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A structural VAR analysis of renewable energy consumption, real GDP and CO2 emissions: Evidence from India

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Abstract

This study has attempted to analyze the dynamics of renewable energy consumption, economic growth, and CO2 emissions. For the analysis, we used structural VAR approach. Results of unit root tests show that all variables are non-stationary at their level form and stationary in first difference form and cointegration analysis, analyzed through Johansen-Juselius (1990), shows that there is no evidence of cointegration among the test variables. The innovations analysis of study reveals that a positive shock on the consumption of renewable energy source increases GDP and decreases CO2 emissions and a positive shock on GDP have a very high positive impact on the CO2 emissions. The variance decomposition shows the share of consumption of renewable energy source explained a significant part of the forecast error variance of GDP and a relatively smaller or negligible part of the forecast error variance of CO2 emissions.

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1. Introduction

Since the negotiation of the Kyoto Protocol (1997), both developing and developed countries have been giving a strong emphasis, on their various national and international meetings, conferences, seminars and last but not least workshops, on the need to replace growing consumption of Non-Renewable Energy Sources (NRES) in general and fossil fuels in particular for Renewable Energy Sources (RES). This protocol demands reduction of the Greenhouse gas emissions (GHGs) by 5.2 % from the level of the 1990 during 2008-2012 and GHGs particularly carbon dioxide (CO_2) emissions, are considered to be the main causes of global warming. In addition, a sharp increase of CO_2 concentration is mostly due to the combustion of fossil fuels (coal, oil and natural gas) (Halicioglu, 2009 and Soytas and Sari, 2009) arising from the energy sector (Jaccard et al., 2003 and Köhler et al., 2006). Specifically, Halicioglu (2009) mentioned that CO_2 emissions are the most important polluting gas and it is responsible for 58.8% of the GHG emissions worldwide.

In this regard BP Statistical Review of World Energy (2010, pp. 2) states that "world primary energy consumption- including oil, natural gas, coal, nuclear and hydro power- fell by 1.1% in 2009, the first decline since 1982 and the largest decline (in percentage terms) since 1980. Consumption in OECD countries fell by 5%, the largest decline on record; OECD consumption reached the lowest level since 1998. Energy consumption declined in all regions except Asia Pacific and the Middle East; Chinese energy consumption growth accelerated to 8.7%. Hydroelectric power generation increased by 1.5%, and was the world's fastest-growing major fuel for a second consecutive year."

In addition , BP Statistical Review of World Energy (2010, pp. 5) document that "Hydroelectric generation grew by a below-average 1.5%, which was nonetheless sufficient to make hydro the world's fastest-growing major fuel in 2009. Growth was led by China, Brazil, and the US." BP Statistical Review of World Energy (2010, pp. 5) has also mentioned, "While other forms of renewable energy remain a small share of the global energy mix, they have continued to grow rapidly. Continued government support, including targeted fiscal stimulus in many countries, helped to boost global wind and solar generation capacity by 31% and 47% respectively." BP Statistical Review of World Energy (2010, pp. 38) states that among the ASIAN countries, India consumes 3.2% of electricity generated through hydropower which is next to China. Therefore, in the present study we have attempted to analyze the role of renewable energy consumption on the economic growth of India.

2. A brief review of literature

There are various studies, which focused on the relationship between energy consumption in general and electricity consumption in particular, and economic growth. Economic growth measured in terms of gross domestic product (real or in per capita) or growth rate of GDP, using different econometric methodologies, countries and time period and have found conflicting results.

Here we provide some brief review of literature on the recent studies, which have analyzed the impact of energy consumption at disaggregated economic growth and employment.[1] Yang (2000) found bidirectional causality between aggregate energy consumption and GDP in Taiwan. However, at the disaggregation of energy sources he found bidirectional causality between GDP and coal, GDP and electricity consumption and GDP and total energy consumption, but unidirectional causality running from GDP to oil consumption and from natural gas to GDP. Sari and Soytas (2004) found that waste had the largest initial impact, followed by oil however; lignite, waste, oil, and hydropower explained the larger amount of GDP variation among energy sources within the 3-year horizon respectively. Wolde-Rufael (2004) found unidirectional Granger causality from coal, coke, electricity, and total energy consumption to real GDP, but no causality in any direction, between oil and real GDP. Domac et al., (2005) argue that bio-energy should help increase the economies’ macroeconomic efficiency through the creation of employment and other economic gains and Awerbuch and Sauter (2006) added that RES had a positive effect on economic growth by reducing the negative effects of oil prices volatility either by providing energy supply security or otherwise. Ewing et al., (2007) found that shocks arises due to NRES consumption like coal, gas and oil had more impact on output variation than the shocks arises due to RES. Chien and Hu (2008) have studied the effects of RES on GDP for 116 economies in 2003 through the Structural Equation Modeling (SEM) approach. They concluded that RES had a positive indirect effect on GDP through the increase in capital formation; however, RES did not show any improvement on the trade balance with no import substitution effect. Sari et al., (2008) by using autoregressive distributed lag (ARDL) approach for the USA found that, in the long-run, industrial production and employment were the key determinants of fossil fuel, hydro, solar, waste and wind energy consumption, but did not have a significant impact on natural gas and wood energy consumption. Chang et al., (2009) by using Panel Threshold Regression (PTR) model for the OECD countries over the period 1997-2006 asserted that there was no direct and simple relationship between GDP and the contribution of RES to energy supply. They concluded by documenting that the level of economic growth of a country influenced the use of RES as a way to respond to oil price shocks. High-economic growth countries used RES to minimize the effects of adverse price shock, but low-economic growth countries were unable to do so. Therefore, the first countries exhibited a substitution effect towards RES to avoid the negative relationship between oil prices and GDP. Sadorsky (2009a) used a panel data model to estimate the impact of RES (which includes geothermal, wind and solar power, waste and wood) on economic growth and CO_2 emissions per capita and oil price for the G7 countries. The author found that, in the long-run, real GDP per capita and CO_2 emissions per capita were the main drivers of renewable energy consumption per capita. Oil prices had a smaller and negative effect on renewable energy consumption. In the short term, movements drove variations in renewable energy consumption back to the long-term equilibrium rather than short term shocks. Sadorsky, (2009b) studied the relationship between RES (wind, solar and geothermal power, wood and wastes) and economic growth in a panel framework of 18 emerging economies for the period 1994-2003 and found that increases in real GDP had a positive and statistically significant effect on renewable energy consumption per capita. Payne (2009) provides a comparative causal analysis of the relationship between RES and NRES and real GDP for the USA over the period 1949-2006 and found no Granger causality between renewable and nonrenewable energy consumption and real GDP. Apergis and Payne (2010)

[1] See Tiwari (2011a, 2011b) for comprehensive review of literature.

attempted to study the relationship between RES and economic growth for 20 OECD countries over the period 1985-2005 within a framework of production function by incorporating capital formation and labor in the analysis and found a long-run equilibrium relationship between real GDP and RES.

3. Methodology and data source

In this paper, we analyze the relationship between the RES, economic growth, and CO_2 emissions in the context of India in SVAR framework as to the best of our knowledge this kind of work do not exist for Indian economy. In most of the studies, VAR approach is used to analyze the dynamic impacts of different types of random disturbances on the variables in the model (Ferreira et al., 2005) as it takes into consideration those interactions and all variables are treated as endogenous as a function of all variables in lags. However, the reduced form VAR does not consider the structural relationships among the variables unless some identification restrictions are assumed. In this sense, SVAR analysis is an attempt to solve the traditional identification problem. Therefore, the SVAR can be used to predict the effects of specific policy actions or of important changes in the economy (Narayan et al., 2008) for example, change in the energy supply mix. Hence, policy makers and economic forecasters the ca use the results obtained from the model to predict how some variables, for example, GDP and RES respond over time to changes in policies (Buckle et al., 2002). For the analysis we used Gross Domestic Product (GDP per capita constant 2000 US$, a measure of economic growth), RES (measured by hydroelectricity consumption) and CO_2 emissions (measured in Million tons).[2] For the purpose of analysis, we have transformed all variables in natural logarithm as it minimizes the fluctuations in the data series (Tiwari, 2010). First of all in order to identify the order of the integration of the series Ng and Perron (2001) unit root test has been employed as it is considered to be better that other tests of unit root like Augmented Dickey Fuller (ADF) (1981) and Phillips and Perron (PP) test and then cointegration analysis has been conducted in order to identify nature of cointegration, if any exist, among the test variables. In the next step, we construct a SVAR and plot the impulse response functions (IRFs) of GDP and CO_2 emissions when a positive shock to RES and GDP occurs and in the final step, we study the forecasts error variance decomposition of SVAR model. Lag-length to be incorporated in our analysis is determined based on Akaike Information Criteria (AIC) because of its better performance in small sample (Liew, 2004). Moreover, in order to compute SVAR we must impose restrictions on the parameter matrices. These restrictions can either be of contemporaneous restrictions type on the parameter matrices of A_0 and B (where A_0 and B are the ($K \times K$) that indicates instantaneous relationship relations of variables in X_t and ε_t respectively[3]) or of long-run restrictions type on the total effects of structural shocks in order to identify the structural parameters. However, in this paper we apply the long-run restrictions method proposed by Blanchard and Quah (1989). The long-run restrictions model sets A_0 as an identity matrix, i.e. $A_0 = I_K$. These restrictions are based on the long-run restrictions that we imposed on the cumulative

[2] Data of GDP is obtained from World Development Indicators accesses form the website of World Bank (on October 12, 2010) and CO_2 emission data and Hydroelectricity consumption data is accessed from http://www.bp.com/bodycopyarticle.do?categoryId=1&contentId=7052055 (accessed on October 25, 2010.)

[3] Where X_t represents vector of four endogenous variables used in our analysis and ε_t represents vector shocks associated with four endogenous variables. K represents the number of variables i.e., four.

impulse response function. Totally, $K(K-1)/2$ restrictions are imposed on the lower triangular matrix where some of the structural shocks do not have contemporaneous impacts on the other variables. The variables are ordered as follows: RES, GDP, and CO_2.[4] Moreover, we assume that the first variable (that is RES) has impacts on all variables below it (i.e., GDP and CO_2 emissions) but it does not receive any impacts from these variables. The second variable (i.e., GDP) only receives the impacts from the first variable (i.e., RES) and does not have any affect the first variable but it can influence the variables below it (i.e., CO_2 emissions). Thus, we have made long-run multiplier matrix, a lower triangular matrix.

4. Data analysis and results

First, unit root test has been carried out for all variables using Ng and Perron (NP) test (2001). Ng and Perron (NP) has given three tests of unit root analysis but MZ_a and MZ_t are said to be more powerful test (Mollick, 2009) so, this study has used these two tests only. Results of unit roots are reported in Table-1 and graphical plot of the log-level data of variables is presented in appendix 1.

Table 1: Unit root analysis

Variables	Unit root tests		
	Constant and trend	NP	
		(MZ_a) (k)	(MZ_t) (k)
Ln(GDPPC)	Yes	0.32935 (0)	0.16462 (0)
D(Ln(GDPPC))	Yes	-22.1745** (0)	-3.32927**(0)
Ln(Hec)	Yes	-5.95680 (0)	-1.68983 (0)
D(Ln(Hec))	Yes	-21.5917** (0)	-3.25524** (0)
Ln(CO_2))	Yes	-7.50956 (0)	-1.85365 (0)
D(Ln(CO_2))	Yes	-21.4943** (0)	-3.27791** (0)
Note: (1) **denotes significant at 5% level. (2) “K” denotes lag length. (3) Selection of lag length in NP test is based on Spectral GLS-detrended AR based on SIC.			
Source: Authors calculation			

It is evident from Table-1 that all variables are nonstationary in their level form and they are turning to be stationary after first difference i.e., I(1). Since all variable are I(1) therefore we can proceed for cointegration analysis. To proceed for cointegration first step is selection of appropriate lag length. Therefore, we have carried out a joint test of lag length selection, which suggests (based on AIC) we should take two lag of each variable. Hence, by choosing lag two we have conducted model selection test and found that both AIC and SIC prefers model 5. Therefore, we have attempted for 5th model to check the possibility of existence of cointegration and also for 4th model (since in the 4th model we have lowest values of SIC and AIC after fifth model) this is because fifth model is argued to be theoretically difficult to interpret. However, we did not find any evidence of cointegrating relationship among the test variable in any of the two

[4] Our restrictions are based on the assumption that as hydro systems allow some storage levels (Amundsen and Bergman, 2002) therefore its consumption affects GDP and in the reduction in the CO_2 emissions and CO_2 has no short-term effect on GDP and hydro consumption since there is no direct causality relation.

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models.[5] Further, for analyzing the non-stationary series in a VAR system Ramaswamy and Sloek (1997) mentions three possible ways to specify. First, either to specify the series in differenced form, second, to specify them in levels, and third to consider the cointegration relationships among the test variables by applying a vector error correction model (VECM) and this is considered when the cointegration relationship is known. In addition, if the cointegration relationship is unknown, VECM can be biased and it could be more appropriate to consider the VAR in levels. In this paper, however, we apply a structural VAR model in differenced form in order to generate efficient estimators, as we do not have cointegrating relationship among the test variables.[6]

Further, since we have a sample size which is not large enough therefore, we have followed Benkwitz et al., (2001) who suggest that for small sample, properties of bootstrap confidence intervals are better in comparison to other asymptotic methodologies. Therefore, we have computed bootstrap percentile 95% confidence intervals (by following Hall, 1992 and Efron and Tibshirani, 1993) with 1000 bootstrap replications to illustrate parameter uncertainty. The horizon of all responses is 20 years. In the following Figures (**1a** to **1c of Figure-1**), we represent the impulse response functions.

Figure-1: IRFs in SVAR

Figure-1a

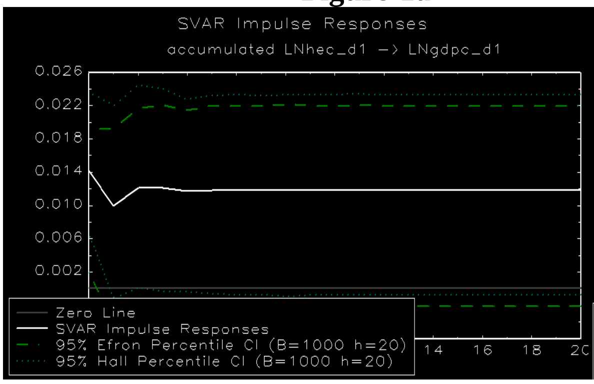


Figure-1b

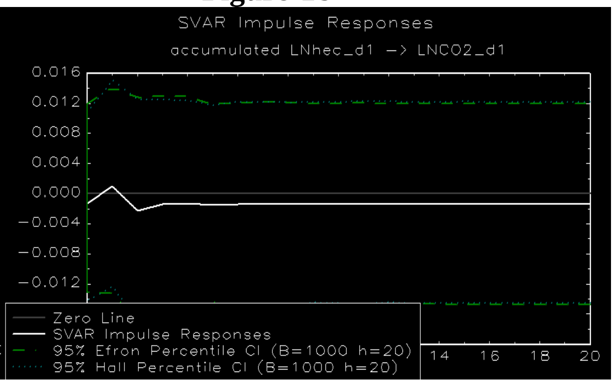
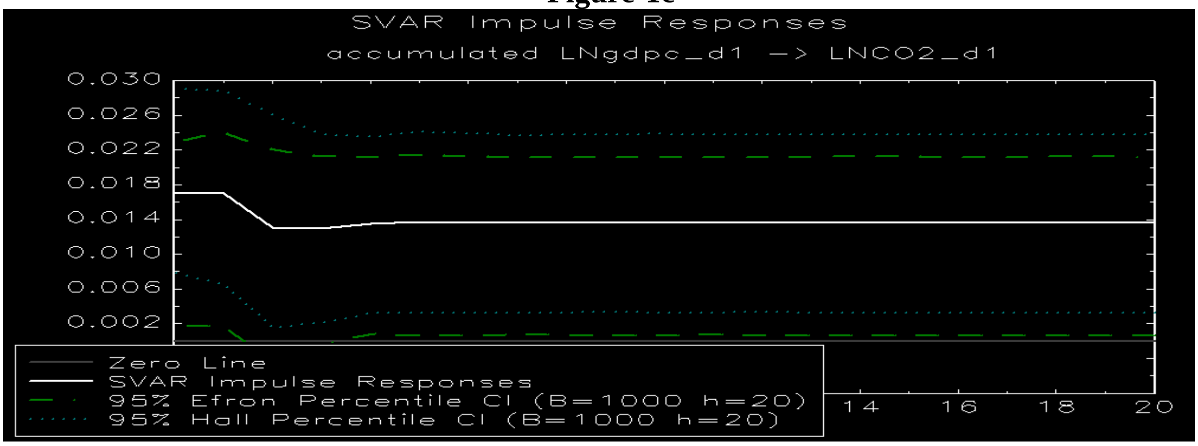


Figure-1c



[5] Results of cointegration relationship of the two models, lag length selection, and model selection are presented in appendix 1.

[6] Structural VAR Estimation Results of contemporaneous impact and long run impact are shown in appendix 2.

It is evident from Figure-1a of Figure-1 that any one positive standard deviation shock/innovation to REs has very high and positive impact on the real GDP of India. Figure-1b reviles that any one positive standard deviation shock/innovation to RES has negative impact on the CO_2 emissions throughout 20 years (except first year in that case its impact is positive). Figure-1c reviles that any one positive standard deviation shock/innovation to GDP has positive impact throughout 20 years on CO_2 emissions. Therefore, we can conclude from IRFs of SVAR analysis that consumption of RES increases GDP in a greater extent and reduces CO2 emissions. Further, higher growth rate increases CO_2 emissions. Hence, this implies that higher growth path achieved via consumption of RES has two fold advantages of attaining and maintaining sustained and safest growth.

Further, we have analyzed the variance decomposition which indicates how much of the forecast error variance of each variable can be explained by exogenous shocks (changes) to the variables in the same VAR model. Innovations/shocks to an individual variable can affect both own changes and changes in the other variables (Ewing et al., 2007). However, in the present context we have analyzed how much of the forecast error variance of real GDP and CO_2 emissions are explained by each variable in the model.

Table-2: Variance Decompositions (VDs) analysis

Proportions of forecast error in D(Ln (GDPC)) accounted for by:			
Period	D(Ln (Hec))	D(Ln (GDPC))	D(Ln (CO_2))
1	0.32	0.58	0.10
2	0.28	0.49	0.23
3	0.28	0.49	0.23
4	0.28	0.49	0.23
5	0.28	0.49	0.23
10	0.28	0.49	0.23
15	0.28	0.49	0.23
20	0.28	0.49	0.23
Proportions of forecast error in D(Ln (CO_2)) accounted for by:			
Period	D(Ln (Hec))	D(Ln (GDPC))	D(Ln (CO_2))
1	0.00	0.29	0.71
2	0.01	0.28	0.71
3	0.02	0.29	0.70
4	0.02	0.29	0.70
5	0.02	0.29	0.70
10	0.02	0.29	0.70
15	0.02	0.29	0.70
20	0.02	0.29	0.70
Source: Authors' calculations			

It is evident from Table-2 that in the first year GDP itself explains 58% of forecast error in its own value and between CO_2 emissions and RES, RES explains largest proportion of forecast error throughout 20 years of period. Though explanatory power of RES has not increased in this duration, yet it is very high. Further, we find that larger proportion of forecast error variations in

CO_2 emissions are explained by its own value, however GDP explains around 30% of the forecast error variation in CO_2 emissions and RES explains a very less i.e., 2% of forecast error variation in CO_2 emissions.

5. Conclusions and policy implications

In recent years, dependence on the non-renewable energy sources has declined due to increasing awareness about environmental concern and focus of energy generation through renewable energy sources. This has increased renewal generation of energy in both developed and developing countries in recent years. This has happened either due to external (i.e., imposed by some international environmental body) or internal (i.e., by recognizing the consequences of environmental degradation on humankind) reasons. In this regards the aim of this paper is to analyze how an increasing share of renewable sources on electricity generation affects Gross Domestic Product (GDP). There are several methodologies that could be used for this purpose however, Structural Vector Autoregressive (SVAR) methodology considers the interactions among all variables in the model and is well suited to predict the effects of specific policy actions or important changes in the economy. Therefore, SVAR approach has been chosen for our analysis. We used a three variables (i.e., RES, GDP and CO_2 emissions) SVAR model for India along the period 1960-2009.

In this study, we use SVAR model and the plotted IRFs and calculated VDs to estimate the impacts on real GDP and CO_2 emissions arising from a positive shock on the RES. Our analysis revels that in general, a positive shock on the RES increases GDP and decreases CO_2 emissions. Further, we find that a positive shock on the GDP has very high positive impact on the CO_2 emissions. The variance decomposition showed that the share of RES explained a significant part of the forecast error variance of GDP and a relatively smaller or negligible part of the forecast error variance of CO_2 emissions. Our results indicate that an increase in the RES share may initially increase CO_2 emissions (in first year) therefore Indian government may need to complement RES support with other policies, such as demand-side management and energy conservation, in order to achieve environmental goals at the least cost. However, we have provided evidence for India in case of only one renewable energy source i.e., consumption of hydroelectricity, yet analysis at more disaggregated level and with inclusion of other renewable sources can be conducted. Further, we recommend to the policy makers of India pertaining to energy related matters, to achieve sustained, safest, and fastest growth, through renewable energy consumption. As it has been found in previous studies conducted for India that energy consumption (in which major proportion was of NRES was higher vis-à-vis RES; for reference on this one my refer Tiwari, 2011a, 2011b) do not contribute to the economic growth. In addition to that a comparative analysis of the impact of RES and NRES on economic growth and pollution can be conducted at the both aggregate and disaggregate level.

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Appendix 1

Figure 1: plots of log-level data of Hydroelectricity Consumption, GDP per capita (constant 2000 US$) and CO2 emissions

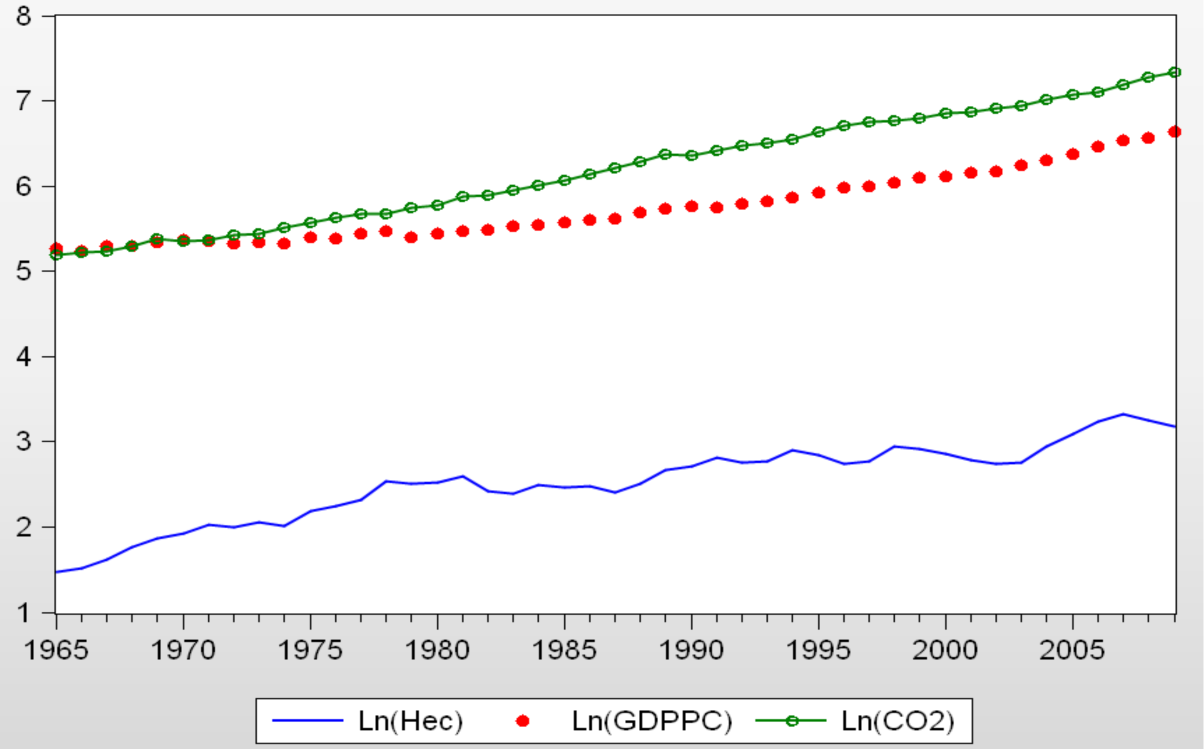

Table 1: VAR Lag Order Selection Criteria

Endogenous variables: Ln(Hec), Ln(GDPPC) and Ln(CO_2)
Exogenous variables: C
Sample: 1965 2009
Included observations: 41

Lag	LogL	LR	FPE	AIC	SC	HQ
0	28.22703	NA	5.86e-05	-1.230587	-1.105204	-1.184929
1	226.5585	357.9640	5.73e-09	-10.46627	-9.964733*	-10.28364*
2	237.8951	18.80224*	5.15e-09*	-10.58025*	-9.702565	-10.26064
3	241.3184	5.176690	6.90e-09	-10.30821	-9.054381	-9.851637
4	246.9256	7.658582	8.46e-09	-10.14271	-8.512728	-9.549161

Note: (1)* indicates lag order selected by the criterion (2) LR, FPE, AIC, SC, HQ, denotes sequential modified LR test statistic (each test at 5% level), Final prediction error, Akaike information criterion, Schwarz information criterion, and Hannan-Quinn information criterion respectively.

Table 2: Model selection test

Sample: 1965 2009
Included observations: 42
Series: Ln(Hec), Ln(GDPPC) and Ln(CO_2)
Lags interval: 1 to 2
Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	3	3	1	0	0
Max-Eig	3	3	0	0	0

*Critical values based on MacKinnon-Haug-Michelis (1999)
Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Log Likelihood by Rank (rows) and Model (columns)					
0	222.8159	222.8159	233.0136	233.0136	241.4392
1	233.5245	234.1401	242.4169	243.5863	249.5805
2	239.7358	242.8777	248.5113	249.7160	252.2852
3	245.1468	248.5826	248.5826	252.3014	252.3014
Akaike Information Criteria by Rank (rows) and Model (columns)					
0	-9.753139	-9.753139	-10.09588	-10.09588	-10.35425
1	-9.977359	-9.959053	-10.25795	-10.26602	-10.45621*
2	-9.987419	-10.04179	-10.26244	-10.22457	-10.29930
3	-9.959371	-9.980123	-9.980123	-10.01435	-10.01435
Schwarz Criteria by Rank (rows) and Model (columns)					
0	-9.008424	-9.008424	-9.227050	-9.227050	-9.361291*
1	-8.984405	-8.924725	-9.140875	-9.107569	-9.215020
2	-8.746227	-8.717855	-8.897132	-8.776511	-8.809865
3	-8.469940	-8.366573	-8.366573	-8.276685	-8.276685

Table 3: Cointegration test for model 5

Sample (adjusted): 1968 2009
Included observations: 42 after adjustments
Trend assumption: Quadratic deterministic trend
Series: Ln(Hec), Ln(GDPPC) and Ln(CO_2)
Lags interval (in first differences): 1 to 2
Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.321371	21.72457	35.01090	0.5935
At most 1	0.120848	5.441959	18.39771	0.9088
At most 2	0.000772	0.032453	3.841466	0.8570

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.321371	16.28261	24.25202	0.3908
At most 1	0.120848	5.409506	17.14769	0.8701
At most 2	0.000772	0.032453	3.841466	0.8570

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Table 3: Cointegration test for model 4

Sample (adjusted): 1968 2009
Included observations: 42 after adjustments
Trend assumption: Linear deterministic trend (restricted)
Series: Ln(Hec), Ln(GDPPC) and Ln(CO_2)
Lags interval (in first differences): 1 to 2
Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.395567	38.57572	42.91525	0.1271
At most 1	0.253147	17.43023	25.87211	0.3835
At most 2	0.115841	5.170979	12.51798	0.5720

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.395567	21.14549	25.82321	0.1840
At most 1	0.253147	12.25925	19.38704	0.3914
At most 2	0.115841	5.170979	12.51798	0.5720

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Appendix 2

Table 1: Structural VAR Estimation Results

Structural VAR Estimation Results: Identified accumulated long run impact matrix is lower diagonal

Estimated contemporaneous impact matrix; in parenthesis Bootstrap t-values with 1000 replications

Ln (Hec)	Ln (GDPC)	Ln (CO_2)
0.0963 (5.9498)	-0.0009 (-0.0551)	-0.0040 (-0.2812)
0.0142 (2.7694)	0.0192 (4.0771)	-0.0082 (-2.0953)
-0.0013 (-0.1789)	0.0171 (2.5674)	0.0267 (4.6891)

Estimated identified long run impact matrix; in parenthesis Bootstrap t-values with 1000 replications

0.1041 (4.0549)	0.0000 (0.0000)	0.0000 (0.0000)
0.0118 (1.7506)	0.0196 (4.0007)	0.0000 (0.0000)
-0.0014 (-0.1822)	0.0136 (1.9837)	0.0206 (3.8425)

Source: Authors' calculation