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ENERGY CONSUMPTION, CO_2 EMISSIONS AND ECONOMIC GROWTH: EVIDENCE FROM INDIA

ABSTRACT

The study examined causality using static and dynamic frameworks, by considering energy consumption, $C0_2$ emissions and economic growth for India. It used the Granger approach (VECM framework) along with the Dolado and Lütkepohl's approach. It found that CO_2 Granger-causes GDP while energy consumption does not Granger-cause GDP, GDP does not Granger-cause CO_2 while energy consumption Granger-causes CO_2 emissions, and CO_2 emissions Granger-causes energy consumption but GDP does not Granger-causes CO_2 emissions. This implies that India should opt for policies that stress on energy conservation and efficient utilization of energy.

Key Words: carbon dioxide emissions, energy consumption, economic growth, causality, IRFs, VDs

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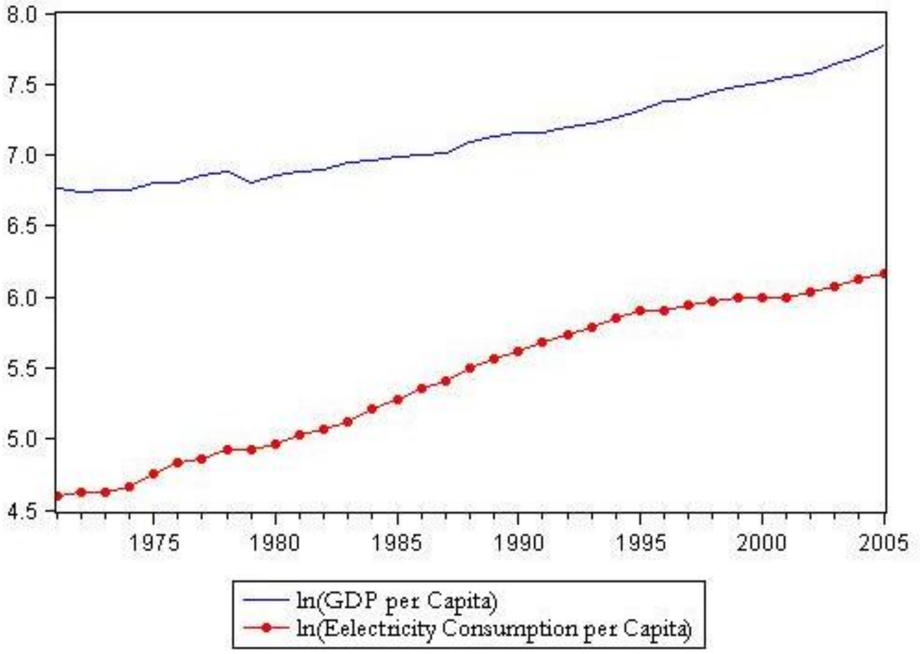
INTRODUCTION

The increasing threat of global warming and climate change has focused attention on the relationship among economic growth, energy consumption, and environmental pollution. Though global warming depends on worldwide Greenhouse Gas (GHG) emissions, its consequences differ among countries, based on their social and natural characteristics. Stern et al. (2006) pointed out that if no action is taken to reduce emissions, the concentration of greenhouse gases in the atmosphere could double as early as 2035 from its pre-industrial level. This implies that in the short run, global average temperature may rise by over 2°C. In the longer term, there is a greater than a 50% chance that the rise in temperature would exceed 5°C. Stern et al. (2006) emphasize that this radical change in temperatures would affect all countries. Among them, the earliest and the hardest hit would be the poorest and populous nations, even though they contributed least to GHG emissions. Stern et al. (2006) have argued that the worst impact of climate change can be substantially reduced by stabilizing the level of greenhouse gases in the atmosphere at a level between 450 and 550ppm CO_2 equivalent (CO_2e).

India is among the fastest growing economies of the world. During 1980-2005, India's GDP grew at an average annual rate of 5.40% (1993-94 prices). During the same time, the growth rate of its secondary sector was 6.7% per annum while its commercial energy sector and electricity consumption grew at about 6% and 9% per annum, respectively. During the pre-liberalization period (1980-1991), the GDP growth rate was sluggish at 3% per annum. However, during the post-liberalization (i.e., 1991-2005) phase, the growth rate was higher, touching 6.09% This occurred due to the widening and deepening of its industrial base and higher levels of per capita income that lead to increasingly energy-intensive consumption patterns. A closer look at the trend of the economic growth and electricity consumption is given in Figure 1.

A closer look of the Figure 1 shows that electricity consumption per capita in kilowatt-hour (KWh) and real GDP per capita in India moved with an upward trend during 1971-2005. This implies that electricity could have been a major input in India's economic growth. During 1979-1992, the annual growth rate of electricity consumption per capita was higher than the annual growth rate of real GDP per capita; from 1992 onwards, it has declined but remains positive (with negative in few years) and very high in most of the years. For example, electricity consumption was 275.79 kWh per capita in 1990, up by 178.30% from the 1971 level (99.099 kWh per capita). By 2005, electricity consumption was 475.6377 kWh per capita (up by 72.46% from the level of 1990). Over the entire period of 1979-1992, real GDP per capita grew by about 37.45% (from Rs. 876.39 Crore per capita to Rs. 1204.59 Crore per capita). By 2005, real GDP per capita grew by about 75.19%: from Rs. 2193.54 Crore per capita (up by 75.19% from the level of 1990).

Figure 1: Plots of log of electricity consumption per capita and real GDP per capita



Ojha (2005) presented a disaggregated pattern of energy consumption and emissions in India. He remarks that about 30% of the total energy requirements are still met by the traditional/non-commercial sources such as fuel wood, crop residue, animal waste, and animal draught power. However, the share of these non-commercial forms of energy in the total energy consumption has been declining. From a high of 50% in 1970, it has decreased to 33% in 1990. This indicates a shift in the energy consumption pattern towards commercial forms of energy such as coal, refined oil, natural gas, and electricity. For example, the consumption of coal, which was more than 36% of the total energy consumption in 1990, had increased to 47% by 2005. Similarly, share of refined oil and natural gas was consistently at a level of about 18% and 5% during 1990-2005, when compared to merely 12% and 0.85% respectively, in 1970. However, non-fossil sources of energy, like hydro-electricity continued to have a small share of about 6.2%. The remaining 0.64% was accounted for by the non-conventional energy sources, such as, nuclear, wind and solar power in 1990. In 2005, the share of hydro-electricity had decreased to 3.62% while the share of non-conventional energy sources had marginally increased to 0.99%.

If we see India's per capita carbon emissions, it is very low at 0.26 tonne per annum. This is one-fourth of the World average per capita emissions of one tonne per annum (Parikh et al., 1991). This indicates that India's per capita contribution to global warming problem is a relatively minor one. However, because of its large and growing population, its total emissions are large and therefore, in the international front, India is expected to stabilize its energy related carbon emissions.[1] Many stoppable CO_2 emissions in India are due to its extensive energy inefficiency, which are an outcome of its energy subsidies. However, the realization of the linkage between energy inefficiency and unnecessary CO_2 emissions lead India to reduce its energy subsidies with the onset of economic reforms in 1991. Even after the reduction in energy subsidies for final consumption, the energy prices remain well below their opportunity cost (Fischer and Toman, 2000). In fact, energy price reforms in India have a long way to go and had an insignificant impact on energy efficiency levels and carbon emissions (Sengupta and Gupta, 2004). Moreover, other measures for emissions abatement such as command-and-control, carbon taxes, and international emissions trading are yet to be implemented in their full form.

A number of studies have examined the relationship between energy consumption and economic growth, between environmental pollution and economic growth and their policy implications. This line of inquiry largely emerges from the oil shocks of the 1970's, and the impact of the Kyoto Protocol agreement.[2] It should be noted that though

[1] At the domestic level, India is concerned with the reduction of carbon emissions whether a global system of tradable emission permits materializes or not. This is being achieved through switching over to non-polluting sources of energy such as, hydro and nuclear. A medium term policy option such as a carbon tax is suspicious largely because of its likely adverse impact on economic growth, income inequality, poverty reduction and employment generation. For a low-income country like India, the more pressing need obviously is achieving poverty reduction, income equality and employment generation rather than controlling carbon emissions. Nevertheless, it would be worthwhile exploring how much, if at all, carbon taxes trade-off growth and poverty reduction, and what compensatory mechanisms can be built into the system to mitigate the undesirable effects of carbon taxes on GDP growth, income equality, employment generation and poverty alleviation.

[2] The Kyoto Protocol requires that industrialized countries reduce their collective emissions of greenhouse gasses by 5.2% of 1990 levels by the period 2008-2012. The country-specific targets in the Kyoto Protocol may be difficult for some nations to achieve. Developing countries, including India, have absolved of any responsibility towards reducing emissions in the first commitment period, that is, 2008-12, of the Kyoto Protocol.

economic theories do not explicitly state a relationship among energy consumption, CO_2 emissions, and economic growth, an empirical investigation on the relationship among these variables have been one of the most attractive areas of energy economics literature since the last two decades. Recent years have seen a renewed interest in examining the relationship between these variables. This line of research focuses on the Environmental Kuznets Curve (EKC) or what is also termed as the Carbon Kuznets Curve (CKC) hypothesis. The hypothesis assumes that initially as per capita income rises, environmental degradation exaggerates; however, after the achievement of a critical level of economic growth, it would tend to fall. Rothman and de Bruyn (1998) see economic growth as a solution, rather than a source of the problem. This can occour due to an increase in the demand for environmental quality as economies grow (Lantz and Feng, 2006) and/or rising awareness among the people regarding the harmful impact of environmental pollution. However, it is noted that the higher economic growth rates that are being pursued by developing countries are being obtained largely through consumption of a increasing quantities of commercial energy, which comes at the cost of ignoring more efficient technologies. Thus, there is dispute whether energy consumption is a stimulating factor for, or is itself a result of economic growth. The increased amount of CO_2 in the atmosphere, which is a product of the use of fossil fuels, had negative impacts on natural systems and is a main factor contributing to climate change. However, it is important to mention that the world does not need to choose between averting climate change and promoting growth and development. Changes in energy technologies and in the structure of economies have created opportunities for decoupling growth from greenhouse gas emissions. Indeed, ignoring climate change will eventually damage economic growth of every country, even if they are not the culprit. Therefore, tackling climate change remains a pro-growth strategy for the longer term. It is the need for each country and it can be achieved in a way that does not cap the aspirations for growth of rich or poor countries.

In this context, in order to reduce emissions we have two options open before us.[3] First, involves the replacement of consumption of coal and oil with renewable alternatives that would involve a change in demand that encourages adoption of clean power, heat and transportation. Second, there should be adoption of new technologies that utilizes /

[3] The standard policy measures for green house gases abatement can be grouped in four heads namely, energy efficiency improvement measures, command-and-control measures (i.e., implementing emission reduction targets by decree), domestic carbon taxes, and an international emissions trading regime of the kind envisaged for the Annex B countries in the Kyoto protocol.

consumes energy more efficiently and hence increases productivity and economic growth.[4] However, command-and-control policy instruments, being traditional would prove to be efficient only in achieving the emissions reduction goal but not the desired level of energy efficiency. Highlighting the efficient use of energy consumption, Stern et al. (2006) point out that the costs of environmental degradation could be lower if energy is efficiently utilized. Stern et al. (2006) remark that the costs will be higher, if innovation in low-carbon technologies is slower than expected or if the policy-makers fail to make the most of economic instruments that allow emissions to be reduced. Stern et al. (2006) mentioned that such actions would require a huge investment and hence developed and developing countries must work together for the same. Further, with a global public good like CO_2 emissions, the non-cooperative Nash equilibrium resulting from individual abatement efforts will not be globally Pareto efficient. Therefore, as Eyckmans et al. (1993) mentions, in order to reach a globally Pareto optimal CO_2 emissions control, international cooperation between countries is required. Developed countries, where carbon markets are mature should deliver flows of finance to support low-carbon development of energy technologies in the developing countries (through the Clean Development Mechanism). Further, these actions will also create significant business opportunities, as new markets are created in low-carbon energy technologies and other low-carbon goods and services.[5] Emissions trading, which was proposed to enable signatories to achieve reductions efficiently, allowed developed countries to trade emissions credits amongst themselves. This trade makes sense only amongst those countries which have agreed to quotas, predominately the OECD countries. However, Environmentalists favor reducing carbon emissions and oppose international trade in emissions permits as opening of new markets may lower welfare, based on the theory of the second best.

[4] There are few studies (for example, Artim et al., 2008; Howland et al., 2009) that show how environmental projects can significantly reduce climate change, and projects within the energy efficiency and renewable energy sectors, reduce fuel dependency and lead to significant direct cost reductions, as well as indirect savings in the health and social sectors. The environmental technology industry and the renewable energy sector have great capacity to create jobs. The emerging eco-innovation networks and incubators have the potential to bridge the technology gap between regions. Hence, renewable energy (RE), energy efficiency (EE) and climate change-related projects can contribute to the aim of transforming whole world into a highly energy efficient and low-carbon economy. These measures can reduce the World's economy vulnerability to volatility in the prices for oil and gas, tackle energy market failures, and reduce energy dependency by diversifying energy sources. These issues have a direct effect on the economy (for example, reducing fuel costs), and employment (for example, labour in agriculture for bio-fuel production). Biomass projects often contribute to rural development.

[5] Under a static emission permits trading regime, it is optimal for a country to sell (buy) permits as long as the market price of a permit is higher (lower) than its own marginal abatement cost. In equilibrium, marginal abatement costs are equalized across all countries in each period. Furthermore, if countries are allowed to allocate the use of permits freely through time (by banking or borrowing), it is optimal for them to distribute abatement across periods such that their present values of marginal abatement costs are equalized (Rubin, 1996; Stevens and Rose, 2002). Therefore, it is obvious that a system of tradable permits is an effective instrument to increase the efficiency of GHG emissions control (Hagen and Westskog, 1998).

In the light of above discussion, the present study focuses on the causal relationship among economic growth (measured by GDP), environmental degradation (measured by carbon dioxide (CO_2) emissions metric tons per capita) and aggregate energy consumption (measured by electricity consumption per capita in kilowatt hour (KWh)), in India.

Tiwari (2010) established four sets of testable hypothesis for testing Granger causality between energy consumption and economic growth. The first hypothesis is termed as "growth hypothesis". The evidence of unidirectional Granger-causality running from energy consumption to economic growth corroborates the "growth hypothesis". According to the "growth hypothesis", energy consumption contributes directly to economic growth within the production process and hence in such situation, if energy conservation policies are adopted, it will have detrimental impact on the economic growth of the country in question. Nonetheless, there is open scope to adopt new technologies that consume energy more efficiently and policies for opening avenues for renewable technologies. The second hypothesis tested is the "conservation hypothesis". The evidence of unidirectional Granger-causality running from economic growth to energy consumption validates the "conservation hypothesis". If this hypothesis is supported, it implies that energy conservation policies designed to reduce energy consumption and waste may not reduce economic growth. In such case we can not only focus on the development of environmental projects that can significantly reduce climate change, and projects within the energy efficiency and renewable energy sectors but also energy consumption can be reduced through policies like carbon tax etc. The third, hypothesis is the "feedback hypothesis" which asserts that energy consumption and real output are interdependent and act as complements to each other. The existence of bidirectional Granger-causality between energy consumption and real output substantiates the feedback hypothesis. In this case, as Rothman and de Bruyn (1998) argue, economic growth itself will become a solution rather than a source of the problem. Therefore, in such case fiscal and monetary policies for boosting economic growth will be desirable options. In addition, the fourth hypothesis is the "neutrality hypothesis". The absence of Granger-causality between energy consumption and economic growth substantiates the "neutrality hypothesis". If we have evidence to accept this hypothesis, it implies that energy conservation policies may not adversely impact economic growth as energy consumption is a relatively minor factor in the factors of production of real output. In this case, therefore, every possible measure to prevent energy consumption, efficient energy utilization projects, and shifting towards non-renewable sources of energy consumption can be adopted.

In a nutshell, if the Granger causality runs from economic growth to electricity consumption or neutral causality is validated through empirical analysis, environmental policies for electricity conservation would not adversely affect economic growth. Contrary to this, if the Granger causality runs from electricity consumption to economic growth, environmental policies to conserve electricity consumption may weaken the economic growth and development. Hence, it is a debatable issue in the economics of energy and therefore, empirical re-investigation of the relationship between electricity consumption and economic growth is important.

The organization of the current study is as follows. The second section would deal with the literature review, followed by discussion on the objectives, data used, and econometric methodology in the third section. The fourth section would present the data analysis along with the empirical results. The results of the study and its policy implications are discussed in the fifth section.

LITERATURE REVIEW

We can classify the studies to date into four groups based on their findings (A summary of the review of literature in terms of country specific and cross-country studies are presented in Appendix Table 1 that includes time period studied, variables analyzed and methodology used).

The First group comprises of those studies that find unidirectional causality running from electricity or energy consumption (both aggregate and disaggregate level) to GDP. Studies worthy of mention are those by Altinay and Karagol (2005) in Turkey for the period 1950-2000, Lee and Chang (2005) in Taiwan for the period 1954-2003, Shiu and Lam (2004) in China for the period 1971-2000, and Soytas and Sari (2003) in Turkey, France, Germany and Japan, Wolde-Rufale (2004) in Shanghai for the period 1952-1999, Morimoto and Hope (2004) in Sri-Lanka for the period 1960-1998.

Second, those studies which find a unidirectional causality running from economic growth or gross domestic product to electricity or energy consumption. Studies worthy of mention are Ghosh (2002) for India during 1950-1997, Cheng (1999) in India for the period 1952-1995, Fatai et al. (2004) in New Zealand and Australia for the period 1960-

1999, Hatemi and Irandoust (2005) in Sweden for the period 1965-2000, Cheng and Lai (1997) in Taiwan for the period 1954-1993, Chang and Wong (2001) in Singapore for the period 1975-1995, and Aqeel and Butt (2001) in Pakistan for the period 1955-1996.

Third, those finding bidirectional causality. Studies worth noting are Soytas and Sari (2003) in Argentina, Oh and Lee (2004) in Korea the period 1970-1999, Yoo (2005) in Korea the period 1970-2002, Glasure (2002) in South Korea for the period 1961-1990, Jumbe (2004) in Malawi for the period 1970-1999, Ghali and El-Sakka (2004) in Canada for the period of 1961-1997, and Hwang and Gum (1992) in Taiwan for the period 1961-1990.

The fourth group comprises studies that that find no causal linkages between energy or electricity consumption and economic growth. These are Cheng (1995) in US for the period 1947-1990, Stern (1993) in USA for the period 1947-1990, Akarca and Long (1980) in US for the period 1950-1968 and 1950-1970, Yu and Hwang (1984) in US for the period 1947-1979.

A marriage of these two literatures that brings together relationship between economic growth, energy consumption and pollution emissions within a Granger causality multivariate framework is a relatively new area of research. There exist only a limited number of studies in this direction either for developed countries (for example, Ang (2007) for France; Soytas et al. (2007) for United States) or developing countries (for example, Zhang and Cheng (2009) for China; Ang (2008) for Malaysia; Halicioglu (2009) and Soytas and Sari (2009) for Turkey; Sari and Soytas (2009) for oil-rich OPEC countries). However, no such study has been done for India, to the best of my knowledge.

DATA, OBJECTIVES, AND ECONOMETRIC METHODOLOGY

DATA AND OBJECTIVES

In the present study, we have taken time series data for the period 1971-2005 from World Development Indicators (WDI) and Hand Book of Statistics of Indian economy from the official website of World Bank (WB) and Reserve Bank of India (RBI) respectively.

The interest of studying of the relationship between energy consumption, CO_2 emissions, and economic growth arises from the need to understand the complex links among the three variables. Such an understanding is basic to regulators and investors in deregulated electricity markets, in order to design a system that ensures reliability and efficiency. Hence, the purpose of our study is to investigate the direction of causal relationship among the test variables in both static and dynamic framework.

ESTIMATION METHODOLOGY

In order to know the causality among the test variables, the standard test to be used in the study is Engle-Granger approach in VECM framework. Nevertheless, this approach requires certain pre-estimations (like unit root and cointegration) without which, conclusions drawn from the estimation will not be valid. Toda (1995) has shown that pretesting for cointegration rank in Johansen-type error correction mechanisms (ECMs) are sensitive to the values of the nuisance parameters, thus causality inference based upon ECM might be severely biased. Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) propose a method of estimating a VAR for series in levels and test general restrictions on the parameter matrices even if the series are integrated or cointegrated. This method is theoretically simpler and computationally relatively straightforward in causality tests. They develop a modified version of the Granger causality test, which involves a Modified Wald (MWALD) test in an intentionally augmented VAR model. Once the optimal order of the VAR process, p, is selected, Toda and Yamamoto (TY) (1995) propose estimating a $VAR(p + d_{max})$ model where d_{max} is the maximal order of integration that we suspect might occur in the true generation process. Linear or nonlinear restrictions on the first p coefficient matrices of the model can therefore be tested using standard Wald (F-) tests ignoring the last d_{max} lagged vectors of the variables. Dolado and Lütkepohl (DL) (1996) also propose estimating an augmented VAR with the difference that they add only one lag to the true lag length of the model. The advantage of DL and TY are that they are computationally relatively simple and do not require pretesting for integration or cointegration of the data series. These tests are especially attractive when one is not sure whether series are stationary or integrated of order one. Toda and Yamamoto (1995) prove that the Wald (F-) statistic used in this setting converges to a χ^2 random variable, no matter whether the process is stationary or nonstationary. The preliminary unit root and cointegration tests are not necessary to implement the DL test, since the testing procedure is robust to the integration and cointegration properties of the process. Consider the following VAR(p) model:

$$Y_{(t)} = \gamma + A_1 Y_{(t-1)} + \ldots + A_p Y_{(t-p)} + \varepsilon_t \qquad (1)$$

where Y_t, γ, and $\varepsilon_t \sim (0,\Omega)$ are n-dimensional vector and A_k is an $n \times n$ matrix of parameters for lag k. To implement the TY test the following augmented VAR(p+d) model to be utilized for the test of causality is estimated,

$$Y_{(t)} = \hat{\gamma} + \hat{A}_1 Y_{(t-1)} + \ldots + \hat{A}_p Y_{(t-p)} + \hat{A}_{p+d} Y_{(t-p-d)} + \hat{\varepsilon}_t \tag{2}$$

where the circumflex above a variable denotes its Ordinary Least Square (OLS) estimates. The order *p* of the process is assumed to be known, and the *d* is the maximal order of integration of the variables. Since the true lag length *p* is rarely known in practice, it can be estimated by some consistent lag selection criteria. In the present study we have used SIC (preferably) and AIC. It is important to note that if the maximal order of integration is 1, TY test becomes similar to DL test. The j^{th} element of Y_t dose not Granger-cause the i^{th} element of Y_t, if the following null hypothesis is not rejected:

H_o: The row *i*, column *j* element in A_k equals zero for $k = 1, \ldots, p$.

The null hypothesis is tested by Wald (F-) test, which is named as modified Wald (MWALD) test in case of the augmented VAR outlined above. For the estimation, we used Seemingly Unrelated Regression (SUR) technique in equation (2).

In this context, we proceed as follows. First, we will follow the traditional methodology for causality i.e., Engle-Granger causality. Second, we will follow the methodology proposed by Dolado and Lütkepohl (1996) and Toda and Yamamoto (1995) to test for linear causality between Indian electricity consumption and GDP in order to check the robustness of the causality results reported by traditional Engle-Granger causality analysis.

To proceed for Granger-causality analysis, the first step is to check the stationary properties of the data series of variables. Therefore, we have carried out unit root analysis by applying three different tests: (Augmented) Dickey Fuller (hereafter, DF/ADF) test, Phillips and Perron (hereafter, PP) (1988) test and Ng and Perron (hereafter, NP) (2001) test. Two tests of Ng and Perron (2001) are said to be more powerful namely MZ(α) and MZ(t) (Mollick, 2009). Hence, in this study results of these two statistics are also reported.

After confirming that the variables used in this study are nonstationary and having same order of integration (preferably variables are integrated of order one i.e., I(1)) we preceded to test for cointegration analysis in framework of Johansen and Juselius (1990) method which employs VAR system to test for numbers of cointegration vectors. Johansen and Juselius (1990) test provides two Likelihood Ratio (LR) test statistics for cointegration analysis. First test is trace (λ_{trace}) statistics and the second one is maximum eigenvalue (λ_{max}) statistics. These tests are specified as follows:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{N} \ln(1-\hat{\lambda}_i) \tag{3}$$

and

$$\lambda \max(r, r+1) = -T \ln(1-\hat{\lambda}_{r+1}) \tag{4}$$

where r is the number of cointegrating vectors under the null hypothesis and $\hat{\lambda}_i$ is the estimated value for the i^{th} ordered eigenvalue from the matrix Π. The trace statistics tests the null hypothesis that the number of cointegrating relations is r against of k cointegration relations, where k is the number of endogenous variables. The maximum eigenvalue test examines the null hypothesis that there are r-cointegrating vectors against an alternative of $r+1$ cointegrating vectors. To determine the rank of matrix Π, the test values obtained from the two test statistics are compared with the critical value from Mackinnon-Haug-Michelis (1999). For both tests, if the test statistic value is greater than the critical value, the null hypothesis of r cointegrating vectors is rejected in favor of the corresponding alternative hypothesis.

After confirming the cointegrating relationship among the test variables, we proceed to carry out VEC modeling analysis. This will enable us to understand the direction of causality among the same set of variables those are used in testing of number of cointegration vectors, as cointegration alone does not talk about the direction of causality and shows only if the long run test variables are in equilibrium. However, VECM not only gives the direction of causality amongst some set of variable but also explains about short run and long run Granger-causality. The long run causal relationship is explained through the significance of (using t-test) lagged error correction term and the short run causal relationship is explained through first difference of explanatory variables. The Granger (1969) approach to the question of whether X causes Y is to determine how much of the current Y can be explained by past values of Y, and then to see whether adding lagged values of X can improve the explanation. Y is said to be Granger-caused by X if X helps in the prediction of Y, or if the coefficients on the lagged Xs are statistically significant. For the two variable case say, variable X and Y the Granger-causality test in VECM framework is estimated with the following equations, provided X and Y are integrated of order one i.e., I(1) and cointegrated:

$$\Delta X_t = \alpha_x + \sum_{i=1}^{k} \beta_{x,i} \Delta X_{t-i} + \sum_{i=1}^{k} \gamma_{x,i} \Delta Y_{t-i} + \varphi_x ECT_{x,t-i} + \varepsilon_{x,t} \tag{5}$$

$$\Delta Y_t = \alpha_y + \sum_{i=1}^{k} \beta_{y,i} \Delta Y_{t-i} + \sum_{i=1}^{k} \gamma_{y,i} \Delta X_{t-i} + \varphi_y ECT_{y,t-i} + \varepsilon_{y,t} \tag{6}$$

where, φ_x and φ_y are the parameters of the ECT term, measuring the error correction mechanism that drives the X_t and Y_t back to their long run equilibrium relationship.

The null hypothesis (H_0) for the equation (5) is $H_0: \sum_i^k \gamma_{x,i} = 0$ suggesting that the lagged terms ΔY do not belong to the regression i.e., it do not Granger cause ΔX. Conversely, the null hypothesis (H_0) for the equation (6) is $H_0: \sum_i^k \gamma_{y,i} = 0$, suggesting that the lagged terms ΔX do not belong to regression i.e., it do not Granger cause ΔY. The joint test of these null hypotheses can be tested by either F-test or Wald Chi-square (χ^2) test.

If the coefficients of $\gamma_{x,i}$ are statistically significant, but $\gamma_{y,i}$ are not statistically significant, then X is said to have been caused by Y (unidirectional). The reverse causality holds if coefficients of $\gamma_{y,i}$ are statistically significant while $\gamma_{x,i}$ are not. However, if both $\gamma_{y,i}$ and $\gamma_{x,i}$ are statistically significant, then causality runs both ways (bidirectional). Independence is identified when the $\gamma_{x,i}$ and $\gamma_{y,i}$ coefficients are not statistically significant in both the regressions.

The statistical (non) significance of the F-tests applied to the joint significance of the sum of the lags of each explanatory variable and/or the t-test of the lagged error-correction term(s) will indicate the econometric (exogenity) endogenity of the dependent variable (or Granger causality). The F-tests of the 'differenced' explanatory variables give us an indication of the 'short-term' causal effects of the variables. On the other hand, the significance of the lagged error-correction term(s) will indicate the 'long-term' causal relationship.[6] The coefficient of the lagged error-correction term, however, is a short-term adjustment coefficient and represents the proportion by which the long-term disequilibrium (or imbalance) in the dependent variable is being corrected in each short period. The non-significance or elimination of any of the lagged error-correction terms affects the implied long-term relationship and may be a violation of theory. The non-significance of any of the 'differenced' variables which reflects only the short-term

[6] The lagged error-correction term contains the log-run information, since it is derived from the long-term cointegration relationship(s). Weak exogenity of the variable refers to ECM-dependence, i.e., dependence upon stochastic trend.

relationship, does not involve such a violation because, the theory typically has nothing to say about short-term relationships.

Diagnostic checks have been performed on the models used for VECM to examine if the stochastic properties of the model viz., residuals autocorrelation, heteroskedasticity, and normality, and to check if any lag is excluded from the model for any variable. This is because if the model is stochastic, then further analysis based on the model would be possible and the inferences drawn from the VEC modelling would be unbiased. For testing the presence of autocorrelation/serial correlation, this study has used Lagrange Multiplier (LM) test, which is a multivariate test statistic for autocorrelation in residuals up to the specified lag order. Harris (1995: 82) mentioned that lag order for this test should be same as that of the corresponding VAR or the lag order used in VECM. The null hypothesis of LM test is absence of serial correlation against the alternative of autocorrelated residuals.

To test the presence of heteroskedasticity, this study uses the White heteroskedasticity test. The null hypothesis of White heteroskedasticity takes errors to be homoskedastic (no heteroskedasticity and independent of the regressors) and absence of model misspecification. If any one of these conditions is not satisfied, the White heteroskedasticity test will turn out to be significant, in most of the cases.

For testing the normality of residuals, the multivariate extension of Jarque-Bera (JB) normality test has been used, which compares third and fourth moments of the residuals to those from the normal distribution. In the present study, Urzua's (1997) method of residual factorization (orthogonalization) has been preferred for testing the normality of residuals in order to check the specification of the VEC model which provides the J-B test statistic. This is because it makes a small sample correction to the transformed residuals before computing JB test as sample elicit size of the present study is small. The null hypothesis in this test is that residuals would follow a normal distribution. Finally, the Wald lag exclusion test has been performed to analyze the possibility of lag exclusion of any variable in VAR system.

Finally, tests for the stability of VECM analysis have been performed, for validating the the conclusions drawn from the above system, If the estimated VECM is stable, then the inverse roots of characteristics Autoregressive (AR) polynomial will have modulus less than one and lie inside the unit circle.

Since F-test and t-test in VECM only indicate the Granger-exogenity or endogenity of the dependent variable within period under consideration (Masih and Masih, 1996), for the purpose of analysis the dynamic properties of the system the forecast error Variance Decompositions (VDs) and Impulse Response Functions (IRFs) are computed.

Impulse response analysis traces out the responsiveness of the dependent variable in VAR to shocks to each of the other explanatory variables over a period of time (10 years in the presented study). A shock to a variable in a VAR not only directly affects that variable, but also transmits its effect to all other endogenous variables in the system through the dynamic structure of VAR.

There are several ways of performing IRFs but generalized approach has been preferred over Choleskey orthogonalization approach or other orthogonalization approaches for the present study because it is invariant of ordering of the variables, as results of IRFs are sensitive to the ordering of the variables.

Variance decomposition measures the proportions of forecast error variance in a variable that is explained by innovations (impulses) in it and by the other variables in the system. For example, it explains what proportions of the changes in a particular variable can be attributed to changes in the other lagged explanatory variables.

DATA ANALYSIS AND RESULTS INTERPRETATION

DESCRIPTIVE ANALYSIS

Summary statistics of the variables are presented in Table 2.

Table 2: Descriptive statistical analysis

Variables	Ln(CO_2PC)	Ln(ECPC)	Ln(GDPPC)
Mean	-0.339	5.430	7.133
Median	-0.304	5.492	7.093
Maximum	0.247	6.164	7.768
Minimum	-1.008	4.596	6.735
Std. Dev.	0.407	0.519	0.309
Skewness	-0.175	-0.185	0.445
Kurtosis	1.671	1.575	1.959
Jarque-Bera	2.753	3.159	2.734
(Probability)	(0.25)	(0.20)	(0.25)

Note: CO_2PC denotes CO_2 emissions per capita; ECPC denotes electricity consumption per capita; GDPPC denotes Gross domestic product per capita and Ln denotes natural log transformation of the series.
Source: Author's calculation

It is evident from Table 2 that SD of electricity consumption is highest and that of GDP is the lowest. Mean value of CO_2 emissions is negative while for other variables it is positive. The J-B statistics shows that all variables used in the analysis have a log normal distribution.

UNIT ROOT, COINTEGRATION, GRANGER-CAUSALITY ANALYSIS IN STATIC FRAME WORK (USING VECM AND DOLADO AND LÜTKEPOHL'S APPROACH) AND DYNAMIC FRAMEWORK (USING IRFS AND VDS)

First, we plot graphs of all variables under consideration (figures are present in Appendix 1). Thereafter, unit root test is carried out using (Augmented) Dickey-Fuller test (ADF/DF), Phillips-Perron (PP) test and Ng and Perron (NP) test basing upon the figure suggest the type of the model to be used. Results of the unit roots are reported in Table 3.

Table 3: Unit root analysis

Variables	Unit root tests					
	Constant	Constant and trend	DF/ADF (K)	PP (k)	NP	
					(MZa) (k)	(MZt) (k)
Ln(CO_2PC)	-	Yes	-1.464 (0)	-1.295 (1)	-5.981 (0)	-1.560(0)
D(Ln(CO_2PC))	Yes	-	-7.078* (0)	-7.073* (1)	-18.46* (0)	-3.038* (0)
Ln(GDPPC)	-	Yes	-1.483 (0)	-1.314 (1)	-1.979 (0)	-0.661 (0)
D(Ln(GDPPC))	Yes	-	-6.314* (0)	-6.294* (3)	-11.35** (0)	-2.218** (0)
Ln(ECPC)	-	Yes	-1.287 (3)	-0.806 (3)	-17.11 (3)	-2.842 (3)
D(Ln(ECPC))	Yes	-	-4.160* (0)	-4.203* (3)	-15.62* (0)	-2.794* (0)

Note: (1) CO_2PC denotes CO_2 emissions per capita; ECPC denotes electricity consumption per capita; GDPPC denotes Gross domestic product per capita and Ln denotes natural log transformation of the series. (2) *denotes significant at 1% level, **denotes significant at 5% level. (3) "K" Denotes lag length and "D" denotes first difference. (4) Selection of lag length in NP test is based on Spectral GLS-detrended AR based on SIC and selection of lag length (Bandwidth) and in PP test it is based on Newey-West using Bartlett kernel.
Source: Author's calculation

It is evident from Table 3 that all variables are nonstationary in their level form and they are turning to be stationary after first difference i.e., (I). Since all variable are (I) therefore we can proceed for cointegration analysis. To proceed for cointegration, the first step is the selection of appropriate lag length.[7] Therefore, we have carried out a joint test

[7] Since JJ test is sensitive to lag-length chosen for the analysis. When the order of VAR i.e., lag-length is too short, problem of serial correlation among the residuals arises and test statistic will become unreliable. Conversely, if lag length (order of VAR) is too high there will be an upward bias in the test statistics, again causing doubts on the reliability of the estimates of parameters. Therefore, it is very important to choose appropriate lag-length in VEC modelling. For this purpose, we conducted lag-length selection test, based on VAR analysis. There are five lag-length selection criteria's namely, Likelihood

of lag length selection, which suggests (basing upon SIC) taking one lag of each variable. However, when we have proceeded with lag length and model as suggested by SIC and VECM analysis has been carried out, we found specification of VECM models to be incorrect by performing diagnostic checks.[8] Then we have chosen lag intervals (1, 3) (as suggested by AIC FPE, and HQIC) and then a joint test[9] for cointegrating vector and model selection has been performed. Further, by choosing model 4[10], and lag interval (1, 3) we have carried out JJ cointegration test. Results of cointegration test are reported in the following Table 4.

Table 4: Cointegration test

Cointegration test

[Trend assumption: Linear deterministic trend (restricted) Lags interval (in first differences): 1 to 3]

Unrestricted Cointegration Rank Test (Trace)

H_0	H_a	Eigenvalue	Trace Statistic	5% Critical Value	Prob.**
None*	At most 1	0.595	45.56	42.91	0.02
At most 1	At most 2	0.348	17.54	25.87	0.37
At most 2	At most 3	0.128	4.258	12.517	0.70

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

H_o	H_a	Eigenvalue	Max-Eigen Statistic	5% Critical Value	Prob.**
None *	At most 1	0.595	28.02	25.82	0.02
At most 1	At most 2	0.348	13.28	19.38	0.30
At most 2	At most 3	0.128	4.258	12.51	0.70

Note: * denotes rejection of the hypothesis at the 0.05 level and **MacKinnon-Haug-Michelis (1999) p-values
Source: Author's calculation

Ratio (LR), Final Prediction Error (FPE), Akaike Information Criteria (AIC), Schwarz Information Criteria (SIC), and Hannan-Quinn Information Criteria (HQIC). However, for analyses this study has employed in all models SIC, because it performed well in Monte Carlo studies (Kennedy, 2003: 117).

[8] We used Wald test for lag exclusion, JB test for normality analysis, White heteroskedastic test to test for problem of heteroskedasticity and LM test for checking problem of serial correlation. Results of all these analysis can be obtained upon request to the authors.

[9] The JJ test is found to be sensitive to the choice of deterministic assumptions used in testing the cointegration. There are five models of VARs based on different assumptions. Model.1 assumes no deterministic trend in data and no intercept or trend in the VAR and in the cointegrating equation. Model.2 assumes no deterministic trend in the data but an intercept in the cointegrating equation, and no intercept in VAR. Model.3 assumes a linear trend in the data, an intercept in cointegrating equation. Model.4 assume a linear deterministic trend in the data, intercept and trend in cointegrating equation, and no trend in VAR. Model.5 assumes a quadratic deterministic trend in the data, intercept and trend in VAR, and linear trend in VAR. Johansen (1991) suggested to choose right model we should test the joint hypothesis of the rank order and the deterministic components. This test is known as Pantula Principal. As we are not very sure that in data used in this study, whether deterministic trend is present and VAR also has linear trend or not we have carried out joint test for all five models. That model chosen which minimizes the value of SIC and in case if it is found that two models are giving the minimum value of SIC, the better (theoretically appropriate) has been chosen which minimizes the value of SIC of VEC modelling.

[10] It should be noted that joint test of model selection and cointegrating vector shows that model 5 is appropriate (basing upon SIC and AIC) for analysis. However, model 1 and model 5 has been said to be theoretically inappropriate therefore, we have preferred the model in which we have obtained minimum value of SIC and AIC i.e., model 4.

It is evident from the Table 4 that both Trace and Eigenvalue criteria reject the null hypothesis of none cointegrating vector against the alternative of at most one cointegrating vectors.

In the next step, the use of lag interval (1, 3), model 4 and one cointegrating error term VECM analysis has been carried out and then the Engle-Granger causality analysis has been performed on those results. Results of Engel-Granger causality analysis are reported below in Table 5.

Table 5: VECM Engle-Granger causality analysis

	VEC Granger Causality Short Run (Wald test/$\chi2$)		
	D(Ln(GDPPC))	**D(Ln(CO2PC))**	**D(Ln(ECPC))**
D(Ln(GDPPC))	-	4.136	2.664
D(Ln(CO2PC))	9.460**	-	9.485**
D(Ln(ECPC))	2.343	13.156*	-
	VEC Granger Causality Long Run		
	.019	-.023**	-.014
CointEq (-1)	(.014)	(.011)	(.012)

Note: (1) CO2PC denotes CO2 emissions per capita; ECPC denotes electricity consumption per capita; GDPPC denotes Gross domestic product per capita and Ln denotes natural log transformation of the series. (2) *, **and ***denotes significant at 1%, 5%, and 10% level respectively; (3) "K" Denotes lag length and "D" denotes first difference.

Source: Author's calculation

It is evident from Table 5 that CO_2 Granger-causes GDP while electricity consumption does not Granger-causes GDP in short run. It is interesting to note that GDP does not Granger-causes CO_2 while electricity consumption Granger-causes CO_2 emissions in the short run. Further CO_2 emissions also found to Granger-cause electricity consumption but GDP does not found to Granger-cause CO_2 emissions in short run.

In the long run, it is found that cointegrating vector of CO_2 equation of VECM is significant. This implies that GDP, CO_2, and electricity consumption Granger-cause CO_2 emissions in the long run.

Next, we have performed diagnostic checks for VECM and the results are reported below in Table 6.

It is evident from Table 6 that the specification of VECM is correct, as no test rejects the null hypothesis. Finally, we have carried out VECM stability test and result is given in Table 7. It is evident from the table that the moduli of all roots are less than unity and lie within the unit circle. So, the estimated VECM is stable or stationary.

Table 6: Diagnostic checks analysis

VEC Lag Exclusion Wald Tests (Chi-squared test statistics for lag exclusion) for Dlag 3 (Joint test)		P-Value
	14.26	[0.113]
VEC Residual Serial Correlation LM Tests		
1lag	7.619	0.57
2lag	6.753	0.66
3lag	11.57	0.23
VEC Residual Normality Tests-Joint J-B test (Orthogonalization: Residual Covariance (Urzua)		
	24.52	0.48
VEC Residual Heteroskedasticity Tests (Joint test of Chi- square)		
	121.88	0.43

Note: (1)*, **and ***denotes significant at 1%, 5%, and 10% level respectively.
Source: Author's calculation

Table 7: VECM stability analysis

Roots of Characteristic Polynomial and Lag specification (1, 3) Endogenous variables: Ln(CO_2PC), Ln(ECPC) and Ln(GDPPC)	
Root	**Modulus**
1.000	1.000
1.000	1.000
0.982	0.982
-0.500 - 0.67i	0.843
-0.500 + 0.67i	0.843
0.309 - 0.712i	0.776
0.309 + 0.712i	0.776
-0.590 - 0.052i	0.592
-0.590 + 0.052i	0.592
0.501	0.501
0.016 - 0.184i	0.185
0.016 + 0.184i	0.185

Note: (1) CO_2PC denotes CO_2 emissions per capita; ECPC denotes electricity consumption per capita; GDPPC denotes Gross domestic product per capita and Ln denotes natural log transformation of the series. (2) The VECM specification imposes 2 unit moduli
Source: Author's calculation

Since VECM has performed well in the diagnostic checks, we conclude that it is stable which allows us to proceed for IRFs and VDs analysis. A graph of IRFs has been drawn and named Figure 2.

Figure 2: IRFs analysis- Response to Generalized One S.D. Innovation

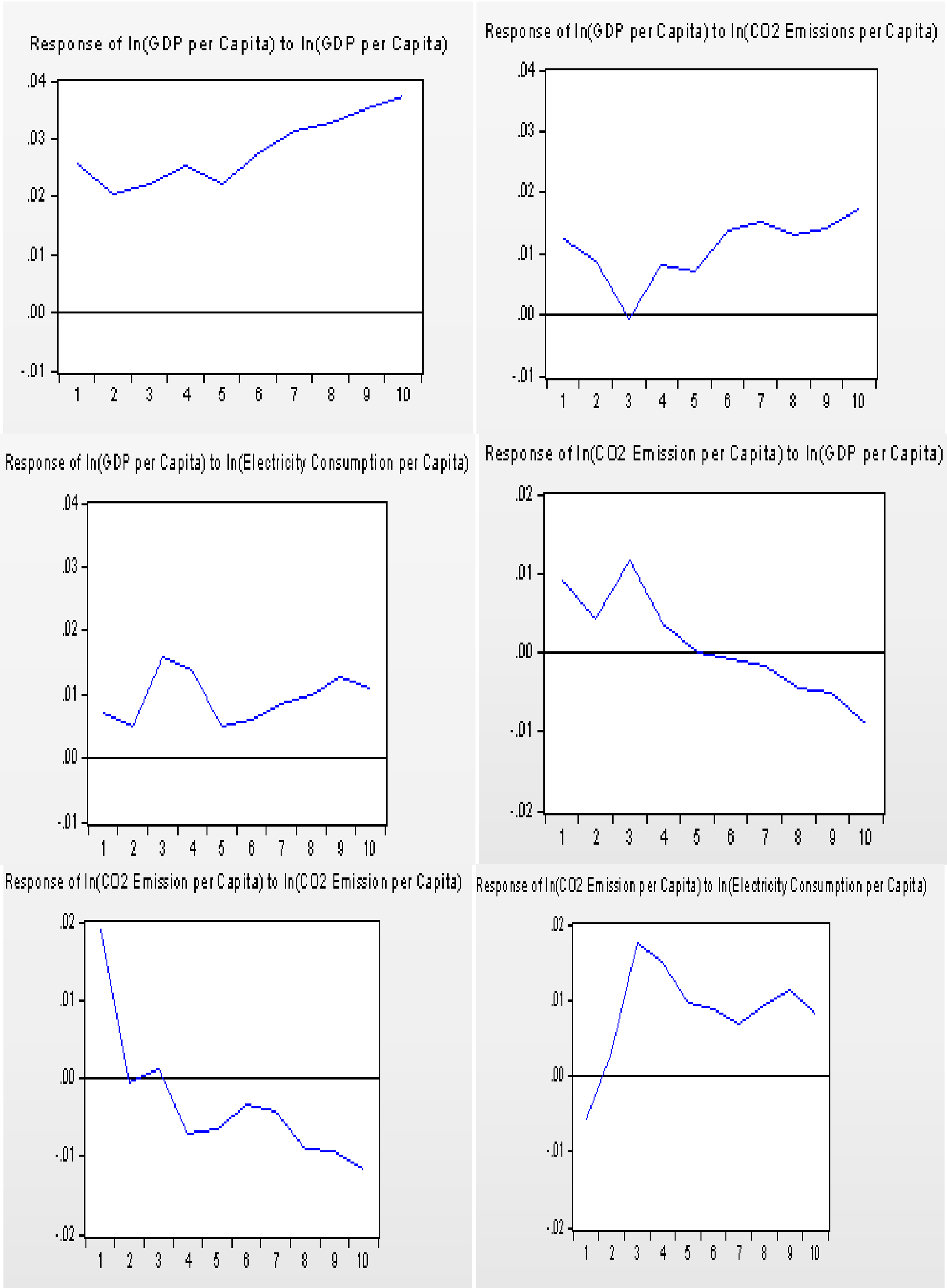
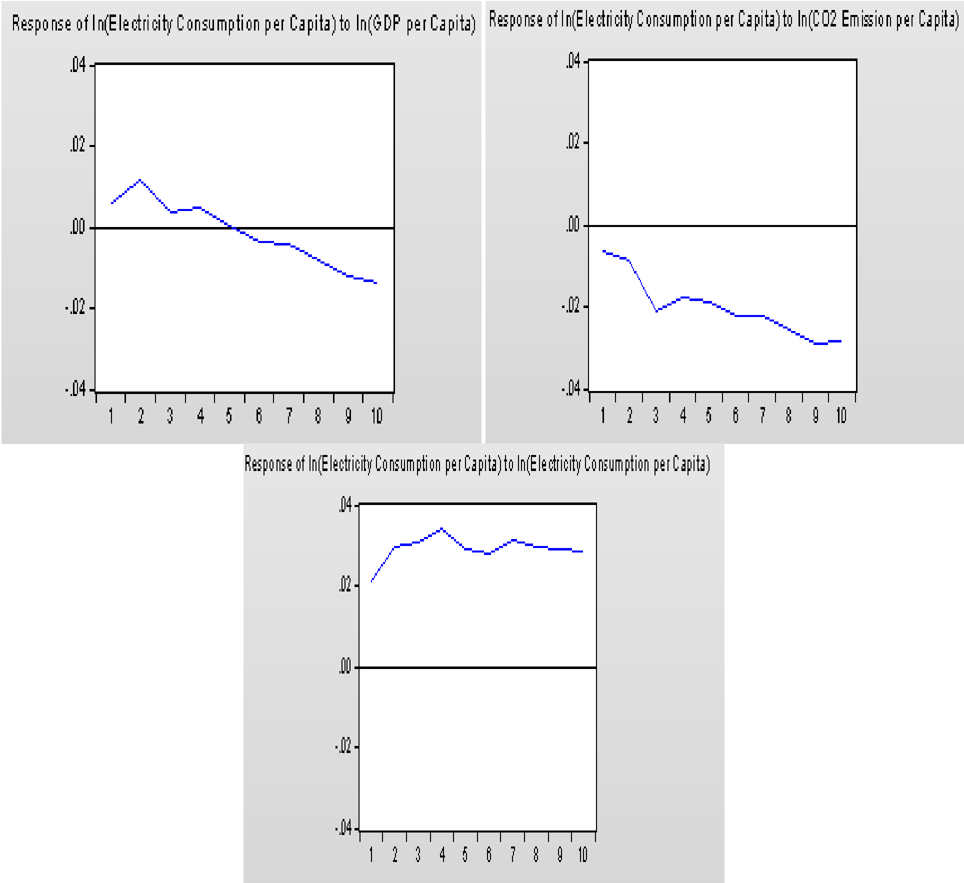


Figure 2: IRFs analysis- Response to Generalized One S.D. Innovation (continue)



It is evident from the figure that in one SD shock/innovation in GDP and electricity consumption, GDP increases throughout the 10 years and effect is positive. In CO_2, GDP first decreases towards zero percentage response line and after just touching it in 3th year GDP increase with marginal fluctuations.

One SD shock/innovation in GDP decreases CO_2 through 10 years, which crosses the zero percentage response line in the 5th year. Similar result holds good for the one SD shock/innovation in its value. In one SD shock in electricity consumption CO_2 emissions increase up to 3rd year; subsequently its impact decreases but remains highly positive.

One SD shock/innovation in GDP decreases electricity consumption throughout the 10 years and touches the zero percentage response line in the 5th year. One SD shock/innovation in CO_2 emissions decreases electricity consumption, it remains negative throughout the 10 years, and its severity increases over years. However one SD shock/innovation in its value increases the electricity consumption marginally over period of time and it is positive throughout the 10 years. One can find similar results by analyzing the results of VDs. Results are reported in Table 2A in Appendix.

DOLADO AND LÜTKEPOHL'S APPROACH

Further, to check the robustness of the Granger-causality analysis of VECM approach, we have adopted Dolado and Lütkepohl's (DL) approach. This approach does not require pretesting of the stationary and cointegration properties of the variable; however, it requires the pre-idea of integration. As it is unknown. we have carried out lag length selection test for VAR. The AIC, FPE and HQIC suggest lag a of 3. Therefore, as per the DL methodology we have carried out VAR estimation analysis using 4 (=3+1) lag into VAR model in the SUR framework and to carry out Granger-causality analysis for VAR model fourth lag has been removed and then joint test has been performed. The results of Granger-causality analysis are presented below in Table 8.

Table 8: Granger-causality analysis

VAR Granger Causality (Modified Wald test/χ^2)			
	Ln(GDPPC)	**Ln(CO_2PC)**	**Ln(ECPC)**
Ln(GDPPC)	-	0.805	4.170
Ln(CO_2PC)	8.427**	-	8.187**
Ln(ECPC)	2.018	19.462*	-

Note: (1) CO_2PC denotes CO_2 emissions per capita; ECPC denotes electricity consumption per capita; GDPPC denotes Gross domestic product per capita and Ln denotes natural log transformation of the series. (2)*, **and ***denotes significant at 1%, 5%, and 10% level respectively; (3) 'D" denotes first difference.
Source: Author's calculation

It is evident from Table 8 that CO_2 Granger-causes GDP while electricity consumption does not Granger-causes GDP, GDP does not Granger-causes CO_2 while electricity consumption Granger-causes CO_2 emissions, and CO_2 emissions Granger-causes electricity consumption but GDP does not Granger-causes CO_2 emissions. These results are similar to the Granger-causality following VECM approach. This implies that results reported for Granger-causality analysis following VECM approach are robust. However, the present study yields mixed and contradictory result in the Indian context (for example, Masih and Masih (1996, 1997) found a bi-directional causality and Paul and Bhattacharya (2004) from the standard Granger causality test found that energy consumption leads to economic growth). This puts a big question to policy makers as to judge whether the country should conserve energy or consume more energy for achieving higher growth rate in the economy.

CONCLUSIONS, DISCUSSION POLICY IMPLICATIONS AND LIMITATIONS

This study examined the linkage among energy consumption, environmental degradation, and economic growth in India. The relationship was examined using Granger causality (using VECM approach and DL approach) test (in static causality analysis) as well as Variance Decomposition (VDs) and Impulse Response Functions (IRFs) analysis (in dynamic causality analysis). The result from the application of Granger causality test supported the fourth hypothesis i.e., the "neutrality hypothesis", as study found the absence of Granger-causality between energy consumption and economic growth. Hence, it implies that energy conservation policies may not adversely affect economic growth as energy consumption is a relatively minor factor among the factors of production in real output. However, the study found that environmental degradation (i.e., CO_2 emissions) Granger causes economic growth in the long-run. This finding is consistent with emissions occurring in the production process and reflects the experience of many industrializing countries and, of course, of the developing countries. However, this does not imply that environmental degradation is an appropriate course to promote economic growth. Rather, the focus of the policymakers should be on sustainability, which suggests that social welfare rather than per capita income should be the focus of government policies. Hence, the focus of policy makers should be on *green growth* than otherwise, as *green growth* has important policy implications for GDP growth. *Green growth* positively affects GDP growth both directly and indirectly (particularly through investment in Research and Development (R&D) activities and technology spillover).[11] Further, *green growth* increases life satisfaction (longevity of life), maximizes social welfare, and brings sustainability in the economic growth process. There are a number of studies which suggest that environmental degradation, including air and noise pollution, had a negative impact on life satisfaction in one hand (Ferrer-i-Carbonell and Gowdy, 2007; Di Tella and MacCulloch, 2008; Van Praag and Baarsma, 2005; Welsch, 2002, 2006; Rehdanz and

[11] Investments into research and development and the follow-up dissemination of innovative products and services have a wide-ranging effect not only on the eco-industry but on regional development issues, for example the enhancement of tourism, the development of the countryside, the halting of depopulation of rural areas, nature protection, the development of the countryside, etc.

Maddison, 2008; Smyth et al., 2008). On the other hand, a persistent decline in environmental quality may generate negative externalities for the economy through reducing health human capital and, hence, productivity in the long-run (Ang, 2008). Given the fact that energy consumption does not fuel GDP but CO_2 emissions, the energy policy in the country should be conservative because energy consumption does not contribute to the growth of the economy on the one hand while increasing CO_2 emissions on the other. Since, the government incurs large amount of expenditure in importing and distributing energies at the subsidized rates, it has substantial implications for maintaining a sound macroeconomic environment.. A limited use of energies can keep the environment clean and and the macro economy stable. Therefore, there should be an effort to exploit the renewable sources of energy for consumption and production purposes, which would economize the use of these natural resources in the economy. Otherwise, given the continued economic growth, there would be more demand for these sources of energy resulting in escalation of prices and macroeconomic imbalances.

Since, variance decomposition analysis suggests that there could be two-way causality between electricity energy consumption and economic growth in the future, the study provides a mixed and contradictory evidence on the relationship between energy consumption and GDP growth rate as compared to the previous studies carried out in the Indian context. Further, in such a situation, the Indian government can utilize the benefits from the environmental technology companies that are key players in the development and dissemination of clean technologies, efficient consumption of energy and thus contribute to the reduction of pressures on the environment as well. In this way, the Indian economy can establish synergies between the economy, the environment, employment, and poverty reduction. Further, efforts towards the development of environmental technology can create new products and services, which would contribute to the improvement of companies' competitiveness. They would create jobs, new skills, possibilities for improved education and vocational training. There are key areas of eco-innovation with strategic relevance for the India, such as sustainable and safe low-carbon technologies, renewable energies, and energy and resource efficiency.

Besides the policy measures mentioned above, two policy instruments - domestic carbon taxes and internationally tradable emissions permits - can bring substantial benefits for the Indian economy vis-à-vis command-and-control measures.[12] In this context, Murthy, Panda and Parikh (2000) have shown, using an activity analysis framework, that India stands to gain both in terms of GDP and poverty reduction, if the emissions permits are allocated on the basis of equal per capita emissions. Fischer-Vanden et al. (1997) have used a CGE model to compare the impacts of the two policy instruments on GDP, and found that tradable permits are preferable to carbon taxes. However, the CGE model of Fischer-Vanden et al. (1997) is based on the assumption of a single representative household and therefore, it does not reflect the impact of carbon taxes on income distribution or on the poverty ratio. In addition, through the use of a market-based instrument like carbon taxes, the government can use the tax revenues in a variety of ways to generate benefits for the economy, besides those emerging from reduced emissions. This would enable a reduction in the net loss in welfare. Further, carbon tax can be used to replace other distorting taxes; or the tax revenue generated from carbon tax could be used for targeted transfers for reducing poverty, or more specifically, recycling the carbon tax revenue into the low-income groups for compensating the latter for the burden imposed on them by the carbon emissions reduction strategy.

One of the limitations of this study is that we have carried out analysis at aggregate level data. Since, different industries have different intensities of electricity, it would have been more appropriate to do analysis at a disaggregate level for geting more insights that would enable better policy decisions.Second, this study uses electricity consumption as a proxy for energy consumption and CO_2 emissions as a proxy for environmental degradation. Future studies that use other proxies for energy consumption and environmental degradation may provide further insight regarding the link between environmental degradation, energy consumption, and economic growth. A third direction for future research would be to examine the causal relationship between economic growth, pollution emissions, and other potentially relevant variables such as automobile use, health expenditure, and urbanization. This could be extended to consider the relationship between economic growth, health expenditure, and alternative forms of pollution emissions within a multivariate Granger causality setting. A Fourth direction would be to consider for structural breaks and carry out causality analysis as if structural breaks exist.

[12] The command-and-control measure, i.e., enforcing carbon emission reduction targets by fiat is not regarded in India as feasible. This is because firstly, there are the usual arguments of command-and-control measures being statically and dynamically inefficient as compared to say market-based instruments, such as, carbon taxes (Pearson, 2000) and secondly, under the command and-control measure, the economic cost of emission abatement (arising mainly due to curtailment of output, given limited input substitution possibilities) represents a deadweight loss in welfare.

Finally and most importantly, the direction for future research would be to carry out non-linear Granger-causality analysis to check the robustness of the present linear causality results

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APPENDIX

Table A1: Summary of Literature on Relationship between Electricity Consumption and Economic Growth

Authors	Time Period	Method-ology	Variables	Cointegr-ation	Findings (country studied)
			Single-Country Studies		
Yang (2000)	1954-1997	GC	Real GDP and Electricity Consumption	No	EC $\leftrightarrow$ Y (Taiwan)
Aqeel and Butt (2001)	1955-1996	GC by Hsiao	Real GDP and Electricity Consumption	No	EC $\rightarrow$ Y(Pakistan)
Ghosh (2002)	1950-1997	JML, GC	Electricity Supply, Employment and Real GDP	Yes	ES $\leftarrow$ Y(India)
Jumbe (2004)	1970-1999	GC,	Real GDP and Electricity Consumption	Yes	EC $\leftarrow$ Y(Malawi)
Shiu and Lam (2004)	1971-2000	JML, VECM	Real GDP and Electricity Consumption	Yes	EC $\rightarrow$ Y(China)
Lee and Chang (2005)	1954-2003	JML, VECM	Real GDP per Capita and Electricity Consumption per Capita	Yes	EC $\rightarrow$ Y(Taiwan)
Narayan and Smyth (2005)	1966-1999	ARDL, VECM	Real GDP per Capita, Electricity Consumption per Capita and Employment	Yes	EC $\leftarrow$ Y(Australia)
Yoo (2005)	1970-2002	JML, VECM	Real GDP and Electricity Consumption	Yes	EC $\rightarrow$ Y(Korea)
Yoo and Kim (2006)	1971-2002	JML, GC by Hsiao	Real GDP and Electricity Supply	No	ES $\leftarrow$ Y(Indonesia)
Ho and Siu (2006)	1966-2002	JML, VECM	Real GDP and Electricity Consumption	Yes	EC $\rightarrow$ Y(Hong Kong)
Altinay and Karagol (2005)	1950-2005	GCDL	Real GDP and Electricity Consumption	N.A	EC $\rightarrow$ Y(Turkey)
Yusof and Latif (2007)	1980-2006	MJL, GC	Real GDP and Electricity Consumption	Yes	$EC \nleftrightarrow Y$ (Malaysia)
Yaun et al. (2007)	1978-2004	JML, VECM	Real GDP and Electricity Consumption	Yes	EC $\rightarrow$ Y(China)
Mozumder and Marathe (2007)	1971-1999	JML, VECM	Real GDP per Capita, Electricity Consumption per Capita	Yes	EC $\leftarrow$ Y(Bangladesh)
Narayan and Singh (2007)	1971-2002	ARDL, VECM	Real GDP, Electricity Consumption and Labor	Yes	EC $\rightarrow$ Y(Fiji Islands)
Zachariadis and Pashourtidou (2007)	1960-2004	JML, VECM, VARGFEVD	Real Income per Capita, Electricity Consumption, pricesand weather	Yes	EC $\leftrightarrow$ Y(Cyprus)
Tang	1972-	ARDL,	Gross National Productand	No	EC $\leftrightarrow$ Y(Malaysia)

Authors	Time Period	Method-ology	Variables	Cointegr-ation	Findings (country studied)
(2008)	2003	TYDL	Electricity Consumption		
Aktas and Yilmaz (2008)	1970-2004	JML, VECM	Gross National Product and Electricity Consumption	No	EC $\leftrightarrow$ Y(Turkey)
Abosedra et al. (2009)	1995-2005	MJL, GC, VARGF EVD	Real GDP, Electricity Consumption, Real Imports, Temperature and humidity	No	EC $\rightarrow$ Y(Lebanon)
Odhiambo (2009a)	1971-2006	JML, VECM	Real GDP per Capita and Electricity Consumption per Capita, Employment	Yes	EC $\leftrightarrow$ Y(South Africa)
Odhiambo (2009b)	1971-2006	ARDL, VECM	Real GDP per Capita and Electricity Consumption per Capita	Yes	EC $\rightarrow$ Y(Tanzania)
Lean and Smyth (2010)	1971-2006	TYDL	Real GDP, Electricity Consumption, Exports, Capita and Labor	Yes	EC $\leftrightarrow$ Y(Malaysia)
Ciarreta and Zarraga (2010)	1971-2005	TYDL	Real GDP and Electricity Consumption	N.A	EC $\leftarrow$ Y (Spain)
Lorde et al. (2010)	1960-2004	JML, VECM	Real GDP, Electricity Consumption, Capital, Labor and Technology	Yes	EC $\leftrightarrow$ Y(Barbados)
Acaravci (2010)	1968-2005	JML, VECM	Real GDP and Electricity Consumption	Existed	EC $\rightarrow$ Y(Turkey)
Chandran et al. (2010)	1971-2003	ARDL, VECM	Electricity consumption, Real GDP and Prices	Yes	EC $\rightarrow$ Y(Malaysia)
Jamil and Ahmad (2010)	1960-2008	JML, VECM, VARGF EVD	Industrial Production, Electricity Consumption and Electricity Prices	Yes	EC $\leftarrow$ Y(Pakistan)
Ouédraogo (2010)	1968-2003	ARDL, VECM	Real GDP, Electricity Consumption and Capital Formation	Yes	EC $\leftrightarrow$ Y(Burkina Faso)
Tiwari (2010)	1971-2006	JJ, GC-TYDL	Electricity consumption and Employment	NA	EC $\leftrightarrow$ Y(India)
Shahbaz et al. (2011)	1971-2009	ARDL, GC-VECM	Electricity consumption, economic growth, and employment	Yes	EC $\leftrightarrow$ Y(Portugal)
Tiwari (2011)	1971-2007	JJ, GC-VAR	Real GDP per capita, Electricity consumption, CO2 emission, Labor and Capital	No	*EC* $\nleftrightarrow$ *Y* (India)
			Multi-Country Studies		
Wolde-Rufael (2006)	1971–2001	ARDL, GC-TYDL	Economic growth, Energy consumption, CO_2 emission, Labor and Capital		EC $\rightarrow$ Y (Benin, CongoDR,Tunisia) Y $\rightarrow$ EC (Cameroon, Ghana,Nigeria, Senegal, Zambia,Zimbabwe)

Authors	Time Period	Method-ology	Variables	Cointegr-ation	Findings (country studied)
					$EC \leftrightarrow Y$ (Egypt, Gabon,Morocco)
					$\boldsymbol{EC \nleftrightarrow Y}$ (Algeria, CongoRep.,Kenya, South Africa,Sudan)
Yoo (2006)	1971-2002	JML, GC Hsiao	Real GDP per Capita and Electricity Consumption per Capita	No	$EC \leftarrow Y$(Indonesia and Thailand)
				No	$EC \leftrightarrow Y$(Singapore and Malaysia)
Squalli and Wilson (2006)	1980-2003	ARDL, TYMWT	Real GDPandElectricity Consumption	Yes	$EC \leftrightarrow Y$(Bahrain, Qatar and KSA)
				Yes	$EC \leftarrow Y$(Kuwait and Oman)
				Yes	$\boldsymbol{EC \nleftrightarrow Y}$ (USA)
Chen et al. (2007)	1971-2001	JML, GC (Yoo, 2005)	Real GDP and Electricity Consumption	Yes	$\boldsymbol{EC \nleftrightarrow Y}$ (China)
				Yes	$EC \leftarrow Y$(Hong Kong, Korea)
				Yes	$EC \rightarrow Y$(Indonesia)
				Yes	$\boldsymbol{EC \nleftrightarrow Y}$ (India, Singapore, Taiwan and Thailand)
				No	$\boldsymbol{EC \nleftrightarrow Y}$ (Malaysia and Philippines)
Squalli (2007)	1980-2003	ARDL, TYMWT	Real GDP per Capita and Electricity Consumption per Capita	Yes	$EC \rightarrow Y$(Indonesia, Nigeria, UAE and Venezuela)
				Yes	$EC \leftarrow Y$(Algeria, Iraq, Kuwait and Libya)
				Yes	$EC \leftrightarrow Y$(Iran, Qatar, and Saudi Arabia)
Narayan and Prasad (2008)	1960-2002	TYBSA	Real GDP andElectricity Consumption	N.A	$EC \rightarrow Y$(Australia, Czech Rep. Italy, Portugal and Slovak Rep.)
					$\boldsymbol{EC \nleftrightarrow Y}$ (Austria, Belgium, Canada, Denmark, France, Germany, Greece, Ireland, Japan, Luxembourg, Mexico, New Zealand, Norway, Poland, Spain, Sweden, Switzerland, Turkey and USA)
					$EC \leftarrow Y$(Finland and Hungary)
					$EC \leftrightarrow Y$(Iceland,

Authors	Time Period	Method-ology	Variables	Cointegr -ation	Findings (country studied)
					Korea and UK)
					EC ← Y(Netherlands)
Yoo and Kwak (2010)	1975-2006	JML, VECM	Real GDP per Capita and Electricity Consumption per Capita	No	EC → Y(Argentina, Brazil, Chile and Ecuador)
				Yes	EC → Y(Columbia)
				No	$EC \nleftrightarrow Y$ (Peru)
				Yes	EC ↔ Y(Venezuela)
Ozturk and Acaravci (2010)	1980–2006	ARDL, GC-VECM	Energy consumption and economic growth		EC ↔ Y (Hungary)
					$EC \nleftrightarrow Y$ (Albania, Bulgaria, and Romania)

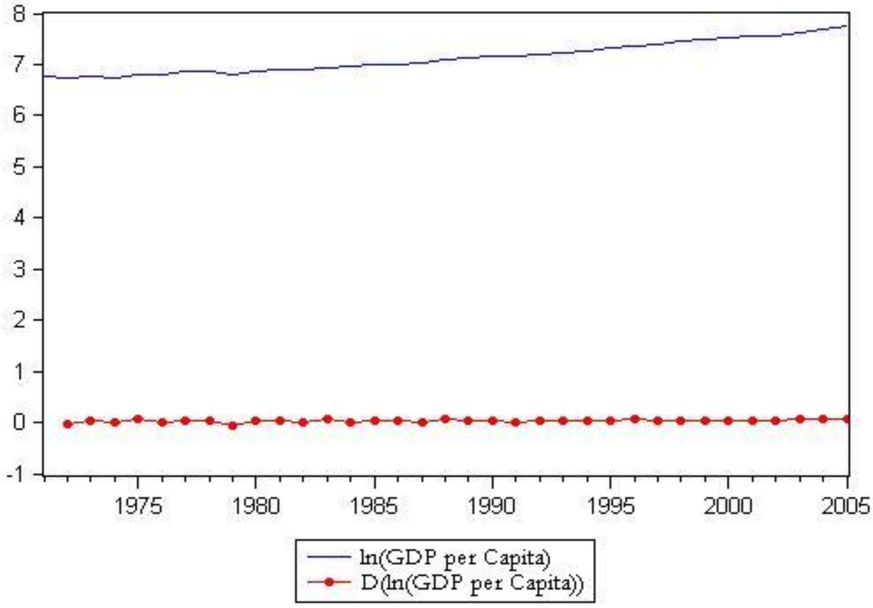
Notes: Y and EC represent economic growth and electricity consumption. The uni-directional causality from economic growth to electricity consumption (electricity supply) is indicated by Y→ EC (ES), from electricity consumption to economic growth by EC → Y, bi-directional causality between electricity consumption and economic growth by EC ↔ Y and no causal relation between both variables by $EC \nleftrightarrow Y$. NA represents not applied. In methodology column EG, GC, VARGFEVD, JML, VECM, ARDL, PC, TYMWT and TYBSA means respectively Engle and Granger, Granger causality, Vector Autoregression Generalized Forecast Error Variance Decomposition, Johansen's Maximum Likelihood, Vector Error Correction Method, Autoregressive Distributed Lag Model to Cointegration, Panel Cointegration, Toda and Yamamoto (1995) M-Wald causality test and Toda and Yamamoto Bootstrapping causality analysis etc.
Source: Author's compilation

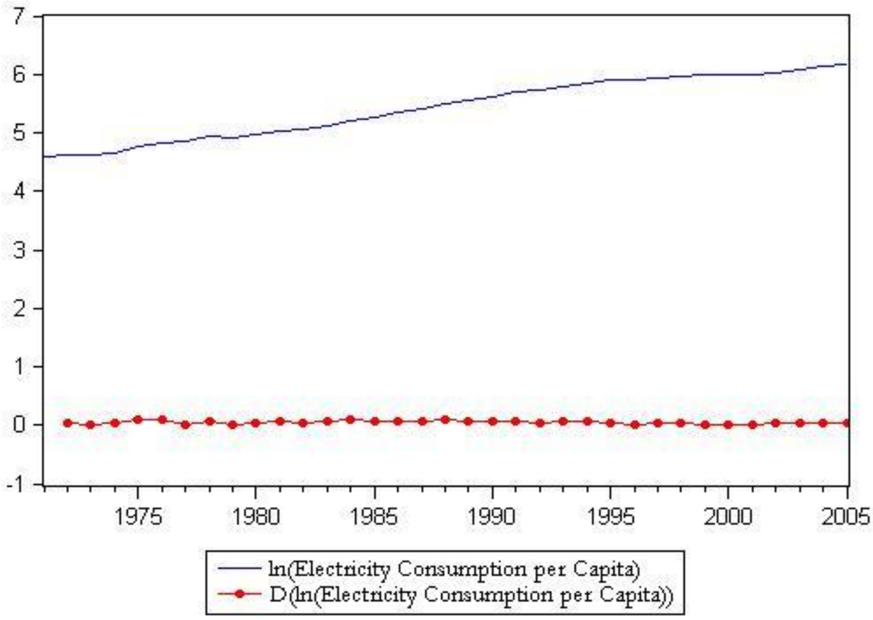
Table A2: Results of variance decompositions (VDs) analysis

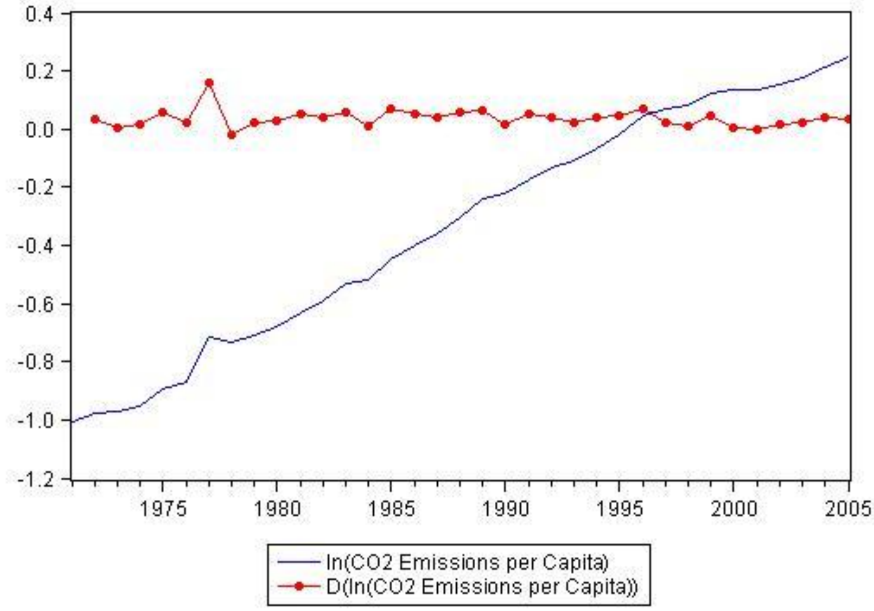
Period	S.E.	Ln(GDPPC)	Ln(CO_2PC)	Ln(ECPC)
Variance Decomposition of Ln(GDPPC):				
1	0.025	100.00	0.000	0.000
2	0.033	99.636	0.152	0.211
3	0.042	89.101	9.719	1.179
4	0.049	90.044	7.865	2.090
5	0.054	90.824	7.018	2.156
6	0.061	92.644	5.606	1.748
7	0.068	94.180	4.435	1.384
8	0.076	95.098	3.770	1.131
9	0.084	95.777	3.233	0.989
10	0.092	96.462	2.706	0.831
Variance Decomposition of Ln(CO_2PC):				
Period	**S.E.**	**Ln(GDPPC)**	**Ln(CO_2PC)**	**Ln(ECPC)**
1	0.018	23.157	76.842	0.000
2	0.019	26.151	73.801	0.046
3	0.027	31.035	41.417	27.546
4	0.031	25.038	42.195	32.765
5	0.033	22.582	43.071	34.345
6	0.034	20.931	40.878	38.190
7	0.035	20.148	40.079	39.772
8	0.037	19.543	40.150	40.305
9	0.039	18.762	38.859	42.378
10	0.042	21.111	37.976	40.911
Variance Decomposition of Ln(ECPC):				
Period	**S.E.**	**Ln(GDPPC)**	**Ln(CO_2PC)**	**Ln(ECPC)**
1	0.021	7.194	24.604	68.200
2	0.036	12.75	27.878	59.368
3	0.049	7.471	42.517	50.011
4	0.060	5.549	42.455	51.995
5	0.067	4.397	43.889	51.712
6	0.074	3.828	45.933	50.237
7	0.082	3.407	45.984	50.608
8	0.089	3.666	46.853	49.480
9	0.096	4.646	47.482	47.870
10	0.103	5.778	47.183	47.037

Note: (1) CO_2PC denotes CO_2 emission per capita; ECPC denotes electricity consumption per capita; GDPPC denotes Gross domestic product per capita and Ln denotes natural log transformation of the series. (2) Cholesky Ordering: Ln(GDPPC), Ln(CO_2PC) and Ln(ECPC)

Figure A1: Graphical analysis of variables






0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
-1.2
1975
1980
1985
1990
1995
2000
2005
ln(CO2 Emissions per Capita)
D(ln(CO2 Emissions per Capita))