

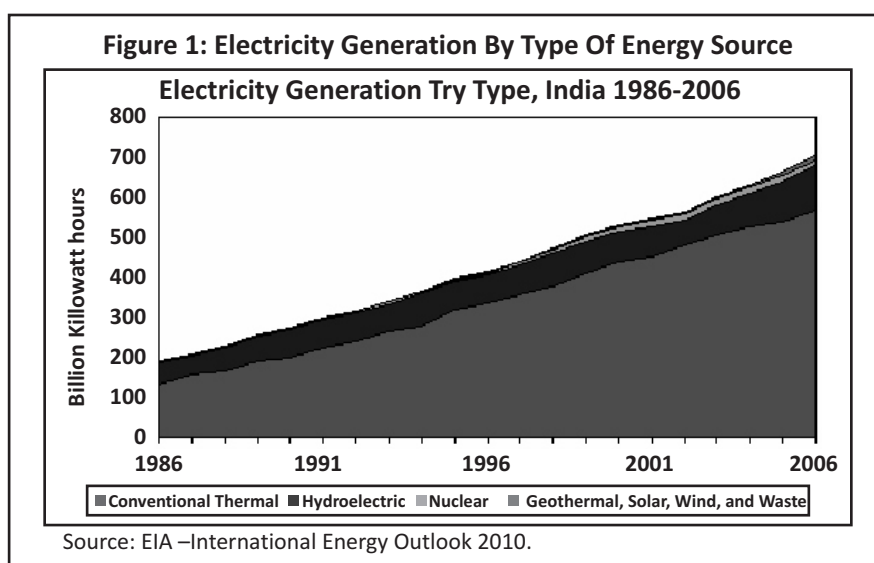
A Causal Study Between Electricity Consumption And CO₂ Emissions In India

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INTRODUCTION

India is one of the fastest growing economies, growing at a projected rate of 8 to 9% annually. Rapid industrialization over the last two decades has also resulted in the development of infrastructure and increasing use of electricity to cope up with the challenging business and managerial processes. India, the world's fourth-largest carbon emitter, is under pressure to cut pollution in the fight against climate change. About 80 to 90 percent of India's commercial energy requirement is fulfilled by fossil fuels like coal, oil and gas. While per-capita emissions are still low as compared to other developing countries, the rapid growth in Information and Communication Technologies (ICT), more economic activity has led to more productive ventures that have made incomes go up, which implies that people demand more energy, all this has resulted in increased use of electricity that causes the exploitation of fossil fuels in generating the required input of electricity, so this cycle of generating electricity from fossil fuels has resulted in increased emissions of carbon dioxide over a period of time. Increasing CO₂ emissions are the primary cause for the rising temperatures across the country that are causing random variations in the climate and the increasing emissions are causing the sea levels to rise. Chen & Li (2007) rightly pointed out that the rise in the sea level and increase in the frequency of tropical storms causes higher incidence of respiratory diseases. India is especially vulnerable to the adverse impacts of climate and over 2% of the GDP is currently spent on measures to adapt to these impacts.

Coal is the bastion of India's energy economy, coal based power plants account for about two – thirds of the total electricity generation installed capacity of about 135,000 MW. The Figure 1 clearly shows how India is dependent on conventional thermal sources for electricity generation. India's electricity consumption is at the sixth position globally, with 606 units of per capita consumption per annum. It was bound to become 1000 units per annum by 2012. Such high demand comes from the large population growth, rapid industrialization and urbanization and increasing per capita income. Electricity has been used as a basic energy input because of its clean and efficient nature ; consumption of electricity in India is currently at some 600TWh annually, and is all set to double in the next ten years. Electricity is considered to be one of the key inputs for accelerating economic growth.



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India has ten percent of the world's coal reserves, the biggest after the US, Russia and China. Most of India's coal is inferior in quality and is highly polluting. Since 1990, CO₂ emissions per person of India have increased from 0.8 to 1.4 tonnes of CO₂ per capita. These changes reflect the large economic development of India, structural reforms in national and global economies, and the impact of climate and energy policies. Moreover, the effects of climate change are beginning to be strongly felt, and the government is taking initiatives and taking a lead in arguing for a reduction in carbon dioxide emission on a global platform - during the agreement of the Kyoto Protocol and in the post Kyoto pacts.

Earlier studies which are limited to developed countries and some studies on other Asian countries on the relationship between economic growth and environment pollution are used as inputs for the present study. Studies done by Coondoo & Dinda (2002), Dinda & Coondoo (2006), Akbostanci et al. (2009), and Lee & Lee (2009) on the relationship between economic growth and environmental pollution were examined for the purpose of inquiry. A study done by Ang (2007) for France on the relationship between energy consumption, economic growth and pollution emissions revealed that there exists a unidirectional causality running from economic growth to energy consumption and pollution emissions in the long run. Ang's (2007) study for Malaysia on the long-run relationship between output, pollutant emissions, and energy consumption revealed that there exists a unidirectional causality running from economic growth to energy consumption growth, both in the short-run and long-run.

Soytas et al.'s (2007) study on United States found that there exists a uni - directional granger causality running from energy consumption to pollution emissions in the long run. A study done by Zhang and Cheng (2009) for China found that there exists a unidirectional causality running from economic growth to energy consumption and energy consumption to pollution emissions in the long run. Halicioglu (2009) for Turkey found that there exists both short run and long run bidirectional causality between economic growth and pollution emissions. A similar study on Turkey done by Soytaş and Sari (2009) revealed that there exists a uni - directional granger causality running from energy consumption to pollution emissions in the long run. The study by Soytaş and Sari (2009) for oil rich OPEC countries – Algeria, Indonesia, Nigeria, South Africa and Venezuela found conflicting results in the short run and long run relationships.

DATA & MODELS

This study covers the period from 1971-2006 for two variable annual time-series data. The data variables are per capita electricity consumption (Billion KWH) and per capita CO₂ emissions (Metric Tons). The secondary data was taken from the source of World Bank data statistics. The time series data was analyzed by using econometric techniques namely Engel-Granger two-step procedure for cointegration and one step error correction mechanism to see the short run behavior of per capita CO₂ emissions. The following Data Analysis section describes the results found through the application of the aforesaid econometric techniques through the use of Gretl econometric software.

DATA ANALYSIS

Notations Used:

- ⊗ **ELEC** = Per capita electricity consumption in Level form
- ⊗ **CO₂** = Per capita CO₂ emissions in level form
- ⊗ **1_ELEC** = Log per capita electricity consumption in Level form
- ⊗ **1_CO₂** = Log per capita CO₂ emissions in level form
- ⊗ **d_1_ELEC** = Log per capita electricity consumption in difference form
- ⊗ **d_1_CO₂** = Log per capita CO₂ emissions in difference form
- ⊗ **uhat1** = OLS residual from co- integrating regression

TESTS FOR NON - STATIONARITY

The time series graphs (Figure 2) clearly shows an upward trend with some fluctuations, however, after testing for non - stationarity using ACF and Correlogram tests, the researcher found that both the per capita CO₂ emissions and

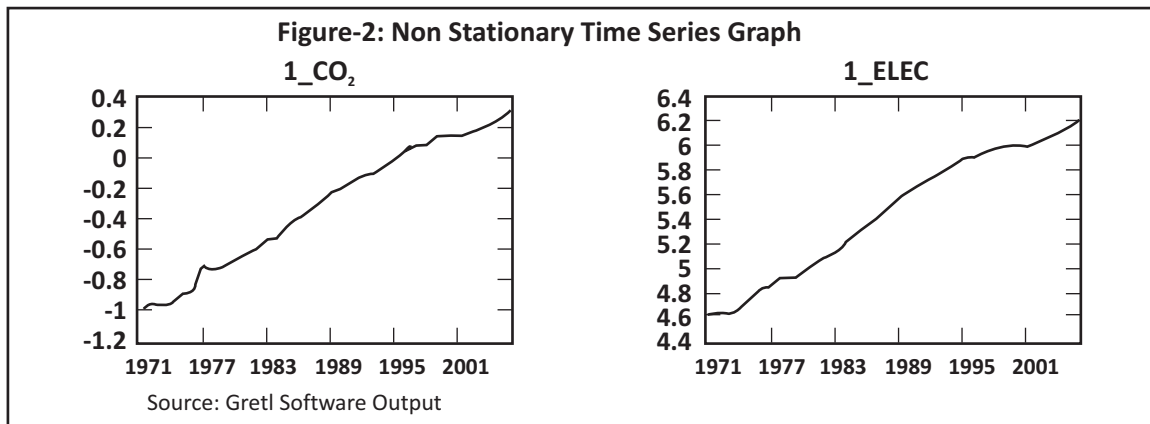
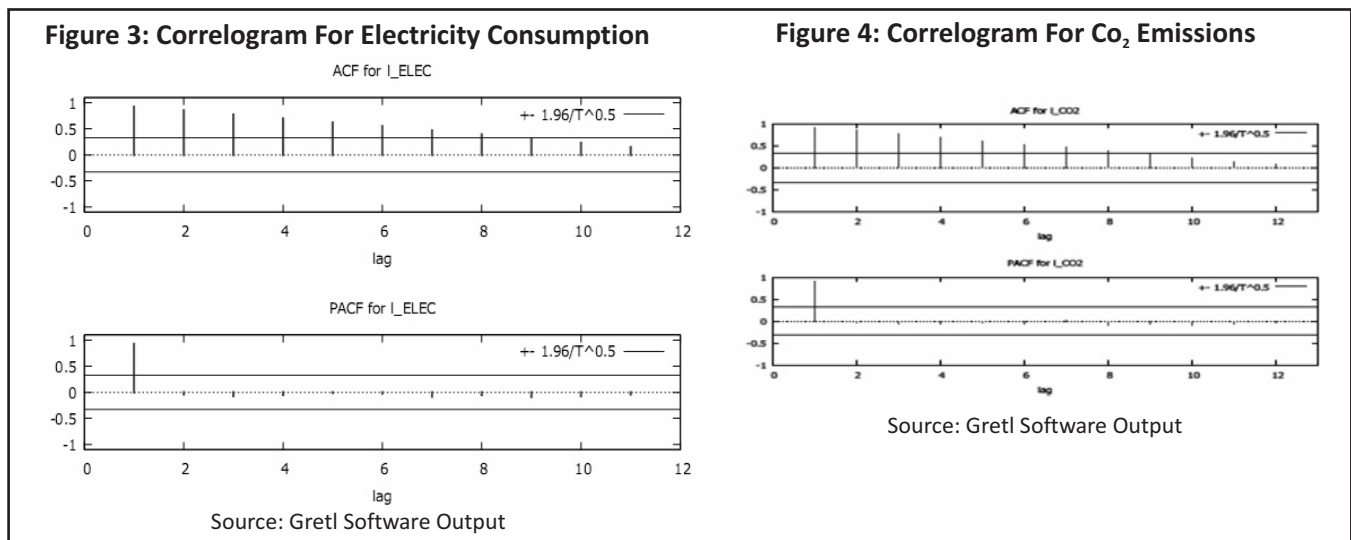


Table 1: Autocorrelation Function For 1_CO ₂				
LAG	ACF	PACF	Q-stat	[p-value]
1	0.92 ***	0.92 ***	33.35	0.00000
2	0.84 ***	-0.02	62.39	0.00000
3	0.77 ***	-0.06	87.02	0.00000
4	0.68 ***	-0.06	107.31	0.00000
5	0.61 ***	-0.03	123.73	0.00000
6	0.52 ***	-0.06	136.46	0.00000
7	0.45 ***	0.01	146.26	0.00000
8	0.37 **	-0.08	153.25	0.00000
9	0.30 *	-0.06	157.81	0.00000
10	0.21	-0.07	160.35	0.00000
11	0.14	-0.05	161.43	0.00000

Source: Gretl Software Output

Table 2: Autocorrelation Function For 1_ELEC				
LAG	ACF	PACF	Q-stat.	[p-value]
1	0.92 ***	0.92 ***	33.53	0.000
2	0.85 ***	-0.04	62.73	0.000
3	0.77 ***	-0.07	87.56	0.000
4	0.69 ***	-0.05	108.15	0.000
5	0.61 ***	-0.01	125.07	0.000
6	0.54 ***	-0.02	138.74	0.000
7	0.47 ***	-0.08	149.17	0.000
8	0.39 **	-0.04	156.74	0.000
9	0.31 *	-0.09	161.66	0.000
10	0.22	-0.07	164.39	0.000
11	0.14	-0.04	165.59	0.000

Source: Gretl Software Output



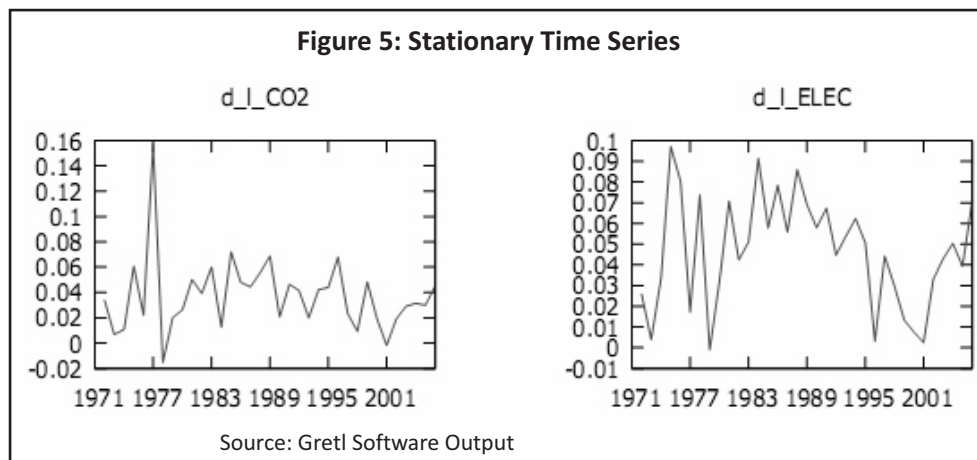
Electricity consumption (in levels) were non- stationary in the log form. The researcher took logs for both variables to eliminate the scale effects and also the possible heteroskedasticity impact. The Q statistic developed by Box and Pierce was used to check the non - stationarity, the *p* value of statistics show the evidence of non - stationarity of both

the variables in level form, and the results are depicted in the Tables 1 & 2 and Figures 3 & 4. Further, the non-stationarity is supported by Augmented Dickey Fuller (ADF) test and KPSS statistics. The KPSS (Kwiatkowski, Phillips, Schmidt and Shin, 1992) is a unit root test in which the hypothesis is opposite to that in the ADF test: under the null, the series in question is stationary; the alternative is the series $I(1)$. If the calculated KPSS is greater than the critical value at the given level of significance, then the null hypothesis is rejected. The resulted p values of ADF and critical values of KPSS statistics show significant evidence of accepting the unit root hypothesis that confirms the non-stationarity, and the results are provided in the Table 3.

Table 3: Tests For Non - Stationary ADF & KPSS							
Variables	ADF Test: Unit-root null hypothesis: a = 1	ADF Test-P Values	KPSS Statistic (H0: Series is Stationary)				
			Calculated Values	Critical Values			
				10%	5%	2.5%	1%
1_CO ₂	without constant	0.437	1.87704	0.347	0.463	0.574	0.739
	with constant	0.7308					
	with constant & trend	0.9423					
1_ELEC	without constant	0.9999	1.87297	0.347	0.463	0.574	0.739
	with constant	0.7699					
	with constant & trend	0.9148					
Source: Gretl Software Output							

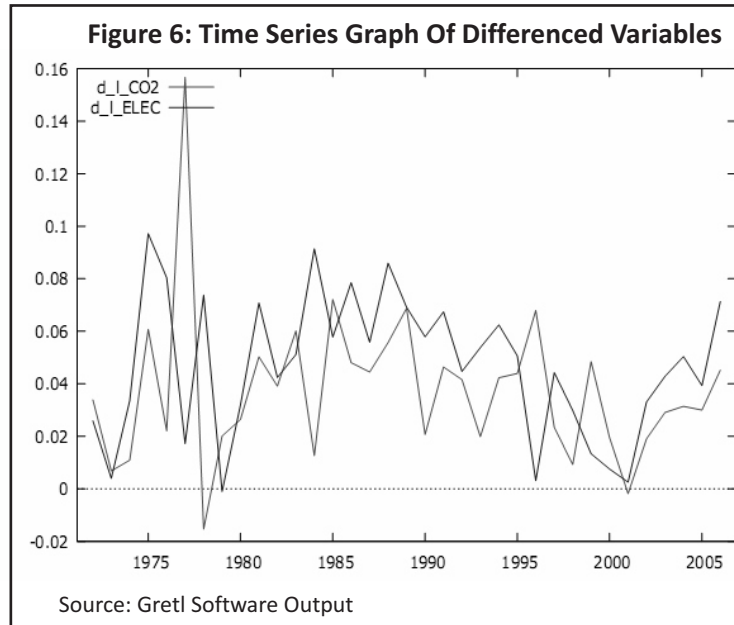
For forecasting purposes, the time series data should be in stationarity, therefore, the researcher took the first difference of the level variables and checked the stationarity of these variables through time series graphs and ADF test statistics. The time series graphs were more or less stable, indicating the stationarity of differenced variables and the same is confirmed by applying the ADF test for unit root (non-stationary). All the p values of ADF statistics are significant and this implies that the unit root hypothesis is rejected, thus, the variables are integrated of order one (stationary). The results are shown in the Table 4 & Figure 5.

Table 4: Tests For Stationarity: ADF		
Variables(In Difference form)	ADF Test: Unit-root null hypothesis: $\alpha = 1$	ADF Test-P Values
d_1_CO ₂	with constant	0.0005322
	with constant and trend	0.001433
d_1_ELEC	with constant	0.01964
	with constant and trend	0.04074
Source: Gretl Software Output		



TEST FOR COINTEGRATION

The next step is to see whether the two variables are co-integrated or not, i.e. whether per capita CO₂ emissions and per capita electricity consumption have long term or equilibrium relationship between them or not. For this, the researcher needed to check the co-integration between these two variables. The Figure 6 time series graph of differenced variables shows an expected co - integration between two variables, which is further confirmed by Engel and Granger Causality Test.



Engel and Granger developed a co - integration test which uses the co-integrating OLS regression using level variables, where the researcher can check the spurious regression results (R-Square value greater than Durbin Watson Statistic), from which it tests the stationarity of the OLS residuals. If the residuals are found to be white noise (stationary) , then the variables are said to be co- integrated. The data variables for the present study were found to be co - integrated, as shown in the Table 5.

Table 5: Model : OLS, Using Observations 1971-2006 (T = 36)				
Dependent variable: 1_CO2				
	Coefficient	Std. Error	t-ratio	p-value
Const	-4.61791	0.0536168	-86.128	<0.00001***
1_ELEC	0.789455	0.00978814	80.6543	<0.00001***
Mean dependent var	-0.31	S.D. dependent var	0.42	
Sum squared resid	0.03	S.E. of regression	0.03	
R-squared	0.99	Adjusted R-squared	0.99	
F(1, 34)	6505.11	P-value(F)	0.00	
Log-likelihood	75.38	Akaike criterion	-146.76	
Schwarz criterion	-143.59	Hannan-Quinn	-145.65	
Rho	0.34	Durbin-Watson	1.31	
Source: Gretl Software Output				

The researcher took the model with a constant, as there was no trend effect and it is a difference stationary process.

Table 6: Augmented Dickey-Fuller test for uhat1				
Dependent variable: d_uhat1				
	Coefficient	Std. Error	t-ratio	p-value
uhat1_1	-0.485921	0.195581	-2.484	0.0126 **
d_uhat1_1	-0.256618	0.170866	-1.502	0.1429
Source: Gretl Software Output				

From the above OLS regression, the researcher found that R-Squared value is less than the Durbin-Watson statistic value, which indicates that there is no spurious regression, but after testing for the stationarity of OLS residuals through ADF test, the researcher found that residuals are white noise, confirming the cointegration between per capita CO₂ emissions and per capita electricity consumption, and the results are presented in the Table 6.

The p value clearly indicates that the OLS residuals are stationary, which confirms the cointegration. The OLS regression is $l_CO2 = -4.61791 + 0.789455 \times l_ELEC$, which is the static or long run per capita CO₂ emission function, and the coefficient 0.789455 represents the long run or equilibrium marginal propensity to emissions (MPC) of CO₂.

The researcher just showed that per capita CO₂ emissions and per capita electricity consumption are co-integrated; that there is a long term or equilibrium relationship between the two. Of course, in the short run, there may be disequilibrium. Therefore, one can treat the above OLS residual as the “*Equilibrium Error*” and this error term can be used to tie the short run behavior of per capita CO₂ emissions to its long run value. This error correction mechanism (ECM) first used by Sargan, and later developed by Engel and Granger corrects the disequilibrium. The following section gives the details of error correction check for short run behavior of the system.

ERROR CORRECTION MODEL

In addition to learning about a potential long-run relationship between two series, the concept of cointegration enriches the kinds of dynamic models. If Y_t and X_t are $I(1)$ processes and are not co-integrated, it might be estimated as a dynamic model in first differences. As an example, consider the equation :

$$\Delta Y_t = \beta_0 + \sum_{j=1}^k \beta_j \Delta X_{t-j} + \sum_{j=1}^h \alpha_j \Delta Y_{t-j} + e_t$$

Where e_t has zero mean given $\Delta Y_{t-1}, \dots, \Delta Y_{t-h}, \Delta X_t, \Delta X_{t-1}, \dots, \Delta X_{t-k}$. If this is viewed as a rational distributed lag model, the impact propensity, long run propensity, and lag distribution for ΔY as distributed lag in ΔX can be found. If Y and X are cointegrated, then the obtained estimated error term must be stationary, i.e., $I(0)$. Now, if the lagged estimated error term is included as :

$$\Delta Y_t = \beta_0 + \sum_{j=1}^k \beta_j \Delta X_{t-j} + \sum_{j=1}^h \alpha_j \Delta Y_{t-j} + \delta Z_{t-1} + \varepsilon_t$$

Where $Z_t = \hat{e}_t = Y_t - \hat{\beta}_0 - \sum_{j=1}^k \hat{\beta}_j \Delta X_{t-j} - \sum_{j=1}^h \hat{\alpha}_j \Delta Y_{t-j}$ is the one-period lagged value of the estimated error of the cointegrating

regression obtained from OLS estimation, this term is called the *Error Correction Term*. The principle behind this model is that there often exists a long run equilibrium relationship between two economic variables. In the short run, however, there may be disequilibrium. With the error correction mechanism, a proportion of the disequilibrium is corrected in the next period. The error correction process is thus, a means to reconcile short-run and long run behavior. Therefore, in the error correction model, the right hand side contains the short-run dynamic coefficients (i.e., α_i, β_i) as well as the long-run coefficient (i.e., δ). The absolute value of δ decides how quickly the equilibrium is restored. The error correction model of the consumption function becomes:

$$\Delta C_t = \beta_0 + \sum_{j=1}^k \beta_j \Delta Y_{t-j} + \sum_{j=1}^h \alpha_j \Delta C_{t-j} + \delta Z_{t-1} + e_t$$

Table 7: Engel Granger One Step Error Correction Model				
Dependent variable: d_1_CO2				
	Coefficient	Std. Error	t-ratio	p-value
const	0.0313149	0.0080229	3.9032	0.00046***
d_1_ELEC	0.129176	0.149135	0.8662	0.39284
uhat1_1	-0.603795	0.130907	-4.6124	0.00006***

Mean dependent var	0.04	S.D. dependent var	0.03
Sum squared resid	0.02	S.E. of regression	0.02
R-squared	0.40	Adjusted R-squared	0.36
F(2, 32)	10.74	P-value(F)	0.00
rho	-0.02	Durbin-Watson	2.02
Source: Gretl Software Output			

The error correction term, $Z_t = C_t - \sum_{i=0}^a \gamma_i Y_{t-i} - \sum_{i=1}^b \vartheta_i C_{t-i}$ is obtained from the OLS regression. Therefore, the error

correction model becomes :

$$d_1_CO2 = 0.0313149 + 0.789455 \times l_ELEC + 0.129176 \times d_1_ELEC - 0.603795 \times uhat1_1.$$

The absolute value of $\delta = 0.603795$ (Table 7) decides how quickly the equilibrium is restored. Statistically, the equilibrium error term (δ) is not zero, suggesting that CO_2 emissions do not adjust to changes in electricity consumption in the same period. Further, more are the short run changes in per capita electricity consumption, the more they have a positive impact on short run changes on CO_2 emissions and one can interpret the value 0.129176 as the short run marginal propensity to CO_2 emissions (MPC) and the long run or equilibrium marginal propensity to CO_2 emissions is given by the coefficient 0.789455, which clearly shows how much electricity consumption is associated with CO_2 emissions.

SELECTION OF LAG LENGTH

After confirming the co - integration relationship, the next step is to determine the lag length by using the respective information criteria, AIC = Akaike criterion, BIC = Schwartz Bayesian criterion and HQC = Hannan-Quinn criterion.

Table 8: Selection of Lag Length					
lags	loglik	p(LR)	AIC	BIC	HQC
1	143.06		-10.15	-9.86*	-10.07
2	148.03	0.04	-10.22	-9.74	-10.08*
3	149.74	0.49	-10.06	-9.38	-9.86
4	156.09	0.01	-10.22*	-9.37	-9.97
5	159.20	0.18	-10.16	-9.11	-9.85
6	163.21	0.09	-10.16	-8.92	-9.79
7	168.09	0.04	-10.23	-8.79	-9.80
8	171.49	0.15	-10.18	-8.55	-9.70
9	174.55	0.19	-10.11	-8.29	-9.57

Source: Gretl Software Output

*The asterisks above indicate the best (that is, minimized) values of the respective information criteria, AIC = Akaike criterion, BIC = Schwartz Bayesian criterion and HQC = Hannan-Quinn criterion.

For the data, the AIC criteria gives lag order four, BIC criteria gives lag order one and HQC criteria gives lag order two. The researcher selected the AIC criteria lag length 4. The selection of lag length results are given in the Table 8.

VECTOR AUTO REGRESSION (VAR) MODEL

The Vector Auto Regressive (VAR) is commonly used for forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables. The VAR approach sidesteps the need for structural modeling by treating every variable as endogenous in the system as a function of the lagged values of all endogenous variables in the system. The term auto regressive is due to the appearance of the lagged values of the dependent variable on the right-hand side, and the term vector is due to the fact that a vector of two (or more) variables is included in the system model. Since there are only lagged values of the endogenous variables appearing on the right-hand side of the equations, simultaneity is not an issue and OLS yields consistent estimates. Moreover, even though the innovations may be contemporaneously correlated, OLS is efficient and equivalent to GLS, since all equations have identical regressors.

$$CO2_t = C_1 + \sum_{i=1}^k a_{1i} CO2_{t-i} + \sum_{i=1}^k b_{1i} ELEC_{t-i} + e_{1t}$$

$$ELEC_t = C_2 + \sum_{i=1}^k a_{2i} CO2_{t-i} + \sum_{i=1}^k b_{2i} ELEC_{t-i} + e_{2t}$$

Where e_{1t} and e_{2t} are stochastic error terms called as "*Impulses or Innovations*".

After selecting the suitable lag length, Vector Auto Regression (VAR) model is used to determine the direction of causality running in between the variables. The VAR calculation results are shown in the Table 9, indicating the directional causality running between Co₂ emissions and electricity consumption at various lags.

Table 9: Direction Of Causality At Different Lags Null Hypothesis: Per capita Electricity Consumption does not (Granger) cause per capita CO₂ emissions and vice versa			
Direction of Causality	Number of lags	F value [p value]	Decision
1_ ELEC → 1_CO2	2	9.1493 [0.0008]	Reject
1_CO2 → 1_ ELEC	2	2.8266 [0.0756]	Reject (At 8%)
1_ ELEC → 1_CO2	3	9.4762 [0.0002]	Reject
1_CO2 → 1_ ELEC	3	3.4402 [0.0313]	Reject
1_ ELEC → 1_CO2	4	10.078 [0.0001]	Reject
1_CO2 → 1_ ELEC	4	4.1357 [0.0114]	Reject
1_ ELEC → 1_CO2	5	8.3497 [0.0002]	Reject
1_CO2 → 1_ ELEC	5	4.0801 [0.0102]	Reject
1_ ELEC → 1_CO2	6	9.9576 [0.0001]	Reject
1_CO2 → 1_ ELEC	6	4.5706 [0.0062]	Reject
1_ ELEC → 1_CO2	7	4.0566 [0.0124]	Reject
1_CO2 → 1_ ELEC	7	2.8316 [0.0462]	Reject
1_ ELEC → 1_CO2	8	2.2339 [0.1083]	Accept
1_CO2 → 1_ ELEC	8	3.5142 [0.0287]	Reject
1_ ELEC → 1_CO2	9	1.3191 [0.3534]	Accept
1_CO2 → 1_ ELEC	9	1.604 [0.2585]	Accept
Source: Gretl Software Output			

Up to lag 7, there exists bi- directional causality running from each variable, but at lag 8, it was observed that there exists uni-directional causality running from per capita Co₂ emissions to per capita Electricity Consumption, and at

Table 10: Forecasting Of Per Capita Co₂ Emissions For 95% confidence intervals, $t(23, 0.025) = 2.069$				
Year	Variable	prediction	std. error	95% interval
2007	1_CO2	0.33	0.02	(0.29, 0.36)
2008	1_CO2	0.39	0.02	(0.35, 0.42)
2009	1_CO2	0.41	0.02	(0.36, 0.46)
Source: Gretl Software Output				

lag 9, it was observed that there was absence of causality from Electricity Consumption to per capita Co₂ emissions and vice versa. Finally, the VAR model with lag 4 is used for forecasting the per capita Co₂ emissions. Though the researcher had only used per capita electricity consumption, the results have showed that forecast for the future years is accurate, with very mild forecast error, as specified in the Table 10. The forecasted values of per capita Co₂ emissions in original level form are 1.388, 1.4757 and 1.5096 respectively.

LIMITATIONS OF THE STUDY

✿ In this study, unrestricted VAR is used to determine the causality and short-term forecast for per capita Co₂ emissions, therefore, in considering the parametric restrictions, the user should be careful in deducing the economic interpretations of the study.

✿ This empirical study is constrained to a small sample; hence, any subsequent economic interpretations and corresponding policy implications must be treated with caution due to the potential small sample, omitted variables and specification bias in considering the other macroeconomic variables.

FINDINGS OF THE STUDY & SCOPE FOR FUTURE RESEARCH

In this study, the researcher used Engel-Granger two step procedures for co - integration, one step procedure for error correction mechanism. The same results can be obtained by using Johansen's rank method, where the rank is found as one, indicating one co -integrating equation. The findings suggest that both the Engel-Granger and Johansen's methods proved to be good in case of two endogenous variable models. This study can be further explored by adding more macroeconomic variables as endogenous variables in studying the per capita Co₂ emissions using multivariable VAR models.

CONCLUSION

This study concludes that there exists cointegration between Co₂ emission and electricity consumption. Granger causality tests provided enough evidence of longer term equilibrium relation between the two variables, which can attract the attention of policymakers in drawing out efficient policy making to drive the economy with less pollutant emissions. Empirical results have shown that up to lag 7, there exists a bilateral causality between the two variables - that shows how these two variables are associated and there is a need for closer look at the consumption of fossil fuels in generating and consuming the electricity in association with the environment.

The primary reason for the higher Co₂ emissions in India is attributed to two causes - one is the generation of electricity from fossil fuels, and the other is indiscriminate use of electricity in the name of economic growth. As the economy is growing, more economic activities take place that need energy in the form of electricity. More emissions of Co₂ not only affect the economy in monetary terms, but it also affects the living conditions of the people, the climatic variations and gives birth to new diseases with long term effects. So, there is an urgent need in the future to cut down the Co₂ emissions by using efficient technology in generating electricity, more use of renewable resources and finally, the efficient utilization of electricity is required.

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