Journal of Applied Economics and Business Research
JAEBR, 4 (3): 150-167 (2014)

Economic growth and Energy consumption nexus in Developing World: The case of China and India

Mousumi Bhattacharya[1]
Assistant Professor, Indian Institute of Management, Shillong

Sharad Nath Bhattacharya
Assistant Professor, Indian Institute of Management, Shillong

Abstract

The global energy demand is continuing to grow unabated and all eyes are on the two most developing nations India and China. Here an attempt is made to study the causal relationship between energy consumption (electricity, coal and petroleum) and economic growth for India and China in a VECM framework. Findings suggest the existence of the long run relationship amongst the various forms of energy consumption and economic growth in both the countries. In case of India a bidirectional causality running between coal consumption and economic growth is observed not only in the short run but also in the long run. A unidirectional causality is observed from petroleum consumption to economic growth both in short run and long run in case of India. However for China, unidirectional causality is observed from economic growth to coal consumption and from petroleum consumption to economic growth in both short run and long run.

Jel code: O10, Q4, Q43

Keywords: *Economic growth, Energy consumption, Granger-causality, Error correction model, Impulse response analysis*

1. Introduction

Whether energy consumption affects economic growth is of great interest in the backdrop of global warming. Energy is needed for economic growth, for improving the quality of life and for increasing opportunities for development along with serious environmental consequences. Energy prices are rising globally making imports very expensive which underscores the need for moderating the growth of energy demand by achieving higher levels of energy efficiency. Global energy demand is continuing to grow unabated. All eyes are on India and China where energy demand is growing at 2 to 3 times of that of the global annual average of about 1.7%. There is a growing concern that the present pattern of energy production and consumption are unsustainable in the long run. In developing countries like India and China, coal acts like a double edged sword. It is not only the new economy's black gold but also the fragile environment's dark cloud. In spite of industrialization and impressive rates of economic growth in the recent years both the countries need to implement environmental protection measures otherwise sustainable development of their economies will be limited. Energy appears to be the key source of economic growth, industrialization and urbanization. Conversely, industrialization and urbanization may induce the use of more energy consumption, particularly commercial energy. Hence whether economic growth boosts energy consumption or whether

[1] Correspondence to Mousumi Bhattacharya, E-mail: mbhattacharya9@gmail.com

energy consumption causes economic growth is the relevant question and the direction of causality is highly relevant to policy makers. If energy causes economic growth then reducing consumption may lead to a decline in income and employment. This is more serious for India and China because any control on energy consumption is expected to have a larger effect on the development of these countries compared to the developed industrialized nations. However, in absence of causality from energy to economic growth, energy conservation policies may be initiated that may not have detrimental side effects on growth and employment (Masih and Masih, 1997). Hence it is important to ascertain empirically whether there is a causal link between disaggregated energy consumption and economic growth. An attempt is made to answer these questions as they have important implications for policy makers.

2. Literature Review

The energy crises which affected India in the 1970s and 1980s and the steadily rising energy prices in the recent years have led to economists and policy makers more concerned with the relationship between energy consumption and economic growth. There are many studies which have focussed on the causality relationship between energy consumption and economic growth. By applying Sims' (1972) causality test, Kraft and Kraft (1978) provides evidence of unidirectional causality running from GNP to energy consumption for USA, using data for the period of 1947-1974. Since then many researchers debated the possible relationships between economic growth and energy consumption. The causal relationship between energy consumption and economic growth in G7 countries and emerging markets was studied by Soytas and Sari (2003), whereas Lee (2006) analyzed the cases of 11 major industrialized countries; Lee (2005) finds evidence of causality running from energy consumption to GDP in 18 developing countries using panel estimation techniques. Yoo (2006a) studied the causality relationship between electricity consumption and economic growth in the ASEAN countries. Shiu and Lam (2004) and Ghosh (2002) gave the examples of electricity consumption and economic growth in China and India respectively; Narayan and Prasad (2008) provided electricity consumption and real GDP causality for 30 OECD countries; Yang (2000) found a causal relationship from economic growth to coal consumption in Taiwan; Yoo (2006b) showed that there existed a bi-directional causality relationship between coal consumption and economic growth in South Korea. Jinke et al. (2008) used Granger causality tests to examine the differences of causal relationships between coal consumption and GDP in major OECD and non-OECD countries, using data for the period of 1980-2005; Apergis and Payne (2010) examined the relationship between coal consumption and economic growth for 25 OECD countries within a multivariate panel framework over period 1980-2005.

Many of the earlier analyses employed simple log-linear models estimated by ordinary least squares OLS without any regard for the nature of the time series properties of the variables involved. However, it has been observed that most economic time series are non-stationary in level form (Granger and Newbold, 1974). Following advances in time series analysis in the previous decades, recent tests of the energy consumption and economic growth relationship rely on bi and trivariate estimations to test for Granger (1969) and Sims' (1972) tests. However, these tests may fail to detect additional channels of causality and can also lead to conflicting results. Apart from error correction model and cointegration approach, more recent tests use autoregressive distributed lag (ARDL) or cointegression regressions like fully modified ordinary least squares (FMOLS) and dynamic OLS (DOLS), often along with Granger causality and cointegration and error correction models (Aslan and Kum, 2010; Nanthakumar and Subramaniam, 2010; Adhikari and Chen, 2013).

The empirical findings on the causal relationship between energy consumption and economic growth are inconclusive and it may be attributed to different structural frameworks and policies followed by different countries under different conditions and time periods,

 ISSN 1927-033X

methodological differences and statistical problems of using proxies for energy consumption and growth, shifting energy consumption patterns, etc. (Ferguson et al., 2000; Toman and Jemelkova, 2003; Arbex and Perobelli, 2010; Pradhan, 2010). In order to explore the possibility of further information on the direction of causality we disaggregated energy consumption into three component coal consumption, petroleum consumption and electricity consumption. Our study attempts to revisit the possible long and short run causal relationship between economic growth and coal, electricity and petroleum consumption in Indian and Chinese economy.

3. Data and Methodology

The annual time series data on India and China [see Figure 1 (a) and Figure 1 (b)] relating to Gross domestic product (GDP) are taken from IMF database. Gross domestic product in US dollars is taken as a proxy for economic growth. Energy has been considered at disaggregated level for both the countries and three most important components of energy consumption in India have been considered which includes Total Electricity Net Consumption (ELEC), Total Coal Consumption (COAL) and Total Petroleum Consumption (PET) (including motor gasoline, jet fuel, kerosene, distillate fuel oil, residual fuel oil, liquefied petroleum gas, other products). Energy data are collected from the U.S. Energy Information Administration.

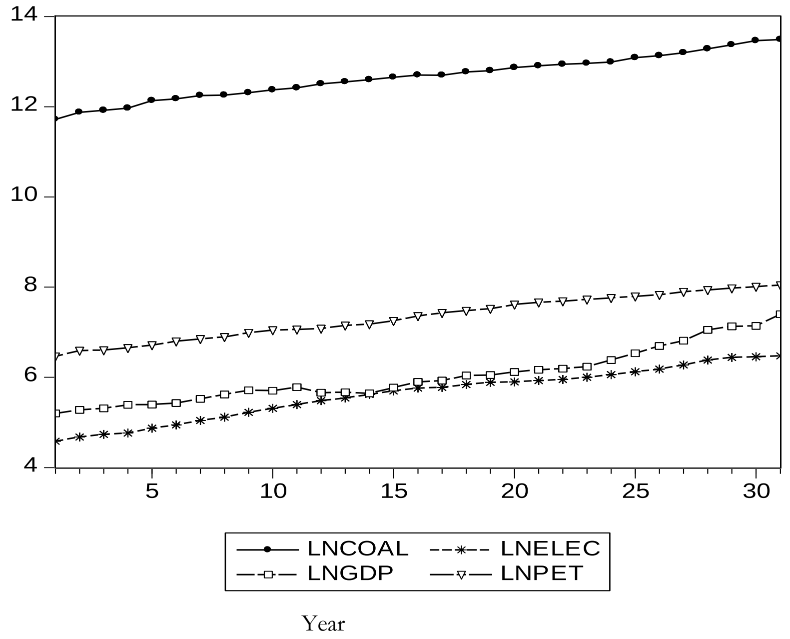

Figure 1(a): Logarithmic values of COAL, GDP, ELEC and PET for India

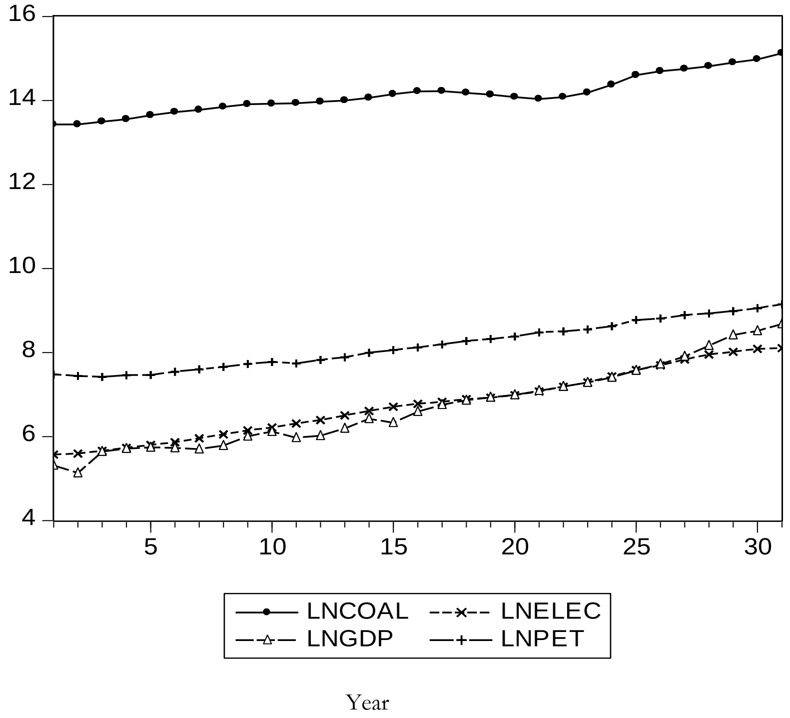

Figure 1(b). Logarithmic values of COAL, GDP, ELEC and PET for China

3.1. Econometric Methodology

The objective of the study is to examine the causal links between GDP, COAL, PET and ELEC in India and China over the period 1980 to 2010 in a Vector Autoregressive (VAR) framework.

3.1.1. Stationarity Test

In order to check the stationarity property of the variables GDP, COAL, PET and ELEC three types of tests are employed. Zivot-Andrews (ZA) (1992) test, which allow for structural breaks in the series along with Augmented Dickey Fuller (ADF) (1979) test and another Phillips-Perron (PP) (1988) is carried out.

3.1.2. Cointegration Test

To see whether the variables involved in the study are tied in a long term relationship cointegration technique of Johansen (1988) and Johansen and Juselius (1990) has been applied which involves the error correction term (ECT). The Cointegration Test of maximum likelihood (based on the Johansen-Juselius Test) has been developed based on a VAR approach initiated by Johansen (1988). According to Johansen (1988), a p-dimensional VAR model, involving up to k-lags, can be specified as below.

$$Z_t = \prod_1 Z_{t-1} + \prod_2 Z_{t-2} + \ldots\ldots\ldots \prod_k Z_{t-k} + \varepsilon_t \qquad \ldots(1)$$

where Z_t is a $(p \times 1)$ vector of p potential endogenous variables and each of the Π_i is a $(p \times p)$ matrix of parameters and ε_t is the white noise term. Equation (1) can be formulated in an Error Correction Model (ECM) form as below.

 ISSN 1927-033X

$$\Delta Z_t = \prod_k Z_{t-k} + \sum_{i=1}^{k-1} \theta_i \Delta Z_{t-i} + \varepsilon_t \quad \ldots(2)$$

where the first difference operator is represented by Δ, and Π and θ are p by p matrices of unknown parameters and k is the order of the VAR translated into a lag of $k-1$ in the ECM and ε_t is the white noise term. Two likelihood ratio tests based on Maximal Eigen value statistic and the Trace statistic has been used in the study. When the variables are I (1), and cointegrated, the Granger Causality Test will be applied in the framework of the error correction mechanism (ECM).

3.1.3. Granger Causality Test with VECM framework

Granger Causality Test is conducted not only to examine the causal linkages between the variables but also to determine the direction of the impact of each of the variables on the other. The optimal lag length chosen (denoted by p) is 4 (Table 1) for India and 2 (Table 2) for China in the present study, obtained through a combination of information criteria like LR or FPE or AIC or SC or HQIC.

Table 1. VAR Lag Order Selection Criteria for India (LnCOAL, LnELEC, LnGDP and LnPET)

Lag	LogL	LR	FPE	AIC	SC	HQIC
0	78.132	NA	4.85e-08	-5.491	-5.299	-5.434
1	234.919	255.504*	1.46e-12	-15.919	-14.960*	-15.634
2	247.689	17.026	2.02e-12	-15.680	-13.952	-15.166
3	271.360	24.547	1.46e-12	-16.248	-13.753	-15.506
4	300.8213	21.82309	9.26e-13*	-17.24602*	-13.98243	-16.27558*

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

Table 2. VAR Lag Order Selection Criteria for China (LnCOAL, LnELEC, LnGDP and LnPET)

Lag	LogL	LR	FPE	AIC	SC	HQIC
0	56.682	NA	3.11e-07	-3.633	-3.444	-3.574
1	200.872	238.659	4.56e-11	-12.473	-11.531	-12.178
2	230.403	40.731*	1.92e-11*	-13.407*	-11.709*	-12.875*

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

If the variables contain cointegrating vector, causality exists in at least one direction. The direction of a causal relationship can be detected in the VECM. Engle and Granger (1987) have found that, in the presence of cointegration, there always exists a corresponding error-correction representation, captured by the error-correction term (ECT). This means that changes in the dependent variable are a function of the level of disequilibrium in the cointegrating relationship as well as changes in other explanatory variable(s). The ECT captures the long-run adjustment of cointegration variables. As such, in addition to the direction of causality, the incorporation of ECT in the VECM allows to detect both short- and long-run causal relationships between the variables. The following equation pertains to both India and China.

$$\Delta LnCOAL_t = \sum_{j=1}^{p-1}\beta_{11}\Delta LnCOAL_{t-j} + \sum_{j=1}^{p-1}\beta_{12}\Delta LnELEC_{t-j} + \sum_{j=1}^{p-1}\beta_{13}\Delta LnGDP_{t-j} + \sum_{j=1}^{p-1}\beta_{14}\Delta LnPET_{t-j} + \alpha_1 ECT_{t-1} + \varepsilon_{1t} .....(3a)$$

$$\Delta LnELEC_t = \sum_{j=1}^{p-1}\beta_{21}\Delta LnELEC_{t-j} + \sum_{j=1}^{p-1}\beta_{22}\Delta LnCOAL_{t-j} + \sum_{j=1}^{p-1}\beta_{23}\Delta LnGDP_{t-j} + \sum_{j=1}^{p-1}\beta_{24}\Delta LnPET_{t-j} + \alpha_2 ECT_{t-2} + \varepsilon_{2t} .....(3b)$$

$$\Delta LnGDP_t = \sum_{j=1}^{p-1}\beta_{31}\Delta LnGDP_{t-j} + \sum_{j=1}^{p-1}\beta_{32}\Delta LnCOAL_{t-j} + \sum_{j=1}^{p-1}\beta_{33}\Delta LELEC_{t-j} + \sum_{j=1}^{p-1}\beta_{34}\Delta LnPET_{t-j} + \alpha_3 ECT_{t-3} + \varepsilon_{3t} .....(3c)$$

$$\Delta LnPET_t = \sum_{j=1}^{p-1}\beta_{41}\Delta LnPET_{t-j} + \sum_{j=1}^{p-1}\beta_{42}\Delta LnCOAL_{t-j} + \sum_{j=1}^{p-1}\beta_{43}\Delta LELEC_{t-j} + \sum_{j=1}^{p-1}\beta_{44}\Delta LnGDP_{t-j} + \alpha_4 ECT_{t-4} + \varepsilon_{4t} .....(3d)$$

where the first difference operator is represented as Δ and $\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t}$ and ε_{4t} are white noise. Error correction term is denoted by ECT, and the order of the VAR is represented by p, which is translated to lag of $p-1$ in the ECM. $\alpha_1, \alpha_2, \alpha_3$ and α_4 represent the pace of adjustment after the COAL, ELEC, GDP and PET deviate from the long-run equilibrium in period t-1.

3.1.4. Dynamic OLS

The Johansen method, being a full information technique, may be exposed to the problem that parameter estimates in one equation are affected by any misspecification in the other equations. For robust analysis, another cointegration regression Dynamic OLS of Stock and Watson (1993) is employed with LnGDP as dependent variable and LnPET, LnELEC and LnCOAL as regressors. The Stock and Watson (1993) method is a robust single equation approach which includes leads and lags of the first differences of the regressors and has the same asymptotic optimality properties as the Johansen distribution. Lag and lead terms included in the Dynamic OLS regression have the purpose of making its stochastic error term independent of all past innovations in stochastic regressors.

3.1.5. Impulse Response Analysis

Impulse responses are the changes in the future predicted values due to a change in the current period values. Typically in a VAR, the coefficient estimates of the individual equations are of little or no importance. Instead of static interpretation of the effects of changes in any of the variables in the system, Impulse Responses (IR) provide a dynamic response curve that depicts the effects of a change in one of the variables, considering the effects of the other variables in the system. In the present study, the orthogonalized IR analysis is done by changing the order of the equations to see whether any change in the IR function is revealed.

 ISSN 1927-033X

4. Findings

4.1. Stationarity Test

Table 3: Test of Unit Root Test Hypothesis of India (1980 -2010)

Country	Variables	ADF		PP		ZA		Remark
		Level	First Difference	Level	First Difference	Level	First Difference	
	LnGDP	2.511	-3.853***	2.511	-3.853***	-1.696	-5.782***	I(1)
	LnCOAL	-1.249	-6.817***	-1.249	-6.817***	-4.487	-8.517***	I(1)
India	LnPET	-1.827	-5.947***	-1.827	-5.947***	-3.148	-6.403***	I(1)
	LnELEC	-1.560	-3.013**	-1.795	-3.013**	-2.502	-5.308**	I(1)
	LnGDP	1.121	-6.861***	1.121	-6.861***	-2.820	-5.948***	I(1)
	LnCOAL	0.960	-2.635*	0.439	-3.023**	-2.623	-4.619*	I(1)
China	LnPET	2.187	-4.793***	2.187	-4.793***	-3.870	-5.607***	I(1)
	LnELEC	0.335	-2.722*	1.079	-15.892***	-3.599	-5.258**	I(1)

(a)The critical values are those of MacKinnon (1991).
*(b)***, ** and * represent the rejection of null hypothesis at 1%, 5% and 10% levels of significance respectively.*

In case of both India and China all the four variables LnCOAL, LnELEC, LnGDP and LnPET are I(1) process according to ADF, PP and ZA test (Table 3).

4.2. Cointegration Test

It is observed from the results of the ADF and PP test that the variables have the same order of integration, i.e., I (1) so Johansen Cointegration Test has been employed to find out the cointegration rank and the number of cointegrating vectors. The null hypothesis is rejected in the cases of both the Trace statistic and Max-Eigen value statistic for India. Table 4 shows that the number of statistically significant cointegration vectors is equal to 3 for the Trace statistic and also for the Max-Eigen value statistic in the case of India. The results suggest that there is a long-run relationship among the variables considered for the study.

In case of China also the null hypothesis is rejected in the cases of both the Trace statistic and Max-Eigen value statistic. Table 4 shows that the number of statistically significant cointegration vectors is equal to 1 for the Trace statistic and also for the Max-Eigen value statistic in the case of China. Here also the results suggest that there is a long-run relationship among the variables considered for the study.

Table 4. Johansen -Juselius Cointegration Test Results

	H_0	H_1	λ_{trace}	$CV_{(trace,5\%)}$	Prob**
India	$r=0$	$r\geq 1$	107.315	47.856	0.0000**
	$r\leq 1$	$r\geq 2$	60.749	29.797	0.0000**
	$r\leq 2$	$r\geq 3$	26.650	15.494	0.0007**
	$r\leq 3$	$r\geq 4$	0.929	3.841	0.3366
	H_0	H_1	$\lambda_{\max}$	$CV_{(\max,5\%)}$	Prob**
	$r=0$	$r=1$	46.566	27.584	0.0001**
	$r\leq 1$	$r=2$	33.099	21.131	0.0005**
	$r\leq 2$	$r=3$	25.721	14.264	0.000**
	$r\leq 3$	$r=4$	0.929	3.841	0.336
China	H_0	H_1	λ_{trace}	$CV_{(trace,5\%)}$	Prob**
	$r=0$	$r\geq 1$	73.801	54.079	0.000**
	$r\leq 1$	$r\geq 2$	33.216	35.192	0.080
	$r\leq 2$	$r\geq 3$	15.164	20.261	0.217
	$r\leq 3$	$r\geq 4$	3.3141	9.164	0.523
	H_0	H_1	$\lambda_{\max}$	$CV_{(\max,5\%)}$	Prob**
	$r=0$	$r\geq 1$	40.584	28.588	0.000**
	$r\leq 1$	$r\geq 2$	18.052	22.299	0.176
	$r\leq 2$	$r\geq 3$	11.849	15.892	0.194
	$r\leq 3$	$r\geq 4$	3.314	9.164	0.523

(a) r is the number of cointegrating vectors.
*(b)** denotes rejection of the null hypothesis at the 5% level of significance*
(c) The critical values (i.e., CVs) are taken from Mackinnon-Haug-Michelis (1999).

4.3. Granger Causality Test with VECM framework

The above Table 4 reveals that the variables under study stand in a long-run relationship among them, thus justifying the use of ECM for showing short-run dynamics in the case of India. In Table 5(a) and Table 5(b) below, the cointegrating equations are given along with the equation for changes in coal consumption (first column), changes in electric consumption (second column), changes in gross domestic product (third column), and changes in petroleum consumption (fourth column) pertaining to India and China respectively. The coefficients of ECT contain information about whether the past values affect the current values of the variable under study. A significant coefficient implies that past equilibrium errors play a role in determining the current outcomes. The information obtained from the ECM is related to the speed of adjustment of the system towards long-run equilibrium. The short-run dynamics are captured through the individual coefficients of the difference terms. The adjustment coefficient on ECT_{t-1} in equation 3(a) is negative and statistically significant at the 1% level of significance, which means that the error term contributes in explaining changes in GDP and a long-term relationship exists between the GDP and coal consumption. The estimates of lagged coefficients $\Delta LnGDP_{t-2}, \Delta LnGDP_{t-3}$ in equation 3 (a) are negative and statistically significant at the 5% level of significance, implying that higher GDP has a negative impact on coal consumption in the short-run. The adjustment coefficient on ECT_{t-3} in equation 3(c) is positive and statistically significant at the 5% level of significance, which means that the error term contributes in explaining changes in coal consumption and petroleum consumption and a long-term relationship exists between the coal and petroleum consumption (independent variables) with GDP. The estimate of the lagged coefficient $\Delta LnCOAL_{t-1}$ in equation 3 (c) is negative and statistically significant at the 5% level of significance, implying that higher coal consumption has a negative impact on economic growth in the short-run. The estimate of the lagged coefficient $\Delta LnPET_{t-3}$ in equation 3 (c) is negative and statistically significant at the 5% level of significance, implying that higher petroleum consumption has a negative impact on GDP in the short-run.

The above results indicate a bidirectional causality running between coal consumption and economic growth in the short run in case of India. A unidirectional causality is observed form petroleum consumption to economic growth in short run for India.

In Table 5 (b) below the adjustment coefficient on ECT_{t-1} in equation 3 (a) is negative and statistically significant at the 5% level of significance, which means that the error term contributes in explaining changes in GDP and electricity consumption so a long-term relationship exists between GDP and electricity consumption with coal consumption. The estimate of the lagged coefficient $\Delta LnGDP_{t-1}$ in equation 3 (a) is negative and statistically significant at the 10% level of significance, implying that higher GDP has a negative impact on coal consumption in the short-run. The estimate of the lagged coefficient $\Delta LnELEC_{t-1}$ in equation 3 (a) is positive and statistically significant at the 1% level of significance, implying that higher electricity consumption has a positive impact on coal consumption in the short-run. The adjustment coefficient on ECT_{t-3} in equation 3(c) is positive and statistically significant at the 1% level of significance, which means that the error term contributes in explaining changes in petroleum consumption and a long-term relationship exists between petroleum consumption and GDP. The estimate of the lagged coefficient $\Delta LnPET_{t-1}$ in equation 3 (c) is negative and statistically significant at the 5% level of significance, implying that higher petroleum consumption has a negative impact on GDP in the short-run. The estimate of the lagged coefficient $\Delta LnELEC_{t-1}$ in equation 3 (d) is positive and statistically significant at the 5% level of significance, implying that higher electricity consumption has a positive impact on petroleum consumption in the short-run.

Unidirectional short run causality from GDP to coal consumption is observed in the case of China. Similarly a unidirectional causality from electricity consumption to coal consumption is observed in case of short run. A short run unidirectional causality is observed from petroleum consumption to economic growth. A short run unidirectional causality is observed from electricity consumption to petroleum consumption.

Table 5(a). Vector Error Correction Estimates for India

Included observations: 27 after adjustments				
Standard errors in ( ) & t-statistics in [ ]				
Cointegrating Eq:	CointEq1			
LnCOAL(-1)	1.000			
LnELEC(-1)	-0.446			
	(0.057)			
	[-7.739]			
LnGDP(-1)	-0.269			
	(0.047)			
	[-5.666]			
LnPET(-1)	-0.1289			
	(0.097)			
	[-1.316]			
C	-7.583			
Error Correction:	D(LnCOAL)	D(LnELEC)	D(LnGDP)	D(LnPET)
CointEq1	-1.274	-0.180	1.731	0.215
	(0.245)	(0.294)	(0.760)	(0.264)
	[-5.201]***	[-0.612]	[2.277]**	[0.815]
D(LnCOAL(-1))	0.319	-0.392	-1.144	-0.108
	(0.202)	(0.243)	(0.627)	(0.218)
	[1.577]	[-1.612]	[-1.823]**	[-0.494]
D(LnCOAL(-2))	0.508	0.251	-0.942	0.232
	(0.214)	(0.257)	(0.664)	(0.231)
	[2.373]	[0.977]	[-1.417]	[1.005]
D(LnCOAL(-3))	0.356	0.239	0.822	-0.192
	(0.163)	(0.196)	(0.507)	(0.176)
	[2.179]	[1.217]	[1.620]	[-1.091]
D(LnELEC(-1))	-0.307	0.818	0.094	0.254
	(0.240)	(0.289)	(0.746)	(0.260)
	[-1.278]	[2.827]	[0.126]	[0.978]
D(LnELEC(-2))	-0.080	-0.283	0.847	-0.227
	(0.313)	(0.377)	(0.973)	(0.339)
	[-0.256]	[-0.751]	[0.870]	[-0.671]
D(LnELEC(-3))	-0.283	0.024	-0.987	0.189
	(0.264)	(0.317)	(0.819)	(0.285)
	[-1.073]	[0.075]	[-1.204]	[0.665]
D(LnGDP(-1))	-0.121	-0.039	0.291	0.0347
	(0.081)	(0.098)	(0.254)	(0.088)
	[-1.483]	[-0.405]	[1.147]	[0.392]
D(LnGDP(-2))	-0.173	-0.084	0.579	0.133
	(0.083)	(0.100)	(0.258)	(0.090)
	[-2.082]**	[-0.840]	[2.240]	[1.479]
D(LnGDP(-3))	-0.203	0.047	0.644	-0.159
	(0.091)	(0.110)	(0.283)	(0.098)
	[-2.225]**	[0.427]	[2.270]	[-1.614]

 ISSN 1927-033X

D(LnPET(-1))	-0.132	-0.100	-0.740	0.385
	(0.204)	(0.246)	(0.634)	(0.221)
	[-0.647]	[-0.407]	[-1.166]	[1.745]
D(LnPET(-2))	-0.273	-0.159	-0.222	-0.414
	(0.198)	(0.238)	(0.614)	(0.213)
	[-1.380]	[-0.668]	[-0.362]	[-1.936]
D(LnPET(-3))	-0.114	-0.005	-1.396	0.395
	(0.203)	(0.245)	(0.632)	(0.220)
	[-0.562]	[-0.020]	[-2.209]**	[1.795]
C	0.094	0.041	0.171	0.021
	(0.027)	(0.033)	(0.086)	(0.029)
	[3.399]	[1.246]	[1.987]	[0.704]
R-squared	0.793	0.581	0.626	0.501
Adj. R-squared	0.586	0.163	0.253	0.003
F-statistic	3.838	1.391	1.678	1.006

**** denotes statistical significance at 1% level of significance, ** denotes statistical significance at 5% level and * denotes statistical significance at 10% level of significance.*

Table 5(b): Vector Error Correction Estimates for China

Included observations: 29 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1			
LnCOAL(-1)	1.000			
LnELEC(-1)	-1.083			
	(0.295)			
	[-3.669]			
LnGDP(-1)	-1.250			
	(0.171)			
	[-7.310]			
LnPET(-1)	2.993			
	(0.393)			
	[7.608]			
C	-22.557			
Error Correction:	D(LnCOAL)	D(LnELEC)	D(LnGDP)	D(LnPET)
CointEq1	-0.105	0.039	0.483	-0.023
	(0.048)	(0.032)	(0.118)	(0.045)
	[-2.174]**	[1.212]	[4.084]***	[-0.519]
D(LnCOAL(-1))	0.541	-0.059	0.149	-0.018
	(0.153)	(0.103)	(0.374)	(0.143)
	[3.516]	[-0.580]	[0.399]	[-0.128]
D(LnELEC(-1))	0.967	0.901	0.3484	0.650
	(0.257)	(0.172)	(0.626)	(0.239)
	[3.755]***	[5.228]	[0.556]	[2.714]**
D(LnGDP(-1))	-0.113	0.014	0.117	0.009
	(0.064)	(0.042)	(0.155)	(0.059)

	[-1.770]*	[0.342]	[0.751]	[0.159]
D(LnPET(-1))	-0.225	-0.078	-1.345	0.109
	(0.230)	(0.154)	(0.560)	(0.214)
	[-0.980]	[-0.506]	[-2.403]**	[0.509]
R-squared	0.645	0.342	0.435	0.038
Adj. R-squared	0.586	0.233	0.341	-0.122
F-statistic	10.948	3.127	4.629	0.237

**** denotes statistical significance at 1% level of significance, ** denotes statistical significance at 5% level and * denotes statistical significance at 10% level of significance.*

4.4. Dynamic OLS

To check for robustness of the estimated coefficients, another cointegrating regression method i.e., dynamic OLS is applied with lead and lag length of one for India and two for China. The findings are summarised in Table 6(a) for India and Table 6(b) for China. Electricity and coal are found to be statistically significant in explaining economic growth for India while petroleum and coal are found to be statistically significant in explaining economic growth for China. The findings clearly suggest energy consumption affects economic growth in both India and China.

Table 6(a): Dynamic OLS estimates for India

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LnELEC	1.676412	0.450270	3.723128	0.0020
LnCOAL	2.504681	0.728500	3.438136	0.0037
LnPET	0.793319	0.502851	1.577643	0.1355
C	-22.45674	5.009386	-4.482932	0.0004
R-squared	0.980335	Durbin-Watson stat		1.911583

Table 6(b): Dynamic OLS estimates for China

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNPET	2.354357	0.595572	3.953102	0.0013
LNELEC	-0.817919	0.549542	-1.488365	0.1574
LNCOAL	0.795612	0.317821	2.503337	0.0243
C	-17.84291	4.989726	-3.575929	0.0028
R-squared	0.994841	Durbin-Watson stat		1.829841

 ISSN 1927-033X

4.5. Impulse Response Analysis

The shock to any one of the four variables considered in the study affects all other variables in the system. The shocks are orthogonalized by using the Choleski decomposition method. The VAR is estimated at the first difference of the variables and the optimum, lag length is chosen to be 3 (minimum of AIC or SBIC or HQIC or FPE value) in the case of India and 1 in the case of China. Thus, IR functions are computed to give an indication of the system's dynamic behaviour. The IR estimates only for the variables that appear to significantly Granger cause other variables (based on Causality Test) are reported. Each of the variables in the study is taken in the natural logarithmic form. The IR function for the VAR system is calculated in the following order – COAL, ELEC, GDP and PET in case of both the countries. The IR function only for COAL and GDP are reported in Figure 2(a) and Figure 2(b) for India.

The response of GDP to a unit shock in Coal consumption is negative in the first four quarters. The initial response of GDP to a unit shock in petroleum consumption is negative in the first quarter, falls further in the second quarter and remains negative in the third quarter. The initial response of Coal consumption to a unit shock in GDP is positive in the first quarter starts falling in the second quarter and becomes negative in the third quarter.

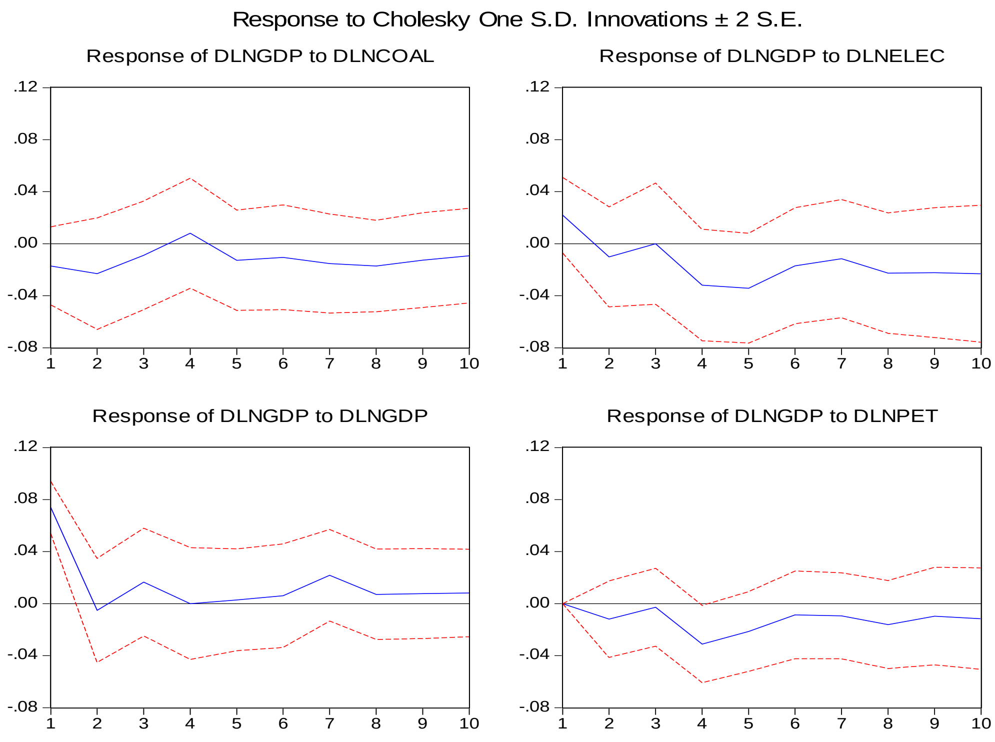

Figure 2(a): Impulse response of D(LnGDP) to One-standard deviation shocks in other variables (India)

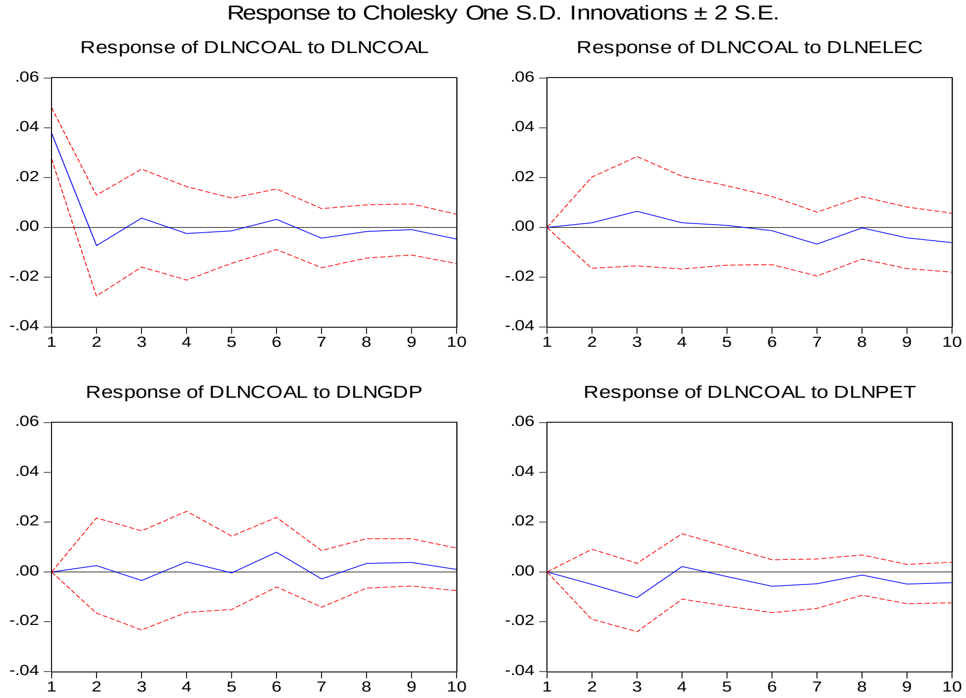

Figure 2(b): Impulse response of D(LnCOAL) to One-standard deviation shocks in other variables (India)

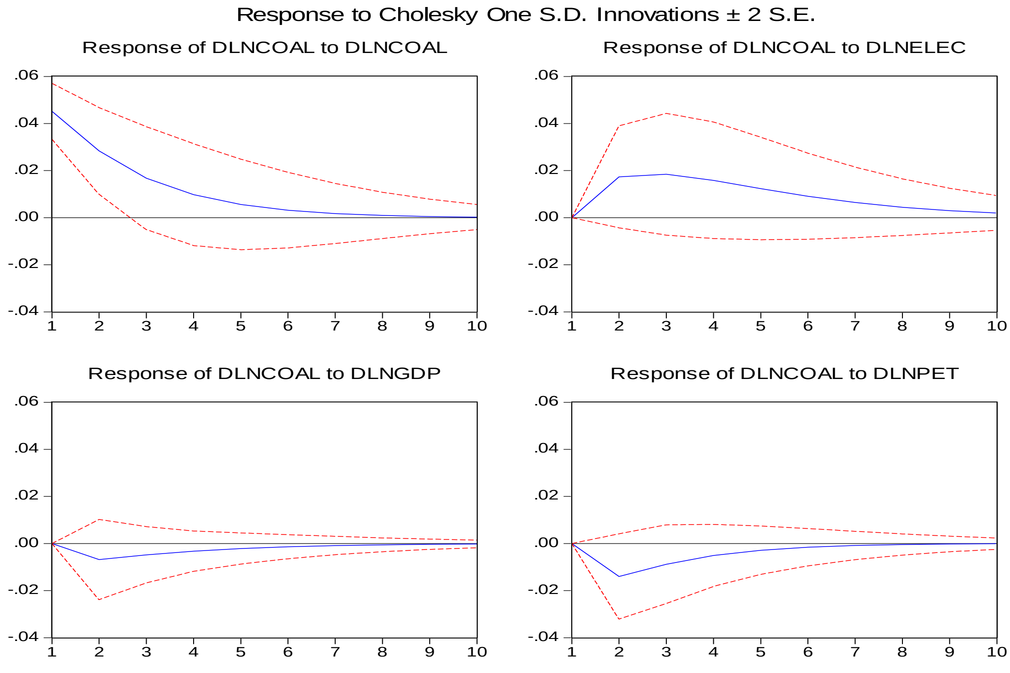

Figure 2(c): Impulse response of D(LnCOAL) to One-standard deviation shocks in other variables (China)

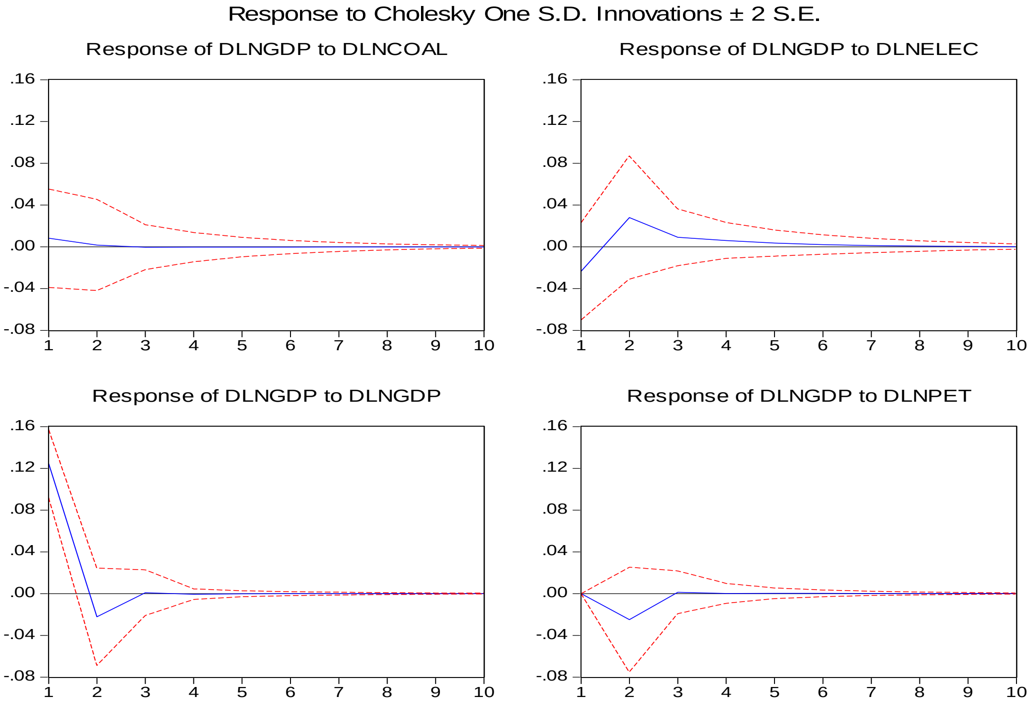

Figure 2(d): Impulse response of D(LnGDP) to One-standard deviation shocks in other variables (China)

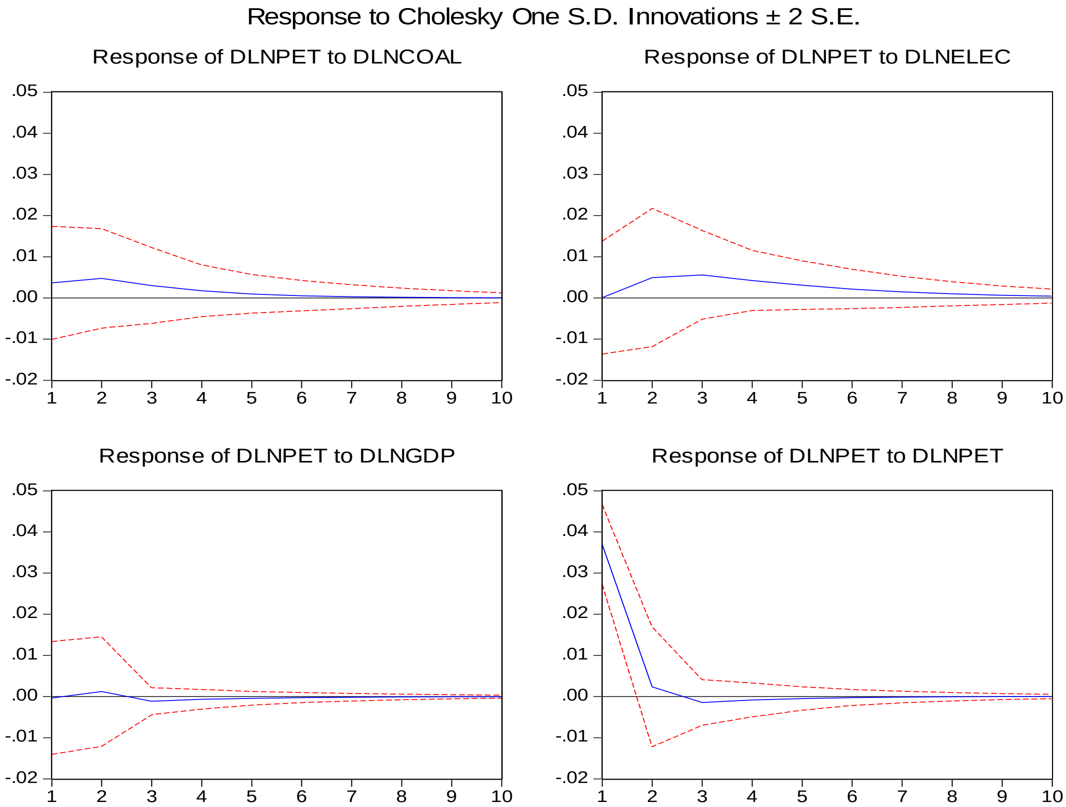

Figure 2(e): Impulse response of D(LnPET) to One-standard deviation shocks in other variables (China)

The IR function only for COAL, GDP and PET are reported in Figure 2(c), Figure 2(d) and Figure 2(e), for China. The response of GDP to a unit shock in petroleum consumption is negative in the first three quarters. The initial response of coal consumption to a unit shock in

GDP is negative in the first few quarters. The initial response of coal consumption to a unit shock in electricity consumption is positive and increases from the second quarter onwards and remains positive. The response of petroleum consumption to a unit shock in electricity consumption is positive in the first quarter increases in the second quarter and remains positive. The results of the impulse response functions are consistent with the t-statistics for differences of the variables in estimated coefficients.

5. Conclusion

Bidirectional causality between coal consumption and economic growth is observed in case of India which indicates that while energy conservation policies may retard economic growth but at the same time fluctuations in economic growth may hamper the consumption of coal i.e. coal consumption and economic growth mutually influence each other. Measures to be taken to conserve coal and overcome the constraints on coal consumption so that growth is not adversely affected. It also supports the argument that an increase in real income also causes an increase in coal consumption. There is also need to explore new sources of coal that must be clean, safe and cheaper in the country. Here, petroleum consumption seems to be an important principal factor in short run as well as in the long run for the Indian economy. The enormous use of petroleum in the industrial and transportation sector has directly pushed the economy. The production process in manufacturing, industries, construction, electricity generation and transportation demand a substantial amount of petroleum. Increased consumption of petroleum also affects employment. So, in any industrialized country like India petroleum is an important ingredient of economic development. No causality is observed from electricity consumption to economic growth which shows that electricity consumption being a highly qualitative energy source as compared to the other forms of energy consumption may contribute towards economic growth of the country in the future.

In case of China the unidirectional causality from economic growth to coal consumption indicates that conservation measures adopted to mitigate the adverse effects of coal consumption and to reduce waste and inefficiency may be taken without hindering economic growth. This suggests that a sustainable development strategy with low levels of CO2 emissions may be possible in China and it may contribute to the fight against global warming directly by implementing energy conservation measures. The coal use in China has nearly doubled since 2000 and with the country expanding rapidly with its large domestic coal deposits, the demand for coal is projected to continue growing strongly. For China mitigating the adverse effects of carbon dioxide emissions is apparent in the country in particular and the world in general. Finding alternative sources of clean energy that reduce carbon dioxide emissions must be a top priority in China's energy policy. Efforts to find alternative energy that reduce CO2 emissions must be supported by investment in R&D and by enhancing investment in the use of renewable energy sources. In China, petroleum consumption is a leading factor of the economic growth in both short run as well as in the long run. The reason may be that the enormous use of petroleum in the manufacturing, construction and transportation sector has directly pushed the economy. However, China is in the process of consuming less standard coal equivalent for electricity generation by 2015 and this will be achieved through development of more non-fossil energies like hydropower, natural gas and improving coal consuming technologies.

 ISSN 1927-033X

References

Adhikari, D., Chen, Y. 2013. Energy Consumption and Economic Growth: A Panel Cointegration Analysis for Developing Countries. *Review of Economics and Finance*, 3:2, 68-80.

Apergis, N., Payne, J. E. 2010. The Causal Dynamics between Coal Consumption and Growth: Evidence from Emerging Market Economies. *Applied Energy*, 87:6, 1972-1977.

Arbex, M., Perobelli, F.S. 2010. Solow meets Leontief: Economic growth and Energy Consumption. *Energy Economics*, 32:1, 43-53.

Aslan, A., Kum, H. 2010. An investigation of cointegration between energy consumption and economic growth: Dynamic evidence from East Asian countries. *Global Economic Review*, 39:4, 431-439.

Dickey, D.A., Fuller W.A. 1979. Distribution of the Estimations for Autoregressive Time Series with a Unit Root. *Journal of American Statistical Association*, 74:366, 427-431.

Engle, R.F., Granger, C.W.J. 1987. Cointegration and Error-Correction: Representation, Estimation, and Testing. *Econometrica*, 55:2, 251-276

Ferguson, R., Wilkinson, W., Hill, R. 2000. Electricity use and Economic Development. *Energy Policy* 28:13, 923-934.

Ghosh, S. 2002. Electricity Consumption and Economic Growth in India', *Energy Policy* 30:2, 125-129.

Granger, C.W.J. 1969. Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica* 37:3, 424–438.

Granger, C.W.J., Newbold, P. 1974. Spurious Regressions in Econometrics. *Journal of Econometrics* 2, 111-120.

Jinke, L., Hualing, S, Dianming, G. 2008. 'Causality Relationship between Coal Consumption and GDP: Difference of Major OECD and non-OECD Countries. *Applied Energy*, 85:6, 421-429.

Johansen, S. 1988. Statistical Analysis of Co-integrating Vectors. *Journal of Economic Dynamics and Control* 12:6, 231-254

Johansen, S., Juselius, K. 1990. Maximum Likelihood Estimation and Inference on Co-integration with Application to the Demand for Money. *Oxford Bulletin of Economics and Statistics* 52:2, 169-210.

Kraft, J., Kraft, A. 1978. On the Relationship between Energy and GNP. *Journal of Energy Development* 3:2, 401-403.

Lee, C. C. 2005. Energy Consumption and GDP in Developing Countries: A Cointegrated Panel Analysis. *Energy Economics* 27:3, 415-427.

Lee, C. C. 2006. The Causality Relationship between Energy Consumption and GDP in G-11 Countries Revisited. *Energy Policy* 34:9, 1086-1093.

MacKinnon, J.G. 1991. Critical Values for Co-integration Tests, in Engle R.F. and Granger C.W.J. (eds.), *Long Run Economic Relationships: Readings in Co-integration*, pp.267-276, Oxford: Oxford University Press.

MacKinnon, J.G., Haug, A.A, Michelis, L. 1999. Numerical Distribution Functions of Likelihood Ratio Tests for Cointegration. *Journal of Applied Econometrics* 14:5, 563-577.

Masih, A.M.M., Masih, R. 1997. On the Temporal Causal Relationship between Energy Consumption, Real Income, and Prices: Some New Evidence From Asian-Energy Dependent NICs based on a Multivariate Cointegration/Vector Error-Correction Approach. *Journal of Policy Modelling* 19:4, 417–440.

Nanthakumar, L., Subramaniam, T. 2010. Dynamic Cointegration Link between Energy Consumption and Economic Performance: Empirical Evidence from Malaysia. *International Journal of Trade, Economics and Finance* 1:3, 261-267.

Narayan, P. K., Prasad, A. 2008. Electricity consumption-real GDP causality nexus: Evidence from a bootstrapped causality test for 30 OECD countries. *Energy Policy* 36:2, 910-918.

Phillips, P.C.B., Perron, P. 1988. Testing for a Unit Root in Time Series Regression. *Biometrika* 75:2, 335–346.

Pradhan, R.P. 2010. Energy Consumption - Growth Nexus in SAARC Countries: Using Cointegration and Error Correction Model. *Modern Applied Science* 4:4, 74-90.

Shiu, A., Lam, P. L. 2004. Electricity Consumption and Economic Growth in China. *Energy Policy* 32:1, 47-54.

Sims, C.A. 1972. Money, Income, and Causality. *The American Economic Review* 62:4, 540–552.

Soytas, U., Sari, R. 2003. Energy Consumption and GDP: Causality Relationship in G-7 Countries and Emerging Markets. *Energy Economics* 25:1, 33-37.

Stock, J., Watson, M.W. 1993. A simple estimator of cointegrating vectors in higher order integrated systems. *Econometrica*, 61:4, 783-820.

Toman, M.T., Jemelkova, B. 2003. Energy and Economic Development: An Assessment of the State of Knowledge. *The Energy Journal, International Association for Energy Economics* 24:4, 93-112.

Yoo, S. 2006a. The Causal Relationship between Electricity Consumption and Economic Growth in the ASEAN Countries. *Energy Policy*, 34:18, 3573-3582.

Yoo, S. 2006b. Causal Relationship between Coal Consumption and Economic Growth in Korea. *Applied Energy* 83:11, 1181-1189

Yang, H. Y. 2000. A Note on the causal relationship between Energy and GDP in Taiwan. *Energy Economics* 22:3, 309-317.

Zivot, E., Andrews, D.W.K. 1992. Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis. *Journal of Business and Economic Statistics* 10:3, 251-270.

 ISSN 1927-033X