THE IMPACT OF ENERGY CONSUMPTION & ECONOMIC GROWTH ON CARBON DIOXIDE (CO_2) EMISSIONS IN SRI LANKA: A MULTIVARIATE TIME SERIES ANALYSIS

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Dissertation submitted in partial fulfillment of the requirements for the degree Master of Science in Business Statistics

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DECLARATION OF THE CANDIDATE AND THE SUPERVISOR

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ABSTRACT

The studies on the impact of fossil fuel energy consumption and the economic growth of a country on carbon dioxide emissions have given high priority by many countries. Moreover, not much study on this approach had done in Sri Lanka, and most of the methods have not been tested statistically in studies of Sri Lanka. Therefore, this study utilized the Vector Error Correction Model (VECM) framework to observe the impact of fossil fuel energy consumption and economic growth on carbon dioxide (CO_2) emissions in Sri Lanka over the period of 1971 - 2014. The required secondary data obtained from one of the World Bank databases known as the world development indicators (WDI). The heterogeneity of variances in each series reduced by considering their natural logarithmic transformations and each series was not significantly different from normality. Entire log-transformed series were formed trend stationary at their first differences, and the Johansen's cointegrating analysis indicated that there was at most one cointegrating relationship among the log series at the first lag. Furthermore, the fitted VECM (1) model identified as a highly stable model, and errors were not significantly different from the white noise process. The long-run variables' trends revealed significantly that a unit increase in the present logarithmic level of both CO_2 emissions and economic growth (GDP) influenced positively, and surprisingly, that for fossil fuel energy consumption, influenced negatively on the continuous change in the logarithmic level of CO_2 emissions, in the long-run association. The analysis of impulse response functions (IRF) suggested that a positive shock of CO_2 emission has a positive influence on its increasing, and the positive influence has relatively long sustained effectiveness. The inferences derived in this study suggested that a significant transformation of sustainable low carbon future and green energy policy implementations could contribute to control the CO_2 emissions while sustaining long-run economic growth in Sri Lanka. Altogether, it recommended that similar studies might be carried out at regular intervals.

Keywords: Carbon dioxide **(**CO_2) emissions, Economic growth, Energy consumption, Johansen's cointegration, VECM

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey- Fuller
AIC	Akaike information criterion
ANN	Artificial neural network
ARCH	Autoregressive conditional hetroscedasticity
ARDL	Autoregressive distributed lag
BIC	Schwarz Bayesian information criteria
DOLS	Dynamic ordinary least squared
ECM	Error correction model
EKC	Environmental Kuznet's curve
FMOLS	Fully modified ordinary least squared
FPE	Final prediction error (criterion)
GHG	Greenhouse gas
GLS	generalized least squares
HQ	Hannan-Quinn (information criterion)
H_o	Null hypothesis
H_a	Alternative hypothesis
I(d)	Integrated of order d
iid	Independently identically distributed
IRF	Impulse response function
JB	Jarque-Bera (test)
LM	Lagrange multiplier (test)
LR	Likelihood ratio (test)
ML	Maximum Likelihood
OLS	Ordinary least squares
VAR	Vector autoregressive (process)
VEC	Vector error correction
VECM	Vector error correction model
Δ	Differencing operator

CHAPTER 1

INTRODUCTION

1.1 Introduction to Climate Change & Global Warming

The earth climate means the long-term average of weather and defines by a structure encompassing five physical systems; (i) atmosphere (air), (ii) biosphere (living organisms), (iii) cryosphere (ice & snow), (iv) hydrosphere (water) and (v) lithosphere (earth's crust & upper mantel), (Wikipedia, 2018). Energy for the earth's climate is encompassed primarily by the sun and a comparatively small amount from earth's interior. The persistent process of the sun's energy absorption (incoming energy) and reflection (outgoing energy) creates the earth's energy balance, which maintains an average global temperature of the earth. If the earth succeeds to absorb, as much energy it radiates, the earth's energy budget is balanced, and the average global temperature is stable.

Climate change causes by an unbalanced earth's energy or unstable global temperature and defines as changes in the earth's climate system. The earth's energy budget is negative, and earth experiences cooling if the earth's radiation is greater than its absorption. The earth's energy budget is positive, and the global temperature is increasing if the earth's energy absorption is greater than its radiation. Global warming defines by the continuous rise in the long-term average global temperature. Formal detection in the climate change impacts are trapping heat within atmosphere, occurrence of frequent & intense heat waves, rise in oceanic temperature & atmospheric water vapor, melt in sea ice, snow cover & glaciers, rise in sea level & high tides, increase in coastal flooding, more severe droughts occurrence, variations in storms & rainfall pattern, contaminations and destructions in water cycle & water table… etc. IPCC (2014) has explained that the earth's surface has been wormed over the last three decades in succession than any preceding decade since 1850 triggering many other fluctuations to the earth's climate.

The fastest-growing global warming and climate change have been deliberated as a dominating threat in ongoing worldwide concern during the last decades, due to rapid industrialization, increasing the population as well as significant transformation in lifestyle effecting on meteorological conditions and ecosystems. In most scientific consensus revealed that the climate change was predominantly due to human activities coming from combustion of fossil fuels; principally coal, petroleum, and natural gas which causes to emit greenhouse gasses (GHGs) into the atmosphere along with additional contributions coming from cement production, tropical deforestation, change in land use and agriculture (including livestock) as well from natural processes such as respiration, volcanic eruptions, and soil erosion, (Global Climate Change: Causes, 2008). The natural cycles within the earth's climate system do not responsible for the continuous rise in the overall heat content of the climate system since it is responsible only for the component of redistributed heat (USGCRP, 2017). There is no significant evidence that accounts the global warming by the natural processes and variability of its pattern over the industrialized era. Furthermore, there are no observational records, which explain modern changes in climate apparent from the natural processes. Hence, climate change observations are explained by identified physical mechanisms on a suitable scale consisting of time in direction, with long term observed trends realistically based on human activities due to the industrial revolution.

1.2 Carbon Dioxide Emissions in the Earth's Atmosphere

A GHG defines by a gas that traps heat within the atmosphere (absorbs & emits radiation from earth to space), forming the greenhouse effect (a natural process that warms the troposphere & the earth's surface). The greenhouse effect considers as one root cause of global warming. The GHGs are water vapor (H_2O, generally assumed to be at a steady-state), Carbon dioxide (CO_2), Methane (CH_4), Nitrous oxide (N_2O), Hydrofluorocarbons (HCFCs & HFCs), Ozone (O_3), and Chlorofluorocarbons (CFCs). CO_2 emissions consider as the most abundant pollutant emissions (GHGs), caused by burning fossil fuels and cement products made from limestone. Since the pre-industrial era, an enormous increment of the atmospheric GHGs has a high concentration of CO_2, CH_4 & N_2O comparatively other emitters, (Figure 1.1).

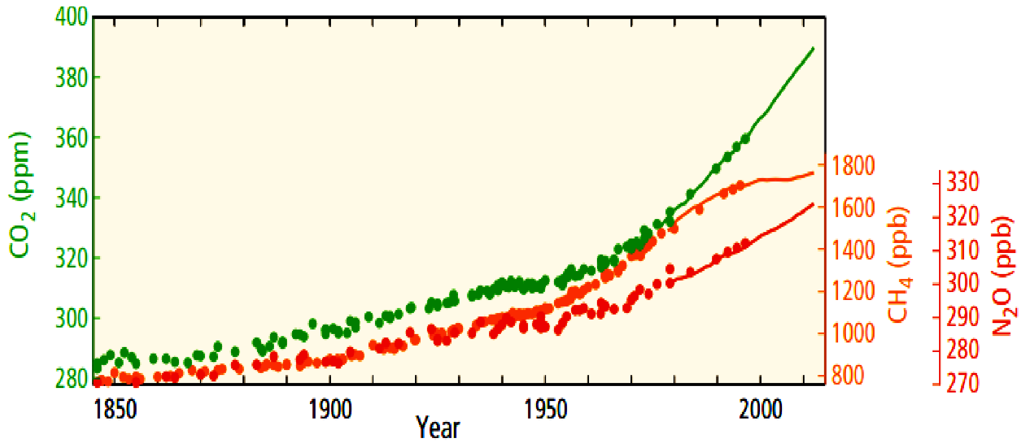

Figure 1.1: Globally averaged greenhouse gas concentrations

Source: IPCC (2014)

The level of atmospheric GHGs significantly increases, harming the green space and imposing severe damages on the atmosphere as a result of the aforementioned human influences. Continued increases in total GHG emissions from1970 to 2010 pointed out a large absolute increase from 2000 to 2010, in the face of broadly forecasted and evolving number of climate change mitigation policies (IPCC, 2014). Hence, most researches, as well as policymakers in both political and economic, worried out to mitigate the adverse effects of global warming and climate change.

1.3 International Conventions on Action of Climate Change

The United Nations is the forefront international family that attempted to the United Nations Conference on Environment and Development (UNCED) on 12^{th} June 1992 in Rio de Janeiro as the first step to mitigate the adverse effects of climate change, (Wikipedia, 2018). The United Nations Framework Convention on Climate Change (UNFCCC) was ratified by 154 nations to stabilize the GHGs concentration with the ultimate intention of preventing “hazardous human interference on the climate system”, (United Nations & Canada, 1992). In 1995, it was succeeded with the attention of many countries launching negotiations to strengthen the global response to climate change. Accordingly, there were few protocols such as the Kyoto Protocol (KP) and Paris agreement (PA).

1.3.1 The Kyoto Protocol (KP)

Among several international attempts, the most notable agreement was the KP, which was working towards curbing collective global GHG emissions. It was adopted in Kyoto (in Japan) on 11th December 1997 as an alteration to the UNFCCC, having the main objective of reducing the collective global GHG emissions and entered in to force on 16th Feb 2005. Its first commitment period spanned from 2008 to 2012, and the second spanned up to 2020, beginning on 1st January 2013. The protocol follows the UNFCCC’s principle of "common but differentiated responsibilities" among developed nations, and then the industrialized countries are responsible for a larger role in emissions reduction targets, concerning their share in the global emissions level. In consideration of the KP, many countries among almost 191 universal participants, which have signed and an endorsement contemporary of the protocol are in progress of moving from fossil fuels reliance, towards the use of more renewable energy sources (RES) (Wikipedia, 2018).

Global industrial production improves with the involvement of both industrialized as well as developing countries. Hence, the third world countries have to face the same challenges just as the developed nations of reducing pollutant emissions, improving efficiency in energy consumption, and sustainable economic development, even though they had not ratified the Kyoto Protocol. Hence, the KP consider as a legally blind obligation among industrialized nations because developing countries were completely exempt from the GHGs reduction targets, but they willingly complied (Kumazawa & Callaghan, 2012).

1.3.2 The Paris Agreement (PA)

The UNFCCC parties at the 21st conference of the Paris (COP) [30th Nov - 12th Dec 2015] in Paris, France reached the PA which was adopted as an amendment to the UNFCCC rather to the KP and is entered in to effect on 4th Nov 2016, (Wikipedia, 2018). It was a landmark convention that is strengthened and accelerated for a sustainable low carbon future, based on an action plan dealing with global GHG emissions, mitigation, adaptation, and financial investment. The PA was the first attempt that brought all nations into a common platform, which was taken on an ambitious effect to mitigate climate change with enhanced support to assist developing counties towards mitigation aims and adaptation to its effects, starting a new chapter in global climate effort. Accordance to United Nations & Canada (1992), long-term central aim of the convention is to make stronger global response to the threat of climate change by keeping the global average temperature rise for the 21st century well below 2°C, above pre-industrial levels and pursue efforts to limit temperature increase even further to 1.5 °C. Further, it explained that 175 world leaders had signed the convention on the Earth day (22nd April 2016), which considered a long way the largest number of nations ever signed an international agreement on a single day. To date, 184 universal parties have ratified the convention.

1.4 The Climate Summit in 2019

The United Nation 2019 Climate Summit (also referred as the Leader's Climate Summit) set up basically on foundation of the PA, towards the climate change actions of the 2030 agenda for sustainable development, and will convene to mobilize the highest level of political as well as economic energy on implementing advanced climate actions on sustainable development goals under the theme, 'A Race We Can Win. A Race We Must Win', in New York on 23rd September 2019, (United Nations & Canada, 1992). It is in progression of bringing climate actions to the highest level of international agenda following the main purpose of challenging; the states, regions, cities, companies, investors and civil society, focusing most emissions on key sectors (where action can make the most difference): energy transition, climate finance & carbon pricing, industry transition, nature-based solutions, cities & local action and resilience. The world leaders and partners are authorized to report their nationally determined contributions with concrete, realistic climate actions and showcase their ambitions in line with reducing GHG emissions by 45% over the next decade and to net zero emissions by 2050 when they convene by 2020 for the UN climate conference. Together with the aforementioned developments, it will make political signals on objectives of the PA & the sustainable development goals amongst countries, cities, companies, and civil society.

Note: The modern sustainable development concept is defined as organizing standards for succeeding human development and goals while sustaining the availability of natural systems at the same time, to provide natural resources and ecosystem services upon, which economy and society depend without compromising the availability of future generation, (Wikipedia, 2018).

1.5 Human Fingerprint on Global Carbon Dioxide Emissions

The CO_2 emissions per capita (CO_2 in Mt per person) is an indicator for CO_2 emissions mainly from burning fossil fuels and cement production excluding LUCF. Other CO_2 emissions from land-use such as deforestation as well from international shipping or bunker fuels exclude in this national figure, but it may have significant differences for small countries or islands with imperative ports (Figure 1.2).

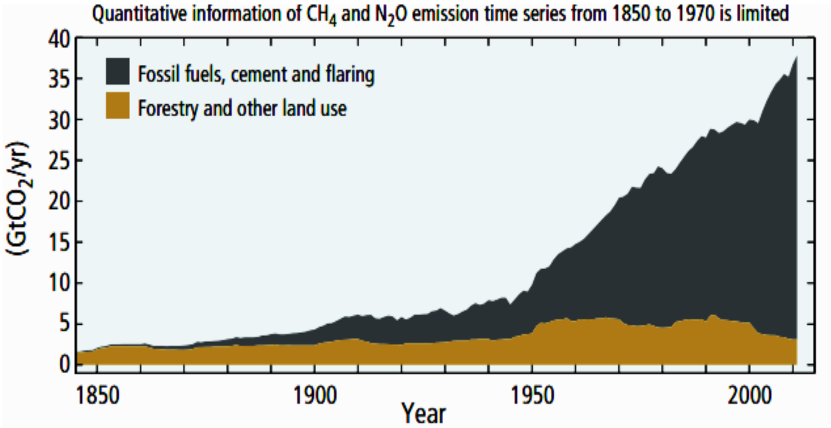

Figure 1.2: Global anthropogenic CO_2 emissions

Source: IPCC (2014)

As IPCC (2014) described, from 1750 to 2011, cumulative atmospheric CO_2 emissions to the atmosphere were 2040 ± 310 $GtCO_2$. Approximately 40% of those CO_2 emissions had remained in the atmosphere (880 ± 35 $GtCO_2$), and balance 60% were removed from the atmosphere storing on land (in plants & soils) as well as in the ocean. Approximately 30% of emitted CO_2 emissions were absorbed by the ocean, causing ocean acidification. More than 50% of the anthropogenic CO_2 emissions from 1750 to 2011 had monitored in the last 40 years, with higher absolute increases from 2000 to 2010, despite the international approaches on climate change mitigation actions and policies. The Global Climate Change: Causes (2008) mentioned that the atmospheric CO_2 level has risen-up from 280 parts per million (ppm) to 413.52 ppm [value in April 2019 accordance with CO_2: Earth records, (McGee, 2013)] in last 150 years.

The CO_2 emissions considered as dominant cause to the global warming, which was responsible at least 76% of total GHGs concentration (all-encompassing 65% by fossil fuel & industrial process then 11% by forestry & land-use changes) with 16% of CH_4, 6% of N_2O and 2% of fluorinated gases. However, Olivier, Janssens-Maenhout, Muntean & Peters (2015) explained that top four CO_2 emitters (which accounted almost two thirds (61%) of the total global CO_2 emissions) as China (30%), the United States (15%), the European Union (EU-28) (10%) and India (6.5%). Accordingly, China was the largest CO_2 emitter followed by United States, European Union, India, the Russian Federation, and Japan in the year 2014 (Figure 1.3).

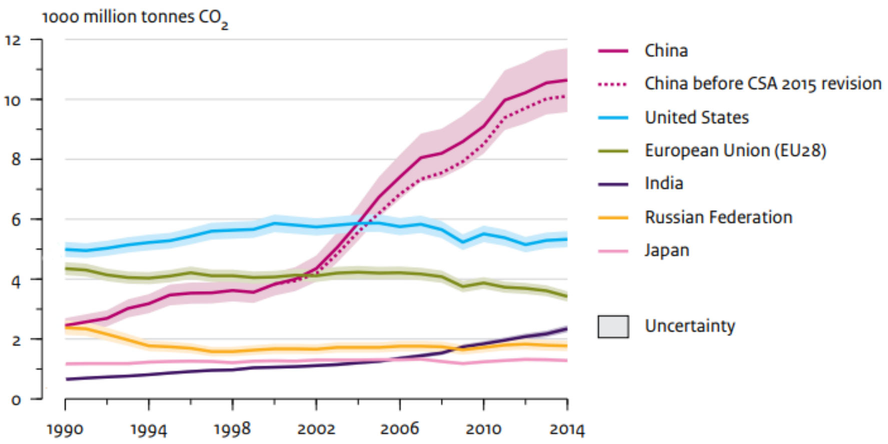

Figure 1.3: CO_2 emissions from fossil fuel consumption & cement product in the top 5 global emitters & the EU

Source: Olivier *et al.* (2015)

China's carbon intensity had been steadily increasing comparatively other emitters indicating sharp increment after the year 2012 by hedging outshined energy-intense in the industrial sector, such as the production of electricity, steel, cement. But the United States topped CO_2 emissions per capita among others followed by the Russian Federation, Japan, China, and the European Union (Figure 1.4) in the year 2014. Though, China's CO_2 emissions per capita were below the global average up to 2004 by indicating a sharp increasing trend thereafter. All other emitters were above the average global emissions level, excluding India, which followed steadily increment through 1990-2014 below the average level.

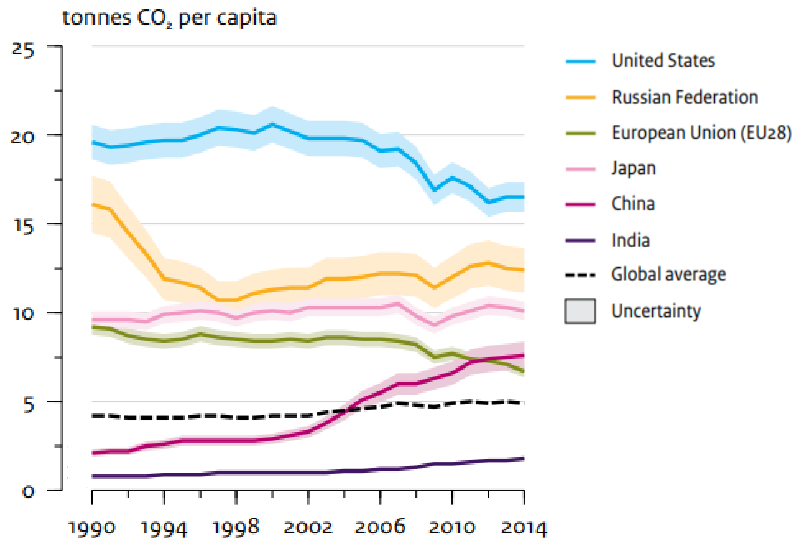

Figure 1.4: CO_2 emissions per capita from fossil fuel consumption & cement productin the top 5 global emitters & the EU

Source: Olivier *et al.* (2015)

The anthropogenic forces have potentially made a significant contribution to an increase of surface temperature over every continental region except Antarctica since the mid-20th century. Due to that, the global water cycle has been affected while retreating of glaciers since 1960, increasing surface melting of the Greenland ice sheet since 1993, contributing to the Arctic sea-ice loss since 1979. IPCC (2014) explained that it had a significant impact on to increase in global upper ocean heat content (0-700 m), and to global mean sea level rise observed from 1970. The significant contribution of global economic growth had risen sharply from the period 2000 to 2010, while that of global population growth remained roughly identical to the previous three decades. Human influence on the climate change particularly abandoned due to combustion of fossil fuels, which had grown up more than 50% of the observed increase in global average of surface temperature from 1951 to 2010, by the cause of an increase in GHGs concentrations and other anthropogenic forces, (IPCC, 2014).

On the view of provided facts, the issues of global warming & climate change are debated universally by exploring nexus between CO_2 emissions and macroeconomic variables such as economic growth, energy consumption, …etc., in modern consideration on environment protection, as well in sustainable development. The significant continued increase of global population growth, economic development, and industrialization considered as the most significant impacts on climate change and increase of CO_2 emissions caused by fossil fuel combustion. Also, any environmental changes in the long-run may have a great impact on the economy. Conversely, control CO_2 emissions while sustaining economic growth is critical and difficult to have a better understanding of long-run causal nexus between income, environmental degradation as well as energy consumption by the population of a specific country, (Muhyidin, Saifullah & Fei, 2015).

1.6 Human Fingerprint on Carbon Dioxide Emissions in Sri Lanka

Sri Lanka began growth economically as a developing country having a strong relationship between its economic growth, demand & supply of energy consumption and pollutant emissions. According to Sri Lanka's profile, (World Data Atlas, 2018); GDP per capita was increased from 1,028 US $ in 1998 to 4,085 US $ in 2017 growing at an average annual rate of 7.77 %, fossil fuel energy consumption was increased from 33.1 % in 1995 to 50.3 % in 2014 growing at an average annual rate of 2.36 % and CO_2 emissions were increased from 8 million Mt in 1996 to 18 million Mt in 2015 at an average annual rate of 4.48 %. Moreover, Sri Lanka's 2011 numbers at a glance in USAID (2015) explained, GHG emissions grew 14 $MtCO_2e$ (43%) from 1990 to 2011, averaging 2% annually with sector-specific average annual change followed by energy (6%), waste (1%), LUCF (land-use change & forestry, -1%), agriculture (0%), and IP (industrial processes, 11%). The GDP grew by 198%, averaging 5% annually, with the carbon intensity of Sri Lanka's economy at approximately 1.5 times the world average, and there is a possibility to reduce Sri Lanka's GHG emissions relative to GDP.

Note: The transport sector emitted 48% of the total CO_2 emissions by fossil fuel combustion and considered as the highest subscriber to GHG emissions. 50% of emitted CO_2 emissions in the country consumed by Trucks operate on diesel fuel since other cars, motorcycles, and three-wheelers consume gasoline.

As a developing country, and small island, Sri Lanka is highly exposed to the adverse effects of climate change such as, rising temperatures, occurring severe droughts, sea-level rise, rainfall pattern variation, variability in storms and increased coastal flooding. Despite that, Sri Lanka's GHG emissions are comparatively minuscule than that of in developed Asian nations such as, China or India. However, Sri Lanka's economic development is critically affected by natural disasters, due to extreme weather conditions such as prolonged droughts, landslides and flash floods deprive the lives and livelihoods of people. On the view of provided facts, it is ideal to debate, whether Sri Lanka is capable of developing its economy while sustaining its environmental conditions.

Even though developing countries are predominantly vulnerable on the climate change mitigation actions since they have lack of basic adaptive capacity, the government of Sri Lanka concerns more about an adaptation to the climate change than mitigation, having established a climate change secretariat under the Mahaweli Development and Environment Ministry. It is noteworthy that, Sri Lanka has implemented many of policy measures focusing on unconditional and conditional energy target within country, that would result in mitigating and adapting to the climate change, such as "National Climate Change Policy in 2012", "National Adaptation Plan for Climate Change Impacts in Sri Lanka, 2016 - 2025", and "National Climate Change Adaptation Strategy, 2011 - 2016". These policy decisions based on adaptive measures and strategies, giving priority to environmental friendly concerns among the industrialists and people generally avoiding pollution of the country. Also, Sri Lanka is an active participant in the PA from 2016 (signed on 22nd April 2016, and ratified on 21st Sep 2016), involving in the global efforts of minimizing GHG emissions within the framework of sustainable development and principles preserved in the PA.

However, it is very difficult to find literature, which has examined the impact of energy consumption and macroeconomic variables on environmental pollutions in Sri Lanka based on a multivariate time series scenario, other than econometric approaches for climate change mitigation perspective of Sri Lanka. In contrast, this study attempts to identify the impact of economic growth and energy consumption on CO_2 emissions by exploring long-run nexus between them based on corresponding data from 1971-2014. Conversely, it will support to have a better understanding of controlling CO_2 emissions, while sustaining the economic growth as well as energy consumption in Sri Lanka.

1.7 Objectives

On the view of the above explanations, the objective of this study is to explore the impact of fossil fuel energy consumption and economic growth on CO_2 emissions in Sri Lanka during the period spanned from1971 to 2014.

1.8 Outline of the Dissertation

There are six chapters in this dissertation. An introduction involving study background and objectives have described in CHAPTER 1and literature reviews of the study have discussed in CHAPTER 2. Materials & methodologies encompassing in the study with corresponding theoretical backgrounds have described in CHAPTER 3. Explanatory data analysis of the study observations and linear impact of fossil fuel energy consumption as well as economic development on CO_2 emissions in Sri Lanka under the univariate OLS scenario have discussed orderly in CHAPTER 4. Multivariate time series approaches based on the Vector Error Correction (VEC) model development have discussed orderly in CHAPTER 5 for identifying the impact of fossil fuel energy consumption and economic development on CO_2 emissions in Sri Lanka's profile. Conclusions with recommendations based on the inferences derived have highlighted in CHAPTER 6.

CHAPTER 2

LITERATURE REVIEWS

2.1 Overview of Literature Citations and Conceptual Framework

Global attention on sustainable development facilitated mitigation targets by the continuous reduction in pollutant emissions (basically CO_2) in recent decades. The industrialized, as well as developing nations, have debated issues of energy consumption and economic development surrounding fossil fuel use and cement productions since carbon emissions and energy consumption directly related to the fossil-fuel economy. Hence, pollutant emissions due to fossil-fuel energy consumption and cement production have been considered as the main source of both global warming and climate change, incorporating other growth relevant macroeconomic factors, which could be enhanced a better understanding of concern of the effects of global warming. Essentially, agricultural production, energy prices, financial development, foreign direct investments, health quality, human capital, industrialization, population, trade openness/international trade, tourism receipts, urbanization considered as the growth relevant macroeconomic factors in most literature. Thus, fossil fuel energy consumption and the aforementioned macroeconomic variables have been considered mostly as possible determinants of pollutant emissions, especially concerning CO_2 emissions.

Then a linear or nonlinear relationship of those determinants under bivariate or multivariate framework has been considered as the empirical model for CO_2 emissions. As an example "$CO_2 = f\,(\mathrm{GDP}, \mathrm{TEC}, \mathrm{FEC}, \mathrm{FDI}, \mathrm{IND}, \mathrm{AGR})$". Where; CO_2 = per capita CO_2 emissions, GDP = per capita GDP, TEC = per capita total energy consumption, FEC = per capita fossil fuel energy consumption, FDI = inflows of foreign direct investment, AGR = agricultural sector production, IND = industrial sector production.

2.1.1 Econometric Approaches of Identifying Nexus Between, CO_2 Emissions and its Determinants

A significant volume of recent empirical studies have focused on two standards; the first was a validation of the prominent theory of the Environmental Kuznet's Curve (EKC) hypothesis as practiced by Lapinskiene, Peleckis & Slavinskaite (2017) & Lu (2017). Then the second was modeling long term bivariate or multivariate relationship between fossil fuel energy consumption, economic development and CO_2 emissions as practiced by Alege, Adediran & Ogundipe (2016), Alkhathlan, Alam & Javid (2012), Asumadu-Sarkodie & Owusu (2017), Begum, Sohag, Abdullah, & Jaafar (2015), Bozkurt & Akan (2014), Chandran & Tang (2013), Farhani & Rejeb (2012), Muhyidin *et al.* (2015), Obradovic & Lojanica (2017), Omri (2015), Pao, Fu & Tseng (2012), Saidi & Hammami (2015), Tang & Tan (2016) and Wang, Li, Fang & Zhou (2016).

Remark: Theoretically, the EKC hypothesis postulates an inverted U-shaped curve relationship between economic development and environment pollutions, when environmental pollutions level increases as economic development of a country, but after a turning point of the increasing economy, it starts to decrease together demanding more energy consumption and higher economic development. Hence, it concluded that more efficient energy consumption requires a higher level of economic development.

The econometric 'energy-economy-GHG emissions nexus' has been explained by the empirical nonlinear regression equation as in regression (2.1), (Lu, 2017).

$$\ln(GHG)_t = \alpha_t + \beta_1 \ln(EC)_t + \beta_2 \ln(GDP)_t + \beta_3 \ln(GDP^2)_t + \epsilon_t \quad \ldots\ldots\ldots.. \ (2.1)$$

Where; GHG = GHG emissions/capita, EC = energy consumption/capita, GDP = real GDP/capita, t=1, …T (year) referred to the time period, parameters β_1 & β_2 & β_3 represented long-term elasticity estimates of pollutant emissions regarding EC, GDP & GDP^2 respectively and parameter α_t represented the time scalar.

Note: Error terms (ϵ_t) were assumed to be independent and identically distributed, with zero mean and constant variance. Sign for each β_1& β_2 parameter expected to be positive, and that of for β_3 was negative if the 'inverted-U theorization' of the EKC applied in the empirical context, (Lu, 2017).

The log-linear formulation for 'energy-economy-CO_2 emissions nexus' can be explained as equation (2.2).

$$\ln(\mathrm{CO}_2)_t = \alpha_t + \beta_1 \ln(EC)_t + \beta_2 \ln(GDP)_t + \epsilon_t \quad \text{………..... (2.2)}$$

2.1.2 Time Series Approaches of Identifying Nexus Between, CO_2 Emissions and its Determinants

The current sound of modeling 'energy-economy-CO_2 emissions nexus' and forecasting techniques have been categorized into three as; univariate time-series analysis, multivariate time-series analysis, and non-linear intelligent models, (Pao *et al.,* 2012). In place essence of publically available expression in econometric energy literature, the causality, cointegration, or regression analysis approaches were well documented and widely analyzed in the multivariate time series analysis. Moreover, the Box-Jenkins autoregressive integrated moving average (ARIMA) model forecasting techniques have been commonly used in the univariate time series analysis as practiced by James, Gubbins, Murray & Gakidou (2012), Jankovic (2017) & Wabomba, Mutwiri & Fredrick (2016). Distinct from the multivariate approaches, univariate approaches required only historical data for desired time series variables in forecasting its future behavior.

Aforementioned all methods are subjective to sample size limitation, which limits their appropriateness to certain forecasting conditions. Accuracy of forecasting performances is subjective to the representativeness of time series data besides the sample size, which has not overcome to date. Hence, a large sample of time series observations is required usually for accurate future forecasting, but corresponding results depend on the reliability and availability of the independent variables over the forecasting period. As an example of that, forecasting 'energy-economy-CO_2 emissions nexus' in rapidly developing countries followed a trend, which was fluctuating rapidly over time. Thus, it is required further efforts in the data collecting and estimation process.

An emerging line of recent literature has focused on the bivariate or multivariate study of observing dynamic nexus between fossil fuel energy consumption, economic development, and CO_2 emissions in the same framework. Such multivariate or bivariate model forecasting is important in policy implementations and developing assessment processes for environmental protection in sustainable and economic development as well as accurate investment planning for energy production and distributions. Empirical findings on such bivariate or multivariate time series approach for detecting relationships between fossil fuel energy consumption, economic development, and CO_2 emissions were ambiguous owing to different approaches for instance; correlation & regression analysis, bivariate causality, unit root tests, multivariate & panel cointegration, Vector Auto Regression (VAR) & Vector Error Correction (VEC) model approach, and innovative accounting approach, (Obradovic & Lojanica, 2017). Although studies employed by different methodologies, the results should be maintained an identical conclusion as a general rule.

Granger causality, as well as cointegration analysis, has been applied as widespread approaches for identifying the 'energy-economy-GHG (CO_2) emissions nexus' in most studies. Numerous time series and panel data approaches have been used on top of most literature to observe such cointegrating or casual nexus. The effects of heteroscedasticity in time series data have eliminated, considering the natural logarithmic transformations of each variable under investigation, before the time series or panel data approach (Wang *et al.,* 2016).

2.2 Global Concern of Fossil Fuel Energy Consumption & Economic Development on CO_2 Emissions

Utmost studies have investigated 'energy-economy-CO_2 emissions nexus' differ in use of econometric methodologies and time frame for a different group of developed as well as developing countries, for instance, European Union Countries, (Lapinskiene *et al.*, 2017), MENA Countries, [(Farhani & Rejeb, 2012) and (Omri, 2015)], and South-Eastern Europe countries, (Obradovic & Lojanica, 2017). Nevertheless, limited numbers of studies were available for Asian countries such as Chandran & Tang (2013) and Lu (2017). Also, the study of 'energy-economy-CO_2 emissions nexus' of the single country was an interest in most energy studies, and that was almost half (9 articles) among this study related literature reviews [Appendix: I]. Correspondingly, certain case studies have investigated the 'energy-economy-CO_2 emissions nexus' on a single country for instance: Cambodia, (Tang & Tan, 2016), China, [(Wang *et al.*, 2016) and (Pao *et al.*, 2012)], Malaysia, [(Begum *et al.*, 2015) and (Muhyidin *et al.,* 2015)], Nigeria, (Alege *et al.,* 2016), Rwanda, (Asumadu-Sarkodie & Owusu, 2017), Saudi Arabia, (Alkhathlan *et al.*, 2012), as well as Turkey, (Bozkurt & Akan, 2014).

In most literature, an empirical indication has evaluated by employing cointegration and granger causality techniques for the 'energy-economy-CO_2 emissions nexus'. In some cases, it has practiced by adding other macroeconomic variables such as; agricultural production, energy prices, financial development, foreign direct investments, health quality, industrialization, population size, trade openness (international trade), tourism receipts, urbanization. All of the 10 studies out of 16 [(Alege *et al.*, 2016), (Alkhathlan *et al.,* 2012), (Asumadu-Sarkodie & Owusu, 2017), (Begum *et al.,* 2015), (Chandran & Tang, 2013), (Lapinskiene *et al.,* 2017), (Muhyidin *et al.,* 2015), (Obradovic & Lojanica, 2017), (Saidi & Hammami, 2015) and (Tang & Tan, 2016)] were considered additional variables except for the studies of Bozkurt & Akan (2014), Farhani & Rejeb (2012), Lu (2017), Omri (2015), Pao *et al.* (2012) and Wang *et al.* (2016).

Initially, the natural logarithmic transformation of the study variables have been considered in their measurement scale, to reduce existing heterogeneity in most literature, before corresponding analysis, when the observations were absence to perform homogeneous variances of the corresponding series as practiced by Alege *et al.* (2016), Alkhathlan *et al.* (2012), Asumadu-Sarkodie & Owusu (2017), Begum *et al.* (2015), Farhani & Rejeb (2012), Lu (2017), Muhyidin *et al.* (2015), Obradovic & Lojanica (2017), Omri (2015), Pao *et al.* (2012), Tang & Tan (2016) and Wang *et al.* (2016). Descriptive statistics and trend distributions of the variables have been practiced infrequently, for recognizing the nature of the observation as practiced by Asumadu-Sarkodie & Owusu (2017), Omri (2015), and Pao *et al.* (2012).

The stationarity of the observed time series, as well as order of the stationarity (integrating order, d), have been observed by using the prominent unit root tests for instance; Augmented-Dickey-Fuller (ADF), Phillips-Perron's (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) individually or simultaneously, for robust conclusions about the time series properties taking their level as well as their differences. Then, the ADF test has been commonly used jointly with the PP & KPSS tests [(Pao *et al.,* 2012) & (Tang & Tan, 2016)], with the PP test [(Alege *et al.*, 2016) & (Muhyidin *et al.,* 2015)], and with the Dickey-Fuller (DF) test (Alkhathlan *et al.*, 2012). Also, the PP test has been used jointly with the KPSS & Zivot-Andrews tests, as practiced by Obradovic & Lojanica (2017). Infrequently, the PP & KPSS tests have been used jointly for that purpose (Asumadu-Sarkodie & Owusu, 2017) instead, the ADF test has been used individually in some cases [(Bozkurt & Akan, 2014) & (Wang *et al.,* 2016)], and the DF generalized least squared (GLS) test has been used [(Begum *et al.,* 2015) & (Chandran & Tang, 2013)]. Further, the panel unit root test has been practiced system wise in most panel data analysis [(Farhani & Rejeb, 2012), (Lu, 2017) & (Omri, 2015)]. But it was failed to find any indication about unit root test approaches in some studies [(Lapinskiene *et al.,* 2017) & (Saidi & Hammami, 2015)], which were respectively based on quadratic EKC model forecasting and Arellano and Bond - GMM estimator based model forecasting.

2.3 Cointegration Approach in Energy-Economic-CO_2 Emissions Nexus

Generally, the optimal lag length has been tested primarily in most multivariate, as well in panel data studies before cointegrating and causality approaches considering as a critical element in the correct specification based on the general VAR model. Then the optimal lag length (p) has been observed simultaneously by the AIC, BIC and HQ information criterions, [(Alege *et al., 2*016), (Bozkurt & Akan, 2014), (Chandran & Tang, 2013), (Lu, 2017), (Obradovic & Lojanica, 2017) and (Pao *et al.,* 2012)]. In some cases, the optimum lag length has been determined on the VAR framework individually by the AIC, [(Alege *et al.,* 2016), (Chandran & Tang, 2013), (Lu, 2017) & (Pao *et al.,* 2012)]. In the presence of contradictory results given by two or more information criterions individually, the maximum representation of the minimum information criterion values has selected as the optimal lag. Further, it can be confirmed by lag order, selected from the maximum value in each sequentially modified likelihood ratio (LR) test statistic, and by the minimum value in each final prediction error (FPE) as practiced by Bozkurt & Akan (2014).

In utmost studies, the corresponding long-run cointegrating nexus between economic development, fossil fuel energy consumption and pollutant emissions have been tested by the Johansen's ML procedure, on a multivariate scenario than that of in a bivariate scenario. Commonly both Trace test statistic and Maximum Eigen Value test statistics under the Johansen ML procedure have been considered simultaneously to determined number of unique cointegrating vectors (cointegrating rank, r) as practiced by, Alege *et al.* (2016), Bozkurt & Akan (2014), Muhyidin *et al.* (2015), Obradovic & Lojanica (2017) and Pao *et al.* (2012) instead, the Trace statistic used individually in some cases [(Chandran & Tang, 2013) and (Wang *et al.,* 2016)]. Then, the VECM approaches have extensively applied for modeling both long-run and short-run cointegration nexus in most studies as experienced by Alege *et al.* (2016), Bozkurt & Akan (2014), Chandran & Tang (2013), Muhyidin *et al.* (2015), Obradovic & Lojanica (2017) and Wang *et al.* (2016).

Finally, the three post estimation tests; the Cholesky (Lutkepohl) for kurtosis, skewness & normality, the Lagrange Multiplier test (or Portmanteau test) for serial correlation and the Breusch-Pagan-Godfrey test for heteroscedasticity of residuals have been applied in line for white noise residuals in the VAR or VECM model specification [(Bozkurt & Akan, 2014) & (Obradovic & Lojanica, 2017)]. Differently, form the VAR or VECM multivariate cointegration approaches, there were another approaches for identifying long-run relationships between the time series variables such as; the autoregressive distributed lag (ARDL) bound cointegration test [(Alkhathlan *et al.,* 2012), (Asumadu-Sarkodie & Owusu, 2017), (Begum *et al.,* 2015) & (Tang & Tan, 2016)], as well as the Generalized Method of Moments (GMM) test, which have been used in presence of arbitrary heteroscedasticity in the time series [(Omri, 2015) and (Saidi & Hammami, 2015)]. In presence of variations in time series variables, an intelligent nonlinear time series forecasting methods have been employed for more efficient forecasting, such as; the nonlinear grey Bernoulli model (NGBM) as practiced by Pao *et al.* (2012), an artificial neural network (ANN) model (Asumadu-Sarkodie & Owusu, 2016) and some fuzzy regressions or hybrid models as experienced by Saidi & Hammami (2015).

2.4 Causality Approach in Energy-Economic-CO_2 Emissions Nexus

Moreover, error correction based granger causality existences have discussed on the VECM framework in most literature [(Alege *et al.,* 2016), (Alkhathlan *et al.,* 2012), (Asumadu-Sarkodie & Owusu, 2017), (Begum *et al.,* 2015), (Bozkurt & Akan, 2014), (Chandran & Tang, 2013), (Muhyidin *et al.,* 2015), and (Obradovic & Lojanica, 2017)]. But, Tang & Tan (2016) & Wang *et al.* (2016) have discussed the existence of long-run causality based on the Toda & Yamamoto non-causality test, and VAR based Granger causality test respectively.

Furthermore, panel diagnostics test methods have practiced in panel data for instance; panel unit root tests, panel cointegration tests, and panel causality approaches, through estimating methods of 'ordinary least squares' (OLS), 'fully modified OLS' (FMOLS) and 'dynamic OLS' (DOLS) to investigate relationship between economic growth, fossil fuel energy consumption and pollutants (CO_2) emissions [(Farhani & Rejeb, 2012) and (Lu, 2017)]. In spite of a large literature studying, it was evident that resultant causal existence among economic development, fossil fuel energy consumption and CO_2 emissions were subject to corresponding time frame, region, and methodological approaches. Hence, the causality directions between the desired variables were indeterminate and debatable (Wang *et al.*, 2016).

2.5 Impact of Fossil Fuel Energy Consumption & Economic Development on CO_2 Emissions

The VAR, VECM, or ARDL approaches have practiced in most studies for estimating long-term relationships between economic development, fossil fuel energy consumption, and CO_2 emissions. The studies of Alege *et al.* in 2016, Muhyidin *et al.* in 2015 & Wang *et al.* in 2016 respectively in the profile of Nigeria over 1970-2013, Malaysia over 1970-2012 & China over 1990-2012 found to be closely related to methodological approaches of this study [Appendix: I]. The study of Alege *et al.* (2016) has followed a conceptual framework incorporating the VECM for investigating cointegration relationship and direction of causality among pollutant emissions (CO_2), energy consumption in both renewable & nonrenewable and economic growth. Then normalized long-run estimates have indicated that the atmospheric concentration of CO_2 emissions was increased approximately 20%, by 1% change in the fossil fuel energy consumption significantly and positively, facing environmental degradation problems challenging in the long-run in Nigeria.

In contrast, electrical Power energy consumption (nonrenewable) was significantly and inversely proportional to the CO_2 emissions, implying that the dwindling of the atmospheric concentration of CO_2 emissions increased as the adoption of cleaner energy sources (electricity). Further economic development (GDP/ capita) & squared value of that influenced inversely and directly on CO_2 emissions respectively contesting the EKC hypothesis. Similarly, the human capital indicator and the institutions had not significant influence on the CO_2 emissions. Further, the results have evidenced that unidirectional long-run causal existence from fossil fuel energy consumption to CO_2 emissions at 5% significance and GDP per capita at 10% significance, but electrical power energy consumption had no relationship to CO_2 emissions. Furthermore, it has evidenced that long-run unidirectional causal existence from human capital indicator to CO_2 emissions, as well as from electrical power energy consumption to GDP at the 5% significance level.

The study of Muhyidin *et al.* (2015) has followed the VECM for investigating causality among economic growth, industrial production index growth (IPIG), pollutant emissions (CO_2), and total energy consumption. Long-run estimates have indicated that coefficients of lagged ECM for total energy consumption and CO_2 emissions equations were only significant and negative respectively at 1% and 10% while that of for IPIG and economic growth (GDP) equations were negative but insignificant. Further, the results have revealed that unidirectional long-run causality from both GDP and IPIG to total energy consumption as well as to CO_2 emissions. Also, it has evidenced a bi-directional long-run causal existence among total energy consumption & CO_2 emissions. Concise the long-run causal existence results have suggested that atmospheric concentration in the CO_2 level in Malaysia increased by the growth of GDP and IPIG. Similarly, it has mainly caused by increases in total energy consumption.

The study of Wang *et al.* (2016) has investigated, the long-run equilibrium relationships, temporal dynamic relationships and causal existence of GHG emissions (CO_2), fossil fuel energy consumption and economic development followed by the VECM approaches. The impacts of a shock in CO_2 emissions on economic development or fossil fuel energy consumption found to be marginally significant by impulse response analysis. Further, the granger casual results have evidenced that a unidirectional causal existence from fossil fuel energy consumption to carbon dioxide emissions, as well as a bi-directional causality, among economic growth and fossil fuel energy consumption. Unexpectedly, it has failed to perform a causal relationship between economic development and CO_2 emissions. Considering long-run effectiveness in the link between pollutant emissions (CO_2), energy consumption, and economic growth in China, the resulting causal directions between the variables have considered as decisive components of designing emissions reduction policies and effective energy conservation (Wang *et al.*, 2016).

2.6 The Outlook of Sri Lanka's Concern of Fossil Fuel Energy Consumption & Economic Development on CO_2 Emissions.

The main motivation of this study was to inspect the long-run impact of "fossil fuel energy consumption and economic growth on CO_2 emissions" in the context of Sri Lanka from 1971 to 2014 and discussed causal existence among the aforesaid three variables. The study objective choice of Sri Lanka was encouraged because of the following two reasons. Firstly, nuclear power was never seriously considered in Sri Lanka since the opposition from ecofriendly civil societies and the strong governors. Further, it has begun emerging renewables towards sustainable development, particularly in the field of solar and wind power energy sources together with other world-leading countries.

Secondly, Sri Lanka has committed to reducing an average of GHG emissions attaining all eligibility criterions which must be satisfied by developing the country for participating in the Clean Development Mechanism (CDM) ("voluntary participation, the establishment of designated national authority, ratification of the KP and become a Party to the Protocol"). Correspondingly, the Sri Lankan government has developed several assessment processes for sustainable development by defining three basic criterions as; "social, economic, and environmental" under the guidelines of the Designated National Authority (DNA), which has obtained from the Ministry of Environment & Natural Resources.

The relationship between environmental deterioration and economic growth are highly dynamic in Sri Lanka. Sustainable economic development goals in Asian countries primarily based on strategies, promoting the efficacy of fossil fuel energy consumptions, as well as renewable energy resources concerning the short-run causality on top of long-run cointegration relationships (Lu, 2017). However, it indicates several gaps in literature reviews related to the study objectives and insufficient attention, which have been paid to case-studies of several Asian countries even though they are growing rapidly and intrinsically.

In place of that essence, there was not any systematic investigation in analyzing the impact of fossil fuel energy consumption and economic development on CO_2 emissions in Sri Lanka. Also, it was challenging to find related literature amongst the limited number of panel data analysis for Asian countries. Hence, the proposed study will attend to fill this gap contributing to the existing empirical literature by emerging a new time series model for pollutant emissions on the energy economy of Sri Lanka.

2.7 Summary of Chapter 2

In almost all studies, the natural logarithmic transformations of desired variables have considered initially. Then integrating orders (d) as well as stationarity of corresponding log series have been identified before the analysis. The optimal lag length (p) of the observations has been observed as a critical element, before the cointegrating approaches by the information criterion values on the VAR framework. Then the cointegrating order (r) of the observations has been identified by the Trace statistic or Maximum Eigenvalue statistic on the Johansen cointegration test. The VAR, VECM, or ARDL approaches have practiced in most studies for obtaining 'energy-economy- CO_2 emissions nexus'. Although there was a significant impact of economic development and fossil fuel energy consumption on pollutant (CO_2) emissions in the long-run equilibrium, foregoing evidence has revealed that those results depend on study period, country, and methodological approach. Hence, directions of causality between corresponding variables have remained quite unspecified and debatable. Furthermore, not much study on this dissertation has practiced in Sri Lanka. Also, most of the methods have not been tested statistically in studies of Sri Lanka. Nonetheless, the results gathered from this extensive literature are useful for this study. The most useful references and a summary of them are separately described in Appendix I.

CHAPTER 3

MATERIALS AND METHODS

3.1 Secondary Data

For this study, an annual time series data on per capita values of (i) CO_2 (carbon dioxide) emissions (in metric tons, Mt), (ii) fossil fuel energy consumption (in Kg) and (iii) gross domestic product-GDP (in constant 2010 US$) spanned from the period 1971 to 2014 obtained from the World Development Indicators of World Bank database (WDI, 2018). The CO_2 emissions per capita considered as the dependent variable while the per capita values of fossil fuel energy consumption and GDP were allowing for determinants of CO_2 emissions, which have coded as; CO_2, EC, and GDP respectively in statistical analyze. Definitions of the desired variables have given in Appendix: II.

3.2 Statistical Approaches for the Problem

As the most adapted methodology, graphical representation of trend distributions and descriptive analysis of the three observations obtained initially for the visualizing nature of their distributions. Straight away, the natural logarithmic transformations of the variables considered for reducing the heterogeneity of variances in the observed data. Then corresponding log series ($\ln EC$, $\ln \mathrm{GDP}$ & $\ln \mathrm{CO}_2$) coded as LEC, LGDP, and LCO_2. Subsequently, significant individual impact of present values of fossil fuel energy consumption and economic development (LEC_t & $LGDP_t$) as well as immediate past values of them (LEC_{t-1} & $LGDP_{t-1}$) on the present level of CO_2 emissions (CO_{2_t}) have discussed under the univariate OLS scenario.

The order of stationarity of each variable along with integrating order and the optimal lag length examined as the main prerequisite for the Johansen cointegration approaches before the vector error correction (VEC) modeling. The cointegration rank of the variables observed from the Trace statistic, as a critical element for the Johansen cointegration approach. The VECM techniques applied to assess the long-run cointegrating relationship of the desired variables and discussed the significant impact of economic growth and fossil fuel energy consumption on CO_2 emissions. Post error diagnostic tests carried out for white noise residuals followed by checking model stability condition on the VECM framework. Finally, the shock of CO_2 emissions on itself and its determinants in the long-run sustained discussed by the VECM (1) forecasted IRF's effects of CO_2 emissions.

3.3 Stationarity Approaches of the Variables

Statistically, stationarity exists with constant and time-invariant mean, variance as well as covariance functions of time series (the first two moments are time-invariant) when there are no deterministic seasonal patterns. Most statistical forecasting methods of time series are followed by the main assumption, that each time series variable is stationary or stationarized over mathematical transformations. But, in the real world, economic time series variables are revealed typically non-stationary such as trends, random walks, or cyclic behavior even after seasonal or deflation adjustment. Also, non-stationary time series can be stationarized, through differencing, as an essential part of ARIMA modeling, and the 1st difference of a time series variable define by series of changes from one time period to next successive period.

Remark: Let $\{y_t\}$ be a non-stationary time series, then the first difference of $\{y_t\}$ is denoted by $D(y_t)$ or Δy_t and explained by $\{y_t - y_{t-1}\} = (1 - B)y_t$. If $\Delta \boldsymbol{y_t}$ is stationary, then $\boldsymbol{y_t}$ is named as integrated of the first order and denoted as I (1).

3.4 Unit Root Tests

There are many approaches in testing equation with none stationary time series based on some eminent unit root tests such as; Augmented-Dickey-Fuller (ADF), Phillips-Perron's (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) [(Alege *et al.*, 2016), (Alkhathlan *et al.*, 2012), (Asumadu-Sarkodie & Owusu, 2017), (Bozkurt & Akan, 2014), (Muhyidin *et al.,* 2015), (Obradovic & Lojanica, 2017), (Pao *et al.,* 2012), (Tang & Tan, 2016) and (Wang *et al.,* 2016)]. The ADF, as well as PP unit root tests considered in this analysis to identify whether the log series belong to a stationary series and integrated of the same order considering the levels as well as the first differences of them. It is important to specify trend existence correctly in the model by visual inspection of the annual trend in each distribution of observed variables.

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

The ADF test used to examine stationarity of the variables under the null hypothesis of 'H_O: a unit root is present in a time series variable'. The regression (3.1) utilized to test the unit root hypothesis for the ADF test (Wang *et al.,* 2016).

$$\Delta x_t = (\rho - 1)x_{t-1} + \sum_{i=1}^{n} \lambda_i \Delta x_{t-i} + \epsilon_t \text{ ………. (3.1)}$$

Where; x_t is the time series variable, and ϵ_t is an independently, identically distributed, unobservable disturbance (error) term, which has a zero mean, and a constant variance (σ^2).

Remark: The corresponding hypotheses explained by, $H_O: \rho \geq 1$ vs. $H_a: \rho < 1$; (x_t is stationary), and insignificance test statistic concludes that non-stationarity of the variable (x_t), (Wang *et al.,* 2016). Then the ADF test statistic can be expressed as; $ADF_{Z_t} = \frac{\hat{\rho}-1}{SE(\hat{\rho})}$, (Tsay, 2005) and abbreviated as the Dickey-Fuller t-statistic, but it does not follow the standard 'student t-distribution', because the sampling distribution of the 'ADF test statistic' is skewed to the left with a long tail.

There exist three trend assumptions in the methodological perspective as ‘include both intercept & trend, exclude both intercept & trend, and includes intercept & no trend’ in the corresponding regression. Then, corresponding regressions in each trend assumption are formulated, as explained in (3.2), (3.3) and (3.4) below, (Wang *et al.,* 2016).

Include both intercept and trend

$$\Delta y_t = \alpha + \beta t + \delta y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta y_{t-i} + \epsilon_t \quad \text{……….. (3.2)}$$

Include intercept and no trend, [random walk with drift]

$$\Delta y_t = \alpha + \delta y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta y_{t-i} + \epsilon_t \quad \text{…………... (3.3)}$$

No intercept and no trend, [random walk]

$$\Delta y_t = \delta y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta y_{t-i} + \epsilon_t \quad \text{……..…….. (3.4)}$$

Where; the parameters α, β & p are respectively a fixed constant, time coefficient and autoregressive lag order. Then, δ is coefficient presenting the process root which is focused on the ADF test.

3.4.2 The Phillips-Perron (PP) Unit Root Test

The PP test is considered the most common alternative for the ADF test adjusting Dickey-Fuller t-statistic none parametrically by use of the Newel-West correction of heteroscedasticity & autocorrelation consistent in covariance matrix estimator (standard deviation). The regression utilizing both the intercepts and trend formulates as in equation (3.5), (Viktoras, 2013).

$$\Delta y_t = \alpha + \beta t + \delta y_{t-1} + \epsilon_t \quad \text{…..………… (3.5)}$$

Where; all α, β, δ & ϵ follow the same meaning as in the ADF test but ϵ_t serially correlates in the PP test.

Note: The ADF and PP tests are recognized to suffer severe sample size and lower power problems theoretically. However, the PP test increases the power of the test compared to the ADF test based on corresponding assumptions, and also lag specification does not require in the PP test regression, unlike the ADF test.

3.5 Specification of the Optimal Lag Length

The determination of optimal lag length 'p' consider as a critical element before the cointegration approaches for the correct specification of the observed data, and that can be selected automatically from the basis of the multivariate model selection criterion developed for the maximum likelihood estimation techniques. In this study, the optimal lag length specified by the majority of commonly used minimum information criterion values of the Akaike (AIC), Schwarz Bayesian (BIC), Hanna-Quinn (HQ), final prediction error (FPE) for a robust conclusion based on the general VAR framework. The information criterion values of AIC, BIC, HQ, modified values of the AIC, BIC & HQ, and FPE, apply in most computer applications just as E-Views.

3.6 Cointegration Approaches in the Multivariate Time Series

Multivariate time series modeling complicates, by the presence of nonstationary time series, particularly in commercial data, in such cases, the cointegration test primarily uses to determine the rank of the long-run cointegrating relationship (r) between the nonstationary time series. The cointegration concept describes the long-run systematic co-movements among the time series. It is necessary to test the integration (stationarity) order of each observation and the optimal lag length of them for the cointegration test to provide significant robust results.

If each time series variables are integrated of same order $'d'$ while satisfying stationarity in a linear combination of the time series (that variable combination $\sim I(0)$), then the corresponding variable combination is abbreviated as cointegrating equations, which interprets by demonstrating a long term equilibrium relationship among the time series, (Wang *et al.*, 2016).

3.7 The Johansen's Maximum Likelihood (ML) Methodology

The Engle-Granger test permits only one cointegrating relationship (*r=1*) based on the ADF test for unit roots in the error term, estimating the single cointegrating relationship, (Wikipedia, 2018). Differently from the Engle-Granger test, the Johansen Cointegration test is the most extensively used approach that permits more than one cointegrating relationship ($r > 1$), but it is subjective to asymptotic properties such as sample size, (Viktoras, 2013). The Johansen Cointegration test often uses with first assessed order of cointegration in corresponding time series (for the unit root or integrated order one, $I(d = 1)$ processes) under the Maximum Likelihood (ML) method in the multivariate context, (Wikipedia, 2018). Ultimate implications of the Johansen ML test have based on two test statistics named Trace & Maximum Eigenvalue, which might be a little bit different and are respectively based on trace value & maximum eigenvalue of the corresponding stochastic matrix. Also, sequential statistical testing procedures based on the likelihood ratio (LR) test.

The null hypothesis for both tests is the same for $H_0: rank(\pi) = \hat{r};\ 0 \le r \le k,$ then the corresponding alternative hypotheses are $H_{A_{Trace}}: \hat{r} < rank(\pi) \le k$ and $H_{A_{Max}} : rank(\pi) = (\hat{r} + 1)$. Both tests follow sequentially for corresponding cointegrating rank, $\hat{r} = 0,1, \ldots, (k - 1)$ until non-rejection at the corresponding null hypotheses observes for the first time. In this study, both Trace & Maximum Eigenvalue test statistic observed under the Johansen ML procedure to provide a robust conclusion about the number of existing stable long-run relationships between corresponding nonstationary time series.

According to Bozkurt & Akan (2014) corresponding, two test statistics explained as;

$$\lambda_{Max}[\hat{r}, \hat{r}+1] = -T\ln\left(1-\hat{\lambda}_{\hat{r}+1}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.6)$$

$$\lambda_{Trace}[\hat{r}] = -T\sum_{i=\hat{r}+1}^{k}\ln(1-\hat{\lambda}_i) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.7)$$

Where;

T is the number of observations, & k is the number of endogenous variables. $\hat{r}$ is the estimate of the number of cointegrating vectors (estimate of $rank(\pi)$; $0 \leq \hat{r} < k$). $\hat{\lambda}_i$ is the estimated value for i^{th} order eigenvalue of the π matrix in the VECM.

Notes:

If k number of stochastically or deterministic trend and I(1) time series presented in the cointegrated regression, then there are $(k-1)$ possible cointegrating vectors and k number of hypotheses in the Johansen ML procedure.

If entire null hypotheses (all included, $\mathrm{H}_0^{\mathrm{k}}$) are rejected, it indicates that no cointegration [$rank(\pi) = 0$] in the regression. Thus, it concluded that the corresponding regression is spurious, suggesting the levels VAR process in the 1st differences for subsequent analysis.

3.8 The Vector Auto Regression (VAR) Approaches

The VAR model is a stochastic process, most commonly used to capture linear interdependencies, generalized by auto-regressive (AR) model evolving multivariate time series. Generally, the VAR process applies for stationary, stable time series vector ($\boldsymbol{Y_t} \sim I(0)$). The VAR structure encompasses variable as a linear function of past lags of itself and that of the other variables. For an evolution of three time-series variables; $\boldsymbol{Y_t} = (y_{1t}, y_{2t}, y_{3t})'$ over same period $(t = 0,1,\ldots,T)$, basic form of the VAR model in lag order 'p' is formulated by regression as in equation (3.8), based on the assumption for instance that a linear trend existence in each variable ($\mu_t = \mu_0 + \mu_1 t$) in the VAR (p), (Lutkepohl & Kratzig, 2004).

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{bmatrix}_{(3\times1)} = \boldsymbol{\nu_0} + \boldsymbol{\nu_1}\mathrm{t} + \sum_{j=1}^{p} \begin{bmatrix} \phi_{11,j} & \phi_{12,j} & \phi_{13,j} \\ \phi_{21,j} & \phi_{22,j} & \phi_{23,j} \\ \phi_{31,j} & \phi_{32,j} & \phi_{33,j} \end{bmatrix}_{(3\times3)} \begin{bmatrix} y_{1t-j} \\ y_{2t-j} \\ y_{3t-j} \end{bmatrix}_{(3\times1)} + \begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \end{bmatrix}_{(3\times1)} \quad \ldots\ldots (3.8)$$

Or it can be formulated in vector form as in regression (3.9).

$$\boldsymbol{Y_t} = \boldsymbol{\nu_0} + \boldsymbol{\nu_1}\mathrm{t} + \sum_{j=1}^{p} \boldsymbol{\Phi_j}\, \boldsymbol{Y_{t-j}} + \boldsymbol{u_t} \qquad \ldots\ldots\ldots\ldots (3.9)$$

If it includes only intercept and no deterministic trending or seasonal dummy variables, the corresponding VAR (p) is formulated as regression (3.10) in vector form, as explained by Lutkepohl (2005).

$$\boldsymbol{Y_t} = \boldsymbol{\nu} + \sum_{j=1}^{p} \boldsymbol{\Phi_j}\, \boldsymbol{Y_{t-j}} + \boldsymbol{u_t} \qquad \ldots\ldots\ldots\ldots (3.10)$$

$$i.e.\ \boldsymbol{Y_t} = \boldsymbol{\nu} + \left(\boldsymbol{\Phi_1 Z} + \ \ldots\ + \boldsymbol{\Phi_p}\, \boldsymbol{Z^p}\right)\boldsymbol{Y_t} \ + \boldsymbol{u_t} \ \ldots\ldots\ldots\ldots (3.11)$$

Where; $\boldsymbol{\nu} = (\nu_1, \nu_2, \nu_3)'$ is a fixed vector of intercept terms allowing for the possibility of none zero mean $E[\boldsymbol{Y_t}]$. $\boldsymbol{u_t} = (u_{1t}, u_{2t}, u_{3t})'$ is an unobservable error term, usually assumed to be a sequence of independently, identically distributed random vectors with zero mean vector, and time-invariant positive definite nonsingular covariance matrix (Σ_{u_i}) (white noise processes).

Remark: $u_{it}{}'s$ are independent stochastic vector with $u_{it} \sim \text{iid}\left(0, \Sigma_{u_i}\right)$,
{i.e. $E[u_{it}] = 0$, $E[u_{it}u_{it}{}'] = \Sigma_{u_i}$ &$E[u_{it}u_{is}{}'] = 0$; $\forall$ s $\neq$ t}, (Lutkepohl, 2005).

Even though the VAR (p) model is general enough to accommodate the stochastic trending of stationary variables, it is not recommended for cointegrating relations of non-stationary variables since it does not appear explicitly, (Lutkepohl & Kratzig, 2004). Wang *et al.* (2016) explained that in most of the differenced methods applying in non-stationary time series, generally disregard important information hidden in the original levels, and long term equilibrium relationship does not reveal by the corresponding regression, then the VECM has been developed in order of dealing with this efficiency.

3.9 The Vector Error Correction Model (VECM) Approaches

The differential VAR modeling for cointegrating time series variables will lose some valuable information leading certain analysis errors; hence the VECM is used instead alternatively to iron out these limitations, as the most suitable modeling framework, with a great advantage of modeling both short-run and long-run cointegrating relationship jointly for nonstationary, cointegrated data. The Error Correction Models (ECMs) are used not only in dealing with cointegrated data but also useful in stationary data. Hence, non-stationary features in the time series with stochastic trends with integrated order one (Y_t~I(1)) for cointegrated data ($r > 0$) generally leads to consider the VECM instead of the VAR process. The VECM is described by the VAR framework that contains the cointegration constraints of non-stationary sequences, and it is also a stochastic process that uses when there be existent of the long-run stochastic trend in underlying multivariate time series. The VECM is also known as a restricted VAR.

Remark: After detecting the number of cointegrating vectors (cointegrating rank '$\hat{r}$'), the VECM applies to study existing short-run and long-run equilibrium relationships between corresponding time series selecting $'\hat{r}'$ as lag order of the VECM. The VECM is obtained by the general VAR (p) process by subtracting $'\boldsymbol{Y_{t-1}}'$ from both sides and rearranging, and it is abbreviated as VECM (p-1).

If there is a linear trend in the time series variables but not in the cointegration relations, then the corresponding VECM (p-1) model is formulated as in regression (3.12), (Lutkepohl, 2005).

$$\begin{bmatrix}\Delta y_{1t}\\ \Delta y_{2t}\\ \Delta y_{3t}\end{bmatrix}_{(3\times1)} = \boldsymbol{\nu} + \boldsymbol{\Pi}\begin{bmatrix}y_{1t-1}\\ y_{2t-1}\\ y_{3t-1}\end{bmatrix}_{(3\times1)} + \sum_{j=1}^{p-1}\begin{bmatrix}\gamma_{11,j} & \gamma_{12,j} & \gamma_{13,j}\\ \gamma_{21,j} & \gamma_{22,j} & \gamma_{23,j}\\ \gamma_{31,j} & \gamma_{32,j} & \gamma_{33,j}\end{bmatrix}_{(3\times3)}\begin{bmatrix}\Delta y_{1t-j}\\ \Delta y_{2t-j}\\ \Delta y_{3t-j}\end{bmatrix}_{(3\times1)} + \begin{bmatrix}u_{1t}\\ u_{2t}\\ u_{3t}\end{bmatrix}_{(3\times1)} \quad \text{………………..} \ (3.12)$$

Or it can be formulated in vector form as in regression (3.13).

$$\Delta\boldsymbol{Y_t} = \boldsymbol{\nu} + \boldsymbol{\Pi}\boldsymbol{Y_{t-1}} + \sum_{j=1}^{p-1}\boldsymbol{\Gamma_j}\,\Delta\boldsymbol{Y_{t-j}} + \boldsymbol{u_t} \quad \text{…...…………… (3.13)}$$

Remarks: Accordance with Lutkepohl & Kratzig (2004);

- $\Delta \boldsymbol{Y_t}$ does not contain stochastic trend by the assumption of all original time series (Y_t) are considered to be $I(1)$, then it assumed to be ΔY_t & $u_t \sim I(0)$.

- $\boldsymbol{\Pi} \coloneqq -(I_k - \boldsymbol{\Phi_1} - \ldots - \boldsymbol{\Phi_p})$, if $rank(\boldsymbol{\Pi}) = r < k$, then "$\boldsymbol{\Pi} = \boldsymbol{\alpha\beta'}$ " which follows "$rank(\boldsymbol{\alpha}) = rank(\boldsymbol{\beta}) = r$". Here $(k \times r)$ matrices of $'\boldsymbol{\alpha}$ & $\boldsymbol{\beta}'$ are referred to as loading matrix and cointegration matrix.

- And $\boldsymbol{\Pi Y_{t-1}}$ term is only one that includes $I(1)$ variables then $\boldsymbol{\Pi Y_{t-1}} \sim I(0)$ because a non-stationary variable cannot explain a stationary one. Hence it must be contained the long-run cointegration relations and sometimes it is called 'long term part' or 'long-un'.

- $\boldsymbol{\Gamma_i} = -(\boldsymbol{\Phi_{i+1}} + \ldots + \boldsymbol{\Phi_p})$; $\forall i = 1,2,\ldots,(p-1)$, and $\boldsymbol{\Gamma_i}$ terms are denoted to as 'Short term parameters' or 'short-run'.

If cointegrating rank, $r = 1$ there exists only one long-run cointegration relationship between the three log series. Then the error correction model can be described by,
$ECT_{t-1} = \hat{\beta}_0 + \hat{\beta}_{LCO_{2(t-1)}} LCO_{2_{t-1}} + \hat{\beta}_{LEC_{(t-1)}} LEC_{t-1} + \hat{\beta}_{LGDP_{(t-1)}} LGDP_{t-1}$,
in association with, the unrestricted long-run cointegration relationship for the CO_2 emissions as described by, $\Delta LCO_{2_t} = \hat{\beta}_{constant} + \hat{\beta}_{ECT_{t-1}} ECT_{t-1} + [\hat{\beta}_{\Delta LCO_{2(t-1)}} \Delta LCO_{2_{t-1}}$ $+ \hat{\beta}_{\Delta LEC_{(t-1)}} \Delta LEC_{t-1} + \hat{\beta}_{\Delta LGDP_{(t-1)}} \Delta LGDP_{t-1}] + u_t$.

3.10 Significance of the Parameter Estimation in the VECM

It is important to estimate statistically significance of parameters in fitted VAR or VECM model using a series of student t-test statistics on lagged values individually, (Wikipedia, 2018) or by using the Wald F-tests under OLS to estimate the joint significance of coefficient of the lagged variables, (Begum *et al.*, 2015). Further, the rank of the $\boldsymbol{\Pi}$ matrix via its eigenvalues consider for cointegration relationships between corresponding time series, then long-run coefficients can be determined by producing resultant error correction model and in effect produces two sets of coefficients say $\boldsymbol{\beta}$, is the coefficients of the cointegrating matrix $\boldsymbol{\alpha}$ is the adjustment parameter (loading coefficients). Then,$\boldsymbol{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$ the amount of each cointegrating vector entering each regression of the VECM and roughly equates to the error correction term. So, the model and parameter significance tests carried out in this study to identify the linear restrictions in the observed long-term cointegrating relationship.

Hence, it is satisfied $\Pi Y_{t-1}(= \alpha\beta' Y_{t-1}) = \Lambda ECT_{t-1}$ as explain in equation (3.14).

$$i.e. \begin{bmatrix} \alpha_{11} & .. & \alpha_{1r} \\ \alpha_{21} & .. & \alpha_{2r} \\ \alpha_{31} & .. & \alpha_{3r} \end{bmatrix}_{(3\times r)} \begin{bmatrix} \beta_{11} & \beta_{21} & \beta_{31} \\ .. & .. & .. \\ \beta_{1r} & \beta_{2r} & \beta_{3r} \end{bmatrix}_{(r\times 3)} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \\ y_{3t-1} \end{bmatrix}_{(3\times 1)} = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \end{bmatrix}_{(3\times 1)} ECT_{t-1} \quad .... (3.14)$$

Then the short-run and long-run relationships between variables in the fitted VECM can be discussed based on the estimator of parameters in the error correction term and the short-run coefficient matrix.

Note: If it observes no cointegration (Π = 0), the VAR framework applies instead of the VECM, then alternatively use the Durbin Watson (DW) test statistic that roughly equal to $2(1-\rho)$, where ρ is a measure of autocorrelation under hypothesis, $H_O: \Pi = 0$ (unit root/ nonstationary) Vs. $H_A: \Pi \neq 0$ (stationary).

3.11 Stability of the VAR and VECM Model

The VAR (p) process is considered as a stable process if its reverse characteristic polynomial or determinantal polynomial has no roots inside and on the complex unit circle (no unit-roots), (Lutkepohl, 2005). The reverse characteristic polynomial defines by the determinant of the AR operator, as mentioned below (3.15).

$$det\left(\boldsymbol{I_k} - \boldsymbol{\Phi_1 Z} - \ \dots - \boldsymbol{\Phi_p}\, \boldsymbol{Z^p}\right) \neq 0;\ \ for\ |\boldsymbol{Z}| \leq 1 \quad \dots\dots\dots (3.15)$$

Note: The $\det\left(\boldsymbol{I_k} - \boldsymbol{\Phi_1 Z} - \ \dots - \boldsymbol{\Phi_p}\, \boldsymbol{Z^p}\right) = 0$; for $Z = 1$ if the VAR (p) process has unit-roots. Then the "$\Pi = -\left(I_k - \boldsymbol{\Phi_1} - \ \dots - \boldsymbol{\Phi_p}\right)$" matrix is singular, and the levels parameter matrices, $\boldsymbol{\Phi_j}$ determined by the coefficients of the VECM. More precisely, $\boldsymbol{\Phi_i} = \Gamma_i - \Gamma_{i-1};\ \forall i = 2, \dots, p-1$, $\boldsymbol{\Phi_1} = \Gamma_1 + \Pi + I_k$ & $\boldsymbol{\Phi_p} = -\Gamma_{p-1}$, (Lutkepohl & Kratzig, 2004).

Further, Lutkepohl (2005) explained that stability suggests stationarity, hence the stability condition in (3.15) is often referred to as 'stationarity condition' in time series, but the converse is not true. If the unit-roots observed by the determinantal polynomial (root on the complex unit circle), then a stochastic and deterministic trend can be generated by the VAR process (Lutkepohl, 2005). Further, sufficient conditions for obtaining a trending behavior of the time series explains as the existence of the unit-roots (that means roots for $Z = 1$), if it is satisfied, then some or all of the variables are integrated. Thus, the stability condition of the fitted VECM verifies by spherically distributed inverse AR roots of the characteristic polynomial in the fitted VECM as in the VAR model. So, the stability condition of the fitted long-term cointegrating model tested in this study, by monitoring the behavior of the spherically distributed inverse AR roots of the characteristic polynomial on the VECM framework.

Note: If there are k number of endogenous variables and r number of cointegrating relations in the estimated VECM, then there are (k-r) possible unit roots in the roots provided by the reverse characteristic polynomial.

3.12 Residual Diagnosing Tests of the VECM

The residual diagnostic approaches, such as the Cholesky (Lutkepohl) test or the Jarque-Bera (JB) test, the Portmanteau test, the Lagrange-Multiplier (LM) test, and the Breusch-Pagan-Godfrey heteroscedasticity test were applied to check for white noise residuals of the fitted VECM.

- The JB test practiced for testing the normality of residual distribution under the null hypothesis $'H_O\!: residuals\ are\ normally\ distributed'$. Further, the absolute value of skewness, kurtosis of residual distribution could be a measure of the deviation of the residual normality (each skewness and kurtosis of normal distribution equal to zero). The corresponding test statistic is defined, as $JB = \frac{T-k}{6}\left[skewness^2 + \frac{(kurtosis-3)^2}{4}\right]$ where k is the number of regressors, and 'T' is the number of observations (Wikipedia, 2018).

- The Portmanteau test practiced for testing the residual autocorrelations under the null hypothesis ' H_O: each residual autocovariance is zero, up to lag h', ($H_O\!: E[u_t u'_{t-i}] = 0\,;\ i = 1,2 \ldots h$) against the alternative hypothesis that 'at least one autocovariance (or one autocorrelation) is zero'.

- The LM test practiced for testing the residual serial autocorrelation of order h, which views to test for zero coefficients in the model under the null hypothesis $'H_O\!: no\ serial\ autocorrelation\ of\ the\ residual'$ and as the test for stability of the residual vector u_t .

- The Breusch-Pagan-Godfrey Heteroscedasticity test practiced for testing the conditional heteroscedasticity in covariances of error distribution under the null hypothesis $'H_O\!: no\ hetroscedasticity\ in\ error\ covariances'$ (residuals covariances are zero) when the null hypothesis is satisfied it assumed that there is no ARCH effect in the residuals.

3.13 The Impulse Response Functions

Causality analysis fails to perform interaction effects between the variables effectually in econometric methodologies, then forecasted error variance decompositions, and impulse response functions (IRFs) analysis use instead to have a better picture of relationships between the time series variables. Generally, IRFs analysis measures the effect of one-time shock (impulse) to one of the innovations on expected current and future values of the endogenous variables. In the most empirical literature, analysis of IRFs widely uses in the VAR (restricted VAR) and VECM (unrestricted VAR) to expose the dynamic relationship between macroeconomic variables that is privileged to analyze the response of one variable towards a shock in another variable to the variable itself. The table of IRFs extensively used in this study, to determine the performance of one variable in response to a shock (or a change), and the graph of IRFs used along with to visualize the performance graphically.

CHAPTER 4

EXPLANATORY DATA ANALYSIS

The descriptive data analysis of the observations and linear impact of fossil fuel energy consumption and economic development on CO_2 emissions in Sri Lanka discussed under the univariate OLS scenario before the VECM development. The times series per capita values of CO_2 emissions (in metric tons, Mt), energy consumption (in Kg of oil equivalent), and gross domestic product (in constant 2010 US $) spanned from 1971 to 2014 coded as CO_2, EC & GDP respectively.

4.1 Descriptive Statistical Analysis

The descriptive results of the observations over 1971- 2014 presented in Table 4.1, confirmed that Sri Lanka's; CO_2 emissions per capita varied from $0.200\,Mt$ (minimum) in the year 1976 to $0.886Mt$ (maximum) in the year 2014, with an annual average of $0.404Mt$ throughout 1971-2014. Likewise, the annual average of CO_2 emissions per capita was spread-out within the (95% CI) range $[0.343Mt$ - $0.464Mt]$. Similarly, the fossil fuel energy consumption per capita varied from $287.014Kg$ (minimum) in the year 1977 to $551.021Kg$ (maximum) in the year 2012, with an annual average of $371.873Kg$, which was spread-out within the range $[348.279\ Kg$ - $395.468\ Kg]$ throughout the study period. Moreover, the GDP (in constant 2010 US\$) per capita varied from 689.679 US\$ (minimum) in the year 1972 to 3506.871 US\$ (maximum) in the year 2014, with an annual average of 1571.655 US \$, which was spread-out within the range $[1331.496\ US\$$ - $1811.813\ US\$]$ throughout the study period.

Further, it indicates that non-significant Jarque-Bera (JB) test statistics for each variable $(p > 0.05)$ except GDP, which has high kurtosis (2.920). Thus, it concluded with 95% confident that distributions of CO_2 emissions & fossil fuel energy consumption are not significantly different from normality.

Table 4.1: Descriptive data analysis of observed time series over 1971-2014

Statistic		CO_2	EC	GDP
Minimum (year)		0.200 (in 1976)	287.014 (in 1977)	689.679 (in 1972)
Maximum (year)		0.886 (in 2014)	551.021 (in 2012)	3506.871 (in 2014)
Mean (S.E. of Mean)		0.404 (0.030)	371.873 (11.700)	1571.655 (119.085)
95% CI for Mean	Lower Bound	0.343	348.279	1331.496
	Upper Bound	0.464	395.468	1811.813
Standard Deviation		0.199	77.607	789.923
Skewness		0.728	0.679	0.956
Kurtosis		2.170	2.009	2.920
Jarque Bera (p-value)		5.148 (0.076)	5.175 (0.075)	6.709 (0.035)

4.2 Temporal Variability of the CO_2 Emissions and its Determinants

The annual trend of Sri Lanka's per capita values of; CO_2 emissions (Mt), Energy consumption (Kg Oil), and GDP (US \$) spanned over the period 1971 - 2014 visualized in Figure 4.1. Corresponding graphical representations indicate exponential growth trends (stochastic trend) in each distribution over time, which implies that both the mean and variance of each series were time-variant (not constant over time).

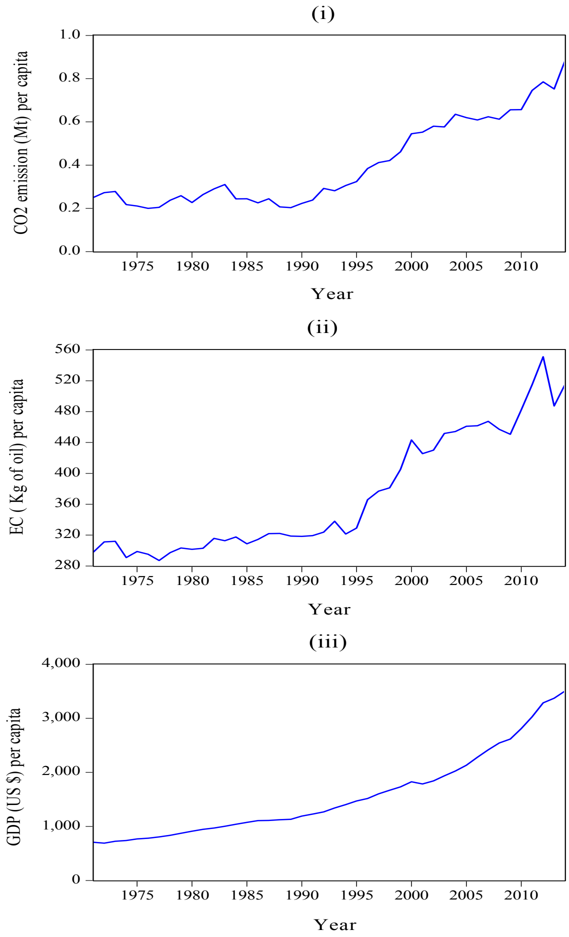

Figure 4.1: Annual trend of the per capita values of (i) CO_2 emissions, (ii) fossil fuel energy consumption and (iii) GDP over 1971-2014

4.3 Test of Variance Homogeneity in the Observed Variables

All variables in this study regarded as weak-form efficient since the present value of each variable reflect all its past information. The conventional variance ratio test carried out to test homogeneity of variances in each series, under the null hypothesis, H_o: a time series follows variance heterogeneity (Or variance ratio is not statistically different from one). Then, variance ratio estimates and test statistics of random walk hypothesis in GDP, CO_2, and EC throughout the study period presented in Table 4.2, 4.3 & 4.4 respectively.

Table 4.2: Results of homogeneity of variance in economic growth (GDP)

Joint Tests	Value	df	p-value
Max. |z| (at period 30)*	8.2755	43	0.0000

Individual Tests				
Period	Variance Ratio	Standard Error	z Statistic	p-value
2	1.6853	0.2496	2.7461	0.0060
6	3.6425	0.5275	5.0098	0.0000
10	4.8074	0.6447	5.9056	0.0000
14	5.2426	0.7193	5.8985	0.0000
18	6.4661	0.7744	7.0589	0.0000
22	7.1165	0.8160	7.4961	0.0000
26	7.3588	0.8497	7.4836	0.0000
30	8.2791	0.8796	8.2755	0.0000
34	7.4514	0.9068	7.1146	0.0000
38	5.8855	0.9319	5.2428	0.0000

Table 4.3: Results of homogeneity of variance in CO_2 emissions (CO_2)

Joint Tests	Value	df	p-value
Max. |z| (at period 18)*	1.6201	43	0.6710

Individual Tests				
Period	Variance Ratio	Standard Error	z Statistic	p-value
2	0.8409	0.1224	-1.2998	0.1937
6	1.2190	0.3188	0.6872	0.4920
10	1.3422	0.4308	0.7942	0.4271
14	1.7935	0.5118	1.5502	0.1211
18	1.9408	0.5807	1.6201	0.1052
22	1.6430	0.6399	1.0049	0.3150
26	1.1588	0.6907	0.2300	0.8181
30	0.6298	0.7356	-0.5032	0.6148
34	1.1343	0.7770	0.1729	0.8628
38	2.1306	0.8152	1.3870	0.1655

Table 4.4: Results of homogeneity of variance in fossil fuel energy consumption (EC)

Joint Tests	Value	df	p-value
Max. |z| (at period 6)*	0.7593	43	0.9974

Individual Tests				
Period	Variance Ratio	Standard Error	z Statistic	p-value
2	0.8370	0.2295	-0.7100	0.4777
6	0.6285	0.4893	-0.7593	0.4477
10	0.7334	0.5883	-0.4531	0.6504
14	0.8659	0.6494	-0.2066	0.8364
18	1.0388	0.7069	0.0549	0.9562
22	0.9329	0.7611	-0.0881	0.9298
26	0.5973	0.8089	-0.4979	0.6186
30	0.4212	0.8496	-0.6812	0.4957
34	0.5737	0.8845	-0.4820	0.6298
38	0.8823	0.9146	-0.1287	0.8976

The highly significant joint and individual Z-test statistic results of the variance ratio test ($p < 0.05$) presented in Table 4.2 concluded with 95% confident, that variances in economic growth not significantly deviate from homogeneity. However, insignificant joint and individual Z-test statistic results ($p > 0.05$) presented in Table 4.3, & 4.4 concluded with 95% confident, that variances in CO_2 emissions, and fossil fuel energy consumption significantly deviate from homogeneity. Hence, it concluded with 95% confident that variances in each series excluding GDP significantly deviate from homogeneity.

4.4 Stabilize Variances by the Transformed Series

It is customary to stabilize the variance of CO_2 emissions and fossil fuel energy consumption before analysis. Also, it demonstrated that economic growth significantly deviates from normality even though its variances are homogeneous. Thus, each time series transformed into its natural logarithmic form ('ln') in their measurement scale and corresponding log transformations coded as LCO_2, LEC & LGDP. Then visual inspections of annual trends and test results for normality of the log series presented in Figure 4.2 and Table 4.5 respectively.

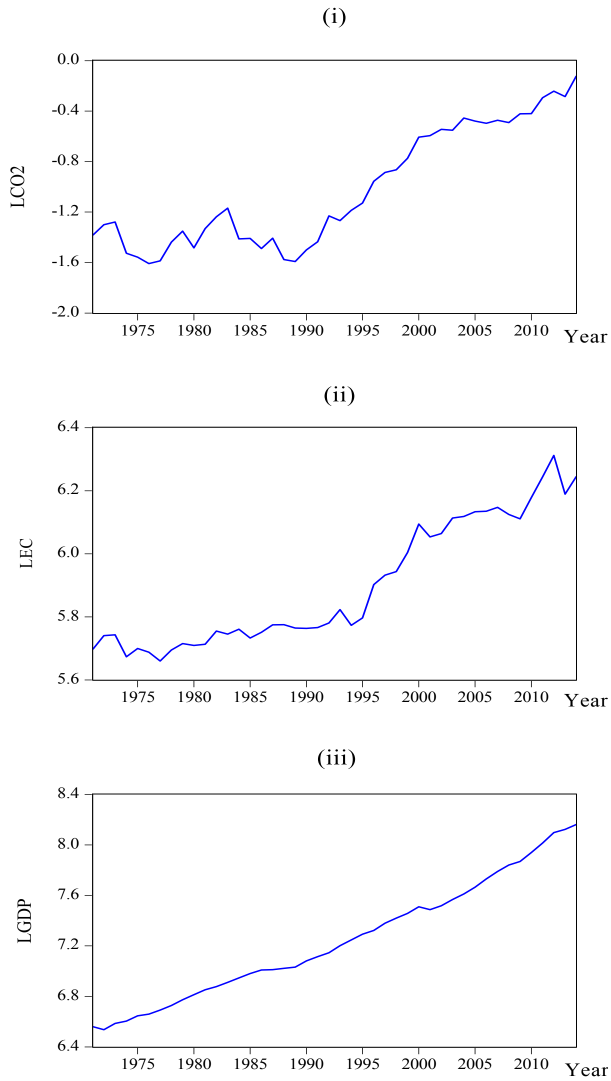

Figure 4.2: Annual trend of the logarithmic values of (i) CO_2 emissions, (ii) fossil fuel energy consumption and (iii) GDP over 1971-2014

Table 4.5: Normality test results of the log series

Variables	LCO_2	LEC	LGDP
Mean	-1.019	5.899	7.246
Standard Deviation	0.472	0.200	0.476
Skewness	0.378	0.536	0.306
Kurtosis	1.603	1.733	2.003
Jarque Bera (p-value)	4.626 (0.099)	5.050 (0.080)	2.512 (0.285)

Annual trend distributions visualized in Figures 4.2 indicate time-variant mean and variance in each log series, excluding LGDP because the annual trend distribution of LGDP indicates increasing linear trend approximately. The insignificant JB statistic results ($p > 0.05$) presented in Table 4.5 concluded with 95% confident, that all three log series are not significantly different from normality.

4.5 Association between CO_2 Emissions, Fossil Fuel Energy Consumption & Economic Development

4.5.1 Correlation Between LCO_{2_t} and the Present Values of its Determinants

The Pearson correlation coefficients computed as presented in Table 4.6 to examine the association between present per capita levels of CO_2 emissions, fossil fuel energy consumption & economic development.

Table 4.6: Correlations between three log series

Study Variables	LCO_{2_t}	LEC_t	$LGDP_t$
LCO_{2_t}	1.0000 -----		
LEC_t	0.9742 (0.0000)	1.0000 -----	
$LGDP_t$	0.9436 (0.0000)	0.9639 (0.0000)	1.0000 -----

( ) indicates the p-values for significance of correlations

The results of Table 4.6 indicate that highly significant, positive correlation between each variable pairs in the present levels of the log series (all $r > 0.90$ & $p = 0.00$). Hence, it concluded with 95% confident that there exists a significant and higher strength of positive association between each variable.

4.5.2 Correlation Between LCO_{2_t} and the Immediate Past Values of its Determinants

The Pearson correlations between immediate past logarithmic per capita values of fossil fuel energy consumption, economic development (LEC_{t-1} & $LGDP_{t-1}$), and the present logarithmic per capita value of CO_2 emissions (LCO_{2_t}) examined to check whether there exists an association between each pair, and reported in Table 4.7.

Table 4.7: Correlations between CO_2 emissions & the immediate past valued of its determinants

Study Variables	LCO_{2_t}	LEC_{t-1}	$LGDP_{t-1}$
LCO_{2_t}	1.0000 -----		
LEC_{t-1}	0.9831 (0.0000)	1.0000 -----	
$LGDP_{t-1}$	0.9285 (0.0000)	0.9519 (0.0000)	1.0000 -----

( ) indicates the p-values for significance of correlations

The results of Table 4.7 indicate that highly significant, positive correlation between corresponding variable pairs (all $r > 0.90$ & $p = 0.00$), which concluded with 95% confident that there exists a significant and higher strength of positive association between immediate past logarithmic values of fossil fuel energy consumption, economic growth and the present logarithmic value of CO_2 emissions.

4.6 Univariate OLS Relationship Between the Present Values of CO_2 Emissions and the Present Values of its Determinants

4.6.1 Univariate OLS Relationship Between LCO_{2_t} and LEC_t

To identify the impact of the present level of LEC on LCO_2, a scatter plot of LCO_{2_t} vs. LEC_t observed as visualized in Figure 4.3. It revealed the existence of a strong positive, approximately linear relationship between LCO_{2_t} & LEC_t, which indicates that a higher concentration of present CO_2 emissions tends to be accompanied by a higher level of present fossil fuel energy consumption in their measurement scale. Thus, a log-linear relationship between LCO_{2_t} & LEC_t observed developing the OLS regression model as $\mathrm{LCO}_{2_t} = \hat{\beta}_c + \hat{\beta}_{LEC_t} LEC_t$ and corresponding results reported in Table 4.8.

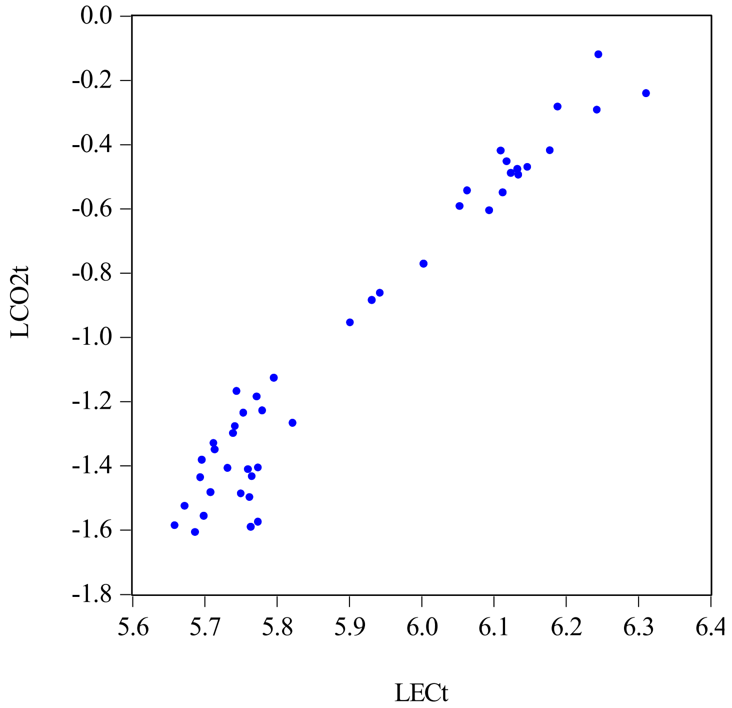

Figure 4.3: Scatter plot between LEC_t & LCO_{2_t} over the period of 1971-2014

Table 4.8: Parameter significance of the OLS estimates in the model, LCO_{2_t} vs. LEC_t

Variable	Coefficient	Standard Error	t Statistic	p-value
C	-14.6305	0.4790	-30.5428	0.0000
LEC_t	2.3076	0.0812	28.4313	0.0000
R^2	95%			
F Statistic	808.3399			
p-value (F Statistic)	0.0000			

The results of Table 4.8 indicate that all parameters are highly significant (all $p = 0.00$) with 95% confident. Then a linear relationship between LCO_{2_t} & LEC_t is observed by model $LCO_{2_t} = -14.63 + 2.31\ LEC_t$, which explained 95% of observed variability ($R^2 = 0.95$). Thus, a unit increases in the logarithmic level of present fossil fuel energy consumption increases the logarithmic level of present CO_2 emissions positively by 2.31.

The residual diagnostics for the white noise process examined, as shown below in Figure 4.4, Table 4.9, & 4.10 respectively.

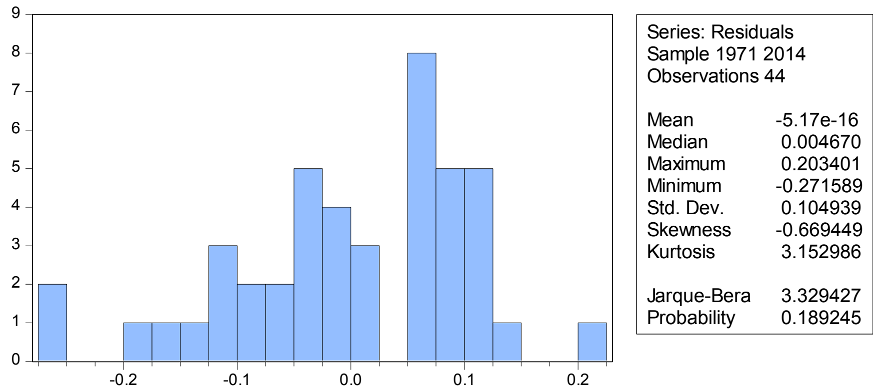

Figure 4.4: The JB test for Normality of residuals in the model, LCO_{2_t} vs. LEC_t

Table 4.9: Test for white heteroscedasticity of the model, LCO_{2_t} vs. LEC_t

F Statistic	0.9992	Probability F(2,41)	0.3770
Obs*R-squared	2.0449	Probability Chi-Square(2)	0.3597
Scaled explained SS	2.0057	Probability Chi-Square(2)	0.3668

The insignificant JB statistic results presented in Figure 4.4 (JB=3.33, $p = 0.19$) concluded with 95% confident, that residuals in the fitted model are not significantly different from normality, and it seems some outlier influence. The results of Table 4.9 indicate that insignificant F-statistic of squared residuals (F=1.00, $p = 0.38$) concluded with 95% confident, that the squared residuals are non-heteroscedastic (homoscedastic).

Table 4.10: Autocorrelation analysis of squared residuals in the model, LCO_{2_t} vs. LEC_t

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.497	0.497	11.609	0.001
		2	0.169	-0.103	12.984	0.002
		3	0.016	-0.034	12.996	0.005
		4	-0.089	-0.089	13.398	0.009
		5	0.180	0.367	15.070	0.010
		6	0.230	-0.025	17.887	0.007
		7	0.115	-0.068	18.607	0.010
		8	-0.089	-0.224	19.048	0.015
		9	-0.198	0.054	21.315	0.011
		10	-0.183	-0.100	23.306	0.010
		11	-0.202	-0.191	25.814	0.007
		12	-0.131	-0.069	26.906	0.008
		13	-0.114	0.040	27.754	0.010
		14	-0.167	-0.067	29.643	0.009
		15	-0.191	-0.129	32.200	0.006
		16	-0.186	-0.002	34.697	0.004
		17	-0.169	-0.013	36.828	0.004
		18	-0.120	-0.040	37.944	0.004
		19	-0.100	-0.136	38.750	0.005
		20	-0.081	0.013	39.308	0.006

The significant Q-statistic results of squared residuals at each lag (all $p < 0.05$) presented in Table 4.10 concluded with 95% confident, that squared residuals are not random, since there exist serial autocorrelation within errors. Thus, the resultant error components in the fitted model $LCO_{2_t} = -14.63 + 2.31\,LEC_t$ are significantly different from white noise process. So, the fitted model cannot accept as the best fit for representing the relationship between LCO_{2_t} vs. LEC_t.

4.6.2 Univariate OLS Relationship Between LCO_{2_t} and $LGDP_t$

To identify the impact of the present level of LGDP on LCO_2, a scatter plot of LCO_{2_t} vs. $LGDP_t$ observed as visualized in Figure 4.5. It revealed the existence of a strong positive, approximately linear relationship between LCO_{2_t} & $LGDP_t$, which indicates that a higher concentration of present CO_2 emissions tends to be accompanied by a higher level of present economic development in their measurement scale. Thus, a log-linear relationship between LCO_{2_t} & $LGDP_t$ observed developing the OLS regression model as $\mathrm{LCO}_{2_t} = \hat{\beta}_c + \hat{\beta}_{LGDP_t} LGDP_t$ and corresponding results reported in Table 4.11.

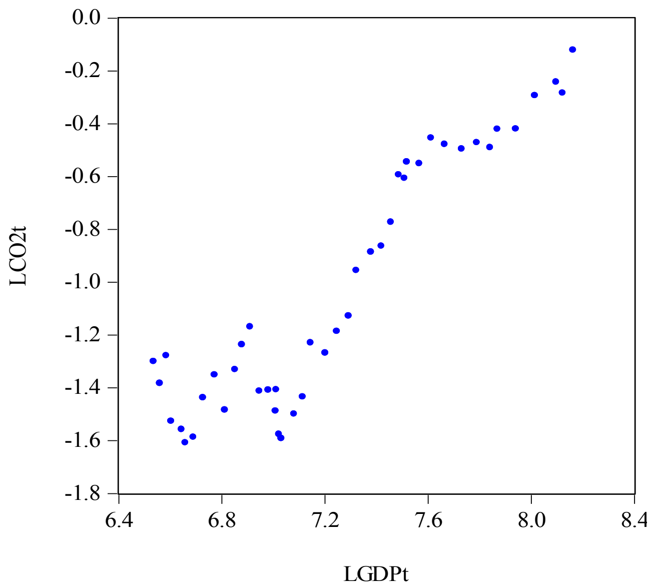

Figure 4.5: Scatter plot between $LGDP_t$ & LCO_{2_t} over the period of 1971-2014

Table 4.11: Parameter significance of the OLS estimates in the model, LCO_{2_t} vs. $LGDP_t$

Variable	Coefficient	Standard Error	t Statistic	p-value
C	-7.6833	0.4171	-18.4189	0.0000
LGDP	0.9197	0.0575	16.0096	0.0000
R^2	86 %			
F Statistic	256.3087			
p-value (F Statistic)	0.0000			

The results of Table 4.11 indicate a highly significant linear relationship between LCO_{2_t} & $LGDP_t$ by model $LCO_{2_t} = -7.68 + 0.92\, LGDP_t$ ($R^2 = 0.86, p = 0.00$). Thus, a unit increases in the logarithmic level of present economic development increases the logarithmic level of present CO_2 emissions positively by 0.92.

The residual diagnostics for the white noise process examined, as shown below in Figure 4.6, Table 4.12, & 4.13 respectively. The insignificant JB statistic results presented in Figure 4.4 (JB = $0.32, p = 0.85$) concluded with 95% confident, that residuals in the fitted model are not significantly different from normality. Also, insignificant F-statistic of squared residuals presented in Table 4.12 (F = $3.11, p = 0.06$) concluded with 95% confident, that the squared residuals are non-heteroscedastic (homoscedastic).

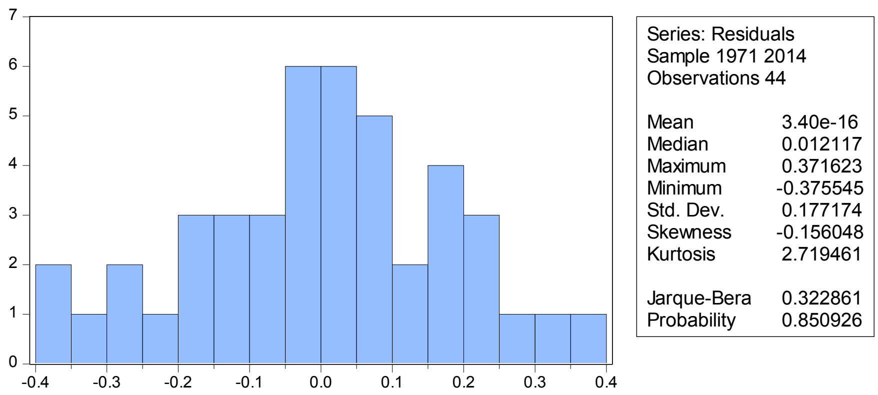

Figure 4.6: The JB test for Normality of residuals in the model, LCO_{2_t} vs. $LGDP_t$

Table 4.12: Test for white heteroscedasticity of the model, LCO_{2_t} vs. $LGDP_t$

F Statistic	3.1069	Probability F(2,41)	0.0554
Obs*R-squared	5.7908	Probability Chi-Square(2)	0.0553
Scaled explained SS	4.5362	Probability Chi-Square(2)	0.1035

Table 4.13: Autocorrelation analysis of squared residuals in the model, LCO_{2_t} vs. $LGDP_t$

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.689	0.689	22.373	0.000
		2	0.370	-0.200	28.984	0.000
		3	0.132	-0.073	29.839	0.000
		4	-0.020	-0.050	29.860	0.000
		5	-0.087	-0.009	30.251	0.000
		6	-0.190	-0.193	32.176	0.000
		7	-0.238	-0.023	35.276	0.000
		8	-0.314	-0.199	40.833	0.000
		9	-0.292	0.044	45.771	0.000
		10	-0.232	-0.065	48.968	0.000
		11	-0.140	0.039	50.172	0.000
		12	-0.104	-0.153	50.849	0.000
		13	-0.005	0.186	50.851	0.000
		14	0.036	-0.181	50.936	0.000
		15	0.140	0.282	52.305	0.000
		16	0.285	0.031	58.188	0.000
		17	0.265	-0.047	63.438	0.000
		18	0.186	-0.126	66.135	0.000
		19	0.007	-0.065	66.139	0.000
		20	-0.091	-0.084	66.832	0.000

The highly significant Q-statistic results of squared residuals at each lag ($p < 0.05$) presented in Table 4.13 concluded with 95% confident, that squared residuals are not random, since there exist serial autocorrelation within errors. Thus, the resultant error components in the fitted model $LCO_{2_t} = -7.68 + 0.92LGDP_t$ are significantly different from white noise process. So, the fitted model cannot accept as the best fit for representing the relationship between LCO_{2_t}vs. $LGDP_t$.

4.7 Univariate OLS Relationship Between the Present Values of CO_2 Emissions and the Immediate Past Values of its Determinants

4.7.1 Univariate OLS Relationship Between LCO_{2_t} and LEC_{t-1}

To identify the impact of the immediate past of LEC on the present level of LCO_2, a scatter plot of LCO_{2_t} vs. LEC_{t-1} observed as visualized in Figure 4.7. It revealed the existence of a strong positive, approximately linear relationship between LCO_{2_t} & LEC_{t-1}, which indicates that a higher concentration of present CO_2 emissions tends to be accompanied by a higher level of immediate past level of fossil fuel energy consumption in their measurement scale. Thus, a log-linear relationship between LCO_{2_t} & LEC_{t-1} observed developing the OLS regression model as $\mathrm{LCO}_{2_t} = \hat{\beta}_c + \hat{\beta}_{LEC_{t-1}} LEC_{t-1}$ and corresponding results reported in Table 4.14.

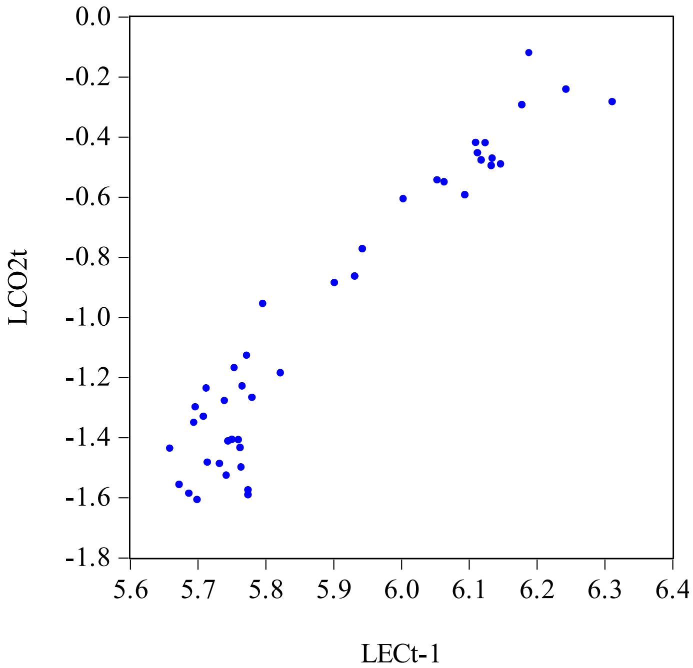

Figure 4.7: Scatter plot between LEC_{t-1} & LCO_{2_t} over the period of 1971-2014

Table 4.14: Parameter significance of the OLS estimates in the model, LCO_{2_t} vs. LEC_{t-1}

Variable	Coefficient	Standard Error	t Statistic	p-value
C	-14.7926	0.6354	-23.2792	0.0000
LEC_{t-1}	2.3397	0.1078	21.7004	0.0000
R^2	92%			
F Statistic	470.9068			
p-value (F Statistic)	0.0000			

The results of Table 4.14 indicate a highly significant linear relationship between LCO_{2_t} & LEC_{t-1} by model $LCO_{2_t} = -14.79 + 2.34\, LEC_{t-1}$ ($R^2 = 0.92, p = 0.00$). Thus, a unit increases in logarithmic immediate past level of fossil fuel energy consumption increases the logarithmic level of present CO_2 emissions positively by 2.34.

The residual diagnostics for the white noise process examined, as shown below in Figure 4.8, Table 4.15, & 4.16 respectively. The insignificant JB statistic results presented in Figure 4.8 (JB = 1.14, $p = 0.56$) concluded with 95% confident, that residuals in the fitted model are not significantly different from normality. Also, insignificant F-statistic of squared residuals presented in Table 4.15 (F = 0.98, $p = 0.39$) concluded with 95% confident, that the squared residuals are non-heteroscedastic (homoscedastic).

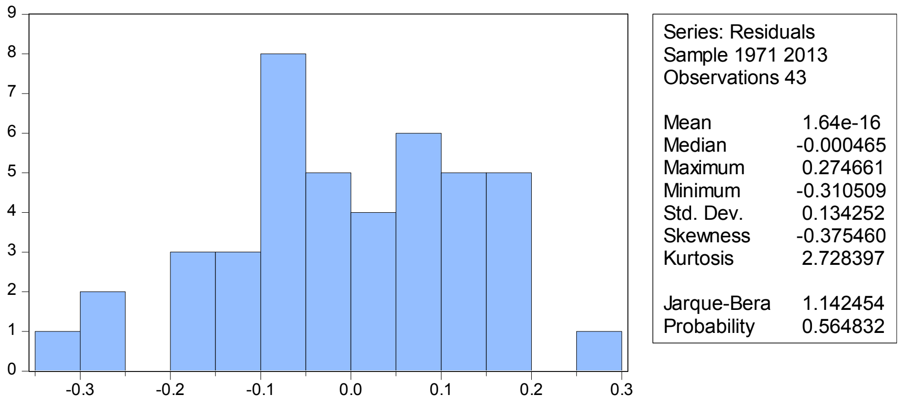

Figure 4.8: The JB test for Normality of residuals in the model, LCO_{2_t} vs. LEC_{t-1}

Table 4.15: Test for white heteroscedasticity of the model, ${LCO_2}_t$ vs. LEC_{t-1}

F Statistic	0.9764	Probability F(2,40)	0.3855
Obs*R-squared	2.0015	Probability Chi-Square(2)	0.3676
Scaled explained SS	1.5725	Probability Chi-Square(2)	0.4555

Table 4.16: Autocorrelation analysis of squared residuals in the model, ${LCO_2}_t$ vs. LEC_{t-1}

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.390	0.390	7.0242	0.008
		2	-0.040	-0.227	7.1010	0.029
		3	-0.132	-0.029	7.9383	0.047
		4	-0.154	-0.111	9.1200	0.058
		5	-0.108	-0.028	9.7150	0.084
		6	0.125	0.188	10.539	0.104
		7	0.275	0.143	14.609	0.041
		8	0.077	-0.118	14.940	0.060
		9	-0.194	-0.179	17.084	0.047
		10	-0.138	0.078	18.202	0.052
		11	-0.108	-0.068	18.912	0.063
		12	-0.105	-0.064	19.598	0.075
		13	-0.080	-0.151	20.006	0.095
		14	-0.033	-0.076	20.080	0.128
		15	-0.184	-0.194	22.412	0.097
		16	-0.188	0.007	24.948	0.071
		17	0.078	0.174	25.399	0.086
		18	0.013	-0.231	25.412	0.114
		19	-0.100	-0.068	26.225	0.124
		20	-0.112	-0.097	27.289	0.127

The significant Q-statistic results of squared residuals at each lag (all $p < 0.05$) presented in Table 4.16 concluded with 95% confident, that squared residuals are not random, since there exist serial autocorrelation within errors. Thus, the resultant error components in the fitted model ${LCO_2}_t = -14.79 + 2.34\, LEC_{t-1}$ are significantly different from white noise process. So, the fitted model cannot accept as the best fit for representing the relationship between ${LCO_2}_t$ vs. LEC_{t-1}.

4.7.2 Univariate OLS Relationship Between LCO_{2_t} and $LGDP_{t-1}$

To identify the impact of the immediate past of LGDP on the present level of LCO_2, a scatter plot of LCO_{2_t} vs. $LGDP_{t-1}$ observed as visualized in Figure 4.9. It revealed the existence of a strong positive, approximately linear relationship between LCO_{2_t} & $LGDP_{t-1}$, which indicates that a higher concentration of present CO_2 emissions tends to be accompanied by a higher level of immediate past level of economic development in their measurement scale. Thus, a log-linear relationship between LCO_{2_t} & $LGDP_{t-1}$ observed developing the OLS regression model as $\mathrm{LCO}_{2_t} = \hat{\beta}_c + \hat{\beta}_{LEC_{t-1}} LGDP_{t-1}$ and corresponding results reported in Table 4.18.

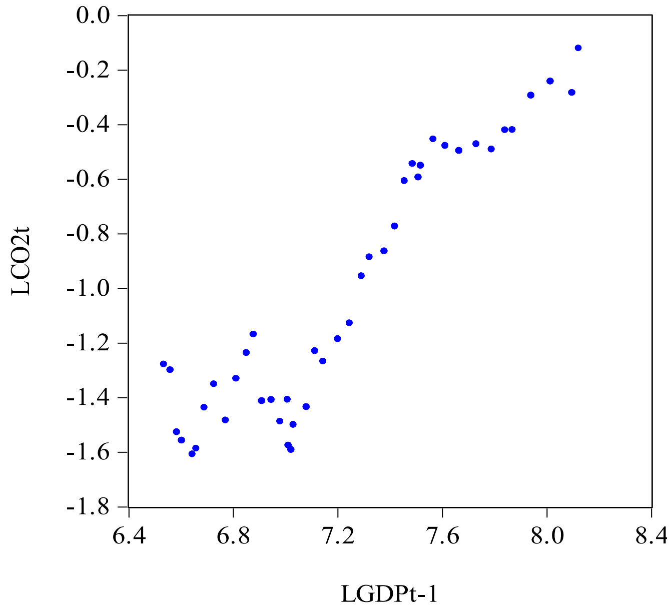

Figure 4.9: Scatter plot between $LGDP_{t-1}$ & LCO_{2_t} over the period of 1971-2014

Table 4.17: Parameter significance of the OLS estimates in the model, LCO_{2_t} vs. $LGDP_{t-1}$

Variable	Coefficient	Standard Error	t Statistic	p-value
C	-7.9430	0.4286	-18.5315	0.0000
$LGDP_{t-1}$	0.9595	0.0592	16.2057	0.0000
R^2	87%			
F Statistic	262.6250			
p-value (F Statistic)	0.0000			

The results of Table 4.17 indicate a highly significant linear relationship between LCO_{2_t} & $LGDP_{t-1}$ by model $LCO_{2_t} = -7.94 + 0.96\, LGDP_{t-1}$ ($R^2 = 0.87$, $p = 0.00$). Thus, a unit increases in logarithmic immediate past level of economic development increases the logarithmic level of present CO_2 emissions positively by 0.96.

The residual diagnostics for the white noise process examined, as shown below in Figure 4.10, Table 4.18, & 4.19 respectively. The insignificant JB statistic results presented in Figure 4.10 (JB = 0.26, $p = 0.88$) concluded with 95% confident, that residuals in the fitted model are not significantly different from normality. Also, insignificant F-statistic of squared residuals presented in Table 4.18 (F = 2.64, $p = 0.08$) concluded with 95% confident, that the squared residuals are non-heteroscedastic (homoscedastic).

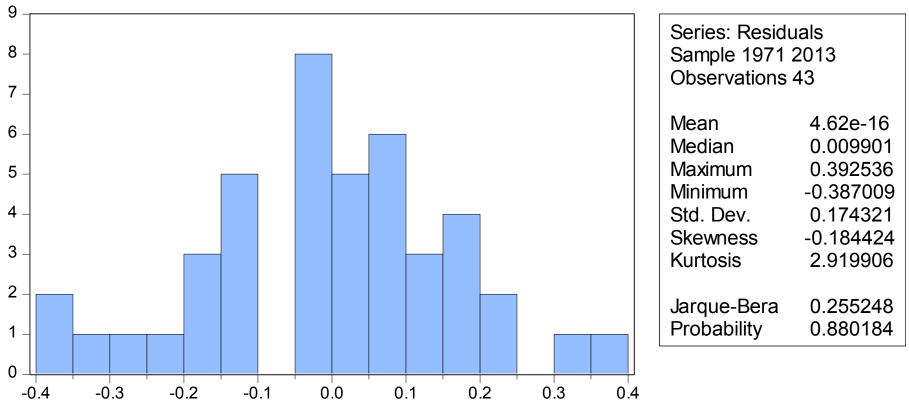

Figure 4.10: The JB test for Normality of residuals in the model, LCO_{2_t} vs. $LGDP_{t-1}$

Table 4.18: Test for white heteroscedasticity of the model, LCO_{2_t} vs. $LGDP_{t-1}$

F Statistic	2.6445	Probability F(2,40)	0.0834
Obs*R-squared	5.0216	Probability Chi-Square(2)	0.0812
Scaled explained SS	4.3825	Probability Chi-Square(2)	0.1118

Table 4.19: Autocorrelation analysis of squared residuals in the model, LCO_{2_t} vs. $LGDP_{t-1}$

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.609	0.609	17.106	0.000
		2	0.290	-0.129	21.079	0.000
		3	0.112	-0.014	21.689	0.000
		4	-0.046	-0.129	21.794	0.000
		5	-0.086	0.029	22.171	0.000
		6	-0.146	-0.126	23.292	0.001
		7	-0.212	-0.097	25.700	0.001
		8	-0.290	-0.175	30.345	0.000
		9	-0.240	0.055	33.617	0.000
		10	-0.185	-0.080	35.616	0.000
		11	-0.133	-0.015	36.681	0.000
		12	-0.120	-0.129	37.572	0.000
		13	0.003	0.179	37.573	0.000
		14	0.053	-0.109	37.759	0.001
		15	0.207	0.293	40.720	0.000
		16	0.366	0.069	50.343	0.000
		17	0.233	-0.139	54.373	0.000
		18	0.117	-0.055	55.434	0.000
		19	-0.051	-0.147	55.639	0.000
		20	-0.118	0.013	56.807	0.000

The highly significant Q-statistic results of squared residuals at each lag ($p < 0.05$) presented in Table 4.19 concluded with 95% confident, that squared residuals are not random, since there exist serial autocorrelation within errors. Thus, the resultant error components in the fitted model $LCO_{2_t} = -7.94 + 0.96\, LGDP_{t-1}$ are significantly different from white noise process. So, the fitted model cannot accept as the best fit for representing the relationship between LCO_{2_t} vs. $LGDP_{t-1}$.

The aforementioned OLS approaches significantly concluded that the fitted univariate regression models failed to perform best fits since the corresponding residuals were not white noises in each OLS association. This may be due to significant autocorrelation of the dependent variables, which violates the correlation requirement of the OLS requirements. Nevertheless, Farhani & Rejeb (2012) explained that in traditional OLS estimation approach observed endogeneity generally and OLS estimator has an asymptotic bias.

4.8 Summary of Chapter 4.

The variances of time series excluding GDP not significantly deviated from heterogeneity, and observed stochastic trends in each series over time. The natural logarithmic transformation of each series considered to reduce existing heterogeneity of the variances, and it concluded with 95% confident that the corresponding series had no extreme deviations from log-normal distributions. Supplementary, highly significant, strong positive correlations observed with 95% confident, between the present level of CO_2 emissions and the present level of its determinant as well as between the present level of CO_2 emissions and the immediate past of its determinant. The univariate OLS regression approaches confirmed, that the present value of fossil fuel energy consumption & economic growth along with immediate past values of them have a highly significant positive linear impact on the present level of CO_2 emissions with 95% confident. But corresponding residuals failed to performed residual diagnostics since there was serial autocorrelation within errors in each OLS approach. Thus, univariate OLS scenarios failed to identify appropriate best fits.

CHAPTER 5

DEVELOPMENT OF THE VECM

In the previous chapter, the impact of present values and immediate past values of LEC and LGDP (LEC_t, $LEC_{t-1,}$ $LGDP_t$ & $LGDP_{t-1}$) on present values of LCO_2 (LCO_{2_t}) studied under the univariate OLS scenario. In this chapter, multivariate time series approaches investigated under the VECM environment. Then stationarity approaches of the log-transformed series over the period 1971-2014 were deliberated in section 5.1.

5.1 Stationarity Order of the Log Series by the Unit Root Tests

The Augmented-Dickey-Fuller (ADF) and Phillip-Perron's (PP) unit root tests were carried out under commonly practiced two trend assumptions, 'model including intercept only' and 'model including both trend & intercept'. Those tests performed for levels, as well as the first differences of each log series and corresponding results shown below.

5.1.1 Stationarity Order of the LCO_2

The ADF test results for the level of LCO_2 based on two scenarios presented in Table 5.1 & 5.2. Similarly, the ADF test results for the 1st differences of LCO_2 based on two scenarios presented in Table 5.3 & 5.4.

Table 5.1: The ADF test results at the level LCO_2 with intercept only

		t Statistic	p-value
ADF test statistic		0.4419	0.9825
Test critical values:	1% Sig. level	-3.5925	
	5% Sig. level	-2.9314	
	10% Sig. level	-2.6039	

Table 5.2: The ADF test results at the level LCO_2 with trend & intercept

		t Statistic	p-value
ADF test statistic		-2.0114	0.5787
Test critical values:	1% Sig. level	-4.1865	
	5% Sig. level	-3.5181	
	10% Sig. level	-3.1897	

Table 5.3: The ADF test results at the 1st differenced LCO_2 with intercept only

		t Statistic	p-value
ADF test statistic		-6.3444	0.0000
Test critical values:	1% Sig. level	-3.5966	
	5% Sig. level	-2.9332	
	10% Sig. level	-2.6049	

Table 5.4: The ADF test results at the 1st differenced LCO_2 with trend & intercept

		t Statistic	p-value
ADF test statistic		-6.6858	0.0000
Test critical values:	1% Sig. level	-4.1923	
	5% Sig. level	-3.5208	
	10% Sig. level	-3.1913	

The ADF test results of Table 5.1 & 5.2 indicate that non-significance at the level of LCO_2 under both trend assumptions, 'with intercept only' (t = 0.44, $p = 0.98$) and 'with trend & intercept' (t = -2.01, $p = 0.58$), which confirmed with 95% confident that the LCO_2 is initially non-stationary under two scenarios. Similarly, Table 5.3 & 5.4 indicate that significant ADF test statistic at the 1st differences of LCO_2 under both trend assumptions, 'with intercept only' (t = -6.34, $p = 0.00$) and 'with trend & intercept' (t = -6.69, $p = 0.00$), which confirmed with 95% confident that the 1st differenced LCO_2 is stationary under two scenarios.

The PP test results for the level of LCO_2 based on two scenarios presented in Table 5.5 & 5.6. Likewise, the PP test results for the 1st differences of LCO_2 based on two scenarios presented in Table 5.7 & 5.8.

Table 5.5: The PP test results at the level LCO_2 with intercept only

		Adj. t Statistic	p-value
PP test statistic		0.5045	0.9850
Test critical values:	1% Sig. level	-3.5925	
	5% Sig. level	-2.9314	
	10% Sig. level	-2.6039	

Table 5.6: The PP test results at the level LCO_2 with trend & intercept

		Adj. t Statistic	p-value
PP test statistic		-1.9646	0.6036
Test critical values:	1% Sig. level	-4.1865	
	5% Sig. level	-3.5181	
	10% Sig. level	-3.1897	

Table 5.7: The PP test results at the 1st differenced LCO_2 with intercept only

		Adj. t Statistic	p-value
PP test statistic		-6.3444	0.0000
Test critical values:	1% Sig. level	-3.5966	
	5% Sig. level	-2.9332	
	10% Sig. level	-2.6049	

Table 5.8: The PP test results at the 1st differenced LCO_2 with trend & intercept

		Adj. t Statistic	p-value
PP test statistic		-6.6839	0.0000
Test critical values:	1% Sig. level	-4.1923	
	5% Sig. level	-3.5208	
	10% Sig. level	-3.1913	

The PP test results of Table 5.5 & 5.6 indicate that non-significance at the level of LCO_2 under both trend assumptions, 'with intercept only' (t = 0.50, $p = 0.99$) and 'with trend & intercept' (t = -1.96, $p = 0.60$), which confirmed with 95% confident that the LCO_2 is initially non-stationary under two scenarios. Likewise, Table 5.7 & 5.8 indicate that significant PP test statistic at the 1st differences of LCO_2 under both trend assumptions, ‘with intercept only’ (t = -6.34, $p = 0.00$) and ‘with trend & intercept’ (t = -6.68, $p = 0.00$), which confirmed with 95% confident that the 1st differenced LCO_2 is stationary under two scenarios. Altogether, it concluded with 95% confident that LCO_2 is stationary at its 1st differences ($LCO_2 \sim I(1)$) based on both tests under two scenarios.

5.1.2 Stationarity Order of the LEC

The ADF test results for the level of LEC based on two scenarios presented in Table 5.9 & 5.10. Similarly, the ADF test results for the 1st differences of LEC based on two scenarios presented in Table 5.11 & 5.12.

Table 5.9: The ADF test results at the level LEC with intercept only

		t Statistic	p-value
ADF test statistic		0.0799	0.9605
Test critical values:	1% Sig. level	-3.5925	
	5% Sig. level	-2.9314	
	10% Sig. level	-2.6039	

Table 5.10: The ADF test results at the level LEC with trend & intercept

		t Statistic	p-value
ADF test statistic		-2.3266	0.4113
Test critical values:	1% Sig. level	-4.1865	
	5% Sig. level	-3.5181	
	10% Sig. level	-3.1897	

Table 5.11: The ADF test results at the 1st differenced LEC with intercept only

		t Statistic	p-value
ADF test statistic		-7.2498	0.0000
Test critical values:	1% Sig. level	-3.5966	
	5% Sig. level	-2.9332	
	10% Sig. level	-2.6049	

Table 5.12: The ADF test results at the 1st differenced LEC with trend & intercept

		t Statistic	p-value
ADF test statistic		-6.5669	0.0000
Test critical values:	1% Sig. level	-4.1985	
	5% Sig. level	-3.5236	
	10% Sig. level	-3.1929	

The ADF test results of Table 5.9 & 5.10 indicate that non-significance at the level LEC under both trend assumptions, 'with intercept only' (t = 0.08, $p = 0.96$) and 'with trend & intercept' (t = -2.33, $p = 0.41$), which confirmed with 95% confident that the LEC is initially non-stationary under two scenarios. Similarly, Table 5.11 & 5.12 indicate that significant ADF test statistic at the 1st differences of LEC under both trend assumptions, 'with intercept only' (t = -7.25, $p = 0.00$) and 'with trend & intercept' (t = -6.57, $p = 0.00$), which confirmed with 95% confident that the 1st differenced LEC is stationary under two scenarios.

The PP test results for the level of LEC based on two scenarios presented in Table 5.13 & 5.14. Likewise, the PP test results for the 1st differences of LEC based on two scenarios presented in Table 5.15 & Table 5.16.

Table 5.13: The PP test results at the level LEC with intercept only

		Adj. t Statistic	p-value
PP test statistic		0.4346	0.9822
Test critical values:	1% Sig. level	-3.5925	
	5% Sig. level	-2.9314	
	10% Sig. level	-2.6039	

Table 5.14: The PP test results at the level LEC with trend & intercept

		Adj. t Statistic	p-value
PP test statistic		-2.1496	0.5045
Test critical values:	1% Sig. level	-4.1865	
	5% Sig. level	-3.5181	
	10% Sig. level	-3.1897	

Table 5.15: The PP test results at the 1st differenced LEC with intercept only

		Adj. t Statistic	p-value
PP test statistic		-7.3578	0.0000
Test critical values:	1% Sig. level	-3.5966	
	5% Sig. level	-2.9332	
	10% Sig. level	-2.6049	

Table 5.16: The PP test results at the 1st differenced LEC with trend & intercept

		Adj. t Statistic	p-value
PP test statistic		-7.7927	0.0000
Test critical values:	1% Sig. level	-4.1923	
	5% Sig. level	-3.5208	
	10% Sig. level	-3.1913	

The PP test results of Table 5.13 & 5.14 indicate that non-significance at the level of LEC under both trend assumptions, 'with intercept only' (t = 0.43, $p = 0.98$) and 'with trend & intercept' (t = -2.15, $p = 0.50$), which confirmed with 95% confident that the LEC is initially non-stationary under two scenarios. Likewise, Table 5.15 & 5.16 indicate that significant PP test statistic at the 1st differences of LEC under both trend assumptions, 'with intercept only' (t = -7.36, $p = 0.00$) and 'with trend & intercept' (t = -7.79, $p = 0.00$), which confirmed with 95% confident that the 1st differenced LEC is stationary under two scenarios. Altogether, it concluded with 95% confident that LEC is stationary at its 1st differences ($LEC{\sim}I(1)$) based on both tests under two scenarios.

5.1.3 Stationarity Order of the LGDP

The ADF test results for the level of LGDP based on two scenarios presented in Table 5.17 & 5.18. Similarly, the ADF test results for the 1^{st} differences of LGDP based on two scenarios presented in Table 5.19 & 5.20.

Table 5.17: The ADF test results at the level LGDP with intercept only

		t Statistic	p-value
ADF test statistic		3.0550	1.0000
Test critical values:	1% Sig. level	-3.5925	
	5% Sig. level	-2.9314	
	10% Sig. level	-2.6039	

Table 5.18: The ADF test results at the level LGDP with trend & intercept

		t Statistic	p-value
ADF test statistic		-0.7178	0.9652
Test critical values:	1% Sig. level	-4.1865	
	5% Sig. level	-3.5181	
	10% Sig. level	-3.1897	

Table 5.19: The ADF test results at the 1^{st} differenced LGDP with intercept only

		t Statistic	p-value
ADF test statistic		-5.8499	0.0000
Test critical values:	1% Sig. level	-3.5966	
	5% Sig. level	-2.9332	
	10% Sig. level	-2.6049	

Table 5.20: The ADF test results at the 1^{st} differenced LGDP with trend & intercept

		t Statistic	p-value
ADF test statistic		-6.4285	0.0000
Test critical values:	1% Sig. level	-4.1923	
	5% Sig. level	-3.5208	
	10% Sig. level	-3.1913	

The ADF test results of Table 5.17 & 5.18 indicate that non-significance at the level of LGDP under both trend assumptions, 'with intercept only' (t = 3.06, $p = 1.00$) and 'with trend & intercept' (t = -0.72, $p = 0.97$), which confirmed with 95% confident that the LGDP is initially non-stationary under two scenarios. Similarly, Table 5.19 & 5.20 indicate that significant ADF test statistics at the 1st differences of LGDP under both trend assumptions, 'with intercept only' (t = -5.85, $p = 0.00$) and 'with trend & intercept' (t = -6.43, $p = 0.00$), which confirmed with 95% confident that the 1st differenced LEC is stationary under two scenarios.

The PP test results for the level of LGDP based on two scenarios presented in Table 5.21 & 5.22. Likewise, the PP test results for the 1st differences of LGDP based on two scenarios presented in Table 5.23 & 5.24 respectively.

Table 5.21: The PP test results at the level LGDP with intercept only

		Adj. t Statistic	p-value
PP test statistic		3.2021	1.0000
Test critical values:	1% Sig. level	-3.5925	
	5% Sig. level	-2.9314	
	10% Sig. level	-2.6039	

Table 5.22: The PP test results at the level LGDP with trend & intercept

		Adj. t Statistic	p-value
PP test statistic		-0.7774	0.9599
Test critical values:	1% Sig. level	-4.1865	
	5% Sig. level	-3.5181	
	10% Sig. level	-3.1897	

Table 5.23: The PP test results at the 1st differenced LGDP with intercept only

		Adj. t Statistic	p-value
PP test statistic		-5.8531	0.0000
Test critical values:	1% Sig. level	-3.5966	
	5% Sig. level	-2.9332	
	10% Sig. level	-2.6049	

Table 5.24: The PP test results at the 1st differenced LGDP with trend & intercept

		Adj. t Statistic	p-value
PP test statistic		-6.4164	0.0000
Test critical values:	1% Sig. level	-4.1923	
	5% Sig. level	-3.5208	
	10% Sig. level	-3.1913	

The PP test results of Table 5.21 & 5.22 indicate that non-significance at the level of LGDP under both trend assumptions, 'with intercept only' (t = 3.20, $p = 1.00$) and 'with trend & intercept' (t = -0.78, $p = 0.96$), which confirmed with 95% confident that the LGDP is initially non-stationary under two scenarios. Likewise, Table 5.23 & 5.24 indicate that significant PP test statistic at the 1st differences of LGDP under both trend assumptions, 'with intercept only' (t = -5.85, $p = 0.00$) and 'with trend & intercept' (t = -6.42, $p = 0.00$), which confirmed with 95% confident that the 1st differenced LGDP is stationary under two scenarios. Altogether, it concluded with 95% confident that LGDP is stationary at its 1st differences (LGDP$\sim I(1)$) based on both tests under two scenarios.

Aforementioned summary of the unit root tests explained in section 5.5.1 to 5.5.3 were consistently fail to reject the null hypothesis indicating a unit root of each log series at their levels, confirming non-stationarity in the levels of each log series under both scenarios with 95% confident (LEC, LCO_2 & LGDP were not I (0)). Nevertheless, it became highly significant at their 1st differences under both scenarios, confirming stationarity in the 1st differences of all the log series with 95% confident (LEC, LCO_2 & LGDP ~ I (1)). In consequence, it is customary to differentiate all the log series to remove the stochastic trends (ΔLEC, ΔLCO_2 & ΔLGDP ~ I (0)). Visual inspection of annual trends of the 1st differenced log series over the period 1971-2014 given in Figures 5.1. It is graphically illustrated that stationarity at the 1st differences of each log series.

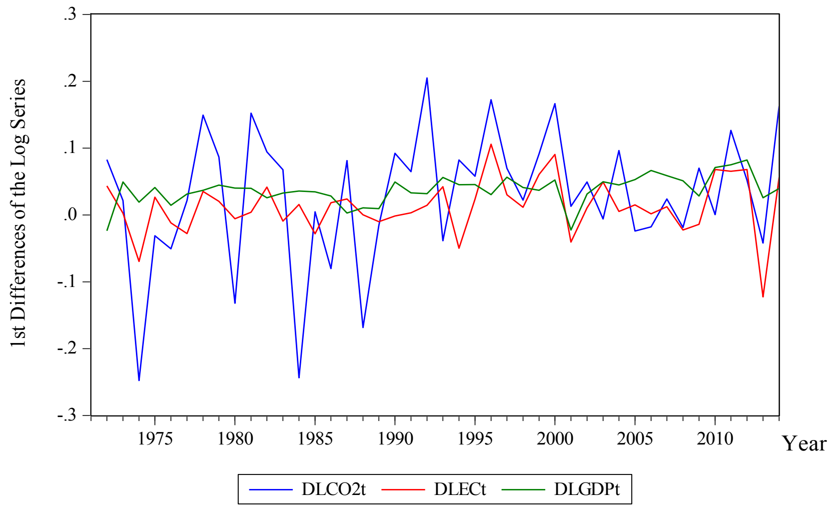

Figure 5.1: Annual trends of the1[st] differenced log series over 1971-2014

5.2 Specification of the Optimal Lag Length

Chandran & Tang (2013) highlighted the importance of selecting the optimal lag length before the Johansen cointegration approach, as too many lags over-consume the degree of freedom (df), while too few lags weaken dynamism properties in cointegration approach. The optimal lag length selection criterions among the truncated lag range (0 to 6) on the VAR framework carried out using Eviews software and corresponding results presented in Table 5.25.

Table 5.25: Results of the VAR Lag order selection

Endogenous variables: LCO_2 LEC LGDP — Sample: 1971 – 2014
Exogenous variables: C — Included observations: 38

Lag Length	Log L	LR	FPE	AIC	BIC	HQ
0	70.0961	NA	5.87e-06	-3.5314	-3.4021	-3.4854
1	218.7375	265.9898	3.79e-09*	-10.8809	-10.3638*	-10.6969*
2	222.4259	6.0179	5.06e-09	-10.6014	-9.6964	-10.2794
3	232.5307	14.8913	4.89e-09	-10.6595	-9.3667	-10.1995
4	240.4500	10.4201	5.44e-09	-10.6026	-8.9219	-10.0047
5	247.3644	8.0062	6.58e-09	-10.4929	-8.4243	-9.7569
6	266.7902	19.4258	4.32e-09	-11.0416*	-8.5852	-10.1676

Note: lag order suggested by the lag length selection criterion is indicated by * mark.

The results of Table 5.25 indicate that the criterion lag order presented by the FPE, BIC & HQ minimized at lag 1, which determined that the optimal lag length is one. Moreover, it is noticed as six by the minimum of the AIC at lag 6. Altogether, it concluded that the optimal lag length is one by the maximum representation of minimum information criterion values.

5.3 Results of the Johansen's Cointegration Approach

The entire log series were deterministic trend stationary at integrated order one, which satisfied the sufficient condition for the Johansen cointegration approaches to obtain short term & long term cointegration nexus between the variables. Then, the Johansen likelihood ratio cointegration test was carried out with the choice of "linear deterministic trend in observed data but not in cointegration relations" to determine whether there exists any cointegrating vector among the log series and the corresponding results presented in Table 5.26.

Remarks: In theory, there exist maximally two cointegrating vectors, for two independent variables ($0 \leq r \leq 2$).

Table 5.26: Results of the unrestricted cointegration rank test in lag 1

Hypothesized No. of Coint. Eqn.(s)	Eigenvalue	Trace Test Statistic (λ_{Trace})	0.05 Critical Value	0.1 Critical Value	p-value
None	0.3360	28.9816	29.7971	27.0670	0.0619
At most 1	0.1673	11.7863	15.4947	13.4288	0.1675
At most 2	0.0929	4.0967	3.8415	2.7055	0.0430
Hypothesized No. of Coint. Eqn.(s)	**Eigenvalue**	**Maximum Eigenvalue Test Statistic (λ_{Eigen})**	**0.05 Critical Value**	**0.1 Critical Value**	**p-value**
None	0.3360	17.1953	21.1316	18.8928	0.1630
At most 1	0.1673	7.6896	14.2646	12.2965	0.4111
At most 2	0.0929	4.0967	3.8415	2.7055	0.0430

The results of the trace statistic in Table 5.26 indicate significance at the first hypothesis (λ_{Trace}=28.98, $p = 0.06$), which concluded with 90% confident that there exists only one long-run cointegrating equation. Also, it noted that both trace, as well as maximum eigenvalue statistics, are significant at the third hypothesis ($\lambda_{Trace} = \lambda_{Eigen}$ =4.10, $p = 0.04$), proposing that there exist three long-run cointegrating equations with 95% confident. Then, it observed a contradiction in selecting the cointegrating rank. In theory, a possible maximum number of cointegrating relationships for three endogenous variables suggested as two. Hence, we can consider one as cointegrating rank ($r = rank(\Pi) = 1$) in the VECM estimation approaches as practiced in the study of Muhyidin *et al.* (2015) as proposed by Asari *et al.* in 2011. In other words, CO_2 emissions and their determinants cointegrated as well as there was at most one long-run cointegration relationship among the three variables at the 10% level of significance. Thus, the unrestricted VAR or VECM (1) model developed for estimating the long-run association between the three variables.

5.4 The VECM (1) Approaches for the Long-run Cointegration

The VECM (1) estimated with one period lag, no restriction imposed on coefficients, and with the choice of "linear deterministic trend in the observed data but not in the cointegration relations as well in the VAR". The E-Views output of the parameter estimation results of the unrestricted VECM (1) model in both the short-run & long-run presented in Table 5.27. Corresponding results indicate that the parameter of $LGDP_{t-1}$is positively significant [$\hat{\beta}_{LGDP_{(t-1)}} = 1.12$ & $(t = 4.06 > 2.02)$], and that of in LEC_{t-1} is negatively significant [$\hat{\beta}_{LEC_{(t-1)}} = -4.55$ & $(t = -7.30 < -2.02)$] in the cointegrating equation, at the 5% level of significance. Thus, it concluded, with 95% confident that, each long run parameter is strongly significant in the cointegrating equation of the fitted VECM (1) model. Hence, the error correction term (ECT_{t-1}) described as equation (5.1).

$$ECT_{t-1} = 19.78 + \ln CO_{2t-1} - 4.55 \ln EC_{t-1} + 1.12 \ln GDP_{t-1} \qquad \ldots\ldots (5.1)$$

Note: There were 42 observations after the adjustments, and then the corresponding degree of freedom is $\nu = n - 1 = 41$. Hence, the critical value at the 5% significance level observed as $t_{(\nu,\alpha/2)} = \pm 2.0195$.

Table 5.27: Parameter estimations of the unrestricted VECM (1)

Cointegrating Eqn:	Coint Eqn.1		
LCO_2(-1)	1.0000		
LEC(-1)	-4.5539 (0.6242) [-7.2953]		
LGDP(-1)	1.1179 (0.2751) [4.0641]		
C	19.7833		
Error Correction:	**D(LCO_2)**	**D(LEC)**	**D(LGDP)**
Coint Eqn.1	0.2332 (0.1056) [2.2073]	0.1540 (0.0361) [4.2678]	0.0337 (0.0203) [1.6624]
D(LCO_2(-1))	-0.2511 (0.2005) [-1.2525]	-0.0154 (0.0685) [-0.2250]	-0.0038 (0.0384) [-0.0995]
D(LEC(-1))	0.6212 (0.5154) [1.2052	0.1518 (0.1761) [0.8623]	0.0390 (0.0988) [0.3944]
D(LGDP(-1))	-0.5118 (0.8244) [-0.6208]	-0.6069 (0.2816) [-2.1552]	0.1040 (0.1581) [0.6578]
C	0.0464 (0.0333) [1.3951]	0.0332 (0.0114) [2.9258]	0.0345 (0.0064) [5.4092]
R^2	11.82%	40.01%	12.83%

The unrestricted VECM (1) model established in the study observed below in matrix form (5.2).

$$\begin{bmatrix} \Delta LCO_{2t} \\ \Delta LEC_t \\ \Delta LGDP_t \end{bmatrix} = \begin{bmatrix} 0.05 \\ 0.03 \\ 0.03 \end{bmatrix} + \begin{bmatrix} 0.23 \\ 0.15 \\ 0.03 \end{bmatrix} ECT_{t-1} + \begin{bmatrix} -0.25 & 0.62 & -0.51 \\ -0.02 & 0.15 & -0.61 \\ -0.004 & 0.04 & 0.10 \end{bmatrix} \begin{bmatrix} \Delta LECO_{2t-1} \\ \Delta LEC_{t-1} \\ \Delta LGDP_{t-1} \end{bmatrix} + \begin{bmatrix} u_{LCO_2,t} \\ u_{LEC,t} \\ u_{LGDP,t} \end{bmatrix} \text{...(5.2)}$$

Then the unrestricted cointegrating relationship for the CO_2 emissions formulated as equation (5.3).

$$\Delta \ln CO_{2_t} = 0.05 + 0.23\{19.78 + \ln CO_{2t-1} - 4.55 \ln EC_{t-1} + 1.12 \ln GDP_{t-1}\} - 0.25\Delta \ln CO_{2t-1} + 0.62\, \Delta\ln EC_{t-1} - 0.51\, \Delta\ln GDP_{t-1} + u_t \quad \ldots\ldots\ldots\ldots (5.3)$$

5.5 Significance of Parameter Estimation in the Long-run Cointegration Relationship for CO_2 Emissions

The linear restrictions in the long-run cointegrating relationship for CO_2 emissions can identify by insignificant parameters in corresponding unrestricted cointegration relationship for CO_2 emissions (Eqn. 5.3). Hence parameter significance in the unrestricted cointegrating relationship for CO_2 emissions is observed by the system equations using Eviews software and corresponding results presented in Table 5.28.

Table 5.28: Parameter significance results of the system equation for CO_2 emissions

Component	Coefficient	Standard Error	t Statistic	p-value
ECT_{t-1}	0.2332	0.1056	2.2073	0.0336
$\Delta \ln CO_{2t-1}$	-0.2511	0.2005	-1.2525	0.2182
$\Delta\ln EC_{t-1}$	0.6212	0.5154	1.2052	0.2358
$\Delta\ln GDP_{t-1}$	-0.5118	0.8244	-0.6208	0.5385
$Constant$	0.0464	0.0333	1.3951	0.1713
R^2	11.82%			
F Statistic	1.2400		p-value (F Statistic)	0.3109

The insignificant F-statistic result (F=1.24, $p = 0.31$) presented in Table 5.28 concluded with 95% confident that the entire log series are jointly insignificant in the cointegration relationship for CO_2 emissions. Further, it indicates that significant t-statistic only for the parameter estimate of the long-run error correction term ($\hat{\beta}_{ECT_{(t-1)}}$=0.23, $p = 0.03$). Thus, it confirmed with 95% confident that only the error correction term has a significant and positive impact on the change of logarithmic level of CO_2 emissions (ΔLCO_{2_t}) in the long run. Though the long-run error correction coefficient ($\hat{\beta}_{ECT_{(t-1)}}$) expected to be negative in the cointegration relationships, here it captured significantly positive (+0.23) value, but its absolute value lied within range of [0, 1] which means that the 23% of short-run errors (immediate errors) in the fitted VECM (1) corrected in the model, converges towards its short-run equilibrium.

Moreover, the short-run parameters estimates of $\Delta \mathrm{L}\, CO_{2t-1}$ & $\Delta \mathrm{L}\, GDP_{t-1}$ have insignificant negative effect on $\Delta \mathrm{L}CO_{2_t}$ [($\hat{\beta}_{\Delta \mathrm{L}CO_{2(t-1)}}$ = -0.25, $p = 0.28$) and ($\hat{\beta}_{\Delta LGDP_{(t-1)}}$ = -0.51, $p = 0.54$)] as well as that of $\Delta \mathrm{L}\, EC_{t-1}$ & $Constant$ have insignificant positive effect on $\Delta \mathrm{L}CO_{2_t}$ [($\hat{\beta}_{\Delta LEC_{(t-1)}}$ = 0.62, $p = 0.24$) and ($\hat{\beta}_{\Delta LGDP_{(t-1)}}$= 0.05 & $p = 0.17$)]. Therefore, all short-run coefficients ($\hat{\beta}_{\Delta \mathrm{L}CO_{2(t-1)}}$, $\hat{\beta}_{\Delta LEC_{(t-1)}}$, $\hat{\beta}_{\Delta LGDP_{(t-1)}}$ & $\hat{\beta}_{constant}$) are considered to be linear restrictions in the cointegrating relationship for CO_2 emissions and concluded with 95% confident that $\Delta \mathrm{L}CO_{2_{(t-1)}}$, $\Delta LEC_{(t-1)}$, $\Delta LGDP_{(t-1)}$ & $Constant$ terms are normalized linear restrictions of the cointegration relationship for CO_2 emissions. Hence, the restricted long-run cointegration relationship for CO_2 emissions inclusive only the long-run parameters observed as equation (5.3).

$$\begin{aligned} \Delta \ln CO_{2_t} &= 0.23\,\{19.78 + \ln CO_{2t-1} - 4.55 \ln EC_{t-1} + 1.12 \ln GDP_{t-1}\} \\ &= 4.55 + 0.23 \ln CO_{2t-1} - 1.05 \ln EC_{t-1} + 0.26 \ln GDP_{t-1} \quad \dots (5.4) \end{aligned}$$

It explained that a significant impact of the present logarithmic level of fossil fuel energy consumption negative on the change of the logarithmic level of CO_2 emissions unexpectedly in the long-run. Similarly, the present logarithmic level of CO_2 emissions and that of for the GDP are positive on the change of the logarithmic level of CO_2 emissions in the long-run. Then, it concluded that a unit increase in the present logarithmic level of CO_2 emissions, as well as in the present logarithmic level economic development (GDP), increases the change in the logarithmic level of CO_2 emissions respectively by 23% and 26%. However, surprisingly, a unit increases in the present logarithmic level of fossil fuel energy consumption (EC) decreases the change in the logarithmic level of CO_2 emissions about 105% in the long-run association.

5.6 Validity of the Unrestricted VECM (1) Model

A most significant model can observe by a high stabilized model, with the white noise residuals. Therefore, the unrestricted VECM (1) verified against residual diagnostics and model stability.

5.6.1 Model Stability of the Unrestricted VECM (1)

For illustration purposes, stability condition of the unrestricted VECM (1) checked and corresponding results reported in Table 5.29. Similarly, the graphical representation of spherically distributed inverse AR roots of the characteristic polynomial in the unrestricted VECM (1) visualized in Figure 5.2.

Table 5.29: Inverse AR roots of the characteristic polynomial in the unrestricted VECM (1)

Inverse AR Root	Modulus
1.0000	1.0000
1.0000	1.0000
0.6681	0.6681
-0.2326	0.2326
0.0694 - 0.2078i	0.2191
0.0694 + 0.2078i	0.2191

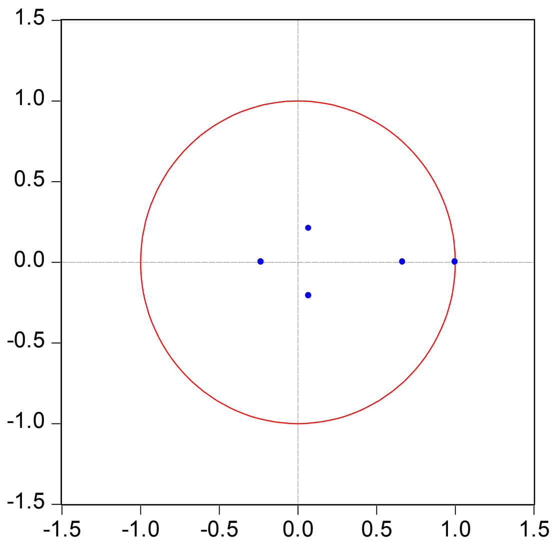

Figure 5.2: Spherical distribution of the inverse AR roots of the unrestricted VECM (1)

The results of Table 5.29 indicate two complex roots ($0.07 \pm 0.21i$), and four real roots, besides the first two roots were unit-roots as visualized in Figure 5.2. Hence, it is clear that the VAR stability condition check does not represent a root outside the unit circle since the modulus of each characteristic root is less than or equal unity. As a result, fitted unrestricted VECM (1) in the regression (5.3) is considered to be a high stabilized (stationary) model.

5.6.2 Residuals Diagnostics of the Unrestricted VECM (1)

The residual diagnostics; the LM test for residual serial correlation, the Cholesky-Lutkepohl test for residual normality, and the Breusch-Pagan-Godfrey test for residual non-heteroscedasticity (homoscedasticity) were checked, for white noise residuals as shown below. Corresponding results presented respectively in Table 5.30, 5.31, & 5.32.

5.6.2.1 ARCH Effect of the Residuals

Table 5.30: The LM test results for residual serial correlations

Lags	LM Statistic	p-value
1	9.0736	0.4305
2	12.1011	0.2077
3	10.6568	0.3000
4	5.2544	0.8116
5	3.0043	0.9641
6	12.2554	0.1993
7	11.5194	0.2418
8	3.9138	0.9170
9	11.1596	0.2649

The results of Table 5.30 indicate that insignificant chi-squared LM statistic values in residual serial correlations, at all lags up to maximum lag length 9 for the VAR (all $p > 0.05$). Thus, it concluded with 95% confident that no serial error correlations in residuals of the unrestricted VECM (1). In other words, it concluded that no ARCH effect in residuals of the unrestricted VECM (1).

5.6.2.2 Normality of the Residuals

Table 5.31: The Cholesky (Lutkepohl) test results for residual normality

Error Component	Skewness	Chi-sq	df	p-value
LCO_2	-0.7651	4.0977	1	0.0429
LEC	-0.4198	1.2338	1	0.2667
$LGDP$	-0.9067	5.7541	1	0.0164
Joint		11.0857	3	0.0113
Error Component	**Kurtosis**	**Chi-sq**	**df**	**p-value**
LCO_2	4.0585	1.9606	1	0.1614
LEC	3.7749	1.0509	1	0.3053
$LGDP$	4.1658	2.3785	1	0.1230
Joint		5.3900	3	0.1454

Error Component	JB-Statistic	df	p-value
LCO_2	6.0583	2	0.0484
LEC	2.2847	2	0.3191
$LGDP$	8.1327	2	0.0171
Joint	16.4757	6	0.0114

The results in Table 5.31 indicate that non-significance at the 1% level of significance in the JB statistic, 3rd moment (skewness), and normalized 4th moments (kurtosis) of each residual component jointly as well as individually. Those are for the error component of the CO_2 emissions explained as (JB = 6.06, $p = 0.05$), (skewness = -0.77, $p = 0.04$), and (kurtosis = 4.06, $p = 0.16$). Hence, it concluded with 99% confident, that the resultant error components in the unrestricted long-run cointegration relationship were satisfied multivariate normality assumption.

5.6.2.3 Heteroscedasticity of the Residuals

Table 5.32: Residual heteroscedasticity test results (without cross terms)

Joint test:

Chi-sq	df	p-value
65.3774	84	0.0483

Individual components:

Dependent $[u_t \times u_t]$	R-squared	F(8,33)	p-value	Chi-sq(8)	p-value
$res_{LCO_2} \times res_{LCO_2}$	0.1550	0.7568	0.6422	6.5107	0.5902
$res_{LEC} \times res_{LEC}$	0.4611	3.5297	0.0047	19.367	0.0130
$res_{LGDP} \times res_{LGDP}$	0.2844	1.6395	0.1514	11.945	0.1537
$res_{LEC} \times res_{LCO_2}$	0.0779	0.3483	0.9398	3.2698	0.9163
$res_{LGDP} \times res_{LCO_2}$	0.2075	1.0803	0.4006	8.7167	0.3668
$res_{LGDP} \times res_{LEC}$	0.5342	4.7310	0.0006	22.437	0.0042

The results of Table 5.32 indicate that insignificant individual F statistics of the residuals in each component pair ($p > 0.01$), exceptional for the residuals within LGDP & LEC components ($p_{(res_{LGDP} \times res_{LEC})} = 0.00$). However, it indicates joint significance in the Chi-square test statistic (χ^2_{84}= 65.38, p = 0.05) at the 1% significance level. Then it concluded with 99% confident, that error components in the unrestricted long-run cointegration relationship for the CO_2 emissions are non-heteroscedastic (homoscedastic).

Thus, it concluded with 95% confident, that the error components of the VECM (1) model are white noise processes. Accordingly, the cointegration relationship for CO_2 emissions, explained by the regression (5.3) considered, as an acceptable model in the statistical sense. Then, we can debate the impact of economic growth, and especially from the combustion of fossil fuel energy on CO_2 emissions, in the contest of Sri Lanka, based on the period from 1971 to 2014.

5.7 The Impulse Response Analysis of the Unrestricted VECM (1)

Impulse response function (IRF) analysis, based on the VECM (1) employed to predict how the present status of fossil fuel energy consumption intensities, economic growth patterns, as well as CO_2 emissions concentrations, influence CO2 emissions concentration for the next 10 years in Sri Lanka. Therefore, the dynamic effects of the unrestricted VECM (1) respond to certain shocks (Cholesky One S.D. innovations of LCO_2), among the three variables presented in Table 5.33, and variations of them illustrated in Figure 5.3.

Table 5.33: The VECM (1) forecasted IRF's effect of (Cholesky One S.D.) LCO_2 shock on LCO_2, LEC & LGDP

Period	Response of;		
	(a) LCO_2	(b) LEC	(c) LGDP
1	0.1001	0.0124	0.0022
2	0.0923	0.0185	0.0041
3	0.1000	0.0204	0.0049
4	0.1018	0.0220	0.0055
5	0.1039	0.0231	0.0059
6	0.1052	0.0238	0.0062
7	0.1060	0.0243	0.0063
8	0.1066	0.0246	0.0064
9	0.1070	0.0249	0.0065
10	0.1072	0.0250	0.0066
Cholesky Ordering: LCO_2 LEC LGDP			

The results of the effect of LCO_2 shocks, shown in Table 5.33 column (a), and Figure 5.3 (a), indicates that a positive shock has a large impact on itself, in the long-run. The LCO_2 initially declines by 0.8% after a positive shock and reach the lowest point in the 2^{nd} period (0.092). Then LCO_2 gradually rises by 0.8% up to the 3^{rd} period, by 0.2% up to the 5^{th} period, by 0.1% up to the 8^{th} period and remains at a stable level (0.107) up to the 10^{th} period. This suggests that a positive shock of CO_2 emission has a positive influence on own its increasing, and the positive influence has relatively long sustained effectiveness.

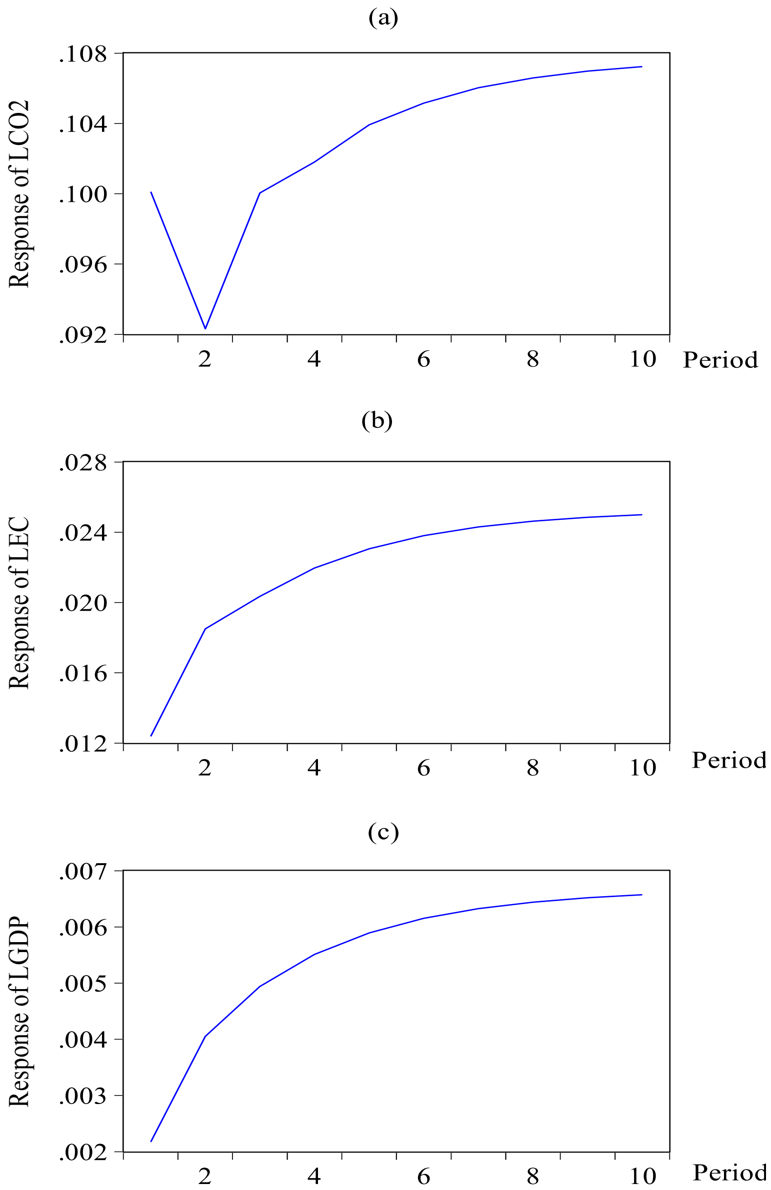

Figure 5.3: The VECM (1) forecasted IRF diagram of (a) LCO_2, (b) LEC & (c) LGDP changes caused by (Cholesky One S.D.) LCO_2 shock

Moreover, Table 5.33 column (b), and Figure 5.3 (b) shown that the 1st positive shock in the 1st period causes LEC sharp rise up to the 2nd period by 0.6%, and reach (0.019). Then LEC gradually rises by 0.2% up to the 4th period, by 0.1% up to the 6th period, and remains at a stable level (0.025) up to the 10th period. This also suggests that a positive shock of CO_2 emissions has a positive influence on EC increasing, and the positive influence has relatively long sustained effectiveness.

Similarly, Table 5.33 column (c), and Figure 5.3 (c) indicate that one SD positive shock, starting from the 1^{st} period causes LGDP to rise gradually, by 0.2% up to the 2^{nd} period, by 0.1% up to the 4^{th} period, and remains at a stable level (0.006) up to the 8^{th} period. Then LGDP reaches 0.007 in the 9^{th} period and again remains stable level up to the 10^{th} period. Hence, the impact of fossil fuel energy consumption and economic growth on CO_2 emissions, in the long-run sustained can be debate effectively, by the observed model (Equation 5.4) inclusive only long-run ECT_{t-1}.

5.8 Summary of Chapter 5

The entire log-transformed series were formed trend stationary at their first differences ($LGDP$, LCO_2 & $LEC \sim$ I (1)). The optimal lag length observed by the use of the FPE, BIC & HQ, on the VAR framework, was one. The Johansen cointegration, Trace test statistic significantly concluded that there was at most one cointegrating relationship among the log series at the first lag. Implementation of unrestricted VECM (1), at the first lag, concluded with 95% confident that each long-run elasticity estimate was significantly involved in the error correction term (ECT_{t-1}). Likewise, it concluded with 95% confident that all the short-run estimates were linear restrictions, and only the error correction term (ECT_{t-1}) was significantly inclusive, in the long-run cointegrating relationship for CO_2 emissions. Then, the long-run cointegrating relationship for CO_2 emissions observed as $\Delta \ln CO_{2_t} = 4.55 + 0.23 \ln CO_{2t-1} - 1.05 \ln EC_{t-1} + 0.26 \ln GDP_{t-1}$. Furthermore, the fitted VECM (1) model observed as a highly stable model, encompassing white noise residuals with 95% confident. The VECM (1) forecasted IRF's effects indicate that a positive shock of CO_2 emissions will have an increasing and positive impact on itself, fossil fuel energy consumption, and economic development in both runs. Thus, a stable cointegration relationship among CO_2 emissions and its determinants, in the contest of Sri Lanka can be debated effectively in the long-run sustained.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

Based on the results of the aforementioned statistical analysis in CHAPTER 4 & 5, conclusions and recommendations are given below.

6.1 Conclusions

- All observations indicated stochastic trends in their distributions and followed heterogeneity of the variances excluding GDP. Thus, natural logarithmic transformations of them considered to reduce heteroscedasticity, and observed with 95% confident that the corresponding series had no extreme deviations from log-normal distributions.

- The Pearson correlation approaches confirmed with 95% confident that there were highly significant strong positive association (all $r > 0.9$ & $p = 0.00$) between each variable pairs at; present logarithmic values of fossil fuel energy consumption, economic development, and CO_2 emissions as well as that of immediate past logarithmic values of fossil fuel energy consumption, economic development, and present logarithmic values CO_2 emissions.

- Even though the univariate OLS scenario indicated that the present, as well as the immediate past values of fossil fuel energy consumption & economic development, had a highly significant positive linear impact on the present level of CO2 emissions, it failed to identify appropriate best fits, since there were serial autocorrelations within errors in each OLS approach.

- In together with ADF & PP unit root tests, it significantly concluded that all the log-transformed series were formed trend stationary at their first differences with 95% confident [$LGDP$, LCO_2 & $LEC \sim$ I (1)].

- The optimal lag length observed as one by the FPE, BIC & HQ concerning criterion lag order on the VAR framework.

- The Johansen cointegration test at the first lag, under the linear deterministic trend assumption, concluded with 90% confident that there was at most one cointegration relationship among the log series.

- Implementation of VECM (1) at the first lag concluded with 95% confident that both long-term parameters were significantly involved in the error correction model (ECT_{t-1}).
  Here, $ECT_{t-1} = 19.78 + \ln CO_{2t-1} - 4.55 \ln EC_{t-1} + 1.12 \ln GDP_{t-1}$

- The parameter significance approaches of the cointegrating relationship for CO_2 emissions significantly concluded with 95% confident that the short-run parameters of $\Delta LCO_{2(t-1)}$, $\Delta LEC_{(t-1)}$, $\Delta LGDP_{(t-1)}$ & $constant$ were linear restrictions, and only the error correction term (ECT_{t-1}) inclusive in the fitted cointegrating relationship for CO_2 emissions.

- The error diagnostics and model stability tests significantly concluded that the fitted VECM (1) as a highly stable model, encompassing white noise residuals with 95% confident.

- The VECM(1) forecasted Impulse response function effects indicated that positive shock of CO_2 emissions would have a positive influence on itself, fossil fuel energy consumption, and economic growth in the long sustained effectiveness.

- A stable cointegration relationship, among CO_2 emissions and its determinants in the profile of Sri Lanka, observed with 95% confident as given below.
  $\Delta \ln CO_{2_t} = 4.55 + 0.23 \ln CO_{2t-1} - 1.05 \ln EC_{t-1} + 0.26 \ln GDP_{t-1}$.

6.2 Recommendations

Even though this study has been carefully analyzed and reached the desired objectives, there exist some deficiencies that need to be concerned such as limitations of the associated variables and availability of observations in the statistics of Sri Lankan profile. Moreover, energy-efficient and climate protection policy implementations or suggestions, based on the empirical result of this study should be interpreted with care, because the estimations on this study might not be robust enough to put up the green energy policy implementations, due to small sample size (44 annual observations) conducted in the analysis. Therefore, few concerns should be made necessarily for further study in this field, as mentioned below.

- Many other determinants in CO_2 emissions (more supportive factors) must be taken into account, considering different countries and different time intervals when developing emissions reduction as well as energy conservation policies.

- CO_2 emissions of a country are deliberated, as only an indicator of GHGs, hence other factors of GHG emissions should be taken in to account for a more comprehensive indication of country influences on climate change, and it is predominantly in agrarian economies.

- The Johansen ML cointegration test statistics bias for small sample and might not be reliable, thus auto-regressive distributed lags method can be applied instead, as an alternative forecasting tool because of their requirement of minimum sample size, to make significant statistical inferences in model forecasting, with small sample, as mentioned by Viktoras (2013).

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APPENDIX I

The Summary of Important Literature Reviews

Authors	Countries	Periods	Variables	EKC	Unit Root Approach	Methodology	Causality Approach
Alege *et al.*, (2016)	Nigeria	1970-2013	GDP, CO_2, EC, Electric Power Consumption EP (Non fossil), Human Capital Indicator, Institution	No	Both ADF & PP	Johansen ML Cointegration Test - Trace & Maximum Eigen Value and VECM for long-run nexus	Box exogeneous Granger Causality Test under VECM
Alkhathlan *et al.*, (2012)	Saudi Arabia	1980-2008	GDP, CO_2, EC, Employment Ratio (ER)	No	Both DF & ADF	ARDL	Box exogeneous Granger Causality Test under VECM
Asumadu-Sarkodie & Owusu, (2017)	Rwanda	1965-2011	GDP, CO_2, EC, Industrialization, Population	No	Both KPSS & PP	ARDL	Box exogeneous Granger Causality Test under VECM
Begum *et al.*, (2015)	Malaysia	1970-2009	GDP, CO_2, EC, Population growth	No	Only DF Generalized Least Squares (DFGLS)	ARDL	Box exogeneous Granger Causality Test under VECM
Bozkurt & Akan, (2014)	Turkey	1960 - 2010	GDP, CO_2, EC	No	Only ADF	Johansen ML Cointegration Test - Trace & Maximum Eigen Value and VECM for long-run nexus	Box exogeneous Granger Causality Test under VECM
Chandran & Tang, (2013)	5 Asian countries	1971-2008	GDP, CO_2, EC, per capita real FDI, square of GDP	No	Only DF Generalized Least Squares (DFGLS)	Johansen ML Cointegration Test - Trace and VECM for long-run nexus	Box exogeneous Granger Causality Test under VECM
Farhani & Rejeb, (2012)	15 MENA Countries	1973-2008	GDP, CO_2, EC	No	Panel unit root tests	Panel cointegration methods and Panel OLS, FMOLS and DOLS estimates	Panel causality test
Lapinskiene *et al.*, (2017)	22 European Union Countries	1995-2014	GDP, CO_2, EC, Squared GDP, Energy Tax	Yes	No unit root indication under quadratic EKC	Quadratic EKC modeling	…
Lu, (2017)	16 Asian countries	1990-2012	GDP, CO_2, EC	Yes	Panel unit root tests on IPS & CIPS	Pedroni panel cointegration and Fully-modified OLS estimates for long-run nexus	Panel causality test
Muhyidin *et al.*, (2015)	Malaysia	1970-2012	GDP, CO_2, EC, Industrial production Index growth (IPIG)	No	Both ADF & PP	Johansen ML Cointegration Test - Trace & Maximum Eigen Value and VECM for long-run nexus	Box exogeneous Granger Causality Test under VECM
Obradovic & Lojanica, (2017)	Greece & Bulgaria	1980-2010	GDP, CO_2, EC, Export , Fixed Capital (C)	No	Together ADF, KPSS & Zivot-Andrews	Johansen ML Cointegration Test - Trace & Maximum Eigen Value and VECM for long-run nexus	Box exogeneous Granger Causality Test under VECM
Omri, (2015)	14 MENA Countries	1990-2011	GDP, CO_2, EC	No	Panel Unit root based on ADF & PP	Panel GMM diagnostic approaches	…
Pao *et al.*, (2012)	China	1980-2008	GDP, CO_2, EC	No	Together ADF, PP & KPSS	Johansen ML Cointegration Test - Trace & Maximum Eigen Value and NGBM	…
Saidi & Hammami, (2015)	58 countries	1990–2012	GDP, CO_2, EC, Capital stock (K), Total population (POP), Labor force (L), Financial development (FD).	No	No unit root indication on the GMM modeling	Generalized Method of Moments and Arellano & Bond (1991)-GMM estimator	…
Tang & Tan, (2016)	Cambodia	1980-2010	GDP, CO_2, EC, Primary energy consumption; Electricity Net energy consumption (PEC, ENC)	No	Together ADF, PP & KPSS	ARDL	Toda and Yamamoto non causality Test
Wang *et al.*, (2016)	China	1990-2012	GDP, CO_2, EC	No	Only ADF	Johansen ML Cointegration Test - Trace and VECM for long-run nexus	Box exogeneous Granger Causality Test under VAR

APPENDIX II
The Definition of the Desired Variables

- Per capita value of gross domestic product (in constant 2010 US dollars),

Gross Domestic Product (GDP) at consumer's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Dollar figures for GDP are converted from domestic currencies using 2010 official exchange rates (WDI, 2018). Here the formula for determining GDP is (Wikipedia, 2018):$GDP = C + I + G + (X - M)$
Where; C = Household Final Consumption Expenditures, I = Gross Private Fixed Investment, G = Government Expenditures and Investment, X = Net Exports & M = Net Imports.

Note: For a few countries where the official exchange rate does not reflect the rate effectively applied to actual foreign exchange transactions, an alternative conversion factor is used.

- Per capita value of fossil fuel energy consumption (in Kg),

Energy use refers to use of primary energy before transformation to other end-use fuels, which is equal to indigenous production plus imports and stock changes, minus exports and fuels supplied to ships and aircraft engaged in international transport (WDI, 2018).

- Per capita value of Carbon (CO_2) emissions (in metric tons, M_t),

CO_2 emissions are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid and gas fuels and gas flaring (WDI, 2018).