LUND UNIVERSITY
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Master in Economic Development and Growth

Long Run Emission-Growth Nexus: An Empirical Evidence

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Abstract: This study presents an empirical investigation of i) testing the Granger Causality between economic growth and aggregated carbon dioxide (CO_2) emission; and economic growth and disaggregated CO_2 emission from burning fossil fuel coal, oil and natural gas respectively; ii) the potential impact on economic growth if countries substitute CO_2 emission from dirty energy, coal, by emission from relatively cleaner energy oil and natural gas. I undertake panel analysis of 30 countries and separate time series analysis for China, United States and United Kingdom during 1960-2010 sample years. The causal relationship between variables has been examined by using a VAR in first differences framework. The results from panel countries show 'Feedback' relationship in all cases except an 'Unidirectional' causality running from economic growth to CO_2 emission from coal. In country level analysis, there is no evidence of causality between economic growth and aggregated emission, whereas a significant 'Unidirectional' causality has been found running from economic growth to emission from coal in highest emitter China and United States. This relevant and expected finding imply that higher GDP growth in China and United States cause higher emission in environment, however, we do not find such relationship for the case of United Kingdom. Utilizing Wald test with linear restriction I found that countries will be environmentally benefited, if they substitute emission from coal by that of oil and natural gas, as if they substitute coal consumption by oil and natural gas consumption. But how much GDP would have to forgo for substituting coal by oil and natural gas is a matter of conflict between capitalists and environmentalists and therefore, deserve further research.

Key words: CO_2 Emission, economic growth, Granger causality, substitution

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Chapter 1

Introduction

1.1 Background

In the recent years, concerned with the increasing environmental degradation, researchers and policy makers are specially receiving attention to examine the nature and direction of causality between economic activity (GDP or growth) and environmental indicators (emission or pollutants). There is large and growing literature in testing the energy-GDP causality, but insignificant numbers in testing emission-growth causality. In existing literature, there are three strands of research. The first strand empirically tested the Environmental Kuznets Curve (EKC) hypothesis (Grossman and Krueger, 1995; Shafik and Bandyopadhyay, 1992; Arrow et el., 1995 etc.). In EKC analysis it is mainly presumed that there is unidirectional causality between income and emission implying income causes environmental change and not the other way around. The second strand examines the emission-growth causality in cross-section perspective. And the third strand combines EKC and causality analysis. In the study of long time series, the causality can be of three types: unidirectional, feedback (or bidirectional) and no causality. A unidirectional causality running from GDP to emission is generally interpreted as economic growth may increase CO_2 emission in environment over time, whereas causation running in opposite direction may imply higher environmental emission lowers economic growth. The feedback causation refers to the mutual interdependence between economic growth and emission. No causal link may indicate that economic growth has no impact on emission or environmental quality is independent of economic activities. However, it is very difficult to make policy decision based on the causality analysis between economic growth and aggregated emission data. Since different fossil fuels emit particulate at different levels, a disaggregated emission data might be more reasonable to examine. For example, one mega joule of coal emits 92 gram CO_2 whereas oil and natural gas produce 74 and 56 gram CO_2/MJ (Levander, 1990). So, it is needed to explore the long run causality between single emission type and economic growth to design the policy for 'electrification', 'oil economy' or 'green economy'.

Almost all research in emission-growth nexus studied the total CO_2 emission and it's association and causality with economic growth. However, total CO_2 emission is the summation of emission from different sources of energy usage (e.g. coal, oil, natural gas etc.). Unless using disaggregated emission series, it would be difficult to decide the policy from causality analysis about the effect of emission from single energy type on economic growth. Bruns and Gross (2013) explained the necessity and implication of the causality between economic growth and single energy type. It is important to have perfect understanding of the nature of cauality between economic growth and emission from single energy type to give the policy for carbon-tax or other emission-tax.

Once examined the causality between emission type and growth, it might be interesting to know if there is any possibility to substitute CO_2 emission in long run from different fossil fuel combustion. As natural gas and oil emit less pollutant than coal, will it be more environmentally healthy if economic system substitute more gas and oil for coal? This is an interesting question to examine. However, the substitution between coal, oil and gas can depend on many other factors such as price, energy content, availability and respective usability. Therefore, under certain assumption of constant relative price of energy and availability; and concerned with the environmentally sustainable development, one possible way would be looking at the effect of substitution between CO_2 emission from coal, oil and gas on economic growth. More explicitly, what will be the long run economic growth if we substitute relatively dirty energy with more clean energy. In fact this issue is completely silent in literature, whether the understanding of substitutability between emission types might be important to take policies.

Hence the empirically testable hypotheses for this study are:

Hypothesis 1: Total emission and emission type do not Granger cause economic growth

Hypothesis 2: The substitution between CO_2 emissions by energy type (dirty to clean) has significant impact in long run environmentally sustainable economic growth.

1.2 Different Extent of Emission: Coal, Oil and Gas

The choice of energy source and amount of energy consumption determine the extent of greenhouse gas emission in environment. Combustion of all fossil fuels emit some CO_2 in atmosphere, but different types of fossil fuel have different amount of net CO_2 (Table 1). Hence, the switch of energy choice from highest emitter to lowest emitter i.e. *decarbonization* could be an environmental friendly option. Theoretically, decarbonisation is a good policy but, it is necessary to think critically and realistically how society can adopt this endeavour (Pielke, 2009). It is important to mention here that, wood, food, fodder etc. also emits CO_2 but it has been absorbed by the environment through photosynthesis process. The standard process of greenhouse gas estimation only includes coal, oil and natural gas (sometimes peat, but it is debateable since peat is a semi-fossil fuel) (IPCC, 2005). Also, collection and calculation of CO_2 with much precision at national and global level is difficult. There is 6-10% uncertainty in annual CO_2 data calculation (Marland and Rotty, 1984).

Table1: CO_2 emission from different energy types

Fossil Type	Energy type	CO_2 emission(gram CO_2/MJ)
Solid	Coal	92
Liquid	Oil	74
Gaseous	Natural gas	56

Source: Levander, 1990

1.3 CO_2 Emission: Recent Pictures

Increased emission of CO_2 in atmosphere and its impact on global climate change has been made growing concern among policy makers, environmentalist, scientists and international parties. In 2010, world CO_2 emission has increased by 4.6% or 1.3 $GtCO_2$

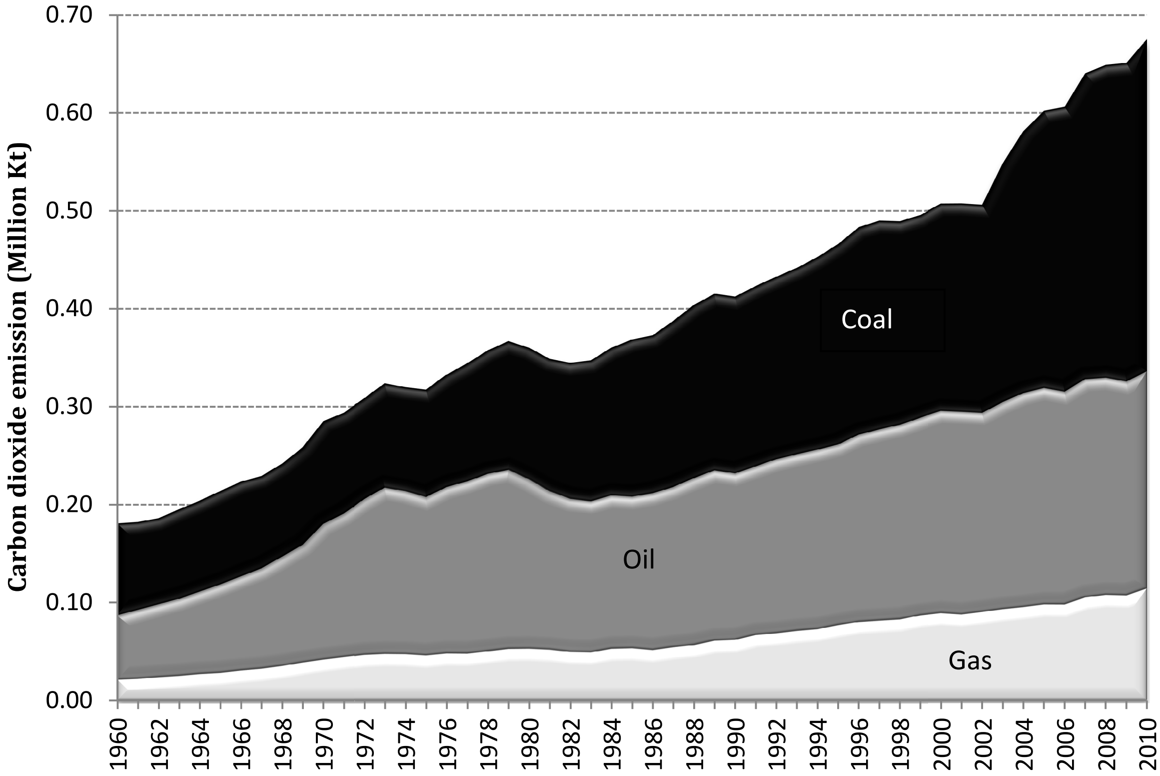
(IEA, 2012); the emission has declined during financial crisis in Western Europe but not in developing countries. Countries of Latin America, Asia and China emit much CO_2 (6%-6.5%), whereas industrialized OECD countries emit moderately (3.3%) and improvement in African countries (-0.1%). The recent IEA statistics reports that CO_2 emission from fossil fuel combustion differs across region, industrialized OECD countries rise emission from coal and gas at almost similar rate, whereas, in developing countries the source of emission growth varies significantly by fuel type: coal(50%), oil (25%) and natural gas (23%). As population rises, higher demand for fossil fuel in major developing countries makes the emission rate faster than industrialized OECD countries. Altogether, China and United States give off 41.5% percent of total world emission.

The Figure 1 shows that the total global (average of total emission of sample country over time period) emission from different energy sources has increasing trend during 1960-2010. Over the time period, coal was the driver of global emission growth. There was noticeable decline in emission from coal and oil in the beginning of 1980s. But it continued to grow following the industrial development in OECD and the then higher income coutries. The emission from all sources has short term decline during the financial crisis in 2009, but it followed its previous trend in 2010 and continuing.

Historically, the early industrialized countries have emitted large amount of CO_2 in environment. Recently, most of these countries (Australia and European countries)have curbed their emission following the commitment of Kyoto Protocol. Whereas the uprising developing countries from Asia and Latin America are emiiting CO_2 without binding the target of Kyoto Protocol. United States, the signatory parties of this environmetnal protocol is not complying with the Kyoto further targets, whereas Canada denounced the treaty. Therefore, United States, Canada and some group of developing countries is becoming the top emitter in recent time and are predicted to continue with high emission growth.

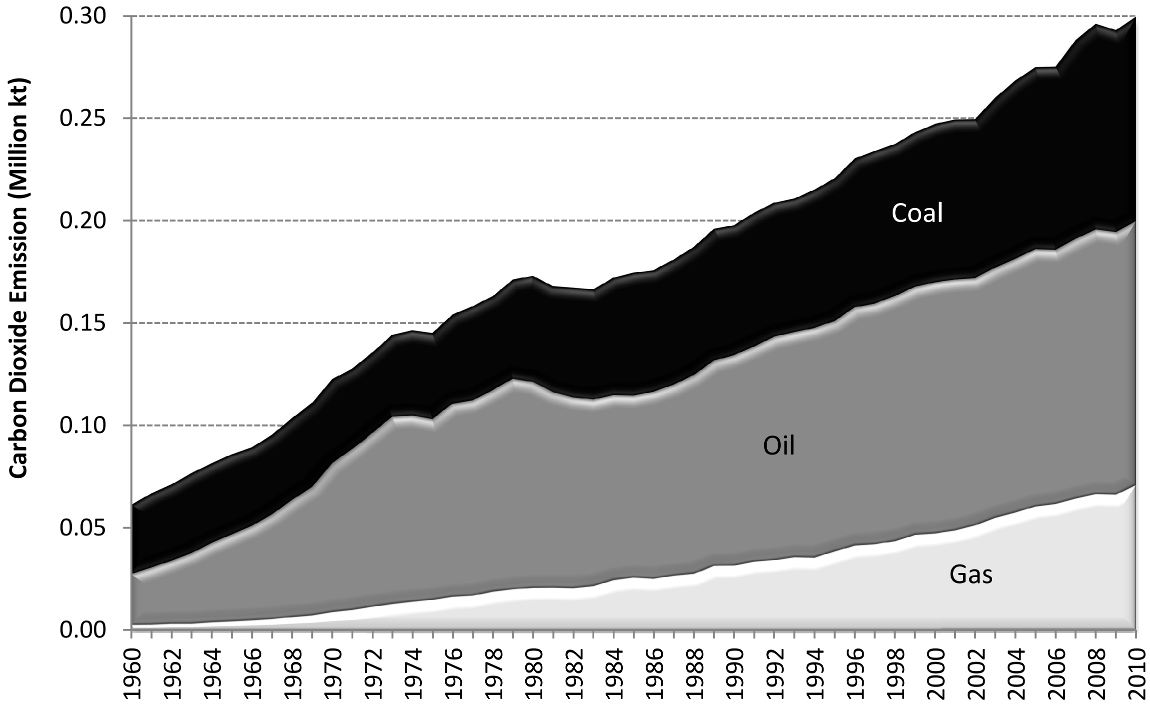
Following Figure 1 and 2 represents the average CO_2 emission from coal, oil and natural gas of sample countries. Figure 2 excludes the country China, United States and United Kingdom while calculating the world average.

Figure 1: CO_2 emission by energy type, average of whole sample (33 countries)



Source: Based on data from World Bank (2014)

Figure 2: Carbon Dioxide Emission by energy source, world average (excluding China, USA and UK)



Source: Based on data from World Bank (2014)

Figure 1 portrays that the world average emission was nearly 0.7 million kt (in 2010) whereas Figure 2 shows it is 0.3 million kt without including China, United States and United Kingdom; which is more than two times lower than world average (including China, US and UK). Therefore, the main contributor to global emission is China and United States. The spur growth of Chinese economy in last three decades has accelerated the share of Chinese emission and it has raised the global conern.

1.4 Outline of the thesis

After describing the introduction and hypothesis, the research proceeds as follows. Chapter 2 describes the theory related to environment and economic growth and empirical evidences of those theories focusing on CO_2 emission. Chapter 3 provides the data and variable details. Chapter 4 lays out the empirical methodology applied in this study. Chapter 5 describes the empirical results for panel countries whereas chapter 6 gives the discussion for China, United States and United Kingdom. Chapter 7 presents a brief discussion and implication of the main results. Finally, chapter 8 concludes the findings and limitation of this research.

Chapter 2

Theory of Environment and Growth

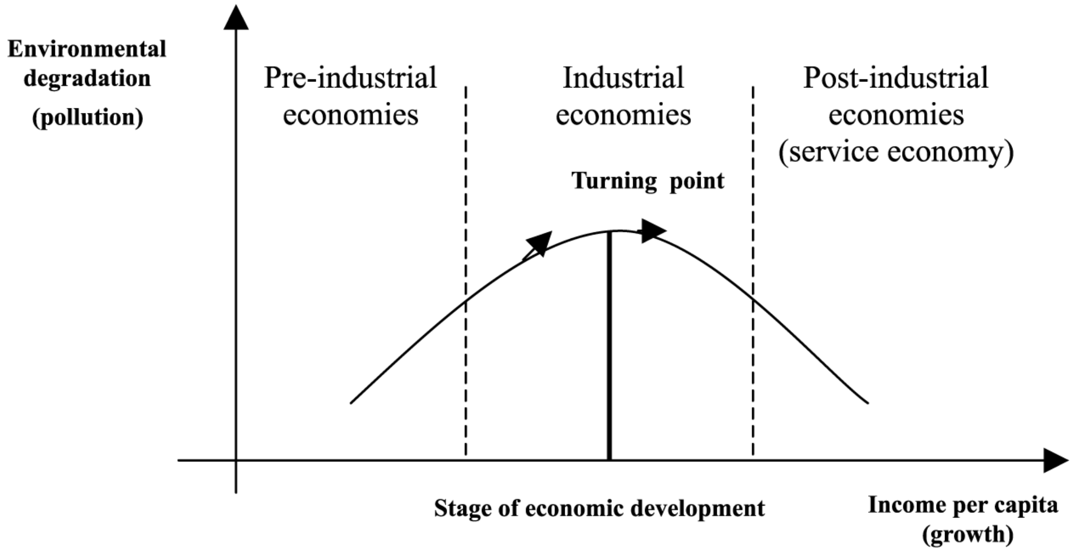
2.1 Environmental Kuznets Curve (EKC)

What is the relationship between environment and economic growth- is being intensively studied in literature. Many scholars warn that continuous environmental pollution will put the sustainable economic growth at risk. As Daly (1977) wrote

> "*Increased extraction of natural resources, accumulation of waste and concentration of pollutants will therefore overwhelm the carrying capacity of the biosphere and result in the degradation of environmental quality and a decline in human welfare, despite rising incomes*."

The well-known paradigm of growth-environment theory is the Environmental Kuznets Curve (EKC), akin to the inverse relation of income and inequality by Kuznets (1955). It postulates an inverted *U*-shaped hypothesis between level of economic activity and environmental degradation. In pre-industrial subsistence economy, environment can naturally adjust the limited quantity of waste. With the initiation of rapid industrialization, resource extraction and depletion escalate, waste disposal expedite. In post-industrial economy, structural transformation from manufacturing sector to service sector, increased demand and affordability of efficient clean technology result in slowdown of environmental decay. So, environmental degradation increases with the rapid industrialization, reaches a turning point with certain income level and start declining with the technological development and transition to service economy. This relationship between economic growth and environmental degradation takes a inverted U-shaped curve. Following Figure 3 represents the EKC.

Figure 3: A representative Environmental Kuznets Curve (EKC)



Source: Panayotou (1993), Working Paper WP238, International Labour Organization (ILO)

The empirical models of economic growth mainly underpin some particular issue. Firstly, does the EKC hypothesis exists in reality? There are a sizeable number of literatures on the debate of economic growth – environmental quality issue. The inherent rationale of EKC hypothesis is intuitively pleading. In pre-development stage people are poor enough to pay for environmental regulatory cost and/or unaware about better environmental quality. In development stage and later, when income exceeds a certain level, people demand environment friendly product, institutions become active, regulations become strict and consequently environmental degradation reduces. However, the straightforward declining EKC relation is very scant in empirical research because there are many important factors which may monotonically increase the relation (Ekins, 1997). In the existence of monotonically increasing relation, a set environmental regulation and planned limit on growth rate may be required for attaining sustainable economic growth (Panayotou, 1993, Ch 2).

An early pioneering research by Grossman and Krueger (1995) found no evidence that economic growth can cause harm to environmental species. Instead they found growth-environment relation may vary from country to country, GDP can worse the environmental conditions in very poor countries and environmental component can get some positive change if certain income level e.g. $8000 (1985 USD) has been reached.

Shafik and Bandyopadhyay (1992) hypothesized the same as Grossman and Krueger (1995), the sign of growth-environment relationship may change from positive to negative, if the country achieves a certain income level by which they can manage to bear the clean technology. A strong opposite findings against EKC proposition is also present in literature. Beckerman (1992), Bhagawati (1993), Panayotou (1993) and others argued that higher economic growth may trim environmental quality particularly in developing countries and thus growth might be a prerequisite for good environmental condition. Before any effective environmental policy, it is required to have enough understanding of nature and causal relationship between economic growth and environmental quality (Coondoo and Dinda, 2002).

2.2 EKC for CO_2: Empirical evidence

The global warning problem makes the scientists, policy makers and environmentalists extremely concerned with the CO_2 emission. On international consensus 'Kyoto Protocol' industrialized countries agreed to reduce five percent greenhouse gas emission based on 1990 emission; developing countries has not made any commitment to reduce emission though. From the international policy to empirical research, there is long debate on about the relationship between economic growth and environmental quality. Since CO_2 emission is global phenomenon and its important impact on global warming make itself interesting topic to research. However, the well known EKC hypothesis i.e. the inverted U shaped curve between economic growth and CO_2 emission in particular results different shapes.

Holtz-Eakin and Selden (1995) have shown the diminishing marginal propensity to emit (MPE) CO_2 against increase in GDP per capita. But observing the recent increase in CO_2 emission they predict emission will continue to grow with higher MPE (1.8 percent per annum) until 2025, because of a higher increase in population and output in developing countries. There is U-shaped curve between sever air pollutants and growth (Selden and Song, 1995). Friedl and Getzner (2003) does not find the U-shaped EKC, rather they found a cubic (N-shaped) relation between GDP and CO_2 in Austria. Shafik and Bandyopadhyay (1992) claim that CO_2 emission increase with income, but no one suggests that an inverted U-shaped curve applies for greenhouse gases. Halkos and

Tsionas (2001) found a monotonic relationship between environmental degradation and income level which eventually rejects the existence of an EKC. For large panel countries, Galeotti and Lanza (1999) also found declining MPE but forecast that future average world emission will be rising (2.2% between 2000 and 2020).

Neumayer (2002) examines the role of natural factors (difference in climatic condition, fossil fuel, renewable energy, transportation requirements etc.) and found, along with main variable income, natural factors significantly explain cross country differences in CO_2 emission. For example, Russia, with extensive transportation, adequate fossil fuel, low temperature but few renewable resources have higher CO_2 emission than Ethiopia which has less transportation network, few fossil fuel but rich renewable resource. Moreover, a massive difference in natural factors might imply a substantial difference in predicted emission for different economies even at the same level of income.

Using a new econometric technique (Pooled Mean Group), Martinez-Zarzoso and Bengochea-Morancho (2004) points to the existence of a N-shaped EKC in most of the OECD countries. A quadratic specification results in turning points between $4914 and $18,364 predicts and a cubic specification predicts decline in CO_2 emission up to a certain level of income and then it would follow an increase of pollution at higher income.

Although not unanimous, but the EKC hypothesis is almost confirmed for the other pollutants, water and land use etc. but the evidence regarding CO_2 emission in still ambiguous (Friedl and Getzner, 2003). The empirical proof of U-shaped curve for CO_2 emission might have less possibility than usual pollutants (SO_2, NO_x etc.) because of its nature. The usual pollutants have local environmental effect whereas, CO_2 has a global impact to increase greenhouse gas. Consequently, a free rider behaviour can push the relation more close at different levels of per capita income (Arrow et al., 1995).

Stern (2004) detailed a nice presentation of EKC development and its backsides. He highlighted EKC becomes questionable in the ground of statistical properties of used data. Most EKC literature lacks in econometric analysis, in particular cointegration (Stern, 2004), heterosecdasticity (Stern et al., 1996), simultaneity (Cole et al., 1997) and omitted variable bias (Stern and Common, 2001). Stern (2004) and Stern (1998) strictly criticized the EKC literature and found that it is not a robust method in statistical and econometric background. Moreover, even using same pollutant, researchers found different result from different transformation of data (levels, log, first difference etc.) and estimation methods (Ekins, 1997). He suggested examining the relationship by using more rigorous time series or panel data models and new generation decomposition analysis.

The theoretical aspects of EKC hypothesis seem easy to interpret under certain assumptions, but persuasive empirical evidence becomes challenging at least for CO_2 emission and growth. However, at least for the case of CO_2, the EKC hypothesis is more descriptive, so a historical time series analysis is more accountable for environmental policy and external shocks (Stern et al., 1996). Hence for more generalization, a panel approach seems more promising.

2.3 Energy Transition and Environmental Quality

Energy transition in recent period is one of the factors that cause the downward slope of the EKC after turning point. Other determinants may include structural change, service economy, technological improvement, energy savings technique etc. Historically, a long energy transition has been occurred in last 200 years (Gales et al., 2007). The usage of water, wind and draft animal as traditional way has been totally disappeared. The usages of human muscle and firewood as a traditional energy source has declined significantly, it is still used in rural area. Since industrial revolution period, consumption of coal and oil has been radically increased. After oil crisis in 1970s, the choice of energy consumption has become diverse, for example, Netherlands become gas-dependent, Sweden goes for nuclear electricity, Italy increased gas consumption significantly, Spain turns back to coal consumption for producing electricity (Gales et al., 2007).

European countries are now turning their energy consumption from coal, oil to natural gas. The dependency of European countries on gas consumption is noticeable, it accounts 25% of primary energy demand (Weijermars et al., 2011).

Oil is the other prime source in global energy system. Szklo and Schaeffe (2006) highlighted the role of alternative energy source, i.e. it is crucial to include oil in the energy equation which describes the decarbonisation economy. According to them,

> "*When mingled with oil, these so-called alternative sources gain through technological learning curves, in parallel to economies of integration, scope and scale, and do not run up against the technological curbs imposed by the existing infrastructure in the global energy system. At the same time, the integration of oil with alternative sources will definitively reduce the market power that light crude oil producers currently have in the international market, also benefiting the energy transition.*"

China and India, two highly populated countries are now demanding large amount of energy both in industrial production and household consumption. According to IEA (2007) forecast, global energy demand will rise by 50% between 2005 and 2030 and more than 45% increase will come from China and India alone. Pachauri and Jiang (2008) evaluate the pattern of energy transition in households of China and India. They found Chinese urban households (77%) demands mostly liquid fuels and grids for household consumption whereas, 10 % rural Indian households still lacks in access to modern energy and 65% of urban household demands.

With the impact of urbanization and industrialization effect, a shift from traditional fuel consumption to modern fossil fuel consumption has become one of the important factors explaining economic growth. In developing countries, people mainly use traditional biomass fuel for household consumption. Of total energy consumption, it accounts 60-95% in developing country, 25-60% in middle income countries and <5% in high income countries (Byer, 1987; Leach and Gowen, 1987). Leach (1992) found energy transition in happening at household level in developing countries and it is strongly dependent on urbanization, household income and relative prices of modern energy.

After reviewing th literature of the economic growth – environmental degradation, the major observations are: i) the EKC hypothesis is more descriptive and the hypothesis does not comply for all pollutants, particulary for CO_2 emission, ii) The cauality analysis between growth-emission has been done mostly in standard time series framework and results significantly varies from country to country. Therefore, it deserves more robust analysis using panel framework for generalizing the conclusion of growth-emission causality, iii) There is no study (to best of my knowledge) in literature observing the cauality using emission from signle energy types (coal, oil and natural gas). But importantly, the understanding of the nature of causality between economic growth and single emission series is essential for policy presciption. Furthermore, how the transition from coal to oil and natural gas can improve the environmental quality is a matter of research. Therefore, the main objective of this study is to examine growth-emission and growth-emission type causality; and show how possible substitution among emission series can affect long run economic growth.

Chapter 3

Data Details

3.1 Data and Variables

In this research I combine the panel data for group of industrialized and developing countries for which the time series data for each variable is available. In particular, I use the series of GDP per capita (in 2005 constant US$), Total CO_2 emission (CO_2^T), CO_2 emission from coal and solid fuel consumption (CO_2^c), CO_2 emission from oil and liquid fuel consumption (CO_2^o) and CO_2 emission from gasoline fuel consumption (CO_2^g). I used the yearly data on these five variables for 33 countries. Data series are taken from World Bank (2014), GDP data for some countries (Switzerland, Poland, New Zealand, and Ireland) are taken from Penn World Table (Hetson et al., 2012). Countries are selected on the basis of data coverage during 1960-2010.

GDP in constant US$ price has been considered as a measure of economic growth for all countries. The measure of environmental degradation has been captured by accounting the CO_2 emission into atmosphere. CO_2 is emitted from biomass burning and fossil fuel combustion through photosynthesis process. It is one of the principal greenhouse gases which is rising global warming. Since the first industrial revolution, the demand of carbon based fuel has increased speedily, the combustion of these fuels left higher concentration of CO_2 in environment. Moreover, CO_2 emission from other activities e.g. heat production, international bunker, residential activities etc. emits additional amount which also add an extra increase of surface temperature and sea level rising. The environmental effects of CO_2 have been examined scientifically in many studies. However, how CO_2 emission can affect environmentally sustainable growth is becoming a great interest of research. There are many conventional research that shows the relation between environmental degradation using pollutants (CO_2 in some cases) and economic growth. In this study, I use CO_2 emission from burning three main fossil fuel coal, oil and natural gas to examine the causality between economic growth and CO_2 and possible substitution analysis. CO_2 emission from burning coal (CO_2^c), CO_2 emission from oil consumption (CO_2^o) and CO_2 emission from gasoline fuel consumption (CO_2^g) has been analyzed to address the hypotheses. The sum of emission from these three sources makes the total CO_2 emission (CO_2^T). Table 2 contains a short description and data source for studied variables.

Table 2: Variables and data description

Variables	Short Description	Unit	Source
GDP	A measure of economic growth.	US$[a]	World Bank (2014)
Total CO_2 emission (CO_2^T)	CO_2 emissions are those stemming from the fossil fuel combustion and biomass burning.	kt	World Bank (2014)
CO_2^c	CO_2 emission from coal and other solid fuel consumption.	kt	World Bank (2014)
CO_2^o	CO_2 emission from liquid oil consumption.	kt	World Bank (2014)
CO_2^g	CO_2 emission from gasoline fuel consumption.	kt	World Bank (2014)

[a]Million US$ constant in 2005 price

kt refers to kiloton metric, 1 kt = 1000000 kg.

3.2 Representative Sample

A list of sample countries has been provided in Table 3. Together, these countries account over 80 percent of total global emission. Figure 1 shows the average world emission during 1960-2010 for different fossil fuel. The trend of increase is similar to the picture in IEA (2012) for all countries. It indicates that, the selection of sample is a good representative of total population countries. However, United States and China are the largest (over 40%) emitter of total CO_2 and United States and United Kingdom have comparatively much higher GDP. So, combining these three countries (China, United States, and United Kingdom) with other countries in a panel framework produces large residual. This makes the result spurious and inconsistent. Hence, I exclude these three countries from main sample and a separate time series analysis for each country has been presented in chapter 6.

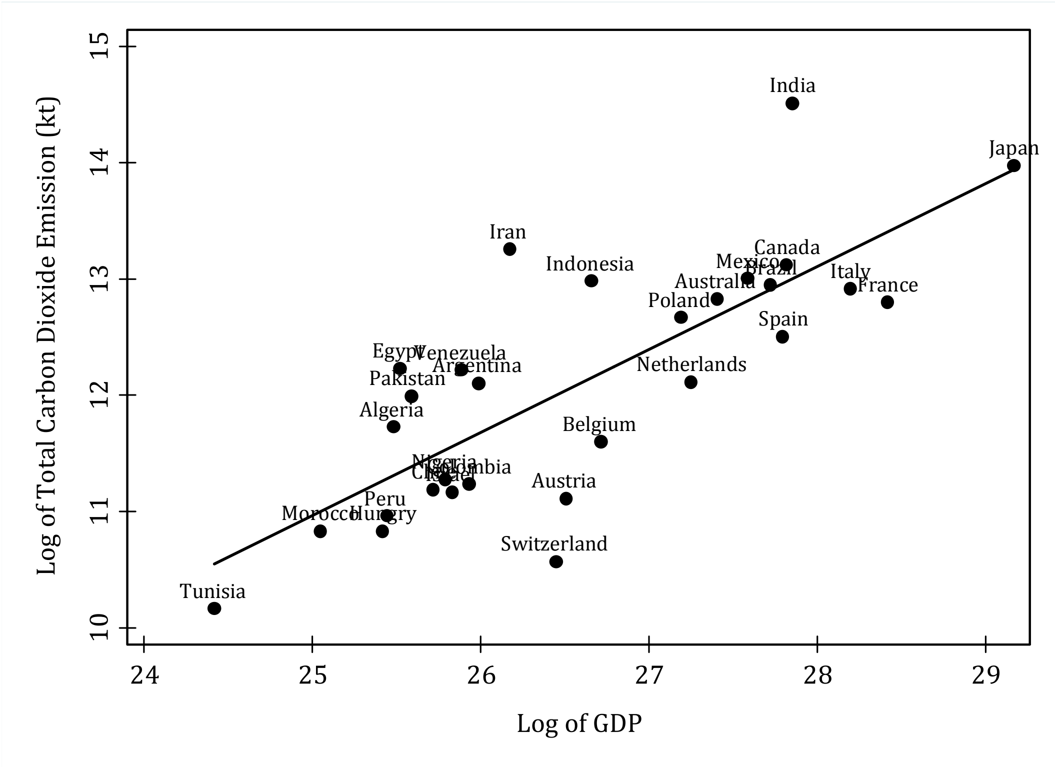
Table 3: Sample countries

Serial	Countries	Code	Sample Year
1.	Algeria	DZA	1960-2010
2.	Argentina	ARG	1960-2010
3.	Australia	AUS	1960-2010
4.	Austria	AUT	1960-2010
5.	Belgium	BEL	1960-2010
6.	Brazil	BRA	1960-2010
7.	Canada	CAN	1960-2010
8.	Chile	CHL	1960-2010
9.	China*	CHN	1960-2010
10.	Colombia	COL	1960-2010
11.	Egypt	EGY	1960-2010
12.	France	FRA	1960-2010
13.	Hungry	HUN	1960-2010
14.	India	IND	1960-2010
15.	Indonesia	IDN	1960-2010
16.	Iran	IRN	1960-2010
17.	Israel	ISR	1960-2010
18.	Italy	ITA	1960-2010
19.	Japan	JPN	1960-2010
20.	Luxemburg	LUX	1960-2010
21.	Mexico	MEX	1960-2010
22.	Morocco	MAR	1960-2010
23.	Netherlands	NLD	1960-2010
24.	Nigeria	NGA	1960-2010
25.	Pakistan	PAK	1960-2010
26.	Peru	PER	1960-2010
27.	Poland	POL	1960-2010
28.	Spain	ESP	1960-2010
29.	Switzerland	CHE	1960-2010
30.	Tunisia	TUN	1960-2010
31.	Unites Kingdom*	GB	1960-2010
32.	United States*	USA	1960-2010
33.	Venezuela	VEN	1960-2010

*Note: China, United States and United Kingdom have been excluded from panel analysis. A separate time series analysis for each country has been provided in Chapter 6.

Figure 4 plots the logarithm of GDP in 2010 against the logarithm of total CO_2 emission in sample countries in 2010. The scatter diagram shows a strong positive relationship. Countries where GDP has increased, a subsequent increase in emission have been occurred too. The rate of increase was highest in India and Japan (except excluding countries). To substantiate this relationship, I conduct VAR Granger causality in the whole panel set in section 3.

Figure 4: Relation between GDP and CO_2 emission



3.3 Descriptive Statistics

Table 4 contains panel summary statistics of the concerned variables. I took data for 29 countries (except excluding countries) over 51 years. The mean values of GDP, CO_2^T, CO_2^c, CO_2^o and CO_2^g has been presented in the table with standard deviation, minimum and maximum values. Moreover, a detail time series line graph for GDP and total CO_2 emission has been presentated in appendix Table A1 and A2.

Table 4: Descriptive Statistics

Variable	Unit	Mean	SD	Minimum	Maximum	Countries	Years
GDP	US$[a]	386892.45	665976.61	701.31	4751193.94	30	51
CO_2^T	Kt	189280	243764	1727	2008822	30	51
CO_2^c	Kt	58035	127318	7.334	1338473	30	51
CO_2^o	Kt	91975	119687	393	695204	30	51
CO_2^g	Kt	28851	39751	2.954	294262.	30	51

[a] Million US$ in constant 2005 price

Note: 1 kt (kiloton metric) = 1000000 kilogram

Source: World Bank, 2014 and Penn World Table, 2014

Chapter 4

Empirical Strategy

The main objective of this study is to examine the i) growth-emission and growth-emission type causality and ii) effect of possible substitution among single emission series on economic growth. I use a panel data vector autoregressive (VAR) methodology and Granger causality analysis. This approach includes the traditional VAR method which considers all the variables in as endogenous system, therefore, with panel data method it allows for unobserved heterogeneity (Love and Zicchino, 2006). The applied methods are described chronologically.

4.1 Panel Unit Root Test

The test begins with unit root test of all variables for T = 51 year and N = 29 countries for checking the asymptotic properties of time series. There are a number of procedures to examine the non-stationarity of panel data. I used the widely used first generation Levin-Lin-Chu (LLC), Im-Pesaran-Shin (IPS); and second generation Fisher type unit root test based on Augmented Dickey Fuller (ADF – Fisher) and Breitung panel unit root test. Using all these methods, the series are tested by both individual countries and combined cross sectional level.

4.1.1 Levin-Lin-Chu (LLC) Test

This is one of popular panel unit root tests, developed by Levin et al. (2002). This powerful test hypothesizes that each specific time series has unit root in null against the stationarity in alternative. It also assumes the cross-sectional independence in individual process. To check the whether the error term is a white noise process or not stationarity, we estimate the following equation.

$$\Delta y_{it} = \gamma y_{it-1} + \sum_{L=1}^{p_i} \theta_{iL} \Delta y_{it-L} + z_{it}\beta + \varepsilon_{it}$$

Where $i = 1,2,3.............,N$ and $t = 1,2,3,...............,T$

We compare the Augmented Dickey Fuller (ADF) critical values to test $H_0 : \theta_{iL} = 0 \ \forall \ i$ against $H_1 : \theta_{iL} < 0 \ \forall \ i$. Rejection of null hypothesis means that the series is stationary in all countries.

4.1.2 Im-Pesaran- Shin (IPS) Test

The other widely used Im-Pesaran-Shin (IPS) test is also a polled Augmented Dickey-Fuller test suggested by Im et al. (2003). It states that the null hypothesis as $H_0 : \gamma_i = 0$ $\forall \ i$ against the alternative hypothesis of $H_1 = \gamma_i < 0 \ \exists \ i$. This alternative hypothesis is different from LLC test and allows γ_i to vary, some series may have unit root. It estimates the same equation as described before.

4.1.3 ADF-Fisher Panel Unit Root Test

In contrast to testing the significant result of N independent countries (individual) the Fisher (1932) type panel unit root test combine the observed significant p values from each cross section countries i to test the unit root in whole panel (Maddala and Wu, 1999; Choi, 2001). This test estimate the following equation

$$P = -2\sum_{i=1}^{N} \ln p_i$$

Then the test statistics is compared with the Chi-square distribution with $2N$ degrees of freedom. In my case, I used similarly standardized ADF-Choi Z-statistics[1] proposed by Choi (2001). This method test whether $p_i \sim 0$ (reject the null hypothesis) or $p_i \sim 1$(do not reject null hypothesis).

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[1] $Z = \dfrac{\sqrt{N}\{N^{-1}P - E[-2\log(p_i)]\}}{\sqrt{Var[-2\log(p_i)]}} = -\dfrac{\sum_{i=1}^{N}\log(p_i) + N}{\sqrt{N}}$

4.1.4 Breitung Unit Root Test

In contrast to LLC and IPs test, Breitung (1999) suggested a different method using bias-adjusted *t*-statistics. Breitung specifies the test equation as follows.

$$y_{i,t} = \alpha_i + x_{i,t}$$
$$\phi_i(L)x_{i,t} = \varepsilon_{i,t}$$

Assuming no nuisance short-term dynamics, $\phi_i(L) = (1-L) - \rho L$

We test the null hypothesis $H_0 : \rho = 0$ against the alternative hypothesis $H_1 : \rho < 0$

4.2 Panel Cointegration Test

In most cases, long time series data of GDP (and CO_2 emission) are found non stationary and they can have cointegrating relation. To check whether there is any cointegrating vector, I applied the most popular three panel cointegration tests. First, in Pedroni Residual Cointegration Test, it uses four[2] panel statistics and three[3] group statistics to test H_0 : no cointegration versus H_1 : cointegration given by Pedroni (1999). Second, I used the Engale and Granger based Kao (1999) residual cointegration test using ADF statistics. The null and alternative hypotheses are same as Pedroni. Third, the number of cointegrating vector has been determined by using Johansen (1988) trace statistics[4] and maximum eigenvalue[5] statistics.

4.3 Vector Auto Regression in First Difference (VARfd)

In this study, I applied vector auto regression in first differenced data (VARfd) and VARfd Granger causality to test hypothesis 1. This technique combines the traditional VAR approach, which treats all the variables in the system as endogenous, with the panel-data approach, which allows for unobserved individual heterogeneity (Love and

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[2] Panel v-Statistics, Panel rho-Statistics, Panel PP-Statistics and Panel ADF-Statistics

[3] Group rho-Statistics, Group PP-Statistics and Group ADF-Statistics

[4] Trace Statistics: $\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1-\widehat{\lambda}_i)$

[5] Maximum Eigenvalue Statistics: $\lambda_{max}(r, r+1) = -T \ln(1-\widehat{\lambda}_{r+1})$

Zicchino, 2006). More explicitly, I estimate the following VAR process. This methodology has also been used in Growth-Energy causality in Bruns and Gross (2013).

$$\begin{bmatrix} \Delta Y_{i,t} \\ \Delta E_{i,t} \end{bmatrix} = \begin{bmatrix} \theta_{10} \\ \theta_{20} \end{bmatrix} + \sum_{i=1}^{p-1} \begin{bmatrix} \theta_{11,i} & \theta_{12,i} \\ \theta_{21,i} & \theta_{22,i} \end{bmatrix} \begin{bmatrix} \Delta Y_{i,t-p} \\ \Delta E_{i,t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \end{bmatrix}$$

Where, Y denotes economic growth measures by GDP in constant 2005 price (US$), E denotes emission of CO_2 in total (CO_2^T) and in three types (CO_2^g, CO_2^l, CO_2^s). *p* refers to lag length. The lag length has been determined when it minimizes the Akaike Information Criteria (AIC) and/or Bayesian Information Criteria (BIC). Here, Δ is the first difference operator i.e. $\Delta Y_t = Y_t - Y_{t-1}$ and $\Delta E_t = E_t - E_{t-1}$. Using F-statistics, VARfd allows us to detect the emission-growth causality by testing the null of $\theta_{12,i} = 0$, $i = 1, \ldots\ldots, p-1$. The counter causality can be tested be $\theta_{21,i} = 0$, $i = 1, \ldots\ldots, p-1$.

4.4 Panel VARfd Granger Causality or Block Exogeneity Wald Test

I then estimate the Granger causlity from the specified VAR (section 4.3) to see the direction of causality between growth-emission and growth-emission type for whole panel. It is important to raise the issue of cointegration relationship among the variable. Since, I do not fiund any evidence of cointegration relationship (see Table 6) among variable; the Vector Error Correction Model (VECM) does not make any sense. Since, short run dynamics are included in VECM specification; the result from VECM could be more powerful than its counterpart VAR framework. But Giles (2011) explained very clearly that there are many acceptable arguments for not using a VECM. Granger causality simply is based on forecasting of two time series. In this case, "*CO_2 Emission is said to Granger cause of Growth if Growth can be better predicted using the past values of both CO_2 Emission and Growth than it could be by using the past values of Growth alone*". Then it is possible to test the Granger causality. For more clarification of the equation in section 4.3, the VARfd can be written as following system of equations.

$$\Delta Y_{i,t} = \alpha_0 + \alpha_1 \Delta Y_{i,t-1} + \ldots\ldots + \alpha_p \Delta Y_{i,t-p} + \beta_1 \Delta E_{i,t-1} + \ldots\ldots + \beta_p \Delta E_{i,t-p} + \varepsilon_{i,t}$$
$$\Delta E_{i,t} = \lambda_0 + \lambda_1 \Delta E_{i,t-1} + \ldots\ldots + \lambda_p \Delta E_{i,t-p} + \delta_1 \Delta Y_{i,t-1} + \ldots\ldots + \delta_p \Delta Y_{i,t-p} + \nu_{i,t}$$

After estimating this VARfd, a test of null hypothesis $H_0 : \beta_1 = \beta_2 = ...\beta_p = 0$ against alternative hypothesis $H_1 : \beta_1 = \beta_2 = ...\beta_p \neq 0$ implies that CO_2 Emission does not Granger cause Growth. Similarly, testing null hypothesis $H_0 : \delta_1 = \delta_2 = ... = \delta_p = 0$ against alternative hypothesis $H_1 : \delta_1 = \delta_2 = ... = \delta_p \neq 0$ is a test that Growth does not Granger cause CO_2 Emission. In both cases, rejection of null hypothesis at certain level of significance indicates the presence of Granger causality between Growth and CO_2 Emission. Moreover, there are documented evidences that VAR is more effective over VECM in order to get the causality result (Toda and Phillips, 1994; Dolado and Lutkepohl, 1996; Zapata and Rambaldi, 1997 ; Clarke and Mirza, 2006). "*We find the practice of pretesting for cointegration can result in severe overrejections of the noncausal null, whereas overfitting* (VARfd) *result in better control of the Type I error probability with often little loss in power."* (Clarke and Mirza, 2006). Therefore, I use VARfd in order to get the effective Granger causality result.

4.5 Methods for Possible Substitution Analysis

Since the VARfd Granger causality test result (see Table 9) shows that there is bidirectional causality in both growth-emission and growth-emission types (coal has unidirectional only). One possible way to see the possible substitution between CO_2 emission types by finding a counterfactual. More explicitly, the main purpose is to predict a 'counterfactual' growth that would have been observed if we use the characteristics of other type emission (i.e. gas instead of coal *or* oil instead of coal) but with the coefficients for coal.

Basically in VARfd Granger causality test for single emission type and economic growth, I estimate the following equations

Coal

$$\Delta Y_{i,t} = \sum_{L=1}^{p} \alpha_L \Delta Y_{i,t-L} + \sum_{L=0}^{p} \beta_L \Delta CO^{c}_{2\,i,t-L} + \varepsilon_{i,t}$$

$$\Delta CO^{c}_{2\,i,t} = \sum_{L=1}^{p} \gamma_L \Delta CO^{s}_{2\,i,t-L} + \sum_{L=0}^{p} \delta_L \Delta Y_{i,t-L} + \upsilon_{i,t}$$

Oil

$$\Delta Y_{i,t} = \sum_{L=1}^{p} \alpha_L \Delta Y_{i,t-L} + \sum_{L=0}^{p} \beta_L \Delta CO^{o}_{2\,i,t-L} + \varepsilon_{i,t}$$

$$\Delta CO^{o}_{2\,i,t} = \sum_{L=1}^{p} \gamma_L \Delta CO^{l}_{2\,i,t-L} + \sum_{L=0}^{p} \delta_L \Delta Y_{i,t-L} + \upsilon_{i,t}$$

Gas

$$\Delta Y_{i,t} = \sum_{L=1}^{p} \alpha_L \Delta Y_{i,t-L} + \sum_{L=0}^{p} \beta_L \Delta CO^{g}_{2\,i,t-L} + \varepsilon_{i,t}$$

$$\Delta CO^{g}_{2\,i,t} = \sum_{L=1}^{p} \lambda_L \Delta CO^{g}_{2\,i,t-L} + \sum_{L=0}^{p} \delta_L \Delta Y_{i,t-L} + \upsilon_{i,t}$$

Once we have the estimated coefficients β_L for each equation, we can multiply the estimated coefficient with other type of emission. For example, we can get the predicted β_L from $\Delta Y_{i,t} = \sum_{L=1}^{p} \alpha_L \Delta Y_{i,t-L} + \sum_{L=0}^{p} \beta_L \Delta CO^c_{2\,i,t-L} + \varepsilon_{i,t}$ equation. Now, keeping the value of coefficient, we will substitute CO_2^c by CO_2^o , this interaction may predict the counterfactual growth that would have been observed if we use oil instead of coal. Then a new total of CO_2 emission will be calculated based on new interaction. The same procedure will be followed for the substitution of emission from coal by emission from natural gas i.e. CO_2^c by CO_2^g . A new total will again be calculated based on new interaction.

Now, the interest will be to see the difference between the impact of actual CO_2 emission and impact of counterfactual emission (by oil and gas). Formally, the difference between the observed growth and the potential growth based on actual and counterfactual emission series.

$$D = E(\widehat{Growth}_{Observed}) - E(\widehat{Growth}_{Potential})$$

That is, $D = E[\hat{Y}_{Observed}] - E[\hat{Y}_{Potential}]$

For empirical testing I will use 'test of equality of means' for the following hypotheses.

$$H_0 : D = 0$$
$$H_1 : D \neq 0$$

4.6 Methods for Time Series Analysis

The smae set of methods has been used for country level analysis of China, United States and United Kingdom, but in a ime series framework.

4.6.1 Unit Root Test

A time series is said to be stationary if its mean and variance are constant over time and the value of the covariance between the two time periods depends only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed (Chu, 2011). A time series is said to be integrated of order zero i.e. I(0) if it is stationary at the level form. In the differenced series, the time series is to be called integrated of order d i.e. I(d) if it has to be differenced d times to make it stationary. For example, the time series is called I(1), if $\Delta y_t = y_t - y_{t-1}$ will be stationary. If a time series is I(2), then $\Delta y_t = y_t - 2y_{t-1} + y_{t-2}$ will be stationary. To examine the stationarity of the variables for each country, I used standard methods of testing unit root i.e. Augmented Dickey-Fuller (ADF) and Phillips Perron (PP) test. Among the three equations by Dickey and Fuller (1979, 1981) speficifation, I use the no constant, no trend specification.

$$\Delta y_t = \gamma y_{t-1} + \sum_{i=0}^{k} \beta_i \Delta y_{t-i} + \varepsilon_t$$

4.6.2 Johansen Cointegration Test

For testing cointegration at country level, I use the test given by Johansen (1988) and Johansen and Juselius (1990) which is a VAR based test. After determining the order of integration, two statistics named trace statistics (λ_{trace}) and maximum eigenvalue (λ_{max}) are used to determine the number of cointegrating vectors. In trace statistics, the following vector autoregression is estimated.

$$\Delta y_t = r_1 \Delta y_{t-1} + r_2 \Delta y_{t-2} + \ldots\ldots\ldots\ldots\ldots\ldots + r_p \Delta y_{t-p+1}$$

On the other hand, in maximum eigenvalue, the following vector autoregression is estimated

$$y_t = r_1 \Delta y_{t-1} + r_2 \Delta y_{t-2} + \ldots\ldots\ldots\ldots\ldots\ldots + r_p \Delta y_{t-p+1}$$

Where, y_t is the vector of the variables involved in the model and p is the order of autoregression. In Johansen's conintegration test the null hypothesis states there is no co-integrating vector ($r = 0$) and the alternate hypothesis makes an indication of one or more co-integrating vectors ($r > 1$).

4.6.3 VAR, Granger Causality and Possible Substitution

I used the same methodology VAR in first differences and Granger causality as described in previous section. The same hypothesis and estimation tecniques has been used for substituion analysis as well.

The employed methodolgy has several distinctive features over the other researches. Firstly, it employes the panel framework. Secondly, this study takes into account the disaggregated emission data to show the causality between economic growth and CO_2 emission. Thirdly, the method of using counterfactual for analyzing possible substitution seems promising and practical. To best of my knowledge, there is no work on this issue in literature.

Chapter 5

Empirical Results: Panel

This section presents the estimation result for the causality and possible substitution effect analysis for 30 panel countries. Firstly, I check the stationarity properties of panel data series and test for cointegration relation. Secondly, I present the VARfd results and VAR Granger causality. And thirdly, I discuss about the effect of possible substitution of coal by natural gas on economic growth.

5.1 Panel Unit Root Test Result

In order to check the stationarity properties of data series in whole panel framework, I applied four different panel unit root testing methods, Levin-Lin-Chu (LLC), Im-Pesaran-Shin (IPS), Fisher type unit root test based on Augmented Dickey Fuller (ADF - Fisher) and Breitung test. These methods test both individual (at least one country) and common (all countries) unit root process of each series.

Table 5: Unit Root Test Result

Variables	Levin-Lin-Chu (LLC)	Im-Pesaram-Shin (IPS)	ADF – Fisher	Breitung	Order of Integration
Panel a: Levels					
LnGDP	17.0281	0.3789	0.4278	4.8074	-
$LnCO_2^T$	17.3615	-0.2354	2.4345	4.2263	-
$LnCO_2^c$	7.7804	-0.5625	6.4604	1.7109	-
$LnCO_2^o$	10.0425	-1.7148	12.9178	3.8887	-
$LnCO_2^g$	12.5018	-0.8525	-0.6358	3.0912	-
Panel b: First differences					
$\Delta LnGDP$	-17.8925***	-26.8817***	-21.4674***	-9.9605***	I(1)
$\Delta LnCO_2^T$	-21.9615***	-30.5498***	-21.0614***	-14.7902***	I(1)
$\Delta LnCO_2^c$	-32.3528***	-34.0512***	-34.3963***	-16.3934***	I(1)
$\Delta LnCO_2^o$	-23.2478***	-28.4698***	-23.3489***	-15.2191***	I(1)
$\Delta LnCO_2^g$	-20.9517***	-25.1314***	-20.2170***	-14.2947***	I(1)

Note: Lag lengths are selected by automatic lag section criteria (SIC); (***) significant 1% level

LLC: Null hypothesis: Unit root (common unit root process); IPS: Null hypothesis: Unit root (individual unit root process); ADF-Fisher: Null hypothesis: Unit root (individual unit root process); Breitung: Null hypothesis: Unit root (common unit root process)

Table 4 contains the unit root test results. Every variable is tested in both levels and first differences. The result shows that, we cannot reject the null hypothesis at level (panel a). It requires the data to be first differenced in order to get stationary series. Results in panel b shows that, all variables become stationary in all methods in differenced series. Henceforth, all variables are integrated of order one i.e. I(1).

5.2 Panel Cointegration Analysis

Since all variables are found I(I), they are now subject to cointegration test. I applied three widely used panel cointegration testing methods: Pedroni Residual Cointegration Test, Kao Residual Cointegration Test and Johansen Fisher Panel Cointegration Test. The cointegration test results are reported in Table 6.

Table 6: Panel Cointegration Test Result

Variables	Pedroni Residual Cointegration Test	Kao Residual Cointegration Test	Johansen Fisher Panel Cointegration Test	
Whole panel	Panel ADF Statistic	Augmented Dickey-Fuller Statistic	Fisher Stat* from trace test	Fisher Stat* from max-eigen test
LnGDP, *Ln* CO_2^T, *Ln* CO_2^o and *Ln* CO_2^c, *Ln* CO_2^g	19,23 (0.28)	2.720384 (0.15)	9.20 (0.52)	6.34 (0.82)

* Probabilities are computed using asymptotic Chi-square distribution.
p-values in parentheses.

In the table the result from Pedroni residual ADF statistics, ADF statistic from Kao test and both Fisher trace and mamimum eigen value statistic cannot reject the null hypothesis of *no cointegration* at preferred significance level. Hence, it implies that there is no evidence of cointegration in GDP and emission in whole panel. Therefore, it indicates to apply VAR model instead of VECM in next step to investigate the Granger causality.

5.3 Growth-Emission and Growth-Emission Type Causality

The result of VAR in first differences (since all variables are I(1) from panel unit root test result) are reported in Table 7 and 8. Table 7 presents the VARfd result between economic growth and total CO_2 emission. Again, I estimate (Table 8) the VARfd between

GDP and disaggregated CO_2 emission series (CO_2^g, CO_2^o and CO_2^c) in order to get Growth-Emission type causality. The model has been estimated by using 1 lag, since the lag lebgth criteria suggests that (Appendix Table B1). The VAR is well specified, since thre is no residual autocorrelation in the model (Appendix Table B2). The graph of inverse roots of AR characteristic polinomial shows that, all points belong inside the unit circle, that implies, the specified VAR satisfied the stability condition (Appendix Figure B1).

Table 7: VARfd of GDP and Total CO2 Emission

Variable	$\Delta lnGDP_t$	$\Delta \ln CO^T_{2\,t}$
C	0.025***	0.026***
	(19.97)	(9.97)
$\Delta lnGDP_{t-1}$	0.297***	0.147***
	(20.37)	(4.97)
$\Delta \ln CO^T_{2\ t-1}$	0.030***	0.060***
	(2.29)	(2.27)
R^2	0.243	0.024
F-statistic	227.77***	17.82***
Akaike AIC	-3.54	-2.13
Schwarz SC	-3.53	-2.12

Note: (***) significant 1% level, (**) significant 5% level, (*) significant 10% level

t-Statistics in parenthesis

Table 8: Economic growth and single emission type: Result of VAR in first difference

Variable	$\Delta LnGDP_t$	$\Delta \ln CO_2^c$	$\Delta \ln CO_2^o$	$\Delta \ln CO_2^g$
C	0.025***	0.018*	0.024***	0.069***
	(19.16)	(1.68)	(7.77)	(6.33)
$\Delta lnGDP_{t-1}$	0.298***	0.429***	0.173***	0.191
	(20.76)	(3.47)	(5.01)	(1.54)
$\Delta \ln CO^c_{2\ t-1}$	-0.001***	-0.120***	0.016**	0.020
	(-2.34)	(-4.58)	(2.26)	(0.79)
$\Delta \ln CO^o_{2\ t-1}$	0.032***	-0.244***	0.013	0.376***
	(2.89)	(-2.59)	(0.49)	(4.12)
$\Delta \ln CO^g_{2\ t-1}$	0.005	-0.063***	0.019***	0.091***
	(1.60)	(-2.37)	(2.63)	(3.46)
R^2	0.246	0.029	0.027	0.024
F-statistic	115.81***	10.81***	10.19***	8.96***
Akaike AIC	-3.54	0.75	-1.80	0.71
Schwarz SC	-3.52	0.77	-1.78	0.73

Note: (***) significant 1% level, (**) significant 5% level, (*) significant 10% level

t-Statistics in parenthesis

Based on the result of Table 7 and 8, I estimate the VAR Granger causality or block exogeneity Wald test reported in Table 9. Results show that, it rejects the null hypothesis at 5% and 1% significance level, that implies there is bidirectional causality between economic growth and total CO_2 emission. This result implies mutual dependence between economic growth and CO_2 emissions, i.e. economic growth causes emission in environment and reverses as well.

Table 9: VAR Granger Causality

Causality	Null Hypothesis	χ^2	Prob.	Decision
Growth-Emission	ΔCO_2^T *does not Granger cause* ΔGDP	5.268**	0.02	Feedback
	ΔGDP *does not Granger cause* ΔCO_2^T	24.74***	0.00	
Growth-Emission Type	ΔCO_2^c *does not Granger cause* ΔGDP	0.19	0.65	Unidirectional
	ΔGDP *does not Granger cause* ΔCO_2^c	9.65***	0.00	
	ΔCO_2^o *does not Granger cause* ΔGDP	8.57***	0.00	Feedback
	ΔGDP *does not Granger cause* ΔCO_2^o	27.38***	0.00	
	ΔCO_2^g *does not Granger cause* ΔGDP	3.06*	0.08	Feedback
	ΔGDP *does not Granger cause* ΔCO_2^g	3.93**	0.04	

All series are in logarithmic value. Δ repressents first differenced series.

Note: (***) significant 1% level, (**) significant 5% level, (*) significant 10% level

The result of causality between economic growth and single emission type emission has different result for different emission series of coal, oil and natural gas. There is unidirectional causality running from economic growth to CO_2 emission from coal combustion, it implies that higher GDP growth may increase the emission from coal in long run. This result may be more relevant for developing and emerging countries with higher economic growth, India, for example. Because of availability and relatively lower price, demand and consumption of coal in India is higher. Although the technological change is happening, there is significant number of manufacturing technology in developing and emerging countries which are mostly fueled by coal and high carbon energy. This picture may be different in developed countries for example, Switzerland.

The causality for other two single oil and natural gas series with economic growth shows statistically significant bidirectional or feedback relationship.

5.4 Possible Substitution Analysis

Table 10 contains the result from possible substitution analysis, if countries substitute coal by oil and coal by natural gas. The variable $\Delta \ln CO_{2\ coal,oil}^{T}$ is the new total emission when countries are presumed to substitute CO_2^c by CO_2^o as if countries substitute coal consumption by oil consumption. And $\Delta \ln CO_{2\ coal,gas}^{T}$ is the new total emission when countries are presumed to substitute CO_2^c by CO_2^g as if they replace coal by natural gas. The estimated coefficient by using panel least squares in differenced data shows the impact of CO_2 emission on economic growth. All coefficients imply that there is positive relationship between economic growth and CO_2 emission. The results can be interpreted as slope/elasticity (since the variables are in first differences). The slope of the positive relationship between economic growth and emission becomes lower when countries substitute the emission from coal to oil and natural gas.

Table 10:Effect of CO_2 emission on economic growth: panel least square estimates

	Observed	Counterfactual (oil)	Counterfactual (gas)
Variable	$\Delta LnGDP_t$	$\Delta LnGDP_t$	$\Delta LnGDP_t$
$\Delta \ln CO_2^T$	0.319*** (13.64)		
$\Delta \ln CO_{2\ coal,oil}^{T}$		0.030*** (5.11)	
$\Delta \ln CO_{2\ coal,gas}^{T}$			0.049*** (8.81)
R^2	0.13	0.26	0.22
Log Likelihood	1594.255	1519.586	1544.457
Durbin Watson Stat	1.94	2.01	1.99

Note: (***) Significant at 1%, (**), Significant at 5% and (*), Significant at 10%

t-Statistics in Parenthesis

Table 11: Wald Test

	Counterfactual (oil)		Counterfactual (gas)	
Null Hypothesis	t-statistic:	11.256***	t-statistic:	8.868***
$D = E[\widehat{Y}_{Observed}] - E[\widehat{Y}_{Potential}] = 0$	F-statistic:	126.781***	F-statistic:	78.643***
	χ^2:	126.781***	χ^2:	78.643***
Null Hypothesis Summary	Value	Std. Error	Value	Std. Error
Normalized Restriction $(=0)$	0.325	0.028	0.258	0.029

Note: (***) Significant at 1%, (**), Significant at 5% and (*), Significant at 10%

Restrictions are linear in coefficients

Table 11 represents the result from Wald test to test the hypothesis of impact of substitution between emission series on economic growth. In null hypothesis, I presume that the effect is equal both in observed and potential (counterfactual) emission. However, in both cases, substitution by oil and natural gas, we reject the null hypothesis. All test statistic are significant at 1% level. That implies that the substitution between emission series has statistically different impact on economic growth than that of observed emission without any substitution.

However, to make any comment on whether the difference between observed effect and potential effect, $D = E[\widehat{Y}_{Observed}] - E[\widehat{Y}_{Potential}]$, is greater than zero or less than zero, is beyond the scope of this research. Environmental economists and technological optimists emphasize the realization of substitution for sustainable development. But on the issue of cutting production at socially and environmentally desired level, there might be many conflicts among capitalists and environmentalists. Henceforth, it is difficult to say whether $D < 0$ or $D > 0$.

Chapter 6

Empirical Results: China, United States and United Kingdom

6.1 China, USA and UK: Time Series Analysis

In this section I present a separate time series analysis for China, United States and United Kingdom for examining my two hypotheses. The main reason for excluding these three countries was about methodological issue. The emission series of China and United States is significantly larger than any other sample countries. Moreover, the GDP of United Kingdom, United States and China is also higher other sample countries. Therefore, inclusion of these countries in whole panel set generates higher variation in data and excessively larger residual. Therefore, I exclude those countries for a consistent estimate.

Besides methodological issues, the amount of CO_2 emission in these countries has significant impact on global environment. In particular, China and United States emit over 40 percent of total greenhouse gas in the atmosphere. China is often called as an ‘economic miracle’ has achieved this growth rate with a higher environmental cost left in global atmosphere. China’s total CO_2 emission has increased from 0.78 million kt in 1960 to 8.29 million kt in 2010. The amount of emission in China has become almost doubled from 2002 to 2008, within a very short period of time. According to IEA (2013), China has continuously been the largest national source of CO_2 emission since 2006. The rapid growth of manufacturing sector has largely contributed to mount the emission over the years. The main drivers of this intense emission are household consumption, capital investment and growth in export trade. An estimate by Yunfeng and Laike (2010) find that 10-26% of China’s CO_2 emission comes from manufacturing process of carbon embodied export goods. This production related emission is expected to increase by three-fold by the year 2030 (Guan et al., 2008). Besides, the coal-dependent fuel consumption has been increased by 9% per annum during 2000-2009, that drove the Chinese economic growth very quickly (NBS, 2010).

Figure 5: CO_2 Emission in China, US and UK, 1960-2010

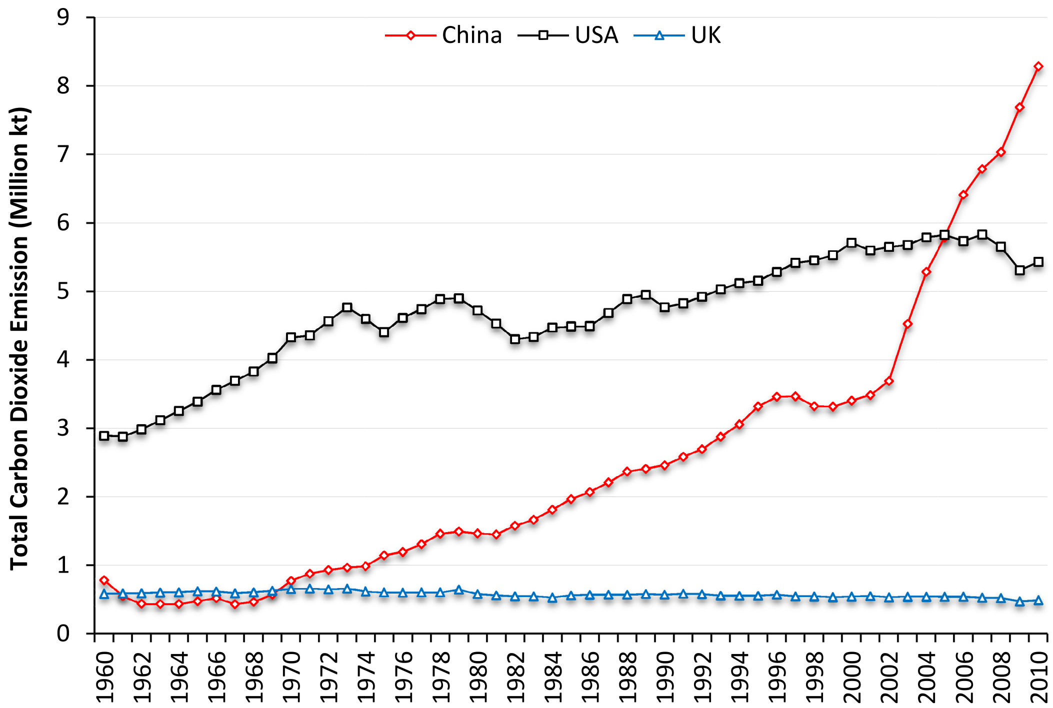


Figure 5 plots the yearly CO_2 emission of China, United States and United Kingdom from 1960 to 2010. Both US and China has a sharp acceleration rate in emission growth. Since the beginning of 1980s the emission from China has been increased followed by a very strong increase in 2000s. In the year 2006, China overtook US- the earlier largest emitter, and continues to with a very high speed. On the other hand, US emission has been increasing at a diminishing rate, although the amount of emission in almost 4 times higher than the average of other sample countries. And the emission trend in United Kingdom is less than 1 million kt during the sample period, but this trend is still higher than the average of other sample countries.

In 2009, the year of financial crisis, the US and UK emission has been curtailed by a small amount, because of the slowdown of economic activities, but it has followed its previous trend in 2010 and continues to grow upward. China was not responsive to financial crisis in CO_2 emission; instead it has the rising trend over the recent years.

6.2 Unit Root Test Result: Time Series

Table 12 presents the Augmented Dickey Fuller (ADF) and Phillips Perron (PP) unit root test for all series of CO_2 emission and GDP for three countries separately.

Table 12: Unit root test result of China, United States and United Kingdom

		Variables	ADF	PP	Order of Integration
China	*Levels*	*LnGDP*	7.3559	7.3517	-
		$Ln\,CO_2^T$	3.1121	2.7060	-
		$Ln\,CO_2^c$	2.7591	2.2891	-
		$Ln\,CO_2^o$	2.3014	3.6083	-
		$Ln\,CO_2^g$	2.5714	3.4672	-
	First Differences	$\Delta LnGDP$	-3.4044***	-3.5580***	I(1)
		$\Delta LnCO_2^T$	-4.2500***	-4.2500***	I(1)
		$\Delta LnCO_2^c$	-4.5305***	-4.5305***	I(1)
		$\Delta LnCO_2^o$	-2.1736**	-2.6355**	I(1)
		$\Delta LnCO_2^g$	-3.7788***	-3.9541***	I(1)
United States	*Levels*	*LnGDP*	10.4814	10.4814	-
		$Ln\,CO_2^T$	2.8913	2.2199	-
		$Ln\,CO_2^c$	2.8525	2.8436	-
		$Ln\,CO_2^o$	0.8046	1.1308	-
		$Ln\,CO_2^g$	2.3645	1.5596	-
	First Differences	$\Delta LnGDP$	-2.3289**	-1.9747**	I(1)
		$\Delta LnCO_2^T$	-4.0856***	-4.0155***	I(1)
		$\Delta LnCO_2^c$	-5.9319***	-6.1374***	I(1)
		$\Delta LnCO_2^o$	-3.5174***	-3.5480***	I(1)
		$\Delta LnCO_2^g$	-4.6301***	-4.8351***	I(1)
United Kingdom	*Levels*	*LnGDP*	4.3272	6.8000	-
		$Ln\,CO_2^T$	-0.7387	-0.9395	-
		$Ln\,CO_2^c$	-1.2059	-1.4312	-
		$Ln\,CO_2^o$	0.5981	0.5275	-
		$Ln\,CO_2^g$	-0.2289	1.3194	-
	First Differences	$\Delta LnGDP$	-2.8829***	-2.6976***	I(1)
		$\Delta LnCO_2^T$	-7.6330***	-7.6920***	I(1)
		$\Delta LnCO_2^c$	-8.0541***	-8.000***	I(1)
		$\Delta LnCO_2^o$	-6.2557***	-6.2557***	I(1)
		$\Delta LnCO_2^g$	-1.9976**	-3.0802***	I(1)

ADF: Null Hypothesis: Unit root; PP: Null Hypothesis: Unit root
Test critical values (no constant, no trend): -2.6120 (1%), -1.9475 (5%), -1.6265 (10%)

The results suggest that, we cannot reject the null hypothesis of unit root at levels. I then test them in first differenced data and all series become stationary at 5% and 10% significance level, resulting all variables as I(1).

6.3 Johansen Cointegration Test

The results from both trace statistics and maximum eigenvalue of Johansen cointegration test shows that, we cannot reject the null hypothesis of no cointegration against at most 1 cointegrating vector at 5% significance level in any countries. The detailed result has been reported in appendix Table C1. Therefore, I proceed in the the VARfd and Granger causality test in next step.

6.4 Growth-Emission: VARfd Results

Table 13 contains the result of VAR in first differences between GDP and total emission ($CO_{2\,t}^{T}$). I use 1 lag for both GDP-emission and GDP-emission type VAR advised by Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Hannan-Quinn (HQ) test. A detail result of lag selection criteria had been provided in appendix Table C2. A VAR of GDP and single emission type ($CO_2^c, CO_2^o\ CO_2^g$) has also been presented for each country in appendix Table C3, C4 and C5. Both VARfd is stable and no residual serial correlation has been found. The inverse *roots of AR characteristics polynomial* graph (appendix Figure C1 and C2) shows that all the lag points are placed inside of the unit circle, that indicates it satisfied the VAR stability condition. Moreover, we cannot reject the null hypothesis of no serial residual correlation at lag order of LM test. Therefore, the specified VARfd has no residual autocorreltion problem (appendix Table C6).

Table 13: VARfd of GDP and Total CO2 Emission by countries

	China		United States		United Kingdom	
Variable	$\Delta lnGDP_t$	$\Delta \ln CO_{2\,t}^{T}$	$\Delta lnGDP_t$	$\Delta \ln CO_{2\,t}^{T}$	$\Delta lnGDP_t$	$\Delta \ln CO_{2\,t}^{T}$
C	0.059***	0.037***	0.025***	0.009	0.013***	-0.013*
	(6.17)	(2.47)	(4.07)	(0.99)	(2.58)	(-1.58)
$\Delta lnGDP_{t-1}$	0.345***	-0.053	0.113	-0.033	0.421***	0.344*
	(2.58)	(-0.25)	(0.51)	(-0.10)	(2.55)	(1.31)
$\Delta \ln CO_{2\,t-1}^{T}$	-0.017	0.477***	0.189	0.403**	-0.097	-0.260*
	(-0.16)	(2.99)	(1.24)	(1.84)	(-0.88)	(-1.58)
R^2	0.24	0.29	0.13	0.14	0.13	0.05
F-statistic	7.54**	9.79***	3.65*	4.02**	3.45*	1.28
Akaike AIC	-3.32	-2.42	-4.91	-4.19	-4.87	-3.94
Schwarz SC	-3.20	-2.31	-4.79	-4.07	-4.75	-3.83

Note: (***) significant 1% level, (**) significant 5% level, (*) significant 10% level

t-Statistics in parenthesis

6.5 Granger Causality Results

Based on these two stable VAR results, the growth-emission and growth-emission type VAR Granger causality has been provided in Table 14. The country-wise result is quite different from the panel VAR Granger causality result. We did not find any significant causality between growth (*ΔGDP*) and total emission (ΔCO_2^T) in any country. Interestingly, we have the evidence of causality between growth and disaggregated emission data. For example, in China, causality runs from growth to emission from coal consumption but not the other way around. This result implies that, higher growth of economic activities through manufacturing expansion, household energy consumption etc. can cause significant emission from coal. We found bidirectional causality between economic growth (*ΔGDP*) and emission from gas combustion (ΔCO_2^g) but no causality between growth and emission from oil combustion (ΔCO_2^o).

Table 14: Granger Causality result of China, Untied States and United Kingdom

	Causality	Null Hypothesis	χ^2	Prob	Decision
China	Growth-Emission	ΔCO_2^T *does not Granger cause ΔGDP*	0.027	0.86	No causality
		ΔGDP does not Granger cause ΔCO_2^T	0.065	0.79	
	Growth-Emission Type	ΔCO_2^c *does not Granger cause ΔGDP*	1.007	0.26	Unidirectional
		ΔGDP does not Granger cause ΔCO_2^c	9.023***	0.00	
		ΔCO_2^o *does not Granger cause ΔGDP*	0.756	0.39	No causality
		ΔGDP does not Granger cause ΔCO_2^o	0.221	0.64	
		ΔCO_2^g *does not Granger cause ΔGDP*	5.109***	0.02	Feedback
		ΔGDP does not Granger cause ΔCO_2^g	11.167***	0.00	
United States	Growth-Emission	ΔCO_2^T *does not Granger cause ΔGDP*	1.539	0.22	No causality
		ΔGDP does not Granger cause ΔCO_2^T	0.011	0.91	
	Growth-Emission Type	ΔCO_2^c *does not Granger cause ΔGDP*	1.178	0.28	Unidirectional
		ΔGDP does not Granger cause ΔCO_2^c	3.44*	0.06	
		ΔCO_2^o *does not Granger cause ΔGDP*	6.562**	0.01	Unidirectional
		ΔGDP does not Granger cause ΔCO_2^o	0.865	0.36	
		ΔCO_2^g *does not Granger cause ΔGDP*	0.299	0.58	No causality
		ΔGDP does not Granger cause ΔCO_2^g	0.157	0.69	
United Kingdom	Growth-Emission	ΔCO_2^T *does not Granger cause ΔGDP*	0.790	0.37	No causality
		ΔGDP does not Granger cause ΔCO_2^T	1.725	0.19	
	Growth-Emission Type	ΔCO_2^c *does not Granger cause ΔGDP*	0.80	0.37	No causality
		ΔGDP does not Granger cause ΔCO_2^c	0.02	0.86	
		ΔCO_2^o *does not Granger cause ΔGDP*	0.125	0.72	No causality
		ΔGDP does not Granger cause ΔCO_2^o	1.608	0.21	
		ΔCO_2^g *does not Granger cause ΔGDP*	0.192	0.66	No causality
		ΔGDP does not Granger cause ΔCO_2^g	0.456	0.50	

Note: (***) Significant at 1%, (**), Significant at 5% and (*), Significant at 10%

In the case of United States, we find unidirectional causality running from growth to emission from coal. It eventually explains the higher GDP growth can Granger cause higher emission from coal. However, we do not find any causal direction either in growth-emission or growth-emission type in United Kingdom.

6.6 Possible Substitution in Three Countries

The possible substitution of CO_2 emission from coal by emission from cleaner energy oil and natural gas has the lower slope than the observed relationship. For each countries the effect is in same direction but different in rate of change (Table 15). However the statistically significance of this substitution varies among the countries. In table 16, the result from Wald test shows that we cannot reject the null hypothesis $D = E[\widehat{Y}_{Observed}] - E[\widehat{Y}_{Potential}] = 0$ for the case of United Kingdom. On the other hand, the result for China and United States implies that the substitution between emission series has different impact on economic growth than that of observed emission without any substitution.

Table 15: Effect of CO_2 emission on economic growth

		Observed	Counterfactual (oil)	Counterfactual (gas)
China	Variable	$\Delta LnGDP_t$	$\Delta LnGDP_t$	$\Delta LnGDP_t$
	$\Delta \ln CO_2^T$	0.787*** (9.29)		
	$\Delta \ln CO^T_{2\,coal,oil}$		0.240*** (4.71)	
	$\Delta \ln CO^T_{2\,coal,gas}$			0.190*** (4.72)
United States	Variable	$\Delta LnGDP_t$	$\Delta LnGDP_t$	$\Delta LnGDP_t$
	$\Delta \ln CO_2^T$	0.834*** (7.24)		
	$\Delta \ln CO^T_{2\,coal,oil}$		0.205*** (5.22)	
	$\Delta \ln CO^T_{2\,coal,gas}$			0.333*** (5.21)
United kingdom	Variable	$\Delta LnGDP_t$	$\Delta LnGDP_t$	$\Delta LnGDP_t$
	$\Delta \ln CO_2^T$	0.268** (1.97)		
	$\Delta \ln CO^T_{2\,coal,oil}$		0.045*** (3.58)	
	$\Delta \ln CO^T_{2\,coal,gas}$			0.046*** (3.58)

Note: (***) Significant at 1%, (**), Significant at 5% and (*), Significant at 10%

t-Statistics in Parenthesis

Table 16: Wald test for China, United States and United Kingdom

		Counterfactual (oil)		Counterfactual (gas)	
China	Null Hypothesis	t-statistic:	4.792***	t-statistic:	4.785***
	$D = E[\hat{Y}_{Observed}] - E[\hat{Y}_{Potential}] = 0$	F-statistic:	22.971***	F-statistic:	22.899***
		χ^2:	22.971***	χ^2:	22.899***
	Null Hypothesis Summary	Value	Std. Error	Value	Std. Error
	Normalized Restriction $(=0)$	0.638	0.133	0.638	0.133
United States	Null Hypothesis	t-statistic:	4.252***	t-statistic:	3.794***
	$D = E[\hat{Y}_{Observed}] - E[\hat{Y}_{Potential}] = 0$	F-statistic:	18.080***	F-statistic:	14.400***
		χ^2:	18.080***	χ^2:	14.400***
	Null Hypothesis Summary	Value	Std. Error	Value	Std. Error
	Normalized Restriction $(=0)$	1.732	0.407	1.666	0.439
United Kingdom	Null Hypothesis	t-statistic:	0.977	t-statistic:	0.960
	$D = E[\hat{Y}_{Observed}] - E[\hat{Y}_{Potential}] = 0$	F-statistic:	0.955	F-statistic:	0.922
		χ^2:	0.955	χ^2:	0.922
	Null Hypothesis Summary	Value	Std. Error	Value	Std. Error
	Normalized Restriction $(=0)$	0.129	0.132	0.127	0.132

Note: (***) Significant at 1%, (**), Significant at 5% and (*), Significant at 10%

Chapter 7

Discussion and Implication

Nowadays carbon emission and its long run environmental impact is a global issue of immense importance. The significant amount of emission basically comes from the burning of fossil fuel, in particular coal, oil and natural gas. Emission from new renewable energy sources, for example, ethanol, biofuel etc. has naturally been balanced when the trees (input of biofuel, ethanol etc.) grew up. Although there is considerable awareness of using renewable energy and raising the 'decarbonization' policy; but in reality, no region is implementing this in their energy supply system. A quick shift from traditional fossil fuel to renewable seems difficult for economies. The relative price, technological utility, availability and energy content of fossil fuel keeps the world to consume fossil at the highest share of world total energy consumption. This energy consumption has a positive impact on CO_2 emission in atmosphere (Arouri et al., 2012). An acceleration of CO_2 emission at global scale has been driven by reversal of declining trend of energy intensity (energy/GDP) and carbon intensity of energy (CO_2 emission/energy consumption), combining with rapid population growth and increase in per capita GDP (Raupach et al., 2007).

The energy combustion is increasing because of industrial process and higher growth of economic activities. So, what could happen if the emission from dirty energy would be replaced by the emission from cleaner energy? As if, we can assume the dirty energy coal will be replaced by oil and natural gas in the long run. How this possible substitution can have impact on economic growth? To answer all this questions, I, first, estimate growth-emission and growth-emission type causality and second, test the effect of substation on economic growth.

In panel countries, result shows that the causality is bidirectional in most cases. Therefore, the economic growth in countries can cause higher emission at global scale. Since, emission is not bound to national territories. For instance, the higher growth of Indian economy can emit higher CO_2 and eventually it may hamper the environmental quality of neighboring countries and the global environment as well. On the other hand, the emission can cause economic growth through its externalities on residential or health sector. The result from substitution analysis is quite relevant and expected. In a word, the result shows that, if countries substitute emission from coal by emission from oil and natural gas, the degree of the positive relationship between economic growth and emission has become weak.

In country level of China, United States and United Kingdom the implication of the result varies from country to country. No causality between economic growth and total emission and significant unidirectional causality from growth to emission from coal again statistically support that higher economic growth in China and United States cause the higher emission in environment. To support this findings, a number of studies have shown that the growth rate of global CO_2 emission in increasing rapidly in developing parts of the world, specially the emission in strong in China (Zhao et al., 2012 and Guan et al., 2008). The structure of Chinese energy demand and fuel mix might be responsible for the rapid growth of coal consumption. According to the projection by IEA (2007), given the Chinese GDP growth rate 5.6 percent in 2002, the total energy consumption would be expected to increase by 3.1 percent by 2030. The coal consumption is expected to grow by 4.7 percent per annum between 2005 and 2015. Whereas the gas consumption will increase less than 4 percent, final oil demand will increase by 3.9 percent (IEA, 2007). Most of the increase in coal demand mainly comes from Chinese uprising manufacturing firms, export sectors and coal-fired plant for electricity production. Therefore, the causality result supports the trends of higher coal consumption over other energy sources.

United States, the second leader of CO_2 emission, has the similar result and implication as China. The direction of causality runs from economic growth to emission from coal in United States as well. A projection by US Energy Information Administration, EIA (2014) says that the coal consumption will increase at 5 percent in recent years as the electricity demand is continuously growing. In the case of United Kingdom, however, I did not find any evidence of causal relationship.

In regards to the possible substitution, the degree of positive relationship between economic growth and emission is expected to decrease in China and United States, if they substitute emission from coal by emission from oil and natural gas. As prior assumption, if countries substitute dirty energy consumption by clean energy, they will be environmentally benefitted. However, how GDP growth will react to this substitution is a matter of another intensive research. Moreover, as slope decreases after substitution, we could say that, the emission from clean energy can contribute more than that of dirty energy to make the Environmental Kuznets Curve downward.

Chapter 8

Conclusion and Final Remarks

8.1 Conclusion

Relationship between economic growth and environmental quality specifically CO_2 emission has mainly been examined by Environmental Kuznets Curve (EKC) hypothesis in literature. There are some research addressing the Granger causality between CO_2 emission and economic growth in single countries (time series) perspective. Using both panel and time series (3 countries) framework, the main objective of this study is to i) examine the growth-emission and growth-emission type causality and ii) investigate if substitution of emission from dirty energy by emission from clean energy has any significant impact on economic growth.

In this research, I estimate the Granger causality between economic growth and aggregated and disaggregated CO_2 emission series. In particular, along with growth-(total) CO_2 emission causality, this research examines the growth-emission type (CO_2 from coal, oil, natural gas) causality. Using the panel framework is one of the advantages of this research to draw generalized conclusion about economic growth and environmental degradation, since emission or pollutant is not fixed in national territories. Moreover, I estimate the relationship for China, United States and United Kingdom separately in a time series framework. Besides, the contribution of analyzing in panel framework, I have shown the possible substitution of CO_2 emission from dirty energy source, coal, by CO_2 emission from relatively cleaner energy source, oil and natural gas. Answering the question of how this possible substitution can influence economic growth is another important contribution of this research.

The analysis begins with the panel unit root tests of variables by using widely used method of checking stationarity. I found all the variables are non-stationary at their levels and become stationary after taking the first differences. That is all the variables are integrated of order 1, i.e. I(1). I used the overfitting of VAR, i.e. using VAR in first differences to estimate the panel Granger causality. The empirical result obtained from panel VAR in first differences indicates that there is *feedback* relationship between economic growth and total CO_2 emission ($\Delta GDP \leftrightarrow \Delta CO_2^T$). In disaggregated emission data, the causality analysis shows *Feedback* relationship in all types ($\Delta GDP \leftrightarrow \Delta CO_2^o$, $\Delta GDP \leftrightarrow \Delta CO_2^g$) except emission from coal. The result strongly supports the *unidirectional* causality running from economic growth to emission from coal ($\Delta GDP \rightarrow \Delta CO_2^c$). In next step, the panel least square estimates suggest that, the slope of the positive relationship between economic growth and CO_2 emission becomes lower, when countries substitute emission from coal by emission from oil and natural gas. This result has been statistically verified by using the Wald test using the linear restriction $D = E[\hat{Y}_{Observed}] - E[\hat{Y}_{Potential}] = 0$.

In the country level time series analysis of China, United States and United Kingdom, I followed the same procedure and address the main questions of two hypotheses. The standard unit root tests shows all variables are I(1) in each country. I do not find any causality between economic growth and (total) CO_2 emission in any of these three countries. However, the result shows there is statistically significant causality running from economic growth to emission from coal ($\Delta GDP \rightarrow \Delta CO_2^c$) in China and United States. As the world's largest CO_2 emitter and having the highest national GDP, this direction of causality is more relevant and expected. In regards to the substitution analysis, the result indicates that, the degree of positive relationship between economic growth and emission is expected to decrease in China and United States, if they substitute emission from coal by emission from oil and natural gas. In United Kingdom, however, I do not find any such causality or statistically significant possible substitution effect on economic growth.

Finally, this research contributes to draw conclusion about causality between economic growth and CO_2 emission for a set of large panel countries. And the substitution of CO_2

emission from coal by emission from oil and natural gas might have a significant impact on environmentally sustainable growth.

8.2 Limitation

Although I followed the standard methodology for panel data and time series analysis, there are some obvious limitation of this research. I used sufficiently large sample periods (51 years) for this analysis, but due to data unavailability on CO_2 emission from natural gas, I cannot include some representative sample countries. For example, Russia is one of countries among highest ten CO_2 emitter, but due to missing observation before 1990, I exclude this potential sample. Regarding methodological issues, I exclude China, United States and United Kingdom from the panel dataset because of excessively higher residual. This may affect the generalization of the result from panel framework, since at least two of the excluding countries are the first and second highest emitter of CO_2 in the world.

Another important limitation goes to the concern of omitted variable bias. Since GDP growth depends on many other factors such as labor, capital, foreign investment etc.; and CO_2 emission depends on energy consumption, growth of manufacturing sector, urbanization and residential energy demand etc., therefore, an analysis based on only GDP and CO_2 emission might suffer from potential omitted variable bias. A relevant issue is the role of CO_2 embodiment in international trade between China and United States. The international trade between the world top two largest emitters has increased global emissions by an estimated 720 million metric tons (Shui and Harriss, 2006). Therefore, not including the US-China trade in time series case is another potential limitation.

Although I estimate my results in differenced series, there may be heterogeneity in data at least in panel set. More explicitly, some countries are mostly coal dependent, whereas they have very insignificant amount of gas consumption. Therefore, the emission series among the countries might have some heterogeneity, which may affect the generalization of the result.

The substitution among CO_2 emission from different energy sources has been conducted, assuming the counterfactual, i.e. if the countries would have substitute the coal consumption by either oil or natural gas consumption. However, this substitution can be dependent on availability, relative price and energy content of other substitutes. Some countries are rich in coal reserve and price is relatively cheaper there. Hence, coupling with higher price of natural gas, possible substitution seems less efficient for coal-rich countries. Moreover, the substitution seems impractical unless the technologies are made up-to-date to use only oil and natural gas as fuel.

References

AROURI, M. E. H., YOUSSEF, A. B., M'HENNI, H. & RAULT, C. 2012. Energy consumption, economic growth and CO_2 emissions in Middle East and North African countries. *Energy Policy*, *45*, 342-349.

ARROW, K., BOLIN, B., COSTANZA, R., DASGUPTA, P., FOLKE, C., HOLLING, C. S., JANSSON, B. O., LEVIN, S., MÄLER, K. G., PERRINGS, C. & PIMENTEL, D. 1995. Economic growth, carrying capacity, and the environment. *Ecological Economics*, 15, 91-95.

BECKERMAN, W. 1992. Economic growth and the environment: whose growth? Whose environment? *World Development*, 20, 481-496.

BHAGWATI, J. 1993. The case of free trade. *Scientific American*, 269, 42-49.

BREITUNG, J. 1999. The local power of some unit root tests for panel data. : Quantification and Simulation of Economic Processes, Discussion Papers, No. 1999-69.

BRUNS, S. B. & GROSS, C. 2013. What if energy time series are not independent? Implications for energy-GDP causality analysis. *Energy Economics*, 40, 753–759.

BYER, T. 1987. Review of household energy issues in Africa. World Bank international memorandum, No.198.

CHOI, I. 2001. Unit root tests for panel data. *Journal of International Money and Finance*, 20, 249-272.

CHU, P.K.K. (2011) Relationship between macroeconomic variables and net asset values (NAV) of equity funds: Cointegration evidence and vector error correction model of the Hong Kong Mandatory Provident Funds (MPFs). *Journal of International Financial Markets, Institutions & Money*, 21 (3) pp. 792- 810.

CLARKE, J. A. & MIRZA, S. 2006. A comparison of some common methods for detecting Granger noncausality. *Journal of Statistical Computation and Simulation*, 76, 207-231.

COLE, M. A., RAYNER, A. J. & BATES, J. M. 1997. The environmental Kuznets curve: an empirical analysis. *Environment and development economics*, 2, 401-416.

COONDOO, D. & DINDA, S. 2002. Causality between income and emission: A country group-specific econometric analysis. *Ecological Economics*, 40, 351–367.

DALY, H. 1977. *Steady-state economics*, San Francisco: Freeman & Co.

DICKEY, F. & FULLER, W.A. 1981. Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, 49, 1057-1072.

DICKEY, D.A. & FULLER, W.A. 1979. Distribution of the estimations for autoregressive time series with a unit root. *Journal of American Statistical Association*, 74, 427-431.

DOLADO, J. J. & LÜTKEPOHL, H. 1996. Making Wald tests work for cointegrated VAR systems. *Econometric Reviews*, 15, 369-386.

EIA (US ENERGY INFORMATION ADMINISTRATION). 2014. Short term energy outlook [Online]. Available: http://www.eia.gov/forecasts/steo/report/coal.cfm [Accessed 13/05/2014].

EKINS, P. 1997. The Kuznets curve for the environment and economic growth: examining the evidence *Environment and Planning*, 29, 805 – 830.

FISHER, R.A. 1932. *Statistical methods for research worker,* London: Oliver and Boyd.

FRIEDL, B. & GETZNER, M. 2003. Determinants of CO_2 emission in a small open economy. *Ecological Economics*, 45, 133-148.

GALEOTTI, M. & LANZA, A. 1999. Richer and cleaner? A study on carbon dioxide emissions in developing countries. *Energy Policy*, 27, 565-573.

GALES, B.,KANDER, A., MALANIMA, P. & RUBIO, M. 2007. North versus South: Energy transition and energy intensity in Europe over 200 years. *European Review of Economic History*, 2, 219-253.

GILES, D. 2011. VAR or VECM When Testing for Granger Causality? [Online]. Available: http://davegiles.blogspot.se/2011/10/var-or-vecm-when-testing-for-granger.html [Accessed:14/04/2014].

GROSSMAN, G. & KREUGER, A. 1993. *Environmental impacts of a North American free trade agreement, the U.S.-Mexico free trade agreement*, Cambridge, MA: The MIT Press.

GROSSMAN, G. M., & KRUEGER, A. B. 1995. Economic growth and the environment. *The Quarterly Journal of Economics*, 110, 353-377.

GUAN, D., HUBACEK, K., WEBER, C. L., PETERS, G. P. & REINER, D. M. 2008. The drivers of Chinese CO2emissions from 1980 to 2030. *Global Environmental Change*, 18, 626–634.

HALKOS, G. E. & TSIONAS, E. G. 2001. Environmental Kuznets Curves: Bayesian evidence from switching regime models. *Energy Economics*, 23, 191-210.

HESTON, A., SUMMERS, R. & ATEN, B. 2012. Penn World Table *Version 7.1*, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania. [Online]. Available: https://pwt.sas.upenn.edu/php_site/pwt_index.php [Accessed 23/02/2014].

HOLTZ-EAKIN, D. & SELDEN, T. M. 1995. Stoking the fires? CO_2 emissions and economic growth. *Journal of Public Economics*, 57, 85–101.

IM, K. S., PESARAN, M. H. & SHIN, Y. 2003. Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 115, 53–74.

INTERNATIONAL ENERGY AGENCY. 2012. CO_2 emission from fuel combustion highlights 2012. OECD/IEA, Paris.

INTERNATIONAL ENERGY AGENCY. 2013. CO_2 emission from fuel combustion highlights 2013. OECD/IEA, Paris.

INTERNATIONAL ENERGY AGENCY. 2007. World Energy Outlook 2007. International Energy Agency, Paris.

IPCC (Intergovernmental Panel on Climate Change). 2005*. IPCC Special Report on Carbon dioxide Capture and Storage*. New York: Cambridge University Press.

KAO, C. 1999. Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics*, 90, 1-44.

JOHANSEN, S. 1988. Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 12, 231-254.

JOHANSEN, S. & JUSELIUS, K. 1990. Maximum likelihood estimation and inference on cointegration—with applications to the demand for money. *Oxford Bulletin of Economics and statistics*, *52*, 169-210.

KUZNETS, S. 1995. Economic growth and income inequality. *American Economic Review,* 45, 1-28.

LEACH, G. & GOWEN, M. (1987). Household energy handbook: an interim guide and reference manual. No. 67.

LEACH, G. 1992. The energy transition. *Energy Policy*, 20, 116-123.

LEVANDER, T. 1990. The relative contribution to the greenhouse effect from the use of different fuels. *Atmospheric Environment*, 24, 2707-2714.

LEVIN, A., LIN, C. F. & CHU, J. C. S. 2002. Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics*, 108, 1-24.

LOVE, I. & ZICCHINO, L. 2006. Financial development and dynamic investment behaviour: Evidence from panel VAR. *The Quarterly Review of Economics and Finance*, 46, 190-210.

MADDALA, G. S. & WU, S. 1999. A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and statistics*, 61, 631-652.

MARLAND, G. & ROTTY, R. M. 1984. Carbon dioxide emissions from fossil fuels: a procedure for estimation and results for 1950-1982. Tellus, 368, 232-261.

MARTÍNEZ-ZARZOSO, I. & BENGOCHEA-MORANCHO, A. 2004. Pooled mean group estimation of an environmental Kuznets curve for CO_2. *Economics Letters*, 82, 121-126.

NATIONAL BUREAU OF STATISTICS (NBS). 2010*. China Rural Statistical Yearbook 2006-2010*. Beijing: China Statistics Press.

NEUMAYER, E. 2002. Can natural factors explain any cross-country differences in carbon dioxide emissions? *Energy Policy*, 30, 7–12.

PACHAURI, S. & JIANG, L. 2008. The household energy transition in India and China. *Energy Policy*, 36, 4022-4035.

PANAYOTOU, T. 1993. Empirical tests and policy analysis of environmental degradation at different stages of economic development. ILO Technology and Employment Programme Working Paper, No. WP238.

PEDRONI, P. 1999. Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bulletin of Economics and Statistics,* 61, 653-670.

PIELKE, R. A. 2009. The British Climate Change Act: a critical evaluation and proposed alternative approach. *Environmental research letters*, 4, 024010.

RAUPACH, M. R., MARLAND, G., CIAIS, P., LE QUÉRÉ, C., CANADELL, J. G., KLEPPER, G. & FIELD, C. B. 2007. Global and regional drivers of accelerating CO_2 emissions. *Proceedings of the National Academy of Sciences*, 104, 10288-10293.

SELDEN, T. & SONG, D. 1994. Environmental quality and development: is there a Kuznets curve for air pollution emissions?. *Journal of Environmental Economics and Management*, 27, 147-162.

SELDEN, T. & SONG, D. 1994. Environmental quality and development: is there a Kuznets Curve for air pollution emission? *Journal of Environmental Economics and Management*, 27, 147-162.

SHAFIK, N. & BANDYOPADHYAY, S. 1992. Economic growth and environmental quality: time-series and cross-country evidence. World Bank Policy Research Working Paper, No. 904.

SHUI, B. & HARRISS, R. C. 2006. The role of CO_2 embodiment in US-China trade*.* *Energy Policy*, 34, 4063–4068.

STERN, D. I. & COMMON, M. S. 2001. Is there an environmental Kuznets curve for sulfur?. *Journal of Environmental Economics and Management*, 41, 162-178.

STERN, D. I. 2004. The rise and fall of the environmental Kuznets curve. *World Development*, *32*, 1419-1439.

STERN, D. I. 1998. Progress on the environmental Kuznets curve?.*Environment and Development Economics*, 3, 173-196.

STERN, D. I., COMMON, M. S. & BARBIER, E. B. 1996. Economic growth and environmental degradation: the environmental Kuznets curve and sustainable development. *World Development*, 24, 1151-1160.

SZKLO, A. & SCHAEFFER, R. 2006. Alternative energy sources or integrated alternative energy systems? Oil as a modern lance of Peleus for the energy transition. *Energy*, 31, 2513-2522.

TODA, H. Y. & PHILLIPS, P. C. B. 1994. Vector autoregressions and causality: a theoretical overview and simulation study. *Econometric Reviews*, 13, 259-285.

WEIJERMARS, R., DRIJKONINGEN, G., HEIMOVAARA, T. J., RUDOLPH, E. S. J., WELTJE, G. J., & WOLF, K. H. A. A. 2011. Unconventional gas research initiative for clean energy transition in Europe. *Journal of Natural Gas Science and Engineering*, 3, 402-412.

WORLD BANK. 2014. *World Development Indicator* [Online]. Available: http://databank.worldbank.org/data/views/variableSelection/selectvariables.aspx?source=world-development-indicators# [Accessed 12/02/2014].

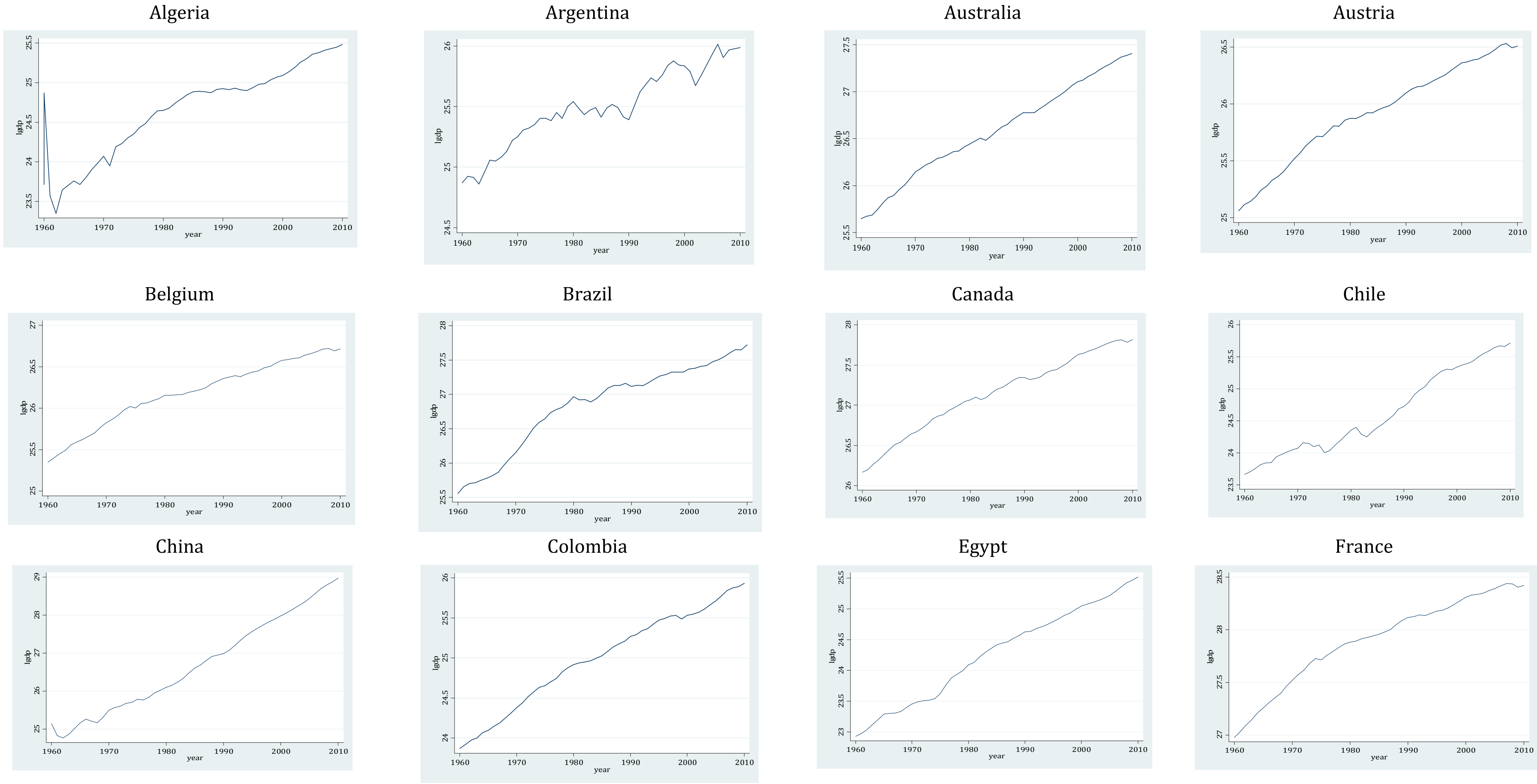
YUNFENG, Y. & LAIKE, Y. 2010. China's foreign trade and climate change: A case study of CO2emissions. *Energy Policy*, 38, 350–356.

ZAPATA, H. O. AND RAMBALDI, A. N. 1997. Monte Carlo evidence on cointegration and causation. *Oxford Bulletin of Economics and Statistics*, 59, 285-298.

ZHAO, Y., NIELSEN, C. P. MCELROY, M. B. 2012. China'sCO2emissions estimated from the bottom up: Recent trends, spatial distributions, and quantification of uncertainties. *Atmospheric Environment*, 59, 214-223.

Appendix A

Figure A1: GDP during 1960-2010: by country



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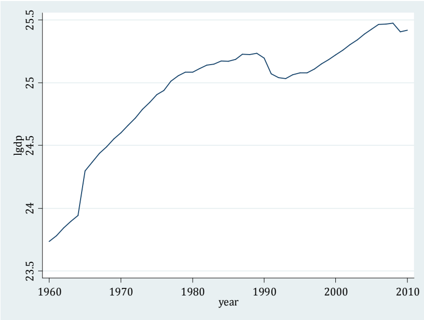

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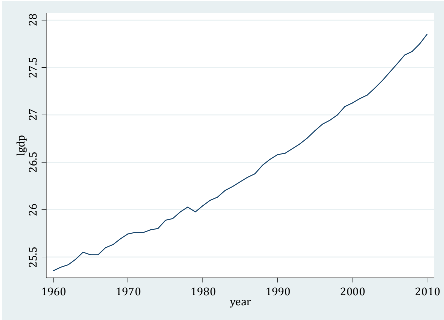

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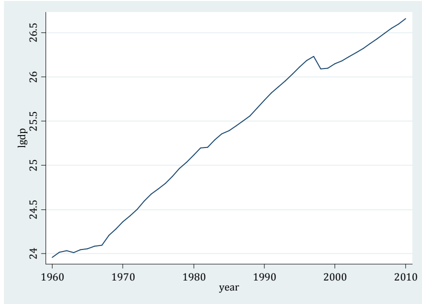

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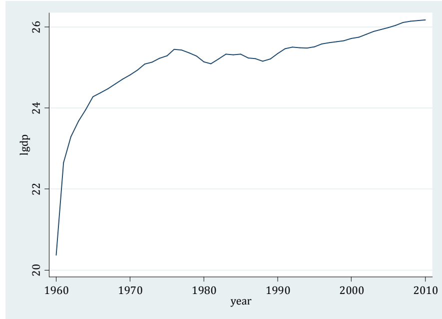

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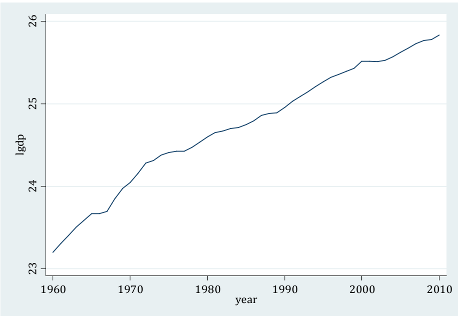

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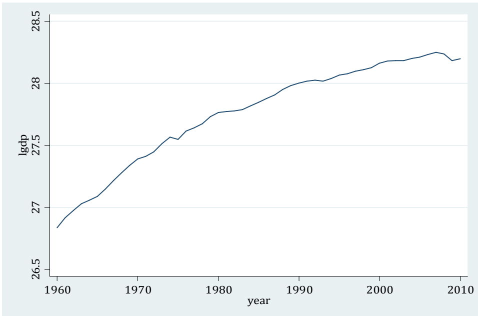

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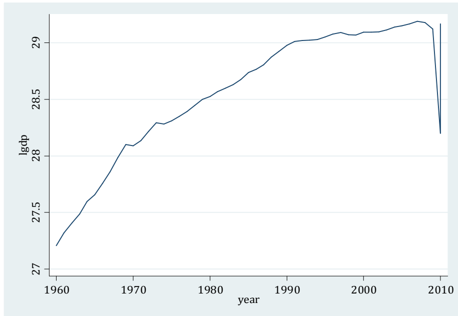
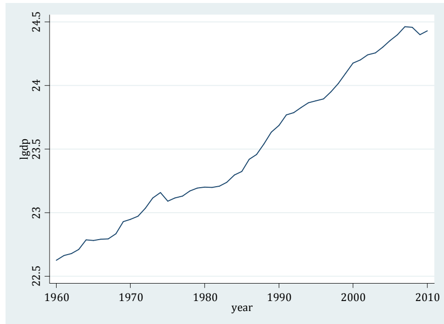


Luxemburg



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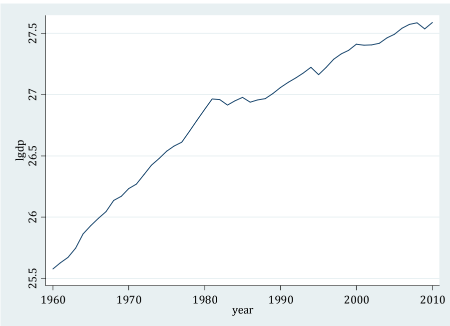

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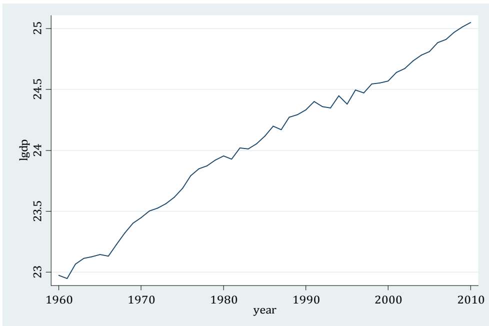

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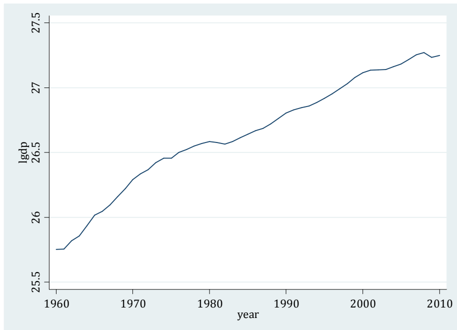

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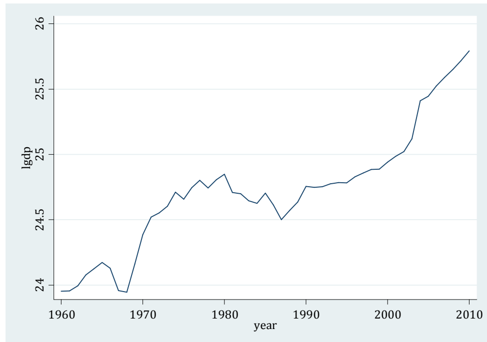

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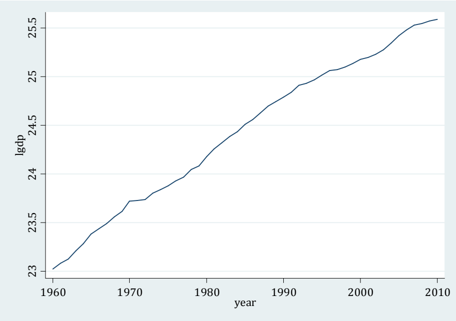

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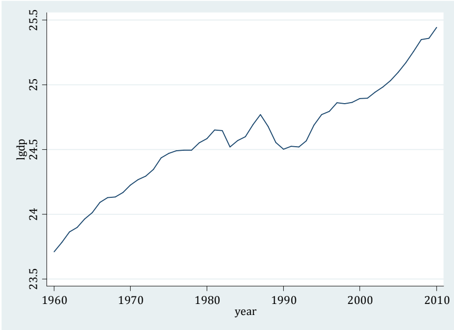

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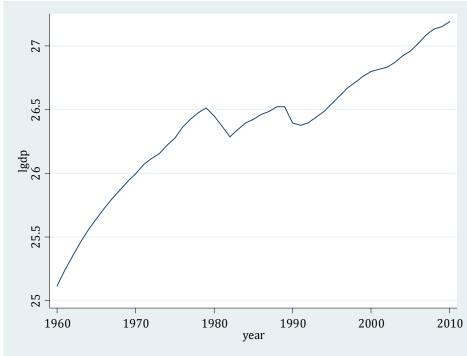

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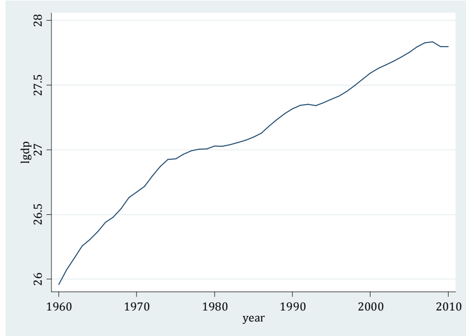

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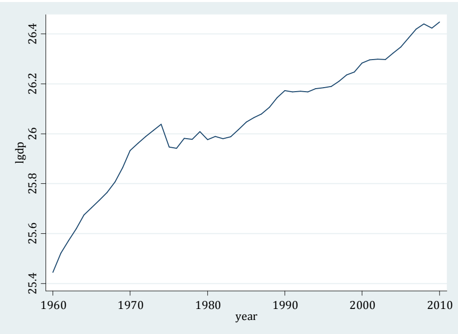

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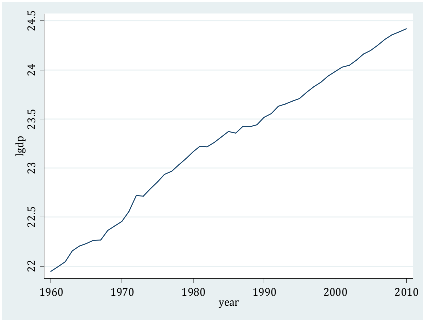

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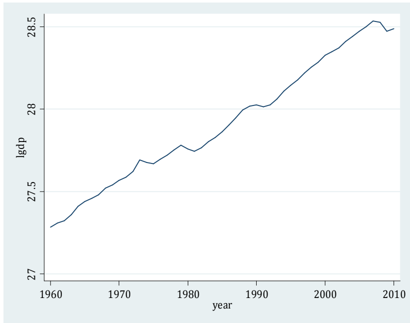
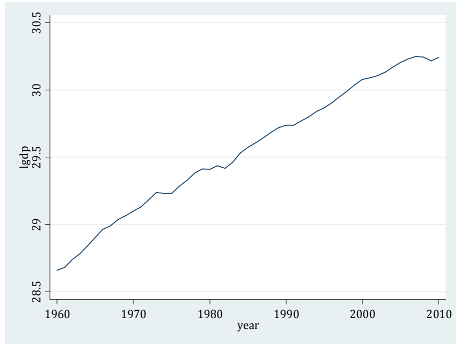


United States



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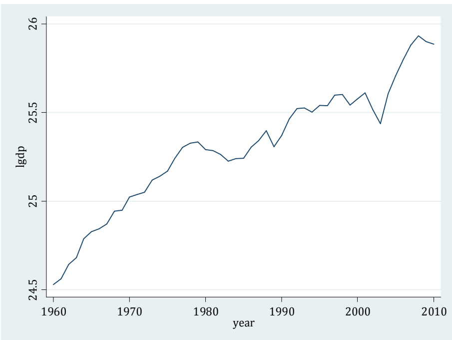
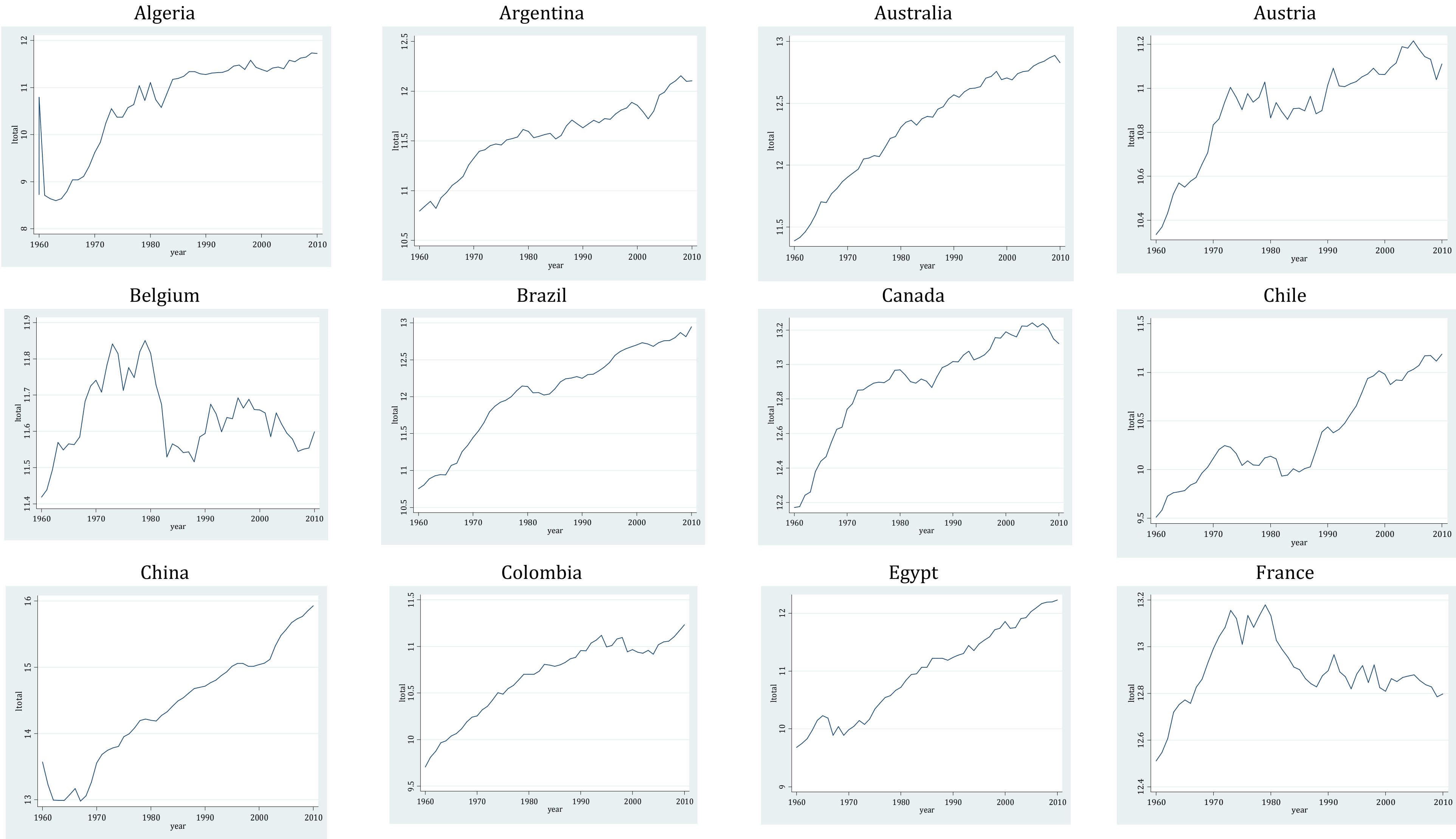
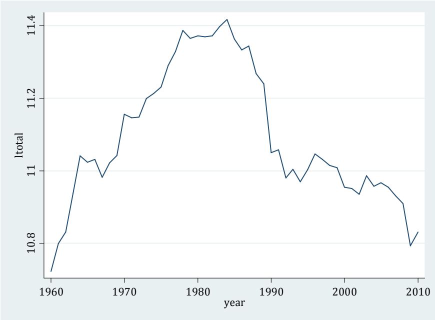


Figure A2: Log of Total CO2 Emission During 1960-2010



Hungry



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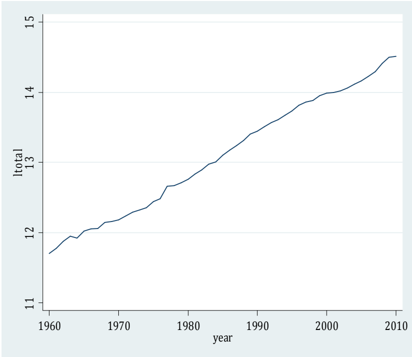

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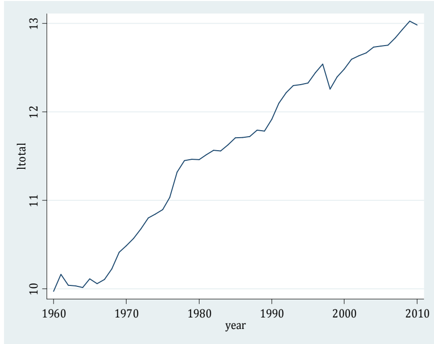

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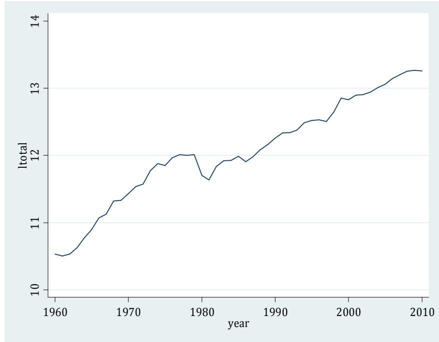

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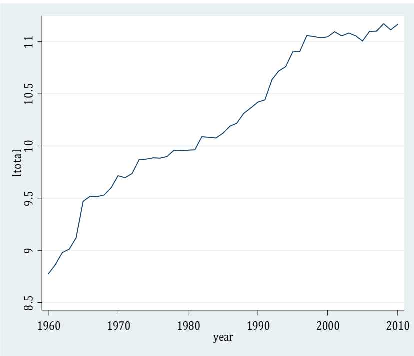

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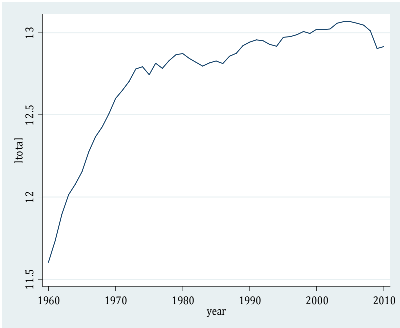

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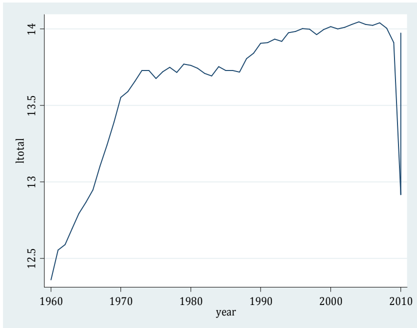

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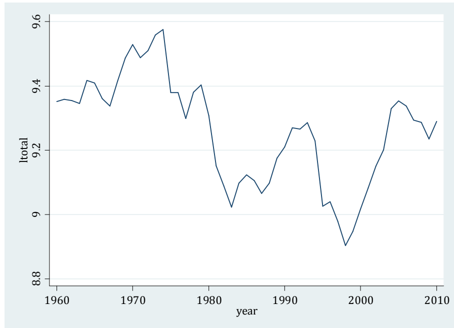

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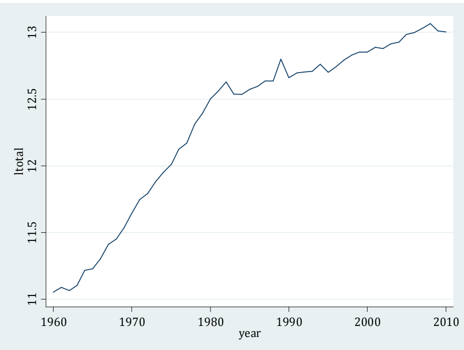

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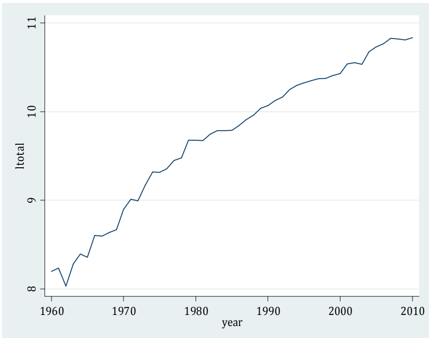

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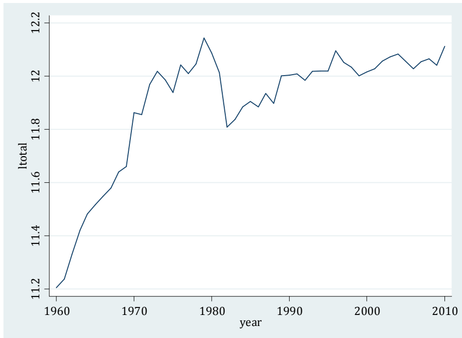

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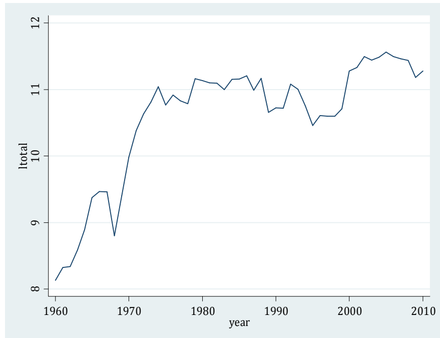

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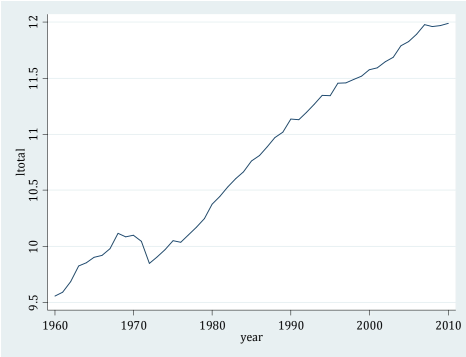

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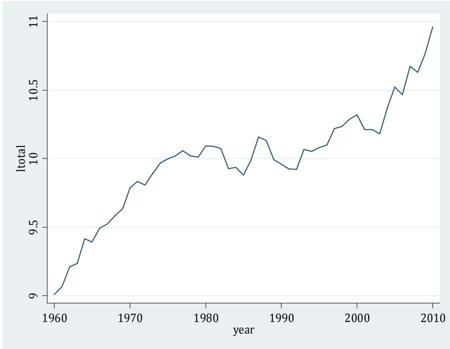

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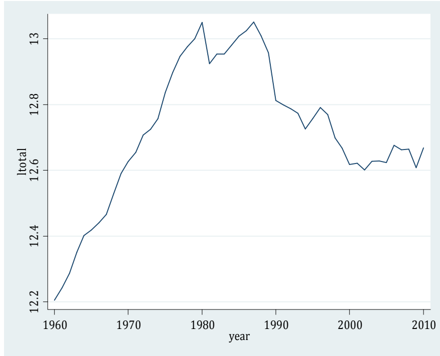

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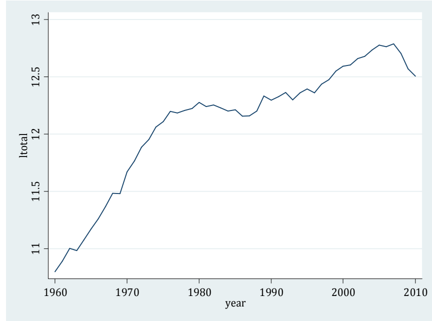

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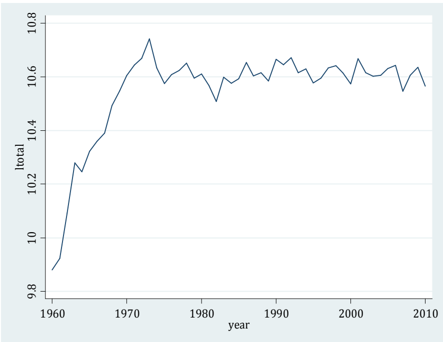
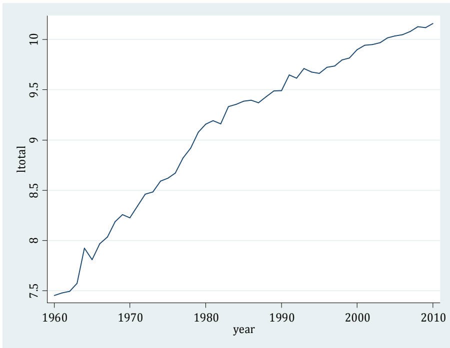
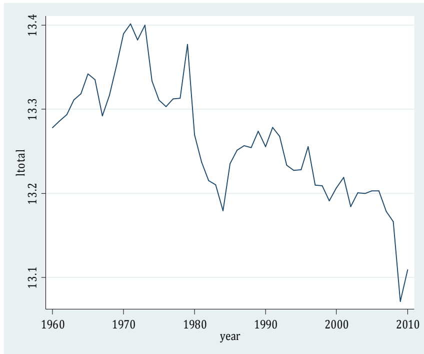


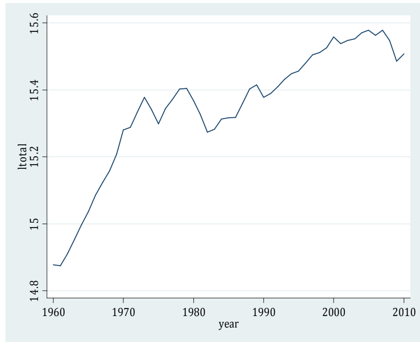
Tunisia



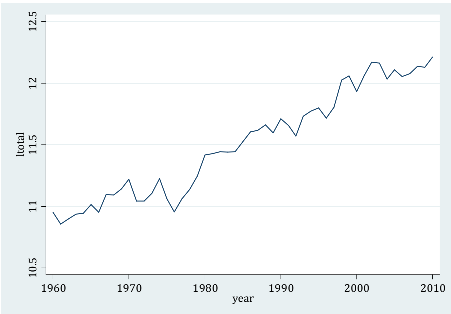
United Kingdom



United States



Venezuela



Appendix B: Panel Countries

Table B1: Lag length selection criteria table

a) Growth – Emission

Lag	LogL	LR	FPE	AIC	SC	HQ
0	3623.730	NA	8.96e-06	-5.947012	-5.938630	-5.943857
1	3696.349	144.8791	8.01e-06	-6.059686	-6.034538*	-6.070220*
2	3704.979	17.18915	7.94e-06	-6.067289	-6.025376	-6.051512
3	3709.085	8.165828	7.94e-06	-6.067464	-6.008786	-6.045376
4	3719.737	21.14669	7.86e-06	-6.078386	-6.002944	-6.049989
5	3732.212	24.72379	7.75e-06	-6.092302	-6.000094	-6.057593
6	3741.676	18.72524	7.68e-06	-6.101273	-5.992300	-6.060254
7	3753.883	24.11385	7.58e-06	-6.114750	-5.989012	-6.067420
8	3763.743	19.44537*	7.50e-06*	-6.124373*	-5.981870	-6.050733

b) Growth – Emission Type

Lag	LogL	LR	FPE	AIC	SC	HQ
0	2515.437	NA	1.90e-07	-4.123870	-4.107105	-4.117560
1	2640.963	250.0214	1.59e-07	-4.353716*	-4.219890*	-4.272163*
2	2657.536	32.90034	1.59e-07	-4.334656	-4.153770	-4.247860
3	2675.050	34.65481	1.58e-07	-4.327143	-4.089197	-4.225105
4	2689.501	28.49945	1.59e-07	-4.324600	-4.019594	-4.197319
5	2704.969	30.40191	1.59e-07	-4.313726	-3.951659	-4.171202
6	2728.590	46.27193	1.57e-07	-4.316239	-3.897112	-4.158474
7	2748.500	38.87204	1.56e-07	-4.322660	-3.836473	-4.139651
8	2777.304	56.04779*	1.53e-07*	-4.343685	-3.790437	-4.135434

* 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

Figure B1: VAR stability graph

Growth-Emission | Growth-Emission Type

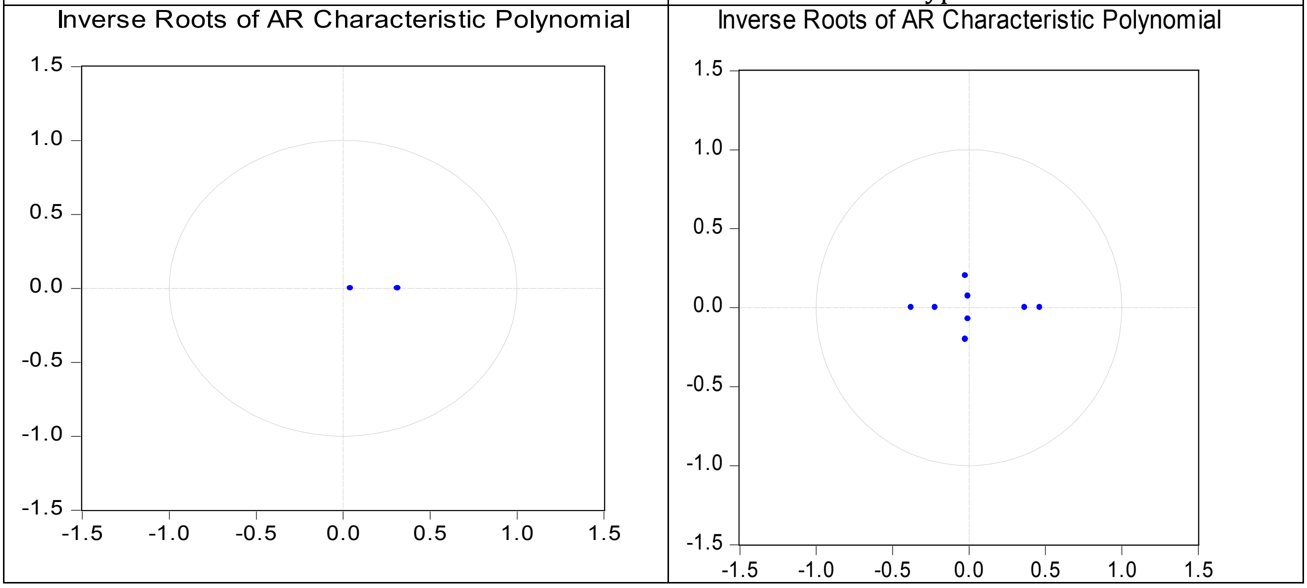


Table B2: VAR specification: Serial Autocorrelation Test

Growth – Emission

VAR Residual Serial Correlation LM Tests
Null Hypothesis: no serial correlation at lag order h
Date: 05/26/14 Time: 15:07
Sample: 1960 2010
Included observations: 1421

Lags	LM-Stat	Prob
1	17.73487	0.1020
2	16.22393	0.1200
3	10.25839	0.0155
4	12.88583	0.0118
5	10.26901	0.0361
6	14.00670	0.0073
7	25.20820	0.0000
8	29.68636	0.0000
9	9.925315	0.0417
10	9.807234	0.0438
11	3.900218	0.4197
12	1.528833	0.8215

Probs from chi-square with 4 df.

Growth – Emission Type

VAR Residual Serial Correlation LM Tests
Null Hypothesis: no serial correlation at lag order h
Date: 05/26/14 Time: 15:08
Sample: 1960 2010
Included observations: 1392

Lags	LM-Stat	Prob
1	21.40558	0.1600
2	14.72203	0.3040
3	27.45908	0.0367
4	20.84528	0.1845
5	33.01046	0.0074
6	34.25904	0.0050
7	42.70782	0.0003
8	37.61315	0.0017
9	28.69604	0.0261
10	42.05290	0.0004
11	16.73146	0.4032
12	20.25950	0.2088

Probs from chi-square with 16 df.

Appendix C: Time series

Table C1: Johansen cointegration test, maximum eigenvalue and trace statistics

China	**Null Hypothesis**	**Alternative Hypothesis**	**Unrestricted Co-integration Rank Test** Trace (λ_{trace})	5% critical value
	r = 0	r = 1	46.74254	47.85613
	r ≤ 1	r = 2	28.72016	29.79707
	r ≤ 2	r = 3	9.037565	15.49471
	r ≤ 3	r = 4	2.686934	3.841466
	Null Hypothesis	Alternative Hypothesis	Maximum Eigenvalue (λ_{max})	5% critical value
	r = 0	r = 1	21.02239	27.58434
	r ≤ 1	r = 2	19.68259	21.13162
	r ≤ 2	r = 3	6.350631	14.26460
	r ≤ 3	r = 4	2.686934	3.841466
United States	Null Hypothesis	Alternative Hypothesis	Trace (λ_{trace})	5% critical value
			39.21407	47.85613
	r ≤ 1	r = 2	26.65214	29.79707
	r ≤ 2	r = 3	10.12039	15.49471
	r ≤ 3	r = 4	2.362145	3.841466
	Null Hypothesis	Alternative Hypothesis	Maximum Eigenvalue (λ_{max})	5% critical value
	r = 0	r = 1	26.78012	27.58434
	r ≤ 1	r = 2	17.45012	21.13162
	r ≤ 2	r = 3	7.63542	14.26460
	r ≤ 3	r = 4	2.00247	3.841466
United Kingdom	Null Hypothesis	Alternative Hypothesis	Trace (λ_{trace})	5% critical value
	r = 0	r = 1	43.12580**	47.85613
	r ≤ 1	r = 2	21.45208	29.79707
	r ≤ 2	r = 3	11.48521	15.49471
	r ≤ 3	r = 4	2.25741	3.841466
	Null Hypothesis	Alternative Hypothesis	Maximum Eigenvalue (λ_{max})	5% critical value
	r = 0	r = 1	21.15784	27.58434
	r ≤ 1	r = 2	13.28179	21.13162
	r ≤ 2	r = 3	9.382636	14.26460
	r ≤ 3	r = 4	2.70291	3.841466

Table C2: VAR Lag Order Selection Criteria

a) China

Lag	LogL	LR	FPE	AIC	SC	HQ
0	143.1914	NA	7.40e-06	-6.138757	-6.059251	-6.108974
1	153.3943	19.07497	5.65e-06	-6.408448	-6.169930*	-6.369098*
2	159.7170	11.27087*	5.11e-06*	-6.509434*	-6.111903	-6.310517
3	162.2494	4.294157	5.47e-06	-6.445628	-5.889085	-6.237143
4	163.0486	1.285610	6.32e-06	-6.306461	-5.590905	-6.038409

b) United Stated

Lag	LogL	LR	FPE	AIC	SC	HQ
0	228.7804	NA*	1.79e-07	-9.860016	-9.630510	-9.740023
1	233.1662	8.199626	1.76e-07*	-9.876792*	-9.788274*	-9.837442*
2	234.5515	2.469371	1.98e-07	-9.763107	-9.365577	-9.614190
3	237.2801	4.626754	2.09e-07	-9.707829	-9.151286	-9.499345
4	242.3924	8.224105	2.01e-07	-9.756189	-9.040634	-9.488138

c) United Kingdom

Lag	LogL	LR	FPE	AIC	SC	HQ
0	210.2093	NA*	4.01e-07	-9.052580	-8.833074	-8.982797
1	214.7313	8.454174	3.93e-07*	-9.075276*	-8.976758*	-9.025926*
2	217.6881	5.270673	4.11e-07	-9.029916	-8.632385	-8.880999
3	219.5169	3.101076	4.53e-07	-8.935518	-8.378975	-8.727033
4	221.0073	2.397579	5.08e-07	-8.826404	-8.110849	-8.558353

* 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

Figure C1: VAR stability graph

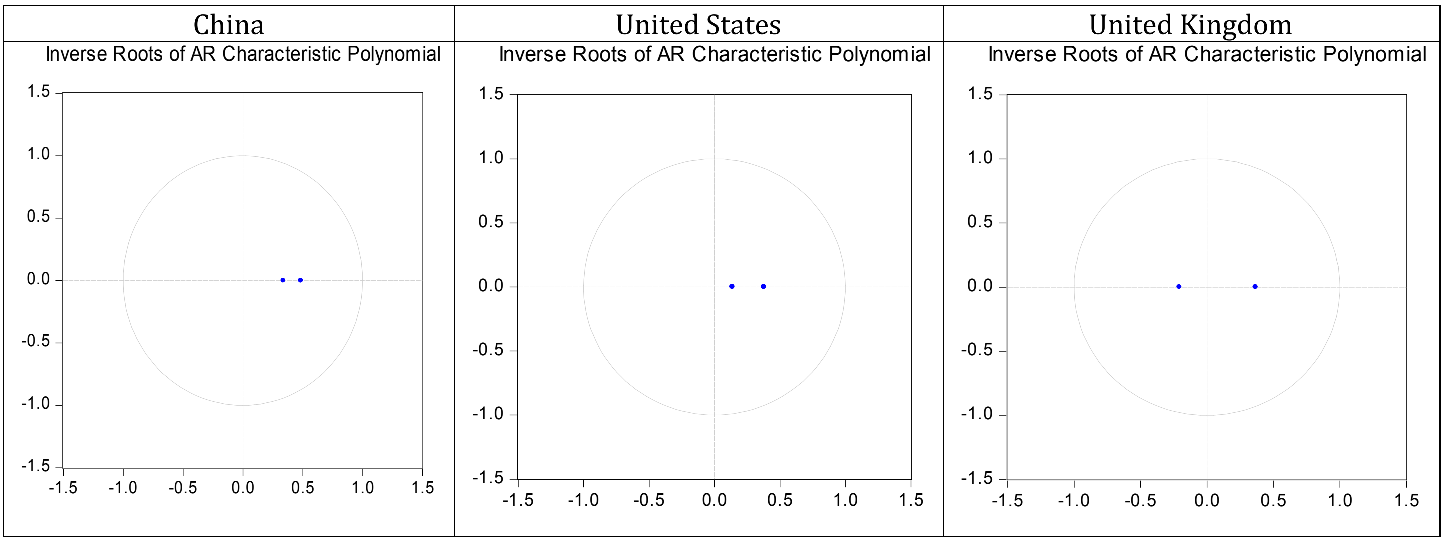


Figure C2: VAR stability graph, single emission series

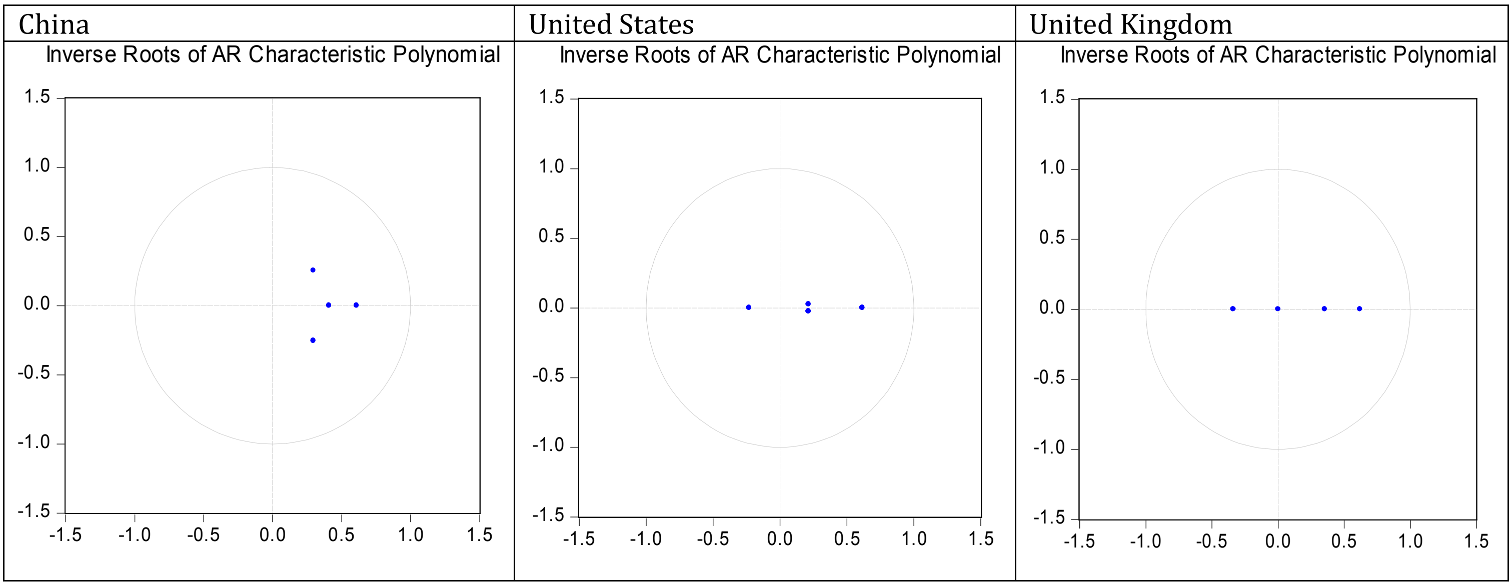


Table C3: VARfd Result by country: China

	$\Delta \ln GDP_t$	$\Delta \ln CO_{2\,t}^{g}$	$\Delta \ln CO_{2\,t}^{o}$	$\Delta \ln CO_{2\,t}^{c}$
$\Delta \ln GDP_{t-1}$	0.263068	-0.140641	-0.188470	-0.085588
	(0.13118)	(0.25523)	(0.21702)	(0.23389)
	[2.00538]	[-0.55103]	[-0.86847]	[-0.36593]
$\Delta \ln CO_{2\,t-1}^{g}$	-0.118551	0.155280	-0.165443	-0.080850
	(0.05730)	(0.11148)	(0.09479)	(0.10216)
	[-2.06913]	[1.39293]	[-1.74545]	[-0.79144]
$\Delta \ln CO_{2\,t-1}^{o}$	0.007818	0.532725	0.700057	-0.025064
	(0.09469)	(0.18423)	(0.15664)	(0.16882)
	[0.08256]	[2.89166]	[4.46914]	[-0.14846]
$\Delta \ln CO_{2\,t-1}^{c}$	-0.004981	0.523693	0.059424	0.498030
	(0.00108)	(0.20250)	(0.17218)	(0.18557)
	[2.47866]	[2.58608]	[0.34512]	[2.68376]
C	0.072620	0.020181	0.052474	0.045040
	(0.01168)	(0.02273)	(0.01933)	(0.02083)
	[6.21523]	[0.88771]	[2.71473]	[2.16198]
R-squared	0.326685	0.565460	0.383764	0.279725
Adj. R-squared	0.265475	0.525957	0.327742	0.214245
Sum sq. Resids	0.081898	0.310031	0.224137	0.260352
S.E. equation	0.043143	0.083941	0.071372	0.076923
F-statistic	5.337087	14.31415	6.850292	4.271944
Log likelihood	87.12748	54.51313	62.46125	58.79179
Akaike AIC	-3.352142	-2.020944	-2.345357	-2.195583
Schwarz SC	-3.159099	-1.827901	-2.152314	-2.002540
Mean dependent	0.084650	0.086648	0.080333	0.049823
S.D. dependent	0.050339	0.121918	0.087049	0.086778

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

Table C4: VARfd Result by country: United States

	$\Delta \ln GDP_t$	$\Delta \ln CO^g_{2\,t}$	$\Delta \ln CO^o_{2\,t}$	$\Delta \ln CO^c_{2\,t}$
$\Delta \ln GDP_{t-1}$	0.153521	0.701358	0.051772	0.612015
	(0.23127)	(0.46018)	(0.42008)	(0.43214)
	[0.66383]	[1.52409]	[0.12324]	[1.41623]
$\Delta \ln CO^g_{2\,t-1}$	-0.066379	0.296734	0.121399	-0.138925
	(0.07158)	(0.14243)	(0.13002)	(0.13376)
	[-0.92732]	[2.08331]	[0.93370]	[-1.03864]
$\Delta \ln CO^o_{2\,t-1}$	0.218377	0.090814	0.578002	0.055919
	(0.08909)	(0.17728)	(0.16183)	(0.16648)
	[2.45114]	[0.51227]	[3.57172]	[0.33590]
$\Delta \ln CO^c_{2\,t-1}$	-0.118424	-0.590598	-0.271748	-0.212666
	(0.00860)	(0.21610)	(0.19726)	(0.20293)
	[-2.39809]	[-2.73301]	[-1.37758]	[-1.04797]
C	0.026177	-0.004335	0.004881	0.000982
	(0.00643)	(0.01280)	(0.01168)	(0.01202)
	[4.07007]	[-0.33876]	[0.41780]	[0.08171]
R-squared	0.238868	0.250046	0.368978	0.092412
Adj. R-squared	0.169675	0.181869	0.311613	0.009904
Sum sq. resids	0.016495	0.065311	0.054423	0.057595
S.E. equation	0.019362	0.038527	0.035169	0.036180
F-statistic	3.452167	3.667570	6.432044	1.120040
Log likelihood	126.3866	92.67221	97.14033	95.75239
Akaike AIC	-4.954555	-3.578457	-3.760830	-3.704179
Schwarz SC	-4.761512	-3.385415	-3.567787	-3.511136
Mean dependent	0.031821	0.014384	0.010349	0.016007
S.D. dependent	0.021248	0.042595	0.042389	0.036360

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

Table C5: VARfd Result by country: United Kingdom

	$\Delta \ln GDP_t$	$\Delta \ln CO^g_{2\,t}$	$\Delta \ln CO^o_{2\,t}$	$\Delta \ln CO^c_{2\,t}$
$\Delta \ln GDP_{t-1}$	0.383235	0.086261	0.439563	-0.165785
	(0.16178)	(1.64676)	(0.49348)	(0.67098)
	[2.36881]	[0.05238]	[0.89073]	[-0.24708]
$\Delta \ln CO^g_{2\,t-1}$	0.006298	0.474452	0.097764	-0.039041
	(0.01297)	(0.13205)	(0.03957)	(0.05380)
	[0.48549]	[3.59299]	[2.47059]	[-0.72562]
$\Delta \ln CO^o_{2\,t-1}$	-0.017251	0.912712	-0.031568	0.245155
	(0.05878)	(0.59831)	(0.17930)	(0.24378)
	[-0.29348]	[1.52547]	[-0.17606]	[1.00562]
$\Delta \ln CO^c_{2\,t-1}$	-0.031508	0.129197	0.102914	-0.186807
	(0.01193)	(0.42681)	(0.12790)	(0.17391)
	[-1.89211]	[0.30270]	[0.80463]	[-1.07419]
C	0.012943	0.073339	-0.016928	-0.024217
	(0.00573)	(0.05830)	(0.01747)	(0.02375)
	[2.25984]	[1.25801]	[-0.96895]	[-1.01951]
R-squared	0.135715	0.372204	0.188258	0.095867
Adj. R-squared	0.057144	0.315132	0.114463	0.013673
Sum sq. resids	0.019320	2.001662	0.179753	0.332308
S.E. equation	0.020954	0.213289	0.063916	0.086905
F-statistic	1.727289	6.521619	2.551097	1.166346
Log likelihood	122.5142	8.819146	67.86785	52.81306
Akaike AIC	-4.796496	-0.155884	-2.566035	-1.951553
Schwarz SC	-4.603453	0.037159	-2.372992	-1.758511
Mean dependent	0.024102	0.146203	0.004780	-0.027065
S.D. dependent	0.021580	0.257730	0.067922	0.087505

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

Table C6

VAR Specification: Serial Autocorrelation Test

China			United States			United Kingdom		
VAR Residual Serial Correlation LM Tests Null Hypothesis: no serial correlation at lag order h Sample: 1960 2010 Included observations: 49			VAR Residual Serial Correlation LM Tests Null Hypothesis: no serial correlation at lag order h Sample: 1960 2010 Included observations: 49			VAR Residual Serial Correlation LM Tests Null Hypothesis: no serial correlation at lag order h Sample: 1960 2010 Included observations: 49		
Lags	LM-Stat	Prob	Lags	LM-Stat	Prob	Lags	LM-Stat	Prob
1	12.07635	0.1081	1	3.147712	0.5334	1	6.196071	0.1850
2	11.86634	0.1205	2	2.760153	0.5987	2	5.723316	0.2208
3	19.21977	0.2574	3	2.102696	0.7169	3	4.074496	0.3960
4	18.44809	0.2983	4	10.29768	0.0357	4	1.720220	0.7870
5	5.940947	0.9887	5	0.485215	0.9749	5	5.190166	0.2683
6	9.079265	0.9101	6	0.295285	0.9901	6	5.700777	0.2226
7	7.533020	0.9616	7	1.039677	0.9037	7	4.796255	0.3088
8	18.62144	0.2888	8	4.543453	0.3374	8	2.071275	0.7227
9	11.42215	0.7827	9	9.423731	0.0513	9	0.395883	0.9828
10	10.87818	0.8169	10	4.825063	0.3057	10	5.159083	0.2714
11	8.361092	0.9374	11	3.748206	0.4412	11	9.727152	0.0453
12	9.195752	0.9051	12	3.951407	0.4126	12	2.987473	0.5599
Probs from chi-square with 4 df.			Probs from chi-square with 4 df.			Probs from chi-square with 4 df.		