IOSR Journal of Environmental Science, Toxicology and Food Technology (IOSR-JESTFT)
e-ISSN: 2319-2402,p- ISSN: 2319-2399.Volume 13, Issue 10 Ser. II (October. 2019), PP 44-57
www.iosrjournals.org

"Impact of Energy Consumption and Economic Growth on Carbon Dioxide (CO_2) Emission in Sri Lanka"

Sakunthala K. A. U.[1], Peiris T. S. G.[2]
[1]*Post Graduate Student in Master's Degree in Business Statistics,*
[2]*Professor in Applied Statistics,*
[1, 2] *Department of Mathematics, Faculty of Engineering, University of Moratuwa, Moratuwa, Sri Lanka*
Corresponding Author: Peiris, T. S. G.

Abstract: *CO_2 emissions caused by fossil fuel combustion & cement products considered as the most abundant greenhouse gas emissions associated with different economic activities in fossil fuel economy, and considered as an important driver of global warming & climate change activities. Global attention on sustainable development facilitated mitigation targets of pollutant emissions basically by continuous reduction in CO_2 emissions & sustainable policy implementations in recent decades. The studies on the impact of energy consumption & economic growth of a country on CO_2 emissions have been given high priority by many countries, but not much study on this aspect have been carried out in Sri Lanka. This study is therefore utilized the Vector Error Correction Model (VECM) framework in order to investigate the impact of energy consumption & economic development on CO_2 emissions in Sri Lanka over the period of 1971 – 2014, using the E-Views computer application. The required secondary data was obtained from the World Bank data base. The analyses confirmed significantly that fitted VECM (1) model was highly stable encompassing white noise residuals. The significant long run variables' trend indicated that, a unit increase in present level of per capita CO_2 emissions & per capita economic growth influenced positively on successive change in level of per capita CO_2 emissions, which concluded that economic developments in Sri Lanka leads to greater CO_2 emissions in long run effectiveness. Surprisingly, a unit increasing demand of per capita fossil fuel energy consumption influenced negatively on successive change in level of per capita CO_2 emissions in long run association, this may because demand of fossil fuel energy in Sri Lanka is well below to trigger any significant conversion in CO_2 emissions compared to developed nations. On the foundation of empirical findings in this study, it indicated that energy conservation policies and sustainable economic growth have no adverse effect on CO_2 emissions in Sri Lanka in short run association. The analysis of impulse response functions suggested that positive shocks of CO_2 emissions have positive influence on its own increasing, on energy demand increase as well as on economic growth, and each positive influence has relatively long sustained effectiveness. The inferences derived in this study suggest that significant transformation of sustainable low carbon energy use and green energy policy implementations could contribute to control the CO_2 emissions while sustaining long run economic growth in Sri Lanka.*

Keywords: CO_2 emissions, Economic growth, Energy consumption, VECM

Date of Submission: 09-10-2019 Date of Acceptance: 25-10-2019

I. Introduction

The fastest growing of global warming and climate change has been deliberated as a dominating threat in ongoing worldwide concern during last decades. Significant impacts on global warming and climate change were predominantly coming from human activities due to rapid industrialization, increasing population, economic development as well as significant transformation in life style, effecting on meteorological conditions and ecosystems. Mostly documented impacts on climate change are trapping heat within atmosphere resulting frequent and intense heat waves, increasing oceanic temperature, increasing atmospheric water vapor, shrinking sea ice, disappearing snow cover, melting glaciers, rising sea level, increasing coastal flooding, shifting more severe droughts, variations in storms & rainfall pattern, … etc. A gas that traps heat within atmosphere forming greenhouse effect (natural process that warms the lowest layer of atmosphere & the earths' surface) is defined as a greenhouse gas (GHG). Environmental contaminants or GHGs; principally Carbon dioxide (CO_2), Chlorofluorocarbons (CFCs), Hydro fluorocarbons (HCFCs & HFCs), Methane (CH_4), Nitrous oxide (N_2O), Ozone (O_3) and water vapor (H_2O) associated with different economic activities are important drivers of the fastest growing of global warming and climate changes. Since pre-industrial era, an enormous increment of the atmospheric GHGs has high concentration of CO_2, CH_4 & N_2O comparatively other emitters (Fig. 1).

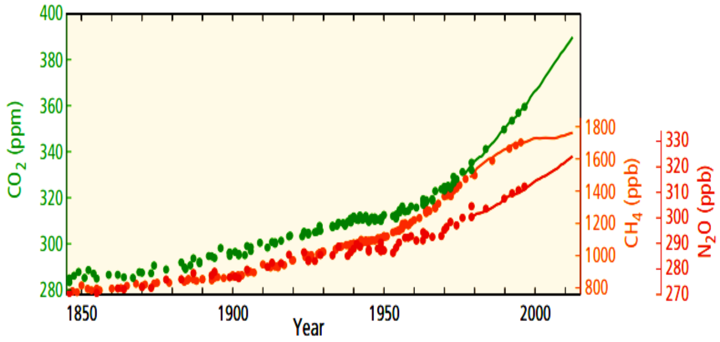

Figure 1: Globally averaged GHG concentrations

Source: IPCC (2014)

The CO_2 emissions per capita (CO_2 in metric tonnes per person) is an indicator for CO_2 emissions mainly from burning fossil fuels (principally coal, petroleum & natural gas) and cement production in the fossil fuel economy. Other CO_2 emissions from land use such as tropical deforestation, agriculture (including livestock), from international shipping or bunker fuels and from natural processes such as respiration, volcanic eruptions & soil erosion are not included in this national figure, but it may have significant differences for small countries or islands with imperative ports (Fig. 2). Since natural cycles within the earth's climate system can only redistribute heat, they cannot be responsible for observed increase in overall heat content of climate system [1]. There is no significant evidence or records, which explain variability of its pattern over the industrialized era up to contemporary climate apparent from the natural processes. Hence, climate change observations are explained by identified physical mechanisms in suitable scale, consisting time in direction with long term observed trends realistically based on human activities due to industrial revolution.

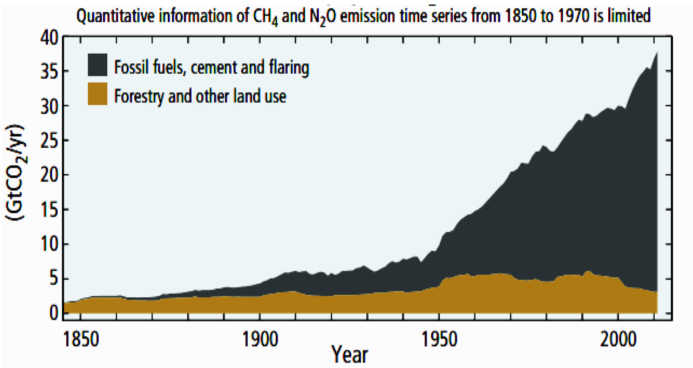

Figure 2: Global anthropogenic CO_2 emissions

Source: IPCC (2014)

1.1 Human Fingerprint on CO_2 Emissions

Continued increases in total GHG emissions over 1970 to 2010 pointed out a large absolute increase from 2000 to 2010, in face of broadly forecasted and evolving number of climate change mitigation policies. The Fifth Assessment Report of the Intergovernmental Panel on Climate Change [2] explained that human influence on 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. CO_2 emissions were considered as dominant cause to global warming, which were responsible at least 76% of total GHGs concentration (all-encompassing 65% by fossil fuel & industrial process, and 11% by forestry & land use changes) with 16% of CH_4, 6% of N_2O and 2% of fluorinated gases. Cumulative anthropogenic CO_2 emissions to the atmosphere during 1750 to 2011were 2040 ± 310 $GtCO_2$, 40% of them (880 ± 35 GtCO2) remained in the atmosphere and balancing 60% were removed from the atmosphere storing on land as well as in the ocean [2]. Approximately, 30% of emitted CO_2 emissions has absorbed by the ocean causing ocean acidification.

The anthropogenic forces have potentially made a significant contribution to increase surface temperature over every continental region except Antarctica since the mid-20th century [2]. Owing to that, 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. Further it explained that, there is a significant impact to increase in global upper ocean heat content (0-700 m) and to raise global mean sea level since 1970. More than 50% of the anthropogenic CO_2 emissions from 1750 to 2011 had monitored in last 40 years, with higher absolute increases during 2000 to 2010, despite the international approaches on climate change mitigation actions and policies. Significant contribution of global economic growth had risen sharply from period 2000 to 2010, while that of in global population growth remained roughly identical to previous three decades. The top four global CO_2 emitters which accounted almost two thirds of total global CO_2 emissions in year 2014 are China (30%), United States (15%), European Union (10%) and India (6.5%) followed by Russian Federation and Japan [3].

1.2 International Attempts to Mitigate CO_2 Emissions

The earth's surface has been wormed over last three decades in succession than any preceding decade since 1850 triggering many other fluctuations to the earth's climate. The United Nations Framework Convention on Climate Change (UNFCCC) was the first attempt to mitigate adverse effects of climate change with ratification of 154 nations, having ultimate intention of preventing hazardous human interference on climate system. As a result, there were few protocols such as Kyoto protocol and Paris agreement (PA). As the UNFCCC recognized, long term central aim of the PA is to maintain global average temperature increase for the 21^{st} century not to exceed 2 degrees Celsius (2 ^{0}C) compared to pre-industrial temperature level. The United Nation 2019 Climate Summit set up on foundation of the PA, on climate change actions for sustainable development in 2030. It is in progression of bringing climate actions to the highest level of international agenda following 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 next decade and to net zero emissions by 2050, when they convene by 2020 for the UN climate conference. Together with aforementioned developments, it will make political signals on objectives of the PA & the sustainable development goals (SDGs) amongst countries, cities, companies and civil society.

Global attention on sustainable development facilitated mitigation targets of pollutant emissions basically by continuous reduction in CO_2 emissions and sustainable policy implementations in recent decades. Hence, most researches as well as policy makers in both political and economic worried out to mitigate adverse effects of global warming and climate change. Significant increase of global population growth, economic development and industrialization are continued to be utmost significant impacts on environment, on climate change and increases in CO_2 emissions basically from fossil fuel combustion. Long run environmental changes may also 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 in long-run causal nexus between income, environmental degradation and energy consumption by population of a specific country [4]. On view of provided facts, issues of global warming & climate change is debated universally by exploring nexus between CO_2 emissions and macroeconomic variables such as economic growth, energy consumption in modern consideration on environment protection as well in sustainable development.

1.3 Objective of the Study

The studies on identifying impact of energy consumption and economic growth of a country on CO_2 emissions have been given high priority by many countries, but not much study on this aspect have been carried out in Sri Lanka. Hence, the objective of this study is to investigate the impact of energy consumption and economic development on CO_2 emissions in Sri Lanka over the period of 1971 - 2014.

II. Literature Reviews

Current sound of modeling relationship between energy consumption, economic growth and CO_2 emissions has become a hot topic in policy implementations and developing assessment processes in sustainable environmental protection and economic development as well as accurate investment planning for energy production and distributions. Significant volume of recent empirical study on modeling 'energy-economy-CO_2 emissions nexus' focused in two standards; the first was validation of prominent theory of the Environmental Kuznet's Curve (EKC) hypothesis [5, 6]. Then the second was bivariate or multivariate time series approaches for modeling the long term 'energy-economy-CO_2 emissions nexus'. Empirical findings in most time series and panel data analysis demonstrated that the Granger causality and cointegration analysis as widespread approaches for identifying the 'energy-economy-CO_2 emissions nexus', in differ of econometric methodologies for a number of different countries and regions in different time frame. Nevertheless, a limited numbers of studies were available for Asian countries. Commonly, empirical indication on the 'energy-economy-CO_2 emissions nexus' was evaluated by adding other macroeconomic variables such as; agricultural production, energy prices, financial development, foreign direct investments, industrialization, population size, trade openness, urbanization, … etc. in most literatures.

In elementary analysis, effects of hetroscedasticity in time series data were eliminated initially taking the natural logarithmic transformations of desired variables under investigation, prior to corresponding analysis [4, 6-16]. Commonly, integrating order (d) as well as stationarity of corresponding series were identified by the prominent unit root tests such as Augmented Dickey & Fuller (ADF), Phillips & Perron's (PP) or Kwiatkowski, Phillips, Schmidt & Shin (KPSS) individually or simultaneously for robust conclusions about the time series properties taking their level as well as their differences [4, 7-10, 12, 14-18]. Further panel unit root test approaches have been practiced system wise in most panel data analysis [6, 11, 13]. In most multivariate as well in panel data studies, optimal lag length (p) was identified as a critical element in correct specification on the VAR framework prior cointegrating or causality approaches based on information criterion values of the Akaike (AIC), Schwarz Bayesian (BIC) and Hanna-Quinn (HQ), which were frequently used simultaneously by identifying the maximum of minimum information criterion values for the optimal lag length (p) or individually [6, 7, 12, 14, 17, 18]. Generally, both Trace and Maximum Eigen Value test statistics under the Johansen ML procedure were considered simultaneously to determine cointegrating rank (r) for long run energy-economy-CO_2 emissions nexus' on multivariate framework than bivariate framework [4, 7, 12, 14, 17]. Instead the Trace statistic was used individually in some cases [16, 18]. The Vector Error Correction Model (VECM) approaches were extensively applied for modeling both long run and short run cointegration relationships in many studies [4, 7, 12, 16-18]. While checking the condition for model stability, three post estimation tests; the Cholesky-Lutkepohl for multivariate normality of residuals, the Lagrange Multiplier test or Portmanteau test for residuals free from serial correlation and the Breusch-Pagan-Godfrey test for non-hetroscedasticity of residuals were applied in line for white noise residuals in the VAR or VECM model specification [12, 17]. Differently from such multivariate cointegration approaches, some have applied another approaches for identifying long-run relationships between the time series variables such as; the autoregressive distributed lag (ARDL) bound cointegration test [8-10, 15] as well as the Generalized Method of Moments (GMM) test which were used in presence of arbitrary hetroscedasticity in the time series [13, 19]. 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) [14], an artificial neural network (ANN) model [20] and some fuzzy regressions or hybrid models [19].

The studies of Nigeria over 1970-2013 by Alege *et al.* [7], Malaysia over 1970-2012 by Muhyidin *et al.* [4], and China over 1990-2012 by Wang *et al.* [16] found to be closely related to methodological approaches of this study. The study of Nigeria [7] investigated cointegration and causality relationship among pollutant emissions basically CO_2, renewable & nonrenewable energy consumption and economic growth on the VECM. Then normalized long run estimates indicated that the atmospheric concentration of CO_2 emissions were increased approximately 20%, by 1% change in the fossil fuel energy consumption significantly and positively, facing long run environmental degradation challenges in Nigeria. In contrast, electrical power energy consumption was significantly and inversely proportional to CO_2 emissions, implying that dwindle of atmospheric concentration of CO_2 emissions increased as adoption of cleaner energy source. Further GDP and squared GDP per capita influenced inversely and directly on CO_2 emissions contesting EKC hypothesis. Similarly, human capital indicator and institutions had insignificant influence on CO_2 emissions. The results 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. Moreover, it was evidenced that long run unidirectional causal existence from human capital indicator to CO_2 emissions and from electrical power energy consumption to GDP at the 5% significance level.

The study of Malaysia [4] investigated causality among pollutant emissions (CO_2), total energy consumption, economic growth (GDP) and industrial production index growth (IPIG) on the VECM. Long run estimates indicated that coefficients of lagged ECM for total energy consumption and CO_2 emissions equations were negative and only significant at 1% and 10%, while that of for IPIG and GDP equations were negative but insignificant, indicating unidirectional long run causality from both GDP and IPIG to total energy consumption and to CO_2 emissions. Further, it was evidenced, bi-directional long run causality between total energy consumption and CO_2 emissions and suggested that atmospheric CO_2 level in Malaysia was increased by growth of GDP and IPIG. It was mainly caused by increasing in total energy consumption.

The study of China [16] investigated long run equilibrium relationships, temporal dynamic relationships and causal existence of pollutant emissions (CO_2), energy consumption and economic growth (GDP) on the VECM. The impacts of a shock in CO_2 emissions on GDP or energy consumption found to be marginally significant by impulse response analysis. The granger casual results were evidenced that unidirectional causality from energy consumption to CO_2 emissions and bi-directional causality among GDP and energy consumption. Unexpectedly, it failed to perform causality between GDP and CO_2 emissions. Those causality existences were considered as decisive components of designing emissions reduction policies and effective energy conservation.

III. Materials and Methods

3.1 Secondary Data Source

Annual time series data on (i) CO_2 (carbon dioxide) emissions (metric tons/capita), (ii) energy consumption (Kg of oil equivalent/capita) and (iii) gross domestic product (GDP constant 2010 US$/capita) from 1971 to 2014 were obtained from the World Bank data base, known as world development indicators (WDI) [21] as the required secondary data. The per capita value of CO_2 emissions was the dependent variable, while other two variables were determinants of CO_2 emissions.

3.2 Statistical Analysis and Estimating Procedures

Initially an explanatory data analysis was considered for visualizing nature of distributions of desired variables and then variance heterogeneity in each series was minimized using their natural logarithmic transformation, which were coded as; LCO_2, LEC & LGDP. Conceptual framework in imperial analyses of this study is outlined as below.

3.2.1 Unit Root Tests and Stationarity

The Augmented Dickey and Fuller (ADF) and the Phillips and Perron's (PP) unit root tests were carried out to check whether all variables are stationary series and integrated at same order (d), under the null hypothesis of 'a unit root is present in a time series variable'. It is important to specify trend existence correctly in the model. If each variable is integrated of the same order (d), while satisfying stationarity in a linear combination of them [i.e. that variable combination $\sim$ I(0)], then corresponding variable combination is abbreviated as "cointegrating equations" and it can be interpreted by demonstrating a long run equilibrium nexus among the variables [16].

3.2.2 Optimal Lag Length

Determination of optimal lag length (p) is considered as a critical element prior the cointegration approaches for correct specification of observed data. It can be observed automatically from the basis of multivariate model selection criterion developed for maximum likelihood estimation techniques; Akaike information criteria (AIC), Schwarz Bayesian information criteria (BIC), Hanna-Quinn information criteria (HQ), modified values of the AIC, BIC & HQ as well as final prediction error (FPE) in computer applications such as E-Views. In this study, it was observed by maximum of commonly used minimum information criterion lag order of the AIC, BIC, HQ and FPE based on general VAR framework.

3.2.3 Johansen Maximum Likelihood Cointegration

Multivariate time series modeling is complicated by presence of nonstationary time series particularly in commercial data, in such cases cointegration test is primarily used to determine rank of long run cointegrating relationship (r) between such nonstationary time series. The Johansen cointegration test often uses with first assessed order of cointegration of the series, I(d=1) under the maximum likelihood (ML) method in multivariate context based on two test statistics named 'Trace' & 'Maximum Eigenvalue', which might be little bit different and are based on trace value & maximum eigen value of corresponding stochastic matrix [22]. Sequential statistical testing procedures are based on the likelihood ratio (LR) test. If 'k' number of stochastically or deterministic trend I(1) time series are presented in the cointegrated regression, then there are 'k-1' possible cointegrating vectors and 'k' hypotheses in the Johansen ML procedure. In this study, the number of long-run cointegration relationships among desired variables was observed by the Trace test statistic under the Johansen's cointegration analysis.

Null hypotheses for the Trace & Maximum Eigenvalue statistics are same, H_0: rank (π) = $\hat{r}$; $0 \leq r \leq k$, then corresponding alternative hypothesis are, $H_{A\ Trace}$: $\hat{r}$ < rank (π) $\leq$ k and $H_{A\ Eigen}$: rank (π) = ($\hat{r}$ + 1). Both tests are followed sequentially for corresponding cointegrating rank, $\hat{r}$ = 0, 1… k-1 until non-rejection at the corresponding null hypotheses is observed for first time. Corresponding two test statistics are [17];

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

$$\lambda_{Eigen[\hat{r},\hat{r}+1]} = -T\ln(1-\hat{\lambda}_{\hat{r}+1})$$

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

3.2.4 Vector Error Correction Model (VECM)

Non-stationary features in time series with stochastic trends with integrated order one ($Y_t \sim I(1)$) for cointegrated data (r > 0) generally leads to consider the VECM instead the VAR process. It is a most suitable framework on this study with great advantage of modeling both short run and long run relationship jointly for nonstationary and cointegrated data, and also it can be used with stationary data [16]. If there is a linear trend in time series variables but not in cointegration relations then corresponding VECM(p-1) model is formulated in vector form as below regression [23].

$$\Delta Y_t = \nu + \Pi Y_{t-1} + \sum_{j=1}^{k-1} \Gamma_j \Delta Y_{t-j} + u_t$$

Where; Γ&Π are coefficient matrices, p is the lag order of the general VAR, Y_t is a (n×1) column vector of k variables, ν is a (n×1) vector of constant terms allowing for the possibility of none zero mean $E[Y_t]$, is a difference operator and $u_t=(u_{1t}, ..., u_{kt})'$ is k-dimensional unobservable error term which assumed to be sequence of independently identically distributed random vectors with zero mean vector and time invariant positive definite nonsingular covariance matrix (i.e. Gaussian or white noise residual; u_{it} ~iid(0, Σ_{ut}).

Remarks as explained in [23];

- ΔY_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 & $u_t \sim I(0)$ and $\Pi Y_{t-1} \sim I(0)$ because a non-stationary variable cannot explain a stationary one.
- Γ_i are referred to as ‘Short term parameters’ or ‘short run’ and $\Gamma_i = -(\Phi_{i+1} + 1 + ... + \Phi_p)$; for all i=1,.,p-1.
- If rank (π) = r < k, then there exists (k×r) matrices of α & β (referred to as loading matrix & cointegration matrix), such that $\Pi = \alpha\beta'$ which follows "$rank(\alpha) = rank(\beta) = r$".
- Π is known as the impact matric which contains information of long run cointegration relations, hence ΠY_{t-1} referred to as ‘long term part’ or ‘long run’ and $\Pi = -(I_k - \Phi_1 - ... - \Phi_p)$.
- Each cointegrating vector entering each regression of the VECM and roughly equate to error correction term. Hence, it is satisfied, $\Pi Y_{t-1} = \alpha\beta' Y_{t-1} = \mathbf{\Lambda} ECT_{t-1}$.

3.2.5 Model Validation & Residual Diagnostic Tests

The stability condition of the fitted VECM model verified by spherically distributed inverse AR roots of characteristic polynomial in the fitted VECM [24]. Residual diagnostic techniques were carried out to check whether the residuals of the fitted VECM were white noise process as outlines below.

Three post estimation tests for white noise residuals;

- The Cholesky (Lutkepohl) test applied for normality of residual distribution, under the null hypothesis “H_0: residuals are normally distributed”.
- The Lagrange-Multiplier (LM) test applied for residual free from serial correlation in order h, which viewed to test for zero coefficients in the model, under the null hypothesis “H_0: no serial autocorrelation of the residual”.
- The Breusch-Pagan-Godfrey hetroscedasticity test applied for conditional hetroscedasticity in covariances of error distribution, under the null hypothesis “H_0: hetroscedasticity in error covariances or residuals covariances are zero”. When it’s failed to satisfy the null hypothesis, it is concluded that there is no ARCH effect in the residuals.

3.2.6 Impulse Response Functions

Causality analysis fails to perform interaction effects between desired variables effectually in econometric methodologies, hence forecast error variance decompositions and impulse responses functions (IRFs) use instead to have a better picture of relationships between time series variables. In empirical literatures, analysis of IRFs is widely used in restricted VAR and VECM (unrestricted VAR) to expose a dynamic relationship between macroeconomic variables, which is privileged to analyze the response of one variable towards a shock in another variable to the variable itself. The graph of IRFs was used in this study to discuss the performance of one variable in response to a shock (or a change) other.

IV. Results and Discussion

4.1 Explanatory Data Analyses

The Appendix (TABLE A1) provides descriptive statistics for desired variables over 1971-2014 and the Appendix (Fig. A1) shows graphical representation of the annual trend in the logarithmic transformed series. It indicated that, Sri Lanka's; CO_2 emissions (metric tons) per capita are varied from 0.200M_t (minimum) in year 1976 to 0.886 M_t (maximum) in year 2014, with an annual average of 0.404 M_t throughout 1971-2014 and energy consumption (Kg of oil equivalent) per capita is varied from 287.014 Kg in year 1977 to 551.021 Kg in year 2012, with an annual average of 371.873 Kg throughout 1971-2014. Moreover, the GDP (in constant 2010 US$) per capita is varied from 689.679 US$ in year 1972 to 3506.871 US$ in year 2014, with an annual average of 1571.655 US$ throughout 1971-2014. It was found that each series was not significantly different from log normal distribution following approximately linear trend.

4.2 Empirical Findings

The results from the TABLE 1 of the ADF & PP unit root tests indicated that all *LGDP*, LCO_2 & *LEC* series found to be not stationary at their levels, but that of from the TABLE 2 indicated that those were stationary at their first differences (*LGDP*, LCO_2 & *LEC* ~ I (1)), and it is graphically illustrated from Appendix (Fig. A2), annual trends of the 1st differenced log series over the time period 1971-2014.

Table 1: The unit root test results of sequence levels

Model Variables	ADF test		PP Test	
	t statistic	P-value	t statistic	P-value
Including Intercept Only				
LGDP	3.0550	1.0000	3.2021	1.0000
LEC	0.0799	0.9605	0.4346	0.9822
LCO_2	0.4419	0.9825	0.5045	0.9850
Including Intercept & Linear Time Trend				
LGDP	-0.7178	0.9652	-0.7774	0.9599
LEC	-2.3266	0.4113	-2.1496	0.5045
LCO_2	-2.0114	0.5787	-1.9646	0.6036

Table 2: The unit root test results of sequence first-order differences

Model Variables	ADF test		PP Test	
	t statistic	P-value	t statistic	P-value
Including Intercept Only				
ΔLGDP	-5.8499	0.0000	-5.8531	0.0000
ΔLEC	-7.2498	0.0000	-7.3578	0.0000
ΔLCO_2	-6.3444	0.0000	-6.3444	0.0000
Including Intercept & Linear Time Trend				
ΔLGDP	-6.4285	0.0000	-6.4164	0.0000
ΔLEC	-6.5669	0.0000	-7.7927	0.0000
ΔLCO_2	-6.6858	0.0000	-6.6839	0.0000

The optimal lag length is a critical element for the cointegration test and the results from the TABLE 3 of the criterion lag order, provided by all the FPE, BIC & HQ on the VAR framework found to be minimized at lag one. Hence, it concluded that the optimal lag length was one.

Table 3: Results of lag order selection on VAR framework

Endogenous variables: LCO_2 LEC LGDP
Exogenous variables: C
Sample: 1971 – 2014

Lag	LogL	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: * indicates lag order selected by the criterion at 5% significance level

4.3 VEC Modeling and Estimation

Since the entire log series were not stationary at levels, and have been integrated of the same order one with deterministic trend stationary encompassing the optimal lag length one, it satisfied all critical conditions for the Johansen cointegration approaches.

Table 4: Johansen's cointegration tests results at the optimal lag one

Hypothesized No. of CE(s) [H_0:]	Eigenvalue	Trace Statistic (λ_{Trace})	5% Critical Value	10% Critical Value	p-value
None (r = 0)	0.3360	28.9816	29.7971	27.0670	0.0619
At most 1 ($r \le 1$)	0.1673	11.7863	15.4947	13.4288	0.1675
At most 2($r \le 2$)	0.0929	4.0967	3.8415	2.7055	0.0430
Hypothesized No. of CE(s) [H_0:]	**Eigenvalue**	**Maximum Eigenvalue Statistic (λ_{Eigen})**	**5% Critical Value**	**10% Critical Value**	**p-value**
None (r = 0)	0.3360	17.1953	21.1316	18.8928	0.1630
At most 1 ($r \le 1$)	0.1673	7.6896	14.2646	12.2965	0.4111
At most 2($r \le 2$)	0.0929	4.0967	3.8415	2.7055	0.0430

The results from the Table 4 of the Johansen's cointegration analysis indicated the very first insignificant trace statistic at the second hypothesis, (λ_{Trace} =11.79, p=0.17) which concluded with 90% confident that there exists only one long run cointegrating equations. It should also be noted that the very first insignificant maximum eigenvalue statistic at the first hypothesis, (λ_{Eigen} =17.20, p=0.16) suggesting there exists no cointegration relation between the variables with 90% confident. Then, it is observed contradiction on selecting cointegrating rank. It was consider one as the cointegrating rank, r [rank(π)=1] based only on the Trace statistic in the VECM approach as practiced in the study of [4], which was proposed by [25].

The Johansen's cointegration demonstrated with 90% confident that CO_2 emissions and their determinants were cointegrated and there was at most one long run equilibrium relationship among the three variables at the one-year lagged. In other words, it can be expressed that there exists a long run relationship between per capita values of CO_2 emissions (CO_2), fossil fuel energy consumption (EC) and economic growth (GDP) in Sri Lanka. Nevertheless, the three were in disequilibrium in the short run. Hence, VEC modeling was further conducted to obtain the short run imbalance and dynamic structure using the E-Views computer application.

Table 5: Results of the cointegration equations

Components of the Cointegration Equation	Cointegration Equation		
	Coefficient	Std. Error	t-statistic
LCO_2(-1)	1		
LEC(-1)	-4.5539	(0.6242)	[-7.2953]
LGDP(-1)	1.1179	(0.2751)	[4.0641]
C	19.7833		

Note: Since were 42 observations after adjustments then df, ν = 41. Thus, critical value at 5% significance level is $t_{(\nu,0.025)} = \pm 2.0195$.

The results from TABLE 5 of the cointegration equation indicated with 95% confident that each long run parameter was strongly significant in cointegration equation of VEC model. Thus the error correction term, ECT_{t-1} can be described as equation (1).

$$ECT_{t-1} = LCO_{2t-1} + 19.78 - 4.55LEC_{t-1} + 1.12LGDP_{t-1} \quad \text{.... (1)}$$

In order to see the directions of these long-run relationships, normalized equations according to CO_2 can be interpreted by at the 5% significance level as below.

$$LCO_{2t-1} = 19.78 - 4.55LEC_{t-1} + 1.12LGDP_{t-1} \quad \text{............ (2)}$$

It concluded that, keeping other things constant, each 1% increase in energy consumption will cause the decrease of 4.55% in CO_2 emissions and each 1% increase in GDP will cause the increase of 1.12% in CO_2 emissions in long run nexus. The VECM(1) equations established in the study were observed as below from TABLE 6 of parameter estimation results of the unrestricted VECM(1).

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

The linear restrictions in the long run cointegration relationships were identified by insignificant parameters in unrestricted long run cointegration relationship. It was observed only the error correction term significantly inclusive in the long run cointegrating relationship for CO_2 emissions with 95% confident as explained by equation (3).

$$\Delta LCO_{2t} = 0.23\ ECT_{t-1} = 4.55 + 0.23 LCO_{2t-1} - 1.05 LEC_{t-1} + 0.26 LGDP_{t-1} \quad \ldots\ldots\ldots\ldots\ldots.. (3)$$

It should also be noted that all the long run coefficients for economic growth were insignificant at 5% level of significant. Similarly, only the ECT_{t-1}, $\Delta LGDP_{t-1}$ and constant terms were significantly inclusive in the long run cointegrating relationship for energy consumption explained by, $\Delta LEC_t = 0.03 + 0.15\, ECT_{t-1} - 0.61 \Delta LGDP_{t-1}$ with 95% confident.

$$\therefore \Delta LEC_t = 3.08 + (0.15 LCO_{2t-1} - 0.70 LEC_{t-1} + 0.17.LGDP_{t-1}) - 0.61 \Delta LGDP_{t-1} \quad \ldots\ldots\ldots\ldots\ldots.. (4)$$

Table 6: Parameter estimations of the unrestricted VECM(1)

Error Correction:	D(LCO_2)	D(LEC)	D(LGDP)
ECT_{t-1}	0.2332	0.1540	0.0337
	(0.1056)	(0.0361)	(0.0203)
	[2.2073]	[4.2678]	[1.6624]
D(LCO_2(-1))	-0.2511	-0.0154	-0.0038
	(0.2005)	(0.0685)	(0.0384)
	[-1.2525]	[-0.2250]	[-0.0995]
D(LEC(-1))	0.6212	0.1518	0.0390
	(0.5154)	(0.1761)	(0.0988)
	[1.2052	[0.8623]	[0.3944]
D(LGDP(-1))	-0.5118	-0.6069	0.1040
	(0.8244)	(0.2816)	(0.1581)
	[-0.6208]	[-2.1552]	[0.6578]
C	0.0464	0.0332	0.0345
	(0.0333)	(0.0114)	(0.0064)
	[1.3951]	[2.9258]	[5.4092]
R^2	11.82%	40.01%	12.83%
Akaike IC	-1.6537	-3.8020	-4.9570
Schwarz IC	-1.4468	-3.5952	-4.7502

Note: Corresponding standard error and t-statistics are shown in () and [] parentheses

From the equation (3) it can be concluded that, a unit increase in present logarithmic level of per capita CO_2 emissions and per capita economic growth influenced positively on successive change in logarithmic level of per capita CO_2 emissions significantly, which rose by 23% and 26% respectively in long run association. Surprisingly, a unit increasing demand of per capita fossil fuel energy consumption influenced negatively on successive change in logarithmic level of per capita CO_2 emissions in long run association. Since, all short run coefficients in unrestricted cointegration relationship for CO_2 emissions were insignificant at 5% level of significant, it concluded that per capita energy consumption and per capita economic growth have no adverse effect on per capita CO_2 emissions in short run association.

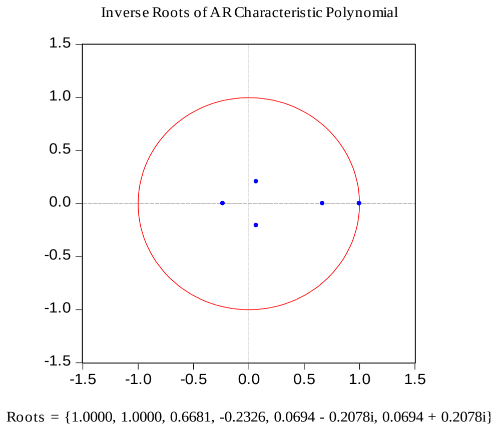

Figure 3: Residual stability test of the unrestricted VECM(1)

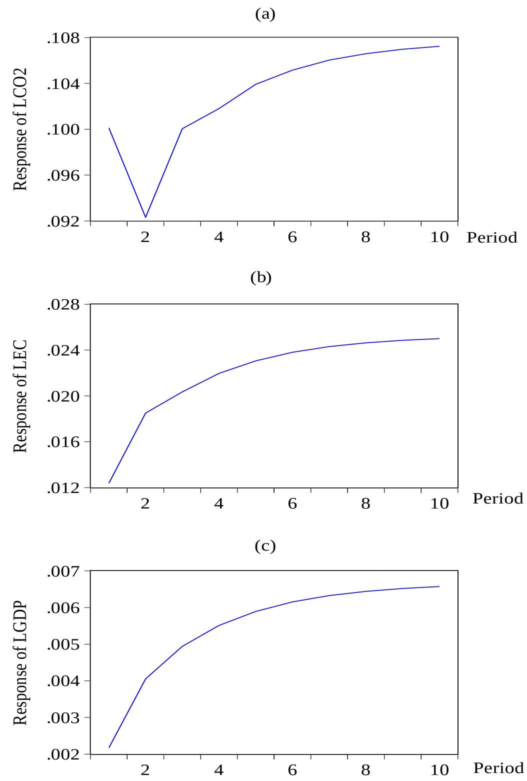

Figure 4: The IRF diagram of (a) LCO_2, (b) LEC & (c) LGDP changes caused by (Cholesky One S.D.) LCO_2 shock

4.4 VECM Stability and Error Diagnostic Tests

Then VECM(1) forecasted results from the Fig. 3 of spherically distributed inverse roots of AR characteristic polynomial confirmed that the VECM (1) model was highly stable, since each characteristic root was not represented a root outside the unit circle. Moreover, the LM test results from the Appendix (TABLE 2) confirmed with 95% confident that error components of the unrestricted VECM(1) has no serial correlations, since all chi squared LM test statistics were insignificant at all lags up to the maximum lag length 9. The Cholesky-Lutkepohl test results from the Appendix (TABLE 3) confirmed that each error components of the unrestricted VECM(1) followed multivariate normal distributions, since all the JB test statistics were insignificant jointly as well as individually at 1% level of significance. The results of the Breusch-Pagan-Godfrey test from the Appendix (TABLE 4) confirmed that error components of the unrestricted VECM(1) satisfied homoscedastic, since the chi squared test statistic was joint significant at 5% level of the significance. Altogether, it was concluded that error components of the unrestricted VECM(1) were not significantly different from white noise process. Thus, the fitted one-year lagged VECM(1) model considered as a consistent model.

4.5 Impulse Response Function

Based on the results from the Appendix (TABLE 5), column (a) and the Fig. 4 (a) of the impulse response analysis of the effects of LCO_2 shock, it was found that positive shock has large impact on itself. This suggests that positive shock of CO_2 emissions has positive influence on its own increasing and the positive influence has relatively long sustained effectiveness. Moreover, the column (b) and the Fig. 4 (b) shown that positive shock of CO_2 emissions has positive influence on EC increasing and the positive influence has relatively long sustained effectiveness. Similarly, the column (c) and the Fig. 4 (c) shown that positive shock of CO_2 emissions has positive influence on GDP increasing and the positive influence has relatively long sustained effectiveness. In conclusion, the analysis of impulse response functions indicated that positive shocks of CO_2 emissions have an increasing positive impact on itself, energy consumption and economic development in long run associations.

V. Discussion

Despite the fact that, this study has been carefully analyzed and reached the desired objectives, a number of deficiencies can be seen that need to be concerned such as limitations of the associated variables, availability of observations in statistics of Sri Lankan profile. Few concerns should be made necessarily for further study in this field as mentioned below;

- Many other determinants in CO_2 emissions should be taken into account for developing extensive emissions reduction and energy conservation policies.
- Other factors of GHG emissions should be taken into account for 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 thus the grey prediction model or auto regressive distributed lags method can be applied instead as an alternative forecasting tool, because of their minimum sample size requirement to make significant statistical inferences in model forecasting with small sample.

It is recommended that similar studies to be carried out in regular intervals.

VI. Conclusions

The purpose of this study is to investigate “impact of energy consumption and economic growth on CO_2 emissions for Sri Lanka, over the period of 1971-2014”. It was found that each series was not significantly different from lognormal distribution. All series found to be stationary at their first differences and the Johansen’s cointegration analysis confirmed that there was at most one cointegrating relationship among the log series at the first lag. The analyses confirmed that fitted VECM(1) model was highly stable and errors were not significantly different from white noise process. The results observed by empirical analysis indicated that, a unit increase in present logarithmic level of per capita CO_2 emissions and per capita economic growth influenced positively on successive change in logarithmic level of per capita CO_2 emissions significantly, which rose by 23% and 26% respectively in long run association. Hence, it is concluded that economic developments in Sri Lanka leads to greater CO_2 emissions in long run effectiveness. Surprisingly, a unit increasing demand of per capita fossil fuel energy consumption influenced negatively on successive change in logarithmic level of per capita CO_2 emissions in long run association, this may because demand of fossil fuel energy in Sri Lanka is well below to trigger any significant conversion in CO_2 emissions compared to developed nations. Moreover, it is noted that energy conservation policies and sustainable economic growth have no adverse effect on CO_2 emissions in Sri Lanka in short run association. The impulse response functions analysis suggested that positive shocks of CO_2 emissions have positive influence on its own increasing, on energy demand increase as well as on economic growth and each positive influence has relatively long sustained effectiveness. Hence, the impact of energy consumption and economic growth on CO_2 emissions in long run sustained can be debate effectively by VECM(1) inclusive only the error correction term, ECT_{t-1} as;

$$\Delta LCO_{2_t} = 4.55 + 0.23 LCO_{2_{t-1}} - 1.05 LEC_{t-1} + 0.26 LGDP_{t-1}.$$

The inferences derived in this study found that over time higher economic growth in Sri Lanka causes to raise more carbon dioxide emissions resulting higher environment pollutions.

APPENDICES

Table A1: Descriptive data analysis of observed variables

Statistic of Variables	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)
Std. Dev.	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)
Statistic of Variables	**LCO_2**	**LEC**	**LGDP**
Mean	-1.019	5.899	7.246
Std. Dev.	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)

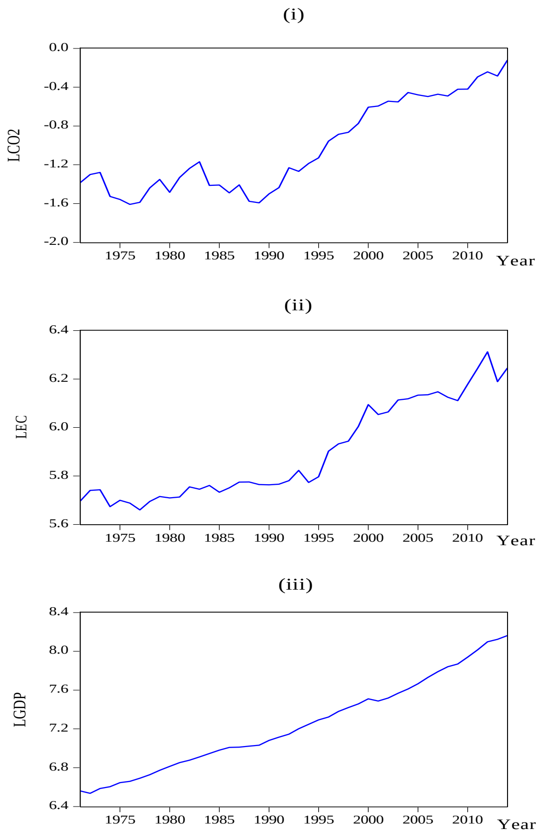

Figure A1: Annual trend of the log series of per capita (i) CO_2 emissions, (ii) energy consumption and (iii) gross domestic product over 1971-2014

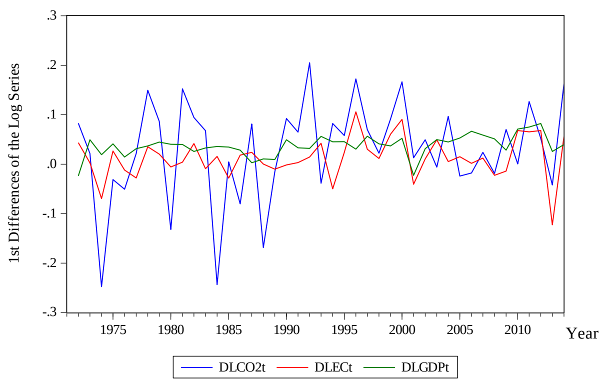

Figure A2: Annual trends of the1st differenced log series over 1971-2014

Table A2: LM test results for residual serial correlations

Lags	LM-Stat	Prob.
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

Table A3: Cholesky (Lutkepohl) test results for residual normality

Error Component	Skewness	Chi-sq	df	Prob.
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**	**Prob.**
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**	**Prob.**	
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	

Table A4: Residual hetroscedasticity test results

Joint test:

Chi-sq	df	Prob.
65.3774	84	0.0483

Individual components:

Dependent [$u_t \times u_t$]	R-squared	F(8,33)	Prob.	Chi-sq(8)	Prob.
$res_{LCO_2} \times res_{LCO_2}$	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
$res_{LEC} \times res_{LGDP}$	0.5342	4.7310	0.0006	22.437	0.0042

Table A5: 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

References

[1]. USGCRP (2017): Climate Science Special Report: Fourth National Climate Assessment (NCA4), Volume I [Wuebbles, D.J., D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock (eds.)]. U.S. Global Change Research Program (USGCRP), Washington, DC, USA, 470 pp. DOI:10.7930/J0J964J6.

[2]. IPCC (2014). Climate Change 2014: Synthesis Report. Contribution of Working Group I, II & III to the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) [Core Writing Team, Pachauri, R., K. & Meyer, L., A. (eds.)]. IPCC, Geneva, Switzerland, 151pp.

[3]. Olivier, J. G. J., Janssens-Maenhout, G., Muntean, M. & Peters, J. A. H. W. (2015). Trends in global CO_2 emissions: 2015 Report. PBL Netherlands Environmental Assessment Agency, The Hague; European Commission, Joint Research Centre (JRC), Institute for Environment and Sustainability (IES). Report No. PBL:1803, JRC:98184.

[4]. Muhyidin, H. bt., Saifullah, Md. K. & Fei, Y. S. (2015). CO_2 emissions, energy consumption and economic development in Malaysia. International Journal of Management Excellence, 6(1), 674-678.

[5]. Lapinskiene, G., Peleckis, K. & Slavinskaite, N. (2017). Energy consumption, economic growth and greenhouse gas emissions in the European Union countries. Journal of Business Economics and Management. 18(6), 1082-1097. pISSN:1611-1699/ eISSN:2029-4433.

[6]. Lu, W. C. (2017). Greenhouse gas emissions, energy consumption and economic growth: A Panel cointegration analysis for 16 Asian countries. International Journal of Environmental Research and Public Health, 14(11), 1-15, DOI:10.3390/ijerph14111436.

[7]. Alege, P. O., Adediran, O. S. & Ogundipe, A. A. (2016). Pollutant emissions, energy consumption and economic growth in Nigeria. International Journal of Energy Economics and Policy, 6(2), 202-207. ISSN:2146-4553.

[8]. Alkhathlan, K., Alam, M. Q. & Javid, M. (2012). Carbon dioxide emissions, energy consumption and economic growth in Saudi Arabia: A Multivariate cointegration analysis. British Journal of Economics, Management & Trade, 2(4), 327-339.

[9]. Asumadu-Sarkodie, S. & Owusu P. A. (2017). Carbon dioxide emissions, GDP per capita, industrialization and population: An Evidence from Rwanda. Environmental Engineering Research, 22(1), 116-124. pISSN:1226-1025/ eISSN:2005-968X.

[10]. Begum, R. A., Sohag, K., Abdullah, S. M. S. & Jaafar, M. (2015). CO_2 emissions, energy consumption, economic and population growth in Malaysia. Renewable and Sustainable Energy Reviews, 41(1), 594-601.

[11]. Farhani, S. & Rejeb, J. B. (2012). Energy consumption, economic growth and CO_2 emissions: Evidence from panel data for MENA region. International Journal of Energy Economics and Policy, 2(2), 71-81. ISSN:2146-4553.

[12]. Obradovic, S. & Lojanica, N. (2017). Energy use, CO_2 emissions and economic growth - causality on a sample of SEE countries. Economic Research- konomska Istrazivanja, 30(1), 511-526.

[13]. Omri, A. (2015). CO_2 emissions, energy consumption and economic growth nexus in MENA countries: Evidence from simultaneous equations models. Working Paper Series: Energy Research Centre, COMSATS Institute of Information Technology, Lahore Campus. 40, 657-664.

[14]. Pao, H. T., Fu, H. C. & Tseng, C. L. (2012). Forecasting of CO_2 emissions, energy consumption and economic growth in China using an improved grey model. Energy, 40(1), 400-409.

[15]. Tang, T. C. & Tan, P. P. (2016). Carbon dioxide emissions, energy consumption & economic growth in a transition economy: Empirical evidence from Cambodia. Labuan Bulletin of International Business & Finance (LBIBF), 14(1), 14-51. ISSN:1675-7262.

[16]. Wang, S., Li, Q., Fang, C. & Zhou, C. (2016). The relationship between economic growth, energy consumption and CO_2 emissions: Empirical evidence from China. Science of the Total Environment, 542, 360-371.

[17]. Bozkurt, C. & Akan, Y., (2014). Economic growth, CO_2 emissions and energy consumption: The Turkish case. International Journal of Energy Economics and Policy, 4(3), 484-494, ISSN: 2146-4553.

[18]. Chandran, V. G. R. & Tang, C. F. (2013). The impacts of transport energy consumption, foreign direct investment and income on CO_2 emissions in ASEAN-5 economies. Renewable and Sustainable Energy Reviews, 24(1), 445-453.

[19]. Saidi, K. & Hammami, S. (2015). The impact of CO_2 emissions and economic growth on energy consumption in 58 countries. Energy Reports, 1, 62–70.

[20]. Asumadu-Sarkodie, S. & Owusu P. A. (2016). Energy use, carbon dioxide emissions, GDP, industrialization, financial development, and population, a causal nexus in Sri Lanka: A Subsequent prediction of energy use using neural network. Energy Sources, Part B: Economics, Planning & Policy, 11(9), 889-899.

[21]. WDI (2018). World Bank, World Development Indicators. Retrieved August, 2018, from https://datacatalog.worldbank.org/dataset/world-development-indicators

[22]. Wikipedia (2018). The Free Encyclopedia. Retrieved October, 2018, from https://en.wikipedia.org/wiki/

[23]. Lutkepohl, H. & Kratzig, M. (2004). Applied time series econometrics. Cambridge University Press (1st Ed.) [eBook]. Retrieved February, 2019, from http://pzs.dstu.dp.ua/DataMining/times/bibl/econometrics.pdf

[24]. Lutkepohl, H. (2005). New introduction to multiple time series analysis (1st Ed.) [eBook]. Berlin Heidelberg: Springer-Verlag. pISBN:3-540-40172-5, eISBN:978-3-540-27752-1.

[25]. Asari, F. F. A. H., Baharuddin, N. S., Jusoh, N., Mohamad, Z., Shamsudin, N. & Jusoff, K. (2011). A Vector Error Correction Model (VECM) approach in explaining the relationship between interest rate and inflation towards exchange rate volatility in Malaysia. World Applied Sciences Journal (Special issue on bolstering economic sustainability), 12(1), 49-56. ISSN:1818-4952.

Peiris, T. S. G. "Impact of Energy Consumption and Economic Growth on Carbon Dioxide (CO_2) Emission in Sri Lanka." IOSR Journal of Environmental Science, Toxicology and Food Technology (IOSR-JESTFT) 13.10 (2019): 44-57