Electricity Generation and Environment: the Causal Linkages Prevailing in India

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Abstract: - This paper examines the causal linkages of carbon dioxide (CO_2) emissions with energy consumption (EC) and investment patterns {both domestic (DI) and foreign (FDI)} in India along with electricity production from three different and main sources i.e. coal (C), renewable (R) and hydroelectric (H) sources in a phased manner. Results indicate unidirectional causalities from CO_2, FDI, C and H to EC indicating that CO_2 emissions, foreign investments, coal-fuelled electricity and use of hydroelectric sources for power generation all become the causes for energy consumption in India. Unidirectional causality is also found from FDI to CO_2 confirming the existence of Pollution Haven Hypothesis (PHH) in India. The unidirectional causality from C to DI and no causality from/to R to/from any other variable indicate that C is the dominant source for electricity production in domestic investments in India as compared to R and H. Electricity production from H is causing FDI in India as evident from the unidirectional causality found from H to FDI.

Key-Words: - CO_2 emissions, energy consumption, electricity generation, investments in energy, domestic investments, foreign direct investment, causality testing

1 Introduction

[1] states that electricity generation is responsible for 42.5% of global carbon dioxide (CO_2) emissions. Out of which, 73% can be attributed to coal-fired power plants. As per [2], China and India, the two of the main emerging economies, have accounted for 70% of the growth in world electricity demand. [2] also mentioned that both of these emerging economies have led to more than 40% of the growth in global energy demand in 2017. As per [2], the global coal demand has grown tremendously which is due to an increasing demand in Asia that is almost entirely driven by an increase in coal-fired electricity generation. The growing pace of economic development in these emerging economies is responsible for all of such un-eco-friendly activities [19]. India, being a developing country, invites foreign investments to achieve economic growth. For which, the country sacrifices its natural environment and relax certain environmental laws and regulations. To facilitate these foreign investments and to cope up with the increasing demand that comes with economic growth, investments at domestic level are also made in energy and electricity generation. All of this gives rise to a concept known as Pollution Haven Hypothesis (PHH). The hypothesis is build on the assumption that the firms of developed countries relocate to countries that are pollution haven (i.e. where environmental laws are un-strict) to avoid the costs of compliance with comparatively higher environmental standards prevailing in their home country [3], [4], [5], [6] and [19].

Hence, a debate on cutting down CO_2 emissions in these developing countries has become a matter of serious concern and that too without interfering in their economic growth. Thus there arises a need to understand causal linkages between the CO_2 emissions, energy consumption, investment patterns and electricity generation in these countries. This paper is an attempt to do examine such linkages with the help of a dynamic multivariate causality testing approach.

The main contribution of this study to the existing literature related to India can be summarised as follows:

- Knowledge on the causal linkages between CO_2 emissions and three major sources of electricity generation namely coal (C), renewable (R) and hydroelectric (H) sources.
- Knowledge on the causal linkages between energy consumption (EC) and three major sources of electricity generation namely C, R and H sources.

- Examine the effects of foreign investments (FDI) on CO_2 emissions and at the same time on energy consumption.
- Analysing the linkages between domestic investments (DI) in energy projects and environmental sustainability.
- And finally, to test for any causal inter-relationships that may exist between all the variables under study.

2 Problem Statement

For the purpose of this study, the electricity generating variables namely C, R and H have been distributed in two models. The first model includes C and R whereas the second model has C and H. This distribution will help in comparing the results from both the models and deriving robust conclusions. These models are discussed next.

2.1 The Models

Initially, the study uses linear regression models to examine the causal relationships between CO_2, energy investments and consumption; and electricity production in India during 1991-2014. CO_2 emissions are taken as the representative of environmental degradation because CO_2 emissions are considered as one of the major global pollutants. The initial models have been discussed next.

2.1.1 First Model

The first model can be written as:

$$CO_2 = f\,(EC, DI, FDI, C, R) \tag{1}$$

and the equation of the model is:

$$(lnCO_2)_t=\alpha+\beta(lnEC)_t+\gamma(lnDI)_t+\delta(lnFDI)_t+\zeta(lnC)_t+\lambda(lnR)_t+\varepsilon_t \tag{2}$$

where, CO_2 is carbon dioxide emissions (metric tons per capita); *EC* is energy consumption or energy use (kg of oil equivalent per capita); *DI* is investment in energy with private participation representing domestic investments (current US$); *FDI* is net inflows of foreign direct investment (current US$); *C* is electricity production from coal sources (% of total); *R* is electricity production from renewable sources, excluding hydroelectric (% of total); α is constant term; $\beta, \gamma, \delta, \zeta$ and λ are coefficients; and ε is the error term or the stochastic random variable; all at time t.

2.1.2 Second Model

The second model can be written as:

$$CO_2 = f\,(EC, DI, FDI, C, H) \tag{3}$$

and the equation of the model is:

$$(lnCO_2)_t=\alpha+\beta(lnEC)_t+\gamma(lnDI)_t+\delta(lnFDI)_t+\zeta(lnC)_t+\lambda(lnH)_t+\varepsilon_t \tag{4}$$

where, CO_2 is carbon dioxide emissions (metric tons per capita); *EC* is energy consumption or energy use (kg of oil equivalent per capita); *DI* is investment in energy with private participation (current US$); *FDI* is net inflows of foreign direct investment (current US$); *C* is electricity production from coal sources (% of total); *H* is electricity production from hydroelectric sources (% of total); α is constant term; $\beta, \gamma, \delta, \zeta$ and λ are coefficients; and ε is the error term or the stochastic random variable; all at time t.

2.2 The Data

The data on all the variables used for the study is sourced from World Development Indicators (WDI) of World Bank Group (2018) Data Reports [7] for India. The start year has been selected as 1991 to examine the relationships in post-liberalisation period. 2014 has been selected as the end year as per the availability of data up to this year at the time of the study.

2.3 The Methodology

The Modified Wald (MWALD) Test proposed by Toda and Yamamoto (TY) [11] is the main econometrics methodology used in this paper. Although literature comprises several methodologies for testing causality such as Granger (non-) causality [8], Sims causality [9] and causality in Johansen and Juselius [10] ECM, TY multivariate approach for testing the causality has its advantages over others. It requires the estimation of an augmented vector autoregressive (VAR) model irrespective of whether the time series is I(0) or I(1) and whether it is cointegrated or not. Also, if the system has a unit root, the conventional ordinary least squares (OLS) of VAR in level-based Wald statistics have non-standard asymptotic distribution that may involve annoying parameters [12]. TY procedure put restrictions on the parameters of VAR (l) from an augmented VAR ($l+i_{max}$) model, where l is the optimal lag length and i_{max} is the maximum order of integration of variables [13]. A general VAR ($l+i_{max}$) model in TY approach is written as:

$$y_t = \alpha + \beta_1 y_{t-1} + \cdots + \beta_{l+i_{max}} y_{t-(l+i_{max})} + \varepsilon_t \quad (5)$$

where y_t consists of K endogenous variables, α is a vector of intercept terms, β are coefficient matrices and ε_t are white noise residuals [18]. The null hypothesis in TY causality is based on zero restrictions on first l parameters (H_0: $\beta_1 = \dots = \beta_l = 0$) of the kth element of y_t. As per [14], the model is valid until $l \geq i_{max}$.

2.3 The Layout of Rest of the Paper

The rest of the paper is organized as follows: at first, the appropriate maximum lag length (l) for the variables has been chosen for the study. A VAR (l) in levels of the data is then set up including an intercept in each equation. To see whether the VAR in levels is well specified, the residuals of the model were then examined. AR Roots Table and AR Roots Graph are used to examine the stability of the VAR model so formed. Serial Correlation Lagrange's Multiplier (LM) test is used for examining serial independence, White Heteroskedasticity (No Cross Terms) test is used to examine homoskedasticity and normality is examined with the help of J-B (Jarque-Bera) statistic through square root of correlation (Doornik-Hansen) method. Then, the maximum order of integration (i_{max}) of the variables is obtained with the help of Phillips and Perron (PP) unit root test. The unit root test with an optimal lag length is performed with deterministic elements i.e. a time trend and a constant. Finally, a levels VAR model is re-estimated with i_{max} additional lags (i.e., $l+i_{max}$ lags in total) of each of the variables into each of the equations to examine the causal linkages among variables.

3 Results

First of all, the optimum lag for the study has been chosen. Five different lag selection criteria were examined, namely, sequential modified LR test statistic (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC) and Hannan-Quinn (HQ) Criterion. Based on various information criteria, a maximum lag length of 1 for each variable has been chosen for both the models (Table 1 and Table 2).

Table 1: Optimum Lag Selection for First Model

Lag	LR	FPE	AIC	SC	HQ
0	NA	5.73e-10	-4.25260	-3.95638	-4.17810
1	168.026*	4.06e-13*	-11.624*	-9.5503*	-11.103*

* indicates lag order selected by the criterion

Table 2: Optimum Lag Selection for Second Model

Lag	LR	FPE	AIC	SC	HQ
0	NA	3.84e-11	-6.95508	-6.65886	-6.88058
1	164.447*	3.41e-14*	-14.103*	-12.029*	-13.581*

* indicates lag order selected by the criterion

Hence, following the results obtained from various criteria, optimum lag (l) selected for the study is 1 (subject to testing) for both the models.

A VAR (1) model in the levels of the data, including an intercept in each equation is then set up, as l=1 here, for both the models. The residuals were then examined to make sure that the VAR is well specified. Results of the various tests performed on the residuals are shown in Table 3 and Table 4. The estimated models were found to be dynamically stable as per the information provided by the AR Roots Table and Graph. The null hypothesis under Serial correlation LM test is "no serial correlation exists", which cannot be rejected in our results. White Heteroskedasticity (No Cross Terms) test has the null hypothesis of "no heteroskedasticity" which again, cannot be rejected in our results. The null hypothesis under J-B statistics of Square root of correlation (Doornik-Hansen) test is "residuals are multivariate normal" that too cannot be rejected in the results. So, optimal lag is finalized to be 1 in the study, i.e. l=1, for both the models.

Table 3: Diagnosis Test Results of Residuals of VAR(1) in Levels for First Model

Test	Test Statistic	p-value
VAR Stability (AR Roots Table)	No root lies outside the unit circle	-
Serial Correlation LM (with l=1)	1.132255 (Rao F-stat)	0.3786
White Heteroskedasticity (No Cross Terms)	270.6091 (Chi-sq)	0.2008
Square Root of Correlation (Doornik-Hansen)	11.80148 (J-B)	0.4618

Table 4: Diagnosis Test Results of Residuals of VAR(1) in Levels for Second Model

Test	Test Statistic	p-value
VAR Stability (AR Roots Table)	No root lies outside the unit circle	-
Serial Correlation LM (with l=1)	1.039600 (Rao F-stat)	0.4677
White Heteroskedasticity (No Cross Terms)	259.2707 (Chi-sq)	0.3630
Square Root of Correlation (Doornik-Hansen)	5.833291 (J-B)	0.9243

[15] and [16] devised a procedure to formally test for non-stationarity known as the Dickey-Fuller unit root test and then an augmented Dickey Fuller (ADF) unit root test was also developed. But in this study, PP unit root test has been used to obtain the

maximum order of integration (i_{max}) of the variables because as per [17] ADF unit root test under rejects when the time-series are subject to both: a deterministic trend and an exogenous trend. The null hypothesis under this test is “the variable has a unit root” which means, the variable is non-stationary. Deterministic elements i.e. a time trend and a constant have also been included in the unit root test. Table 5 displays the p-values of PP unit root test results for all the data series at levels and at first differences.

Table 5: PP Unit Root Test Results

Variable	At Level	At First Difference	Order of Integration
$lnCO_2$	0.9276	0.0105**	I(1)
lnEC	0.9590	0.0089***	I(1)
lnDI	0.0417**	-	I(0)
lnFDI	0.0830*	-	I(0)
lnC	0.8934	0.0026***	I(1)
lnR	0.1674	0.0000***	I(1)
lnH	0.4460	0.0088***	I(1)

***, ** and * indicate significance level at 1%, 5% and 10%, respectively

The PP unit root test results indicate that $lnCO_2$, *lnEC*, *lnC*, *lnR* and *lnH* are non-stationary at level but are integrated of first order, which means they all are I(1) whereas *lnDI* and *lnFDI* are I(0) or stationary at level. Thus, the maximum order of integration (i_{max}) has been determined as 1 in this study for both the models.

Separate VAR models in levels were then set up again but with 1 additional lag (i.e., $l+i_{max}= 1+1=2$ lags) of each of the variables into each of the equations this time as i_{max} is 1. Granger (non-) causality is then tested using a standard Wald test with the hypothesis that the coefficients of (only) the first *l* lagged values of variables are zero in the equations of the other variables. The model in Eq. (5) can be written in six different equations i.e. for all the six variables under consideration.

The coefficients for the 'extra' lag are not included while performing the Wald tests. They are there just to fix up the asymptotics. It is important to note that the Wald test statistics will be asymptotically chi-square distributed with 1 degree of freedom under the null and the extra lag that was introduced by adding i_{max} to *l*, is not included in the test results. Rejection of the null implies a rejection of Granger (non-) causality i.e., a rejection supports the presence of Granger causality. The results of the Granger (non-) causality test are shown in Table 6 and Table 7.

Table 6: Causality Results for First Model

Dependent Variable	MWALD Test						Causality Inference
	CO_2	*EC*	*DI*	*FDI*	*C*	*R*	
CO_2	-	0.7846 (0.3757)	0.3756 (0.5400)	6.053** (0.0139)	2.2383 (0.1346)	1.2366 (0.2661)	CO_2←FDI
EC	3.1812* (0.0745)	-	0.0002 (0.9901)	3.4323* (0.0639)	4.2117** (0.0401)	0.3787 (0.5383)	EC←CO_2 EC←FDI EC←C
DI	0.4785 (0.4891)	0.0130 (0.9094)	-	1.3709 (0.2417)	6.7684*** (0.0093)	0.2091 (0.6474)	DI←C
FDI	0.0317 (0.8587)	0.0378 (0.8459)	0.5436 (0.4610)	-	0.2902 (0.5901)	0.5615 (0.4537)	-
C	0.1956 (0.6583)	0.6564 (0.4178)	0.0009 (0.9759)	0.1455 (0.7029)	-	2.6282 (0.1050)	-
R	0.1540 (0.6947)	0.0779 (0.7802)	0.0512 (0.8210)	0.1177 (0.7316)	0.4613 (0.4970)	-	-

Note: ***, ** and * indicate significance level at 1%, 5% and 10%, respectively; p-values are in parentheses; and ← denotes a unidirectional causality

Table 7: Causality Results for Second Model

Dependent Variable	MWALD Test						Causality Inference
	CO_2	*EC*	*DI*	*FDI*	*C*	*H*	
CO_2	-	0.1268 (0.7218)	0.0986 (0.7536)	2.0452 (0.1527)	0.2400 (0.6242)	2.1052 (0.1468)	-
EC	2.0672 (0.1505)	-	0.6640 (0.4151)	0.3105 (0.5774)	0.3607 (0.5481)	4.868** (0.0274)	EC←H
DI	0.0021 (0.9632)	1.1826 (0.2768)	-	0.0102 (0.9195)	0.4280 (0.5130)	1.0959 (0.2952)	-
FDI	0.0113 (0.9153)	0.6865 (0.4074)	0.1001 (0.7517)	-	1.3633 (0.2430)	3.2557* (0.0712)	FDI←H
C	0.0916 (0.7621)	0.0292 (0.8643)	0.0342 (0.8534)	0.0444 (0.8331)	-	1.7848 (0.1816)	-
H	0.0521 (0.8194)	1.4511 (0.2284)	0.1163 (0.7331)	0.4042 (0.5250)	1.1782 (0.2777)	-	-

Note: ***, ** and * indicate significance level at 1%, 5% and 10%, respectively; p-values are in parentheses; and ← denotes a unidirectional causality

The causal linkages found among all the variables can be summarized as follows:

- ***Unidirectional causalities from CO_2, FDI, C and H to EC:*** These findings clearly indicate and authenticate the universal truth that both CO_2 emissions and electricity production (mainly from coal and hydroelectric sources) cause energy consumption in India. Foreign investments are also becoming the cause for more of energy consumption in India.

- ***Unidirectional causality from FDI to CO_2:*** This finding, along with the previous finding about FDI in relation to EC, indicates that FDI is causing CO_2 emissions as-well-as energy consumption in India. Both these results confirm the existence of PHH in India. Hence, it can be said that it is the relaxed environmental regulations that are attracting FDI to India and that too, mostly, in the dirty industries.
- ***Unidirectional causality from C to DI:*** This finding reveals that coal has been a dominant source for domestic investments in electricity production in India post-liberalisation. This finding also validates the findings of [2].
- ***Unidirectional causality from H to FDI:*** This finding reveals that hydroelectric sources have been a dominant source for foreign investments in electricity production in India post-liberalisation.
- ***No causality from/to R to/from any other variable:*** This finding validates the above findings of coal and hydroelectric sources being the most invested sources for electricity production in India.

4 Conclusion

This study examineses dynamic Granger (non-) causal linkages in India among CO_2 emissions, energy consumption, investments (both domestic and foreign) and electricity production from three main sources namely, coal, renewable and hydroelectric sources. Results show proofs of causal linkages from CO_2 emissions, foreign investments and electricity production (from coal and hydroelectric sources) to energy consumption. It clearly indicates that CO_2 emissions, foreign investments and production of electricity (from coal and hydroelectric sources) consume energy in India. Similarly, unidirectional causality found from FDI to CO_2 and the previous finding of causal linkage from FDI to EC indicate that investments from foreign developed countries are mostly in dirty industries that consume energy and cause CO_2 emissions in India. This finding, thus, mainly concludes that PHH exists in India. Two main unidirectional causalities were also found with regard to electricity production and investments. The first is from coal-fuelled electricity production to domestic investments in energy and the second is from hydroelectric sources for power generation to FDI. These findings reveal that most of the domestic investments are in coal related electricity production whereas hydroelectric sources cause foreign investments in India. Although no causality in either direction was found between electricity production from renewable energy sources and all other variables under study.

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