	6.378412	0.0000
D(LNPOP(-5),2)	0.009232	0.012540	0.736252	0.4625
D(LNPOP(-6),2)	-0.013569	0.011929	-1.137457	0.2568
D(LNPOP(-7),2)	0.029410	0.010122	2.905588	0.0041
D(LNPOP(-8),2)	-0.105110	0.009539	-11.01851	0.0000
D(LNPOP(-9),2)	-0.034106	0.011707	-2.913336	0.0040
C	-0.000788	0.000477	-1.652795	0.1001

R-squared	0.795444	Mean dependent var	-0.000779
Adjusted R-squared	0.784446	S.D. dependent var	0.013887
S.E. of regression	0.006447	Akaike info criterion	-7.196092
Sum squared resid	0.007732	Schwarz criterion	-7.012766
Log likelihood	719.8150	Hannan-Quinn criter.	-7.121880
F-statistic	72.32851	Durbin-Watson stat	2.037375
Prob(F-statistic)	0.000000		

Appendix 4: The ADF Unit Root Test on Trade

(a) Level Form with Trend and Intercept

Null Hypothesis: LNTRD has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 9 (Automatic based on SIC, MAXLAG=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.319787	0.4209
Test critical values:	1% level	-4.005076	
	5% level	-3.432682	
	10% level	-3.140127	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LNTRD)

Method: Least Squares

Date: 08/01/15 Time: 20:08

Sample (adjusted): 1962Q3 2011Q4

Included observations: 198 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNTRD(-1)	-0.020360	0.008777	-2.319787	0.0214
D(LNTRD(-1))	0.714380	0.069138	10.33270	0.0000
D(LNTRD(-2))	0.216860	0.079959	2.712131	0.0073
D(LNTRD(-3))	0.068664	0.081506	0.842443	0.4006
D(LNTRD(-4))	-0.729513	0.082425	-8.850647	0.0000
D(LNTRD(-5))	0.523918	0.090355	5.798450	0.0000
D(LNTRD(-6))	0.100811	0.081203	1.241473	0.2160
D(LNTRD(-7))	0.023405	0.081719	0.286403	0.7749

D(LNTRD(-8))	-0.466356	0.085803	-5.435220	0.0000
D(LNTRD(-9))	0.322280	0.072905	4.420579	0.0000
C	0.033037	0.013066	2.528509	0.0123
@TREND(1960Q1)	0.000269	0.000124	2.166474	0.0315

R-squared	0.635150	Mean dependent var	0.009688
Adjusted R-squared	0.613573	S.D. dependent var	0.039026
S.E. of regression	0.024260	Akaike info criterion	-4.541307
Sum squared resid	0.109467	Schwarz criterion	-4.342018
Log likelihood	461.5894	Hannan-Quinn criter.	-4.460642
F-statistic	29.43626	Durbin-Watson stat	2.011820
Prob(F-statistic)	0.000000		

(b) First Difference with Intercept

Null Hypothesis: D(LNTRD) has a unit root

Exogenous: Constant

Lag Length: 8 (Automatic based on SIC, MAXLAG=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.989655	0.0018
Test critical values:	1% level	-3.463405	
	5% level	-2.875972	
	10% level	-2.574541	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LNTRD,2)

Method: Least Squares

Date: 08/01/15   Time: 20:09

Sample (adjusted): 1962Q3 2011Q4

Included observations: 198 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNTRD(-1))	-0.305564	0.076589	-3.989655	0.0001
D(LNTRD(-1),2)	0.024678	0.081930	0.301206	0.7636
D(LNTRD(-2),2)	0.234370	0.080861	2.898433	0.0042
D(LNTRD(-3),2)	0.291072	0.081762	3.559968	0.0005
D(LNTRD(-4),2)	-0.457829	0.082979	-5.517415	0.0000
D(LNTRD(-5),2)	0.060885	0.070575	0.862701	0.3894
D(LNTRD(-6),2)	0.159306	0.070652	2.254816	0.0253
D(LNTRD(-7),2)	0.179086	0.072341	2.475590	0.0142
D(LNTRD(-8),2)	-0.305946	0.073220	-4.178466	0.0000
C	0.002879	0.001870	1.540172	0.1252

R-squared	0.453041	Mean dependent var	-7.57E-06
Adjusted R-squared	0.426857	S.D. dependent var	0.032341
S.E. of regression	0.024484	Akaike info criterion	-4.532370
Sum squared resid	0.112704	Schwarz criterion	-4.366296
Log likelihood	458.7047	Hannan-Quinn criter.	-4.465149
F-statistic	17.30205	Durbin-Watson stat	2.002880
Prob(F-statistic)	0.000000		

Appendix 5: The PP Unit Root Test on CO2 Emissions

(a) Level Form with Trend and Intercept

Null Hypothesis: LNCO2 has a unit root

Exogenous: Constant, Linear Trend

Bandwidth: 9 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.862037	0.0005
Test critical values:	1% level	-4.003005	
	5% level	-3.431682	
	10% level	-3.139538	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000581
HAC corrected variance (Bartlett kernel)	0.002953

Phillips-Perron Test Equation

Dependent Variable: D(LNCO2)

Method: Least Squares

Date: 08/05/15 Time: 21:22

Sample (adjusted): 1960Q2 2011Q4

Included observations: 207 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNCO2(-1)	-0.068840	0.010497	-6.557905	0.0000
C	-0.042727	0.006410	-6.665372	0.0000
@TREND(1960Q1)	0.000879	0.000116	7.608604	0.0000
R-squared	0.253166	Mean dependent var	0.007981	

Adjusted R-squared	0.245844	S.D. dependent var	0.027962
S.E. of regression	0.024283	Akaike info criterion	-4.583708
Sum squared resid	0.120290	Schwarz criterion	-4.535408
Log likelihood	477.4138	Hannan-Quinn criter.	-4.564176
F-statistic	34.57659	Durbin-Watson stat	0.450730
Prob(F-statistic)	0.000000		

(b) First Difference with Intercept

Null Hypothesis: D(LNCO2) has a unit root

Exogenous: Constant

Bandwidth: 16 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.782760	0.0001
Test critical values:	1% level	-3.462095	
	5% level	-2.875398	
	10% level	-2.574234	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000248
HAC corrected variance (Bartlett kernel)	0.000152

Phillips-Perron Test Equation

Dependent Variable: D(LNCO2,2)

Method: Least Squares

Date: 08/05/15 Time: 21:25

Sample (adjusted): 1960Q3 2011Q4

Included observations: 206 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNCO2(-1))	-0.209312	0.039441	-5.306974	0.0000
C	0.002202	0.001145	1.922495	0.0559

R-squared	0.121311	Mean dependent var	0.000547
Adjusted R-squared	0.117003	S.D. dependent var	0.016832
S.E. of regression	0.015817	Akaike info criterion	-5.445814
Sum squared resid	0.051036	Schwarz criterion	-5.413504
Log likelihood	562.9188	Hannan-Quinn criter.	-5.432747
F-statistic	28.16398	Durbin-Watson stat	2.301173
Prob(F-statistic)	0.000000		

Appendix 6: The PP Unit Root Test on GDP

(a) Level Form with Trend and Intercept

Null Hypothesis: LNGDP has a unit root

Exogenous: Constant, Linear Trend

Bandwidth: 6 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-0.920345	0.9507
Test critical values:	1% level	-4.003005	
	5% level	-3.431682	
	10% level	-3.139538	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000823
HAC corrected variance (Bartlett kernel)	0.002305

Phillips-Perron Test Equation

Dependent Variable: D(LNGDP)

Method: Least Squares

Date: 08/05/15 Time: 21:27

Sample (adjusted): 1960Q2 2011Q4

Included observations: 207 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNGDP(-1)	-0.001073	0.007555	-0.142002	0.8872
C	0.028708	0.183003	0.156874	0.8755
@TREND(1960Q1)	0.000222	0.000175	1.269814	0.2056
R-squared	0.144764	Mean dependent var		0.023260

Adjusted R-squared	0.136379	S.D. dependent var	0.031090
S.E. of regression	0.028893	Akaike info criterion	-4.236068
Sum squared resid	0.170297	Schwarz criterion	-4.187767
Log likelihood	441.4330	Hannan-Quinn criter.	-4.216536
F-statistic	17.26526	Durbin-Watson stat	0.775583
Prob(F-statistic)	0.000000		

(b) First Difference with Intercept

Null Hypothesis: D(LNGDP) has a unit root

Exogenous: Constant

Bandwidth: 23 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-6.525951	0.0000
Test critical values:	1% level	-3.462095	
	5% level	-2.875398	
	10% level	-2.574234	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000524
HAC corrected variance (Bartlett kernel)	0.000458

Phillips-Perron Test Equation

Dependent Variable: D(LNGDP,2)

Method: Least Squares

Date: 08/05/15 Time: 21:29

Sample (adjusted): 1960Q3 2011Q4

Included observations: 206 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNGDP(-1))	-0.349080	0.051571	-6.768851	0.0000
C	0.008556	0.002000	4.277436	0.0000

R-squared	0.183403	Mean dependent var	0.000456
Adjusted R-squared	0.179400	S.D. dependent var	0.025396
S.E. of regression	0.023005	Akaike info criterion	-4.696522
Sum squared resid	0.107966	Schwarz criterion	-4.664213
Log likelihood	485.7418	Hannan-Quinn criter.	-4.683455
F-statistic	45.81734	Durbin-Watson stat	2.194506
Prob(F-statistic)	0.000000		

Appendix 7: The PP Unit Root Test on Population Growth

(a) Level Form with Trend and Intercept

Null Hypothesis: LNPOP has a unit root

Exogenous: Constant, Linear Trend

Bandwidth: 6 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.306829	0.0037
Test critical values:	1% level	-4.003005	
	5% level	-3.431682	
	10% level	-3.139538	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.007428
HAC corrected variance (Bartlett kernel)	0.018612

Phillips-Perron Test Equation

Dependent Variable: D(LNPOP)

Method: Least Squares

Date: 08/05/15 Time: 21:31

Sample (adjusted): 1960Q2 2011Q4

Included observations: 207 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNPOP(-1)	-0.073512	0.025242	-2.912233	0.0040
C	0.094768	0.037577	2.521969	0.0124
@TREND(1960Q1)	-0.000112	0.000114	-0.981920	0.3273

R-squared	0.040787	Mean dependent var	-0.004207

Adjusted R-squared	0.031383	S.D. dependent var	0.088210
S.E. of regression	0.086815	Akaike info criterion	-2.035688
Sum squared resid	1.537517	Schwarz criterion	-1.987387
Log likelihood	213.6937	Hannan-Quinn criter.	-2.016155
F-statistic	4.337193	Durbin-Watson stat	0.628606
Prob(F-statistic)	0.014300		

(b) First Difference with Intercept

Null Hypothesis: D(LNPOP) has a unit root

Exogenous: Constant

Bandwidth: 16 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-6.130086	0.0000
Test critical values:	1% level	-3.462095	
	5% level	-2.875398	
	10% level	-2.574234	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.004076
HAC corrected variance (Bartlett kernel)	0.001260

Phillips-Perron Test Equation

Dependent Variable: D(LNPOP,2)

Method: Least Squares

Date: 08/05/15 Time: 21:32

Sample (adjusted): 1960Q3 2011Q4

Included observations: 206 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNPOP(-1))	-0.354522	0.050671	-6.996528	0.0000
C	1.98E-05	0.004475	0.004431	0.9965

R-squared	0.193521	Mean dependent var	0.001520
Adjusted R-squared	0.189568	S.D. dependent var	0.071261
S.E. of regression	0.064152	Akaike info criterion	-2.645460
Sum squared resid	0.839559	Schwarz criterion	-2.613151
Log likelihood	274.4824	Hannan-Quinn criter.	-2.632393
F-statistic	48.95140	Durbin-Watson stat	1.883849
Prob(F-statistic)	0.000000		

Appendix 8: The PP Unit Root Test on Trade

(a) Level Form with Trend and Intercept

Null Hypothesis: LNTRD has a unit root

Exogenous: Constant, Linear Trend

Bandwidth: 8 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.816696	0.1930
Test critical values:	1% level	-4.003005	
	5% level	-3.431682	
	10% level	-3.139538	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.001495
HAC corrected variance (Bartlett kernel)	0.005353

Phillips-Perron Test Equation

Dependent Variable: D(LNTRD)

Method: Least Squares

Date: 08/05/15 Time: 21:33

Sample (adjusted): 1960Q2 2011Q4

Included observations: 207 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNTRD(-1)	-0.026462	0.011144	-2.374530	0.0185
C	0.044378	0.018051	2.458446	0.0148
@TREND(1960Q1)	0.000389	0.000153	2.538664	0.0119
R-squared	0.030762	Mean dependent var	0.007810	

Adjusted R-squared	0.021259	S.D. dependent var	0.039364
S.E. of regression	0.038943	Akaike info criterion	-3.639047
Sum squared resid	0.309378	Schwarz criterion	-3.590747
Log likelihood	379.6414	Hannan-Quinn criter.	-3.619515
F-statistic	3.237289	Durbin-Watson stat	0.651610
Prob(F-statistic)	0.041296		

(b) First Difference with Intercept

Null Hypothesis: D(LNTRD) has a unit root

Exogenous: Constant

Bandwidth: 11 (Newey-West using Bartlett kernel)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-6.202480	0.0000
Test critical values:	1% level	-3.462095	
	5% level	-2.875398	
	10% level	-2.574234	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000836
HAC corrected variance (Bartlett kernel)	0.000746

Phillips-Perron Test Equation

Dependent Variable: D(LNTRD,2)

Method: Least Squares

Date: 08/05/15 Time: 21:34

Sample (adjusted): 1960Q3 2011Q4

Included observations: 206 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNTRD(-1))	-0.330555	0.051446	-6.425234	0.0000
C	0.002830	0.002064	1.370718	0.1720

R-squared	0.168310	Mean dependent var	0.000215
Adjusted R-squared	0.164233	S.D. dependent var	0.031773
S.E. of regression	0.029047	Akaike info criterion	-4.230169
Sum squared resid	0.172116	Schwarz criterion	-4.197860
Log likelihood	437.7074	Hannan-Quinn criter.	-4.217102
F-statistic	41.28363	Durbin-Watson stat	2.173700
Prob(F-statistic)	0.000000		

Appendix 9: Optimal Lag Selection in Co-integrated VAR Model

VAR Lag Order Selection
Criteria
Endogenous variables: LNCO2 LNGDP
LNPOP LNTRD
Exogenous variables: C
Date: 08/01/15 Time: 20:14
Sample: 1960Q1 2011Q4
Included observations: 198

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-43.80588	NA	1.90e-05	0.482888	0.549317	0.509776
1	1801.560	3597.532	1.80e-13	-17.99556	-17.66341	-17.86112
2	2073.253	518.6866	1.36e-14	-20.57831	-19.98045*	-20.33632
3	2080.309	13.18456	1.49e-14	-20.48797	-19.62438	-20.13842
4	2084.081	6.897168	1.69e-14	-20.36446	-19.23515	-19.90735
5	2150.627	118.9750	1.01e-14	-20.87502	-19.47999	-20.31036
6	2215.842	113.9628	6.18e-15	-21.37214	-19.71140	-20.69993
7	2220.626	8.166156	6.94e-15	-21.25885	-19.33239	-20.47908
8	2226.608	9.969474	7.71e-15	-21.15765	-18.96548	-20.27033
9	2302.878	124.0361	4.21e-15	-21.76645	-19.30855	-20.77157
10	2385.779	131.4684*	2.16e-15*	-22.44221*	-19.71859	-21.33978*

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5%
level)
FPE: Final prediction error
AIC: Akaike information
criterion
SC: Schwarz information
criterion
HQ: Hannan-Quinn information criterion

Appendix 10: Johansen Co-integration Test

Date: 08/01/15 Time: 20:23

Sample (adjusted): 1960Q4 2011Q4

Included observations: 205 after adjustments

Trend assumption: Linear deterministic trend

Series: LNCO2 LNGDP LNPOP LNTRD

Lags interval (in first differences): 1 to 2

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.234247	75.18367	47.85613	0.0000
At most 1	0.067286	20.46994	29.79707	0.3915
At most 2	0.018794	6.190413	15.49471	0.6730
At most 3	0.011162	2.301037	3.841466	0.1293

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.234247	54.71373	27.58434	0.0000
At most 1	0.067286	14.27953	21.13162	0.3425
At most 2	0.018794	3.889376	14.26460	0.8708
At most 3	0.011162	2.301037	3.841466	0.1293

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

LNCO2	LNGDP	LNPOP	LNTRD
-2.572271	0.308668	-5.901179	0.137087
7.233838	-2.410998	-0.732014	-2.147328
1.309479	-1.287146	-0.303209	2.045685
-0.143412	-1.805712	0.514594	2.356774

Unrestricted Adjustment Coefficients (alpha):

D(LNCO2)	0.000108	-0.003292	-0.000492	-0.000835
D(LNGDP)	-0.000223	-0.000276	0.002333	-0.001540
D(LNPOP)	0.029869	-1.16E-06	-0.000569	-0.000909
D(LNTRD)	-0.000740	0.004358	-0.001768	-0.002037

1 Cointegrating Equation(s):	Log likelihood	1800.989

Normalized cointegrating coefficients (standard error in parentheses)

LNCO2	LNGDP	LNPOP	LNTRD
1.000000	-0.119998	2.294152	-0.053294
	(0.10624)	(0.29461)	(0.16954)

Adjustment coefficients (standard error in parentheses)

D(LNCO2)	-0.000277
	(0.00283)
D(LNGDP)	0.000572
	(0.00413)
D(LNPOP)	-0.076831
	(0.01010)
D(LNTRD)	0.001904
	(0.00528)

2 Cointegrating Equation(s):		Log likelihood	1808.129
Normalized cointegrating coefficients (standard error in parentheses)			
LNCO2	LNGDP	LNPOP	LNTRD
1.000000	0.000000	3.641746	0.083725
		(0.46659)	(0.14339)
0.000000	1.000000	11.23013	1.141842
		(1.67778)	(0.51559)
Adjustment coefficients (standard error in parentheses)			
D(LNCO2)	-0.024091	0.007970	
	(0.00826)	(0.00261)	
D(LNGDP)	-0.001423	0.000596	
	(0.01234)	(0.00391)	
D(LNPOP)	-0.076839	0.009222	
	(0.03015)	(0.00955)	
D(LNTRD)	0.033427	-0.010735	
	(0.01558)	(0.00493)	

3 Cointegrating Equation(s):		Log likelihood	1810.074
Normalized cointegrating coefficients (standard error in parentheses)			
LNCO2	LNGDP	LNPOP	LNTRD
1.000000	0.000000	0.000000	-1.238154
			(0.27186)
0.000000	1.000000	0.000000	-2.934461
			(0.81244)
0.000000	0.000000	1.000000	0.362979
			(0.08186)
Adjustment coefficients (standard error in parentheses)			
D(LNCO2)	-0.024735	0.008603	0.001924
	(0.00837)	(0.00296)	(0.00640)
D(LNGDP)	0.001632	-0.002406	0.000808
	(0.01245)	(0.00440)	(0.00951)
D(LNPOP)	-0.077584	0.009954	-0.176089
	(0.03059)	(0.01080)	(0.02338)
D(LNTRD)	0.031112	-0.008459	0.001713
	(0.01578)	(0.00557)	(0.01206)

Appendix 11: Vector Error Correction Model (VECM) Estimation

Vector Error Correction Estimates

Date: 08/01/15 Time: 21:27

Sample (adjusted): 1960Q4 2011Q4

Included observations: 205 after adjustments

Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1			
LNCO2(-1)	1.000000			
LNGDP(-1)	-0.119998			
	(0.10624)			
	[-1.12948]			
LNPOP(-1)	2.294152			
	(0.29461)			
	[7.78717]			
LNTRD(-1)	-0.053294			
	(0.16954)			
	[-0.31434]			
C	0.036996			
Error Correction:	**D(LNCO2)**	**D(LNGDP)**	**D(LNPOP)**	**D(LNTRD)**
CointEq1	-0.000277	0.000572	-0.076831	0.001904
	(0.00283)	(0.00413)	(0.01010)	(0.00528)
	[-0.09775]	[0.13849]	[-7.60535]	[0.36043]
D(LNCO2(-1))	0.625529	0.017135	0.166085	-0.006994
	(0.07292)	(0.10639)	(0.26004)	(0.13595)
	[8.57880]	[0.16107]	[0.63870]	[-0.05145]

D(LNCO2(-2))	0.167132	0.083180	0.471871	0.025247
	(0.07349)	(0.10722)	(0.26208)	(0.13702)
	[2.27421]	[0.77576]	[1.80046]	[0.18425]
D(LNGDP(-1))	0.000997	0.525784	0.058432	-0.015330
	(0.04985)	(0.07273)	(0.17777)	(0.09294)
	[0.02000]	[7.22947]	[0.32870]	[-0.16495]
D(LNGDP(-2))	-0.003181	0.096972	0.120453	-0.043375
	(0.04970)	(0.07251)	(0.17724)	(0.09266)
	[-0.06400]	[1.33733]	[0.67961]	[-0.46809]
D(LNPOP(-1))	0.003412	0.009373	0.595178	0.003647
	(0.01772)	(0.02586)	(0.06321)	(0.03305)
	[0.19251]	[0.36246]	[9.41645]	[0.11035]
D(LNPOP(-2))	0.015576	0.006221	0.055945	-0.006568
	(0.01805)	(0.02633)	(0.06436)	(0.03365)
	[0.86312]	[0.23626]	[0.86926]	[-0.19520]
D(LNTRD(-1))	0.005037	0.000882	0.018450	0.578742
	(0.03838)	(0.05599)	(0.13686)	(0.07155)
	[0.13124]	[0.01575]	[0.13481]	[8.08822]
D(LNTRD(-2))	0.009843	0.021473	0.076553	0.127623
	(0.03828)	(0.05585)	(0.13651)	(0.07137)
	[0.25715]	[0.38448]	[0.56080]	[1.78820]
C	0.002382	0.008473	-0.009145	0.003851
	(0.00151)	(0.00220)	(0.00538)	(0.00281)
	[1.57828]	[3.84697]	[-1.69870]	[1.36813]
R-squared	0.658718	0.444851	0.553902	0.458411

Adj. R-squared	0.642967	0.419229	0.533313	0.433414
Sum sq. resids	0.048481	0.103204	0.616583	0.168539
S.E. equation	0.015768	0.023005	0.056231	0.029399
F-statistic	41.81951	17.36188	26.90265	18.33906
Log likelihood	564.9516	487.5085	304.2913	437.2367
Akaike AIC	-5.414162	-4.658620	-2.871135	-4.168163
Schwarz SC	-5.252064	-4.496521	-2.709037	-4.006065
Mean dependent	0.008928	0.024049	-0.000989	0.008424
S.D. dependent	0.026388	0.030188	0.082312	0.039057

Determinant resid covariance (dof adj.)	3.36E-13
Determinant resid covariance	2.75E-13
Log likelihood	1800.989
Akaike information criterion	-17.14136
Schwarz criterion	-16.42813

Appendix 12: Granger Causality Test

Pairwise Granger Causality Tests

Date: 08/02/15 Time: 02:44

Sample: 1960Q1 2011Q4

Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
DLNGDP does not Granger Cause DLNCO2	205	0.00715	0.9929
DLNCO2 does not Granger Cause DLNGDP		1.52310	0.2206
DLNPOP does not Granger Cause DLNCO2	205	0.18427	0.8319
DLNCO2 does not Granger Cause DLNPOP		0.01454	0.9856
DLNTRD does not Granger Cause DLNCO2	205	1.03204	0.3582
DLNCO2 does not Granger Cause DLNTRD		0.42576	0.6539
DLNPOP does not Granger Cause DLNGDP	205	0.25908	0.7720
DLNGDP does not Granger Cause DLNPOP		0.15259	0.8586
DLNTRD does not Granger Cause DLNGDP	205	0.56773	0.5677
DLNGDP does not Granger Cause DLNTRD		0.03390	0.9667
DLNTRD does not Granger Cause DLNPOP	205	0.00445	0.9956
DLNPOP does not Granger Cause DLNTRD		0.04888	0.9523