Indian Journal of Economics and Financial Issues
Vol. 3, No. 1, 2022, pp. 89-110
ISSN : 2582-5186

https://DOI: 10.47509 /IJEFI.2022.v03i01.06

ARF INDIA
Academic Open Access Publishing
www.arfjournals.com

THE CHAIN CAUSALITIES BETWEEN ENERGY CONSUMPTION AND ENVIRONMENTAL DEGRADATION ON THE INDIAN SUBCONTINENT

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Article History

Received : 10 February 2022
Revised : 21 March 2022
Accepted : 26 March 2022
Published : 23 June 2022

To cite this article

Ranajit Kumar Bairagi & Protap Kumar Ghosh (2022). The Chain Causalities between Energy Consumption and Environmental Degradation on the Indian Subcontinent. *Indian Journal of Economics and Financial Issues*, Vol. 3, No. 1, pp. 89-110. https://DOI: 10.47509 / IJEFI.2022.v03i01.06

Abstract: This study investigates a chain of causalities among energy consumption and socioeconomic development in the Indian subcontinent with an annual dataset of 43 years from 1972-2014. By applying Dynamic Ordinary Least Squares (DOLS), Fully Modified Ordinary Least Squares (FMOLS) and Vector Error Correction Model (VECM), it documents that the household final consumption expenditure positively determines the electricity consumption. The chain of causalities is reported in the order that energy consumption causes economic development which causes household final consumption expenditure and household final consumption expenditure causes electricity consumption. The main findings document that economic development led higher living standard positively drives carbon emissions through electricity consumption.

Keywords: Environmental degradation, household final consumption, CO_2, causality.

Jel: O, Y

INTRODUCTION

Economic development led higher living standard can influence household CO_2 emissions through boosting consumption of more electricity intensive appliances Park and Heo (2007) because the household income enormously affects CO_2 emissions through indirect energy consumption Zhen *et al.* (2011). The effects of electricity consumption on CO_2 emissions need to be specifically identified along with its driver because per capita electricity consumption drives socioeconomic development led living standard and contributes to CO_2 emissions from electricity production and consumption. The CO_2 emissions however can be minimized by adopting contemporary advanced technologies, techniques and sources, for example, Australian government is providing incentives for installing solar panels to generate solar electricity at households.

Developing countries, particularly in tropical regions, can provide such incentives instead of further extending electricity production from non-renewable resources. These countries are gradually contributing considerably more to environmental degradation as reported in the recent available US air quality index (AQI, 2019) which ranked both cities and countries in the Indian subcontinent the top worst in the world. Being a highly populated, the Indian subcontinent is emitting more CO_2 through consumption of more electricity appliances to lead the higher living standard of its increased urban population. The detection of chain of causalities particularly the drivers of electricity production and consumption and CO_2 emissions may help policymakers formulate and implement sustainable socioeconomic development policies through fiscal policy intervention or incentives for installation of solar panels at household or institutional levels. The policy intervention may help produce renewable electricity and meet the household electricity needs, transfer the excess production to the power grid and thereby minimize the environmental degradation at national levels.

The Indian subcontinent warrants the detection of such chain of causalities because of its large population size along with gradually rising socioeconomic development through rising industrialization and environmentally highly polluted major traditional cities with alarmingly rising carbon emissions as detailed in the literature. The research significance of the subcontinent is reinforced by its representation of socioeconomic development in the South Asia and even in the world[1] as well as the arguments of Bairagi (2017) that the inherent integration of sociocultural, geographical, and even administration among these countries over time may gear up the spillover effect of any innovations or shocks originated from the economies in the region.

This study thus intends to specifically investigate the contribution of electricity production and consumption to CO_2 emissions along with its chain of causal drivers. The study specifically computes CO_2 emissions from electricity production that averages annually 230kg per capita and documents that household final consumption expenditure drives both electricity consumption and CO_2 emissions.

The study proceeds with an introduction in Section 1. The contemporary literature is reviewed in section 2. Data sources and methods of study are detailed in section 3 whereas the empirical findings are explained and reported in section 4; and lastly, the study is concluded in section 5 by suggesting the findings based relevant policy formulations.

2. LITERATURE REVIEW

This section reviews and presents the contemporary literature on nexuses between energy consumption and environmental degradation through carbon emissions from electricity production.

2.1. Energy Consumption – Environmental Degradation

According to a report by the Global Carbon Project,[2] even almost all countries are contributing to the rise of carbon emissions, however, this has increased by 2.5% in the US, 4.7% in China, and 6.3% in India in 2018. The increase in both China and India is attributed to the usage of more coal-burning fuel in electricity, oil in transport and gas in industry to support their economic growth. The current World Bank data reports that the worldwide per capita carbon emissions in metric tons has increased from 4.2 in 1990 to 4.97 in 2014 and this increase is the highest in the South Asia from 0.6 to 1.5 whereas high income countries experienced a declining trend despite their greatest contribution in both absolute and per capita measures. Recognizing the mounting impacts of carbon emissions on lives and livelihoods, the World Bank Group announced on 3 December 2018 a major climate targets for 2021-2025 by doubling its existing 5-year investments to around $200 billion to support poorest countries to take ambitious climate action. Grossman and Krueger (1991) pioneered the studies on causal relations among carbon emissions, energy consumption and economic development. Shafik and Bandyopadhyay (1992) and Shafik (1994), among others document environmental degradation as a gradually increasing function of income with theoretical appealing because at the initial stage of industrial development, people prioritize material output in expense of environmental quality, they cannot pay for abatement, and/or neglects the development led environmental consequences (Dasgupta *et al.*, 2002). The relationship between energy consumption and environmental degradation is also inconclusive as reported in the literature review on the Environmental Kuznets Curve EKC hypothesis by Stern 2004, Dinda 2004 and Bo (2011). The recent non-existence EKC evidence in the USA (Dogan and Turkekul, 2016) and an inverted-N trajectory relationship with Chinese evidence (Kang *et al.*, 2016) reinforce the inconclusive EKC hypothesis.

2.2. Economic Development-Environmental Degradation

Irrespective of EKC validation, the literature also shows different causalities between economic development and carbon emissions with important policy implications. More specifically, Apergis and Payne (2009) document positive impact of economic development on CO_2 emissions using data from 1971-2004 on six Central American countries; Pao and Tsai (2011) document feedback causalities between economic development and carbon emissions in BRIC countries from 1980-2007. Karakas (2014) reports the similar impact on both OECD and non-OECD countries from 1990-2011. Ali *et al.* (2016) document a unidirectional positive causal effect of both economic development and energy consumption on CO_2 emissions in Nigeria. Acheampong (2018) documents mixed causalities between economic development and carbon emissions for different regional groups of 116 countries from 1990-2014. Similar mixed effects have also been empirically documented by others (Liu *et al.*, 2007; Narayan and Narayan, 2010; Chandran and Tang, 2013; Farhani and Ozturk, 2015).

Irrespective of causalities, the literature reveals cointegration among energy consumption, economic development, and CO_2 emissions (Tang and Tan, 2016) and economic growth, FDI and electricity consumption as stimulating determinants of CO_2 emissions (Salahuddin *et al.*, 2018). The adverse impact of economic development on environmental degradation is reinforced by the suggestion of Khobai (2018) to use renewable energy to lead sustainable economic growth and development by curbing the emissions.

2.3. Energy Consumption-Economic Development-Environmental Degradation in the Indian Subcontinent

Gupta and Sahu (2009) document that electricity consumption Granger-causes economic development in India, however, Saeki and Hossain (2011) completely contradict with the preceding evidence by reporting unidirectional causality from economic development to electricity consumption. Solarin *et al.* (2017) supported the EKC hypothesis and also documented the long-run positive contribution of both urbanization and real GDP but long-run negative contribution of hydroelectricity consumption on CO_2 emissions. Fan and Hossain (2018) document unidirectional causality from economic development to CO_2 emissions.

In Pakistan, Aqeel and Butt (2001) and Gupta and Sahu (2009) document that electricity consumption Granger-causes economic development. Jamil and Ahmad (2010) and Saeki and Hossain (2011) report unidirectional causal effect of real economic development on electricity consumption. Shahbaz and Lean (2012) find bidirectional Granger causality between economic development and electricity consumption. Mirza and Kanwal (2017) document bidirectional causal evidence among energy consumption, economic development and CO_2 emissions and their findings emphasize on gradually extending the renewable energy supplies in the overall energy mix. Lin and Ahmed (2017) document per capita GDP and population growth as leading factors behind rising carbon emissions.

In Bangladesh, the findings of Saeki and Hossain (2011) that electricity consumption unidirectionally causes economic development contrast the earlier evidence of Mazumder and Marathe (2007) that per capita GDP unidirectionally causes per capita electricity consumption. Regarding the effect of energy consumption on environmental degradation through CO_2 emissions, Alam, *et al.* (2012) document feedback relationship between them but unidirectional effect of economic development on CO_2 emissions. The evidence of Islam, *et al.* (2013), however, complement Alam et.al. (2012) by documenting energy consumption as a significant contributor to CO_2 emissions whereas urbanization worsens but trade openness lowers it.

Thus, the existing literature reveals inconclusive causalities among energy consumption, economic development and environmental degradation and mainly attributes this to the application of different sample sizes, sample periods, data types, proxies and econometric methods even over time and across economies. As the Indian subcontinent experienced gradual socioeconomic development along with alarmingly rising carbon emissions (Global Carbon Project, 2018), it warrants contemporary causal drivers of CO_2 emissions. This motivates us to revisit the contemporary causal relation between energy consumption and economic development and to detect their causal effect on environmental degradation.

3. DATA AND METHODS

The study uses the seven key annual times series variables for the period of 1972-2014[3] to investigate a chain of integrated causalities between energy consumption and carbon emissions in the Indian subcontinent comprising three economies viz. Bangladesh, India and Pakistan. Six of the them are in per capita denomination such as real gross domestic product GDP in 2010US$ GDP, real household final consumption expenditure in 2010 US$ HFC, oil equivalent energy consumption use in kilogram EC, kilo watt electric electricity power use consumption EPC, and carbon emissions from electricity and heat production CEEHP, and real import and export in 2010US$ as a proxy for trade openness TO. The urban population as a percentage of total population is used as a proxy for urbanization URB. The time series data are mainly sourced from the World Development Indicators of the World Bank as updated in November 2017. Further, the collected data are cross checked with that available from the IMF, UNCTAD, the central banks of the respective economies and the Datastream database.

Trade openness and urbanization have been incorporated to control for their effect on socioeconomic development because the energy literature argues that the trade openness Fan and Hossain (2018) and urbanization Wang *et al*. (2018) positively influences the demand for electricity intensive appliances which, in turn, pushes up the production and consumption of electricity and, hence, carbon emissions. Ding and Li (2017) argue that urbanization affects CO_2 through enhancing energy intensity while findings of Wang *et al.* (2018) suggest that corruption moderately affects the relationship of trade and urbanization on carbon emissions.

We use the panel data method as stated in the following functions, that is, economic development as a main function of energy consumption (1a); household final consumption expenditure as a main function of economic development (1b); electricity consumption as a main function of household final consumption expenditure (1c); and finally, carbon emissions from electricity production as a main function of electricity consumption (1d). Our panel method incorporated three economies in the Indian subcontinent to allow for higher degrees of freedom and to minimize the effect of multicollinearity between variables. These functions can empirically be expressed in the following panel regression models:

$$GDP_{it} = \alpha_i + \beta_1 EC_{it} + \beta_2 TO_{it} + \beta_3 URB_{it} + \varepsilon_{it} \quad \text{1a}$$

$$HFC_{it} = \alpha_i + \beta_1 GDP_{it} + \beta_2 TO_{it} + \beta_3 URB_{it} + \varepsilon_{it} \quad \text{1b}$$

$$EPC_{it} = \alpha_i + \beta_1 HFC_{it} + \beta_2 TO_{it} + \beta_3 URB_{it} + \varepsilon_{it} \quad \text{1c}$$

$$CEEHP_{it} = \alpha_i + \beta_1 EPC_{it} + \beta_2 TO_{it} + \beta_3 URB_{it} + \varepsilon_{it} \quad \text{1d}$$

where *i* ranges from 1 to 3 to represent each of the countries in the Indian subcontinent and t ranges from 1 to 43 to indicate each year during 1972 and 2014. The unknown parameters

α_i, β_1, β_2, β_3 are to be estimated while ε_{it} is an error term with standard properties of zero mean and unit variance. The parameters $\acute{a}_i$ controls for the country specific fixed effects by permitting cointegrating vectors to be heterogeneous across the panel through changing their slope coefficients.

This study tested the stationary properties of the series applying the following five unit root tests such as two Fisher Chi-squares (Dickey Fuller, 1979; and Phillips and Perron, 1988; Breitung, 2000[4])'s t-statistic, LLC's test (Levin *et al.*, 2002), and Im, Pesaran and Shin IPS-W-statistic (Im *et al.*, 2003). These different unit root tests are used to provide consensus in determining the order of integration because each of the panel unit root test has statistical shortcomings with respect to its size and power properties. After detecting the stationarity, we tested panel cointegration by using Johansen's (1988) Fisher panel, Kao's (1999) and Pedroni's (2004).

We have estimated the long run equilibria by using Stock and Watson's (1993) dynamic OLS (DOLS) because DOLS can correct for possible simultaneity and small biases amongst the regressors by including the lead and lagged values of change in the regressors. Further, DOLS can more efficiently estimate the long run relationship because panel OLS suffers from robustness and consistency in the presence of cointegration. We have also used the Fully Modified OLS (FMOLS) suggested by Pedroni (2000; 2001) to overcome the limitation of DOLS in controlling for cross sectional heterogeneity (Kao and Chiang, 2000) because FMOLS can provide consistent and efficient long run estimates even in small size by controlling for cross sectional endogeneity, heterogeneity, and serial correlation.

To estimate the short-run dynamics among the cointegrated variables, this study used Engle and Granger's (1987) two steps panel vector error correction model (VECM); the first of which derives the error correction term ECT by estimating the long-run parameters from equations 1a – 1d while the second one estimates the parameter of short-run speed of adjustment. The resulting generic equations can be used to estimate the panel Granger causality as follows:

$$\Delta \mathrm{Y_{it}} = \alpha_{1,it} + \Upsilon_{1i} ECT_{it-1} + \sum_{r=1}^{m} \beta_{11}\, \Delta Y_{it-r} + \sum_{r=1}^{m} \beta_{12}\, \Delta X_{it-r} + \varepsilon_{1,it} \tag{2a}$$

$$\Delta \mathrm{X_{it}} = \alpha_{2,it} + \Upsilon_{2i} ECT_{it-1} + \sum_{r=1}^{m} \beta_{21}\, \Delta Y_{it-r} + \sum_{r=1}^{m} \beta_{22}\, \Delta X_{it-r} + \varepsilon_{2,it} \tag{2b}$$

where Δ refers the first difference; i ranges from 1 to 3 to control for country fixed effect; ECT_{it-1} denotes the lagged error correction term which uses lagged residual term estimated from equations 2a and 2b, in which $ECT_{it} = Y_{it} - \alpha_i - \hat{\beta}_i X_{it,}$ where are predicted coefficients; and r ranges from 1 to m to represent the Akaike Information Criterion AIC selected optimal lag length. The is the error correction coefficient and measures the speed of adjustment; ε_{it} denotes the error term with standard properties whereas *X's* are the exogenous variables used to explain *Y* variable.

The above specifications 2a-2b estimate both short-run and long-run causalities by using Wald test and t-statistics of the ECT, respectively. The Wald test imposes zero restriction on parameters of first-differenced variables. More specifically, the above generic VECM can be expanded with our four functions as follows[5]:

$$\Delta \mathrm{GDP}_{\mathrm{it}} = \alpha_{it} + Y_i ECT_{it-1} + \sum_{r=1}^{m} \beta_{11,it}\, \Delta GDP_{t-r} + \sum_{r=1}^{m} \beta_{12,it}\, \Delta EC_{t-r} + \sum_{r=1}^{m} \beta_{13,it}\, \Delta TO_{t-r} + \sum_{r=1}^{m} \beta_{14,it}\, \Delta URB_{t-r} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots 3a$$

$$\Delta \mathrm{HFC}_{\mathrm{it}} = \alpha_{it} + Y_i ECT_{it-1} + \sum_{r=1}^{m} \beta_{11,it}\, \Delta HFC_{t-r} + \sum_{r=1}^{m} \beta_{12,it}\, \Delta GDP_{t-r} + \sum_{r=1}^{m} \beta_{13,it}\, \Delta TO_{t-r} + \sum_{r=1}^{m} \beta_{14,it}\, \Delta URB_{t-r} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots 3b$$

$$\Delta \mathrm{EPC}_{\mathrm{it}} = \alpha_{it} + Y_i ECT_{it-1} + \sum_{r=1}^{m} \beta_{11,it}\, \Delta EPC_{t-r} + \sum_{r=1}^{m} \beta_{12,it}\, \Delta HFC_{t-r} + \sum_{r=1}^{m} \beta_{13,it}\, \Delta TO_{t-r} + \sum_{r=1}^{m} \beta_{14,it}\, \Delta URB_{t-r} + \varepsilon_{it} \ldots\ldots\ldots..3c$$

$$\Delta \mathrm{CEEHP}_{\mathrm{it}} = \alpha_{it} + Y_i ECT_{it-1} + \sum_{r=1}^{m} \beta_{11,it}\, \Delta CEEHP_{t-r} + \sum_{r=1}^{m} \beta_{12,it}\, \Delta EPC_{t-r} + \sum_{r=1}^{m} \beta_{13,it}\, \Delta TO_{t-r} + \sum_{r=1}^{m} \beta_{14,it}\, \Delta URB_{t-r} + \varepsilon_{it} \ldots\ldots\ldots\ldots..3d$$

where Δ refers the first difference; *i* ranges from 1 to 3 and controls for country fixed effect; r ranges from 1 to m to represent the Akaike Information Criterion AIC selected optimal lag length; and ECT_{it-1} refers to lagged error correction term which is actually the lagged residual term as estimated from equations 3s which allow ECT_{it} to change. For example, ECT_{it} GDP= $GDP_{it} - \alpha_i - \hat{\beta}_1 EC_{it} - \hat{\beta}_2 TO_{it} - \hat{\beta}_3 URB_{i,}$ where are predicted coefficients. The is the error correction coefficient and measures the speed of adjustment whereas ε_{it} denotes the error term with standard properties. The *X's* are exogenous variables and explain the *Y* variable. The specifications 3a-3d estimate both short-run and long run causalities using the same test statistics as in 2a-2b.

To test the robustness and strength of causality beyond the sample period, we have used the innovative accounting approach IAA of Pesaran and Shin (1998) because the panel VECM can only detect the direction but not the sign of causality beyond the sample period. The functions of IAA can measure the out of sample reverberation of shocks over different time-horizons. Following Shahbaz *et al.* (2012), we use pair wise panel causality of Dumitrescu-Hurlin (2012) to detect causality in panel data. The underlying regression can be written as follows:

$$Y_{it} = \alpha_i + \sum_{r=1}^{m} \beta_{11,t} Y_{ir,t-r} + \sum_{r=1}^{m} \beta_{12,rt-r} X_{it-r} + \varepsilon_{it} \tag{4a}$$

$$X_{it} = \alpha_i + \sum_{r=1}^{m} \beta_{21,t} Y_{ir,t-r} + \sum_{r=1}^{m} \beta_{22,rt-r} X_{it-r} + \varepsilon_{it} \tag{4b}$$

where Y_{it} and X_{it} are the observations of a pair of endogenous and exogenous stationary variables i in period t. The coefficients are time-invariant but vary across variables. The model requires balanced panel with identical lag order of m. The existence of bidirectional causality requires the summation of both sets of coefficients to be statistically non-zero, i.e., both $\Sigma\beta_i$ of *Y* and $\Sigma\beta_i$ of *X* need to be statistically non-zero.

4. EMPIRICAL FINDINGS

4.1. Descriptive Statistics of Data

Table 1 reports the descriptive statistics and the correlation matrices of the seven variables used in the study which shows that GDP, household final consumption expenditure HFC, and import and export as a proxy for trade openness TO at 2010US$ average $658.27, $511.37 and $386.38, respectively. The oil equivalent energy consumption EC in kilograms, electricity consumption EPC in kilowatts and carbon emissions in metric tons from electricity and heat production CEEHP average 310.45, 245.65, and 0.23 respectively. All variables are denominated in per capita except the urbanization URB which averages 26.21, indicating 26.21% of the population live in urban areas. The statistically significant probability of Jarque-Bera suggests non-normality of data series which are thence transformed into natural logarithm to get valid statistical inference.

Using five autoregressive residual tests in the panel context, Table 2 reports the stationary properties of the data series. The results report the corresponding statistics accompanied by the probability for both level and 1st difference of data series. The statistics significantly confirm their non-stationarity at levels but stationarity at first difference for all variables except URB. Hence, we use URB at the level.

Table 1: Descriptive statistics of the variables

Panel Data Subcontinent	*CEEHP*	*EC*	*EPC*	*GDP*	*HFC*	*TO*	*URB*
Mean	0.23	310.45	245.65	658.27	511.37	386.38	26.21
Median	0.16	315.98	201.25	580.82	465.54	105.31	27.02
Maximum	0.93	637.43	805.60	1646.78	927.87	3355.86	38.30
Minimum	0.01	86.88	10.50	317.70	253.40	7.25	8.22
Std. Dev.	0.20	146.65	181.11	285.94	172.34	715.56	6.55
Skewness	1.45	0.02	0.77	1.10	0.64	2.79	-0.68
Kurtosis	4.59	1.92	3.12	3.97	2.48	10.14	3.28
Jarque-Bera	58.69	6.29	12.96	31.17	10.23	441.39	10.31
Probability	0.00	0.04	0.00	0.00	0.01	0.00	0.01
			Correlation Matrices				
CEEHP	1.00	0.77	0.92	0.82	0.47	0.19	0.53
EC	0.77	1.00	0.91	0.82	0.67	0.54	0.80
EPC	0.92	0.91	1.00	0.95	0.73	0.49	0.77
GDP	0.82	0.82	0.95	1.00	0.86	0.55	0.78
HFC	0.47	0.67	0.73	0.86	1.00	0.75	0.73
TO	0.19	0.54	0.49	0.55	0.75	1.00	0.63
URB	0.53	0.80	0.77	0.78	0.73	0.63	1.00

Table 2: The Statistics of Unit Root Tests

	CEEHP	EC	EPC	GDP	HFC	*TO*	*URB*
Breitung-t-Stat							
Level	0.220.59	3.771.00	0.290.40	3.241.00	1.220.89	3.891.00	-1.640.05
1st Difference	-4.490.00	-6.480.00	-3.790.00	-8.700.00	-5.530.00	-3.180.00	
IPS-W-Stat							
Level	0.950.83	4.171.00	-0.610.27	3.331.00	-0.430.33	0.080.53	-5.580.00
1st Difference	-11.830.00	-10.130.00	-8.800.00	-11.290.00	-11.730.00	-9.780.00	
LLC-t*							
Level	-0.050.48	2.651.00	-0.240.40	1.000.84	-1.280.10	-1.520.06	-5.910.00
1st Difference	-11.830.00	-10.490.00	-8.000.00	-11.690.00	-12.110.00	-9.780.00	
ADF-Fisher-Chi-Square							
Level	5.290.51	0.141.00	13.060.04	0.541.00	13.580.03	5.330.50	40.670.00
1st Difference	98.350.00	88.880.00	64.530.00	51.330.00	95.010.00	72.400.00	
PP-Fisher-Chi-Square							
Level	5.430.49	0.081.00	12.430.05	0.511.00	13.130.04	5.300.61	10.570.10
1st Difference	98.690.00	132.450.00	114.410.00	64.530.00	119.180.00	71.700.00	

IPS-W-Stat is Im, Pesaran and Shin W-stat, LLC-t* is Levin, Lin and Chu-t*, *PP* is Philips-Perron PP unit root test with constant, and *ADF* Fisher-Chi-Square *is* Augmented Dickey Fuller ADF Chi-Square. Asymptotic normality is assumed in all tests except Fisher- Chi-Squares where asymptotic χ^2 distribution is used to compute the probabilities. All variables are in the natural logarithms LN and the lag length is selected based on the Modified Schwarz-Bayesian Information Criteria.

4.2. Panel Cointegration

This section estimates and reports the panel cointegration results estimated using Johansen (1988)'s and Kao (1999)'s Fisher panel cointegration tests and Pedroni (2004)'s residual test. The results of Pedroni (2004)'s test are reported for functions of GDP, HFC, EPC and

CEEHP; each of which uses one single endogenous variable along with two common control variables, TO and URB and the last function incorporates all four endogenous variables. The statistics of Pedroni (2004)'s residual cointegration test in Tables from 3a to 3e can reliably reject most of the null of no cointegration for functions of GDP, HFC and CEEHP and for the four endogenous variables. Johansen (1988)'s and Kao (1999)'s Fisher panel cointegration tests are conducted only for seven variables and reported in Tables 3f and 3g, respectively.

Table 3a: Cointegration test estimates of Pedroni (2004) for GDP function

H_o: No Cointegration					
H_1: Individual AR coefficients			*H_1: Common AR coefficients*		
Between Dimension			*Within Dimension*		
Name of Test	*Estimate*	*Probabilities*	*Name of Test*	*Estimate*	*Probabilities*
Group PP	-2.81***	0.00	Panel PP	-3.22***	0.00
Group ADF	-2.73***	0.00	Panel ADF	-3.22***	0.00
Group rho	-1.10	0.14	Panel rho	-1.85**	0.03
			Panel v	0.82	0.21

Table 3b: Cointegration test estimates of Pedroni (2004) for HFC function

H_o: No Cointegration					
H_1: Individual AR coefficients			*H_1: Common AR coefficients*		
Between Dimension			*Within Dimension*		
Name of Test	*Estimate*	*Probabilities*	*Name of Test*	*Estimate*	*Probabilities*
Group PP	-3.26***	0.00	Panel PP	-4.11***	0.00
Group ADF	-2.82***	0.00	Panel ADF	-2.80***	0.00
Group rho	-0.98	0.16	Panel rho	-1.98**	0.02
			Panel v	0.87	0.19

Table 3c: Cointegration test estimates of Pedroni (2004) for EPC function

H_o: No Cointegration					
H_1: Individual AR coefficients			*H_1: Common AR coefficients*		
Between Dimension			*Within Dimension*		
Name of Test	*Estimate*	*Probabilities*	*Name of Test*	*Estimate*	*Probabilities*
Group PP	-0.79	0.22	Panel PP	-0.73	0.23
Group ADF	0.22	0.59	Panel ADF	-0.14	0.45
Group rho	0.17	0.57	Panel rho	-0.24	0.41
			Panel v	2.18***	0.02

Table 3d: Cointegration test estimates of Pedroni (2004) for CEEHP function

H_o: No Cointegration					
H_1: Individual AR coefficients			*H_1: Common AR coefficients*		
Between Dimension			*Within Dimension*		
Name of Test	*Estimate*	*Probabilities*	*Name of Test*	*Estimate*	*Probabilities*
Group PP	-3.88***	0.00	Panel PP	-3.43***	0.00
Group ADF	-3.41***	0.00	Panel ADF	-3.21***	0.00
Group rho	-0.90	0.19	Panel rho	-1.76**	0.04
			Panel v	2.44***	0.01

Table-3e: Cointegration test estimates of Pedroni (2004) for GDP, HFC, EPC, and CE

H_o: No Cointegration					
H_1: Individual AR coefficients			*H_1: Common AR coefficients*		
Between Dimension			*Within Dimension*		
Name of Test	Estimate	Probabilities	Name of Test	Estimate	Probabilities
Group PP	-3.21***	0.00	Panel PP	-2.25***	0.01
Group ADF	-3.37***	0.00	Panel ADF	-3.44***	0.00
Group rho	-0.99	0.16	Panel rho	-0.83	0.20
			Panel v	0.09	0.47

Table 3f reports the trace statistics and maximum eigen statistics of Johansen's (1988) Fisher panel cointegration test. The statistics confirm the presence of at least five significant cointegrations, suggesting the existence of long-run equilibrium relationship among the seven variables.

Table 3f: Johansen's (1988) Fisher panel cointegration test for GDP, HFC, EPC, EC, CEEHP, TO, and URB

Null	*Alternative*	*Trace Statistics*	*Prob.*	*Max-Eigen Statistics*	*Prob.*
Rank = 0	r ≥ 1	208.6	0.00	76.0	0.00
Rank ≤ 1	r ≥ 2	102.6	0.00	64.3	0.00
Rank ≤ 2	r ≥ 3	71.7	0.00	31.7	0.00
Rank ≤ 3	r ≥ 4	47.5	0.00	23.7	0.00
Rank ≤ 4	r ≥ 5	28.7	0.00	16.9	0.01
Rank ≤ 5	r ≥ 6	15.6	0.02	10.9	0.09
Rank ≤ 6	r ≥ 7	9.4	0.15	10.5	0.11
Rank ≤ 7	r ≥ 8	3.4	0.75	3.4	0.75

Asymptotic Chi-square distribution is used to compute the probabilities.

Table 3g reports the estimates of Kao's (1999) residual-based panel cointegration test. The t-statistics of the result suggest to significantly reject the null of no cointegration among all seven variables used in the study.

Table 3g: Estimate of residual based cointegration test of Kao's (1999) for GDP, HFC, EPC, CEEHP, EC, TO and URB.

	t-statistics	*Probability*
Augmented Dicky Fuller Test	-2.82***	0.00

The *** indicates rejecting the null of no cointegration at 1% significance.

The above cointegration tests suggest the data series are significantly cointegrated and can be used in the statistical inference.

4.3. Panel Cointegration Regression

The results of panel OLS, Stock and Watson's (1993) panel dynamic OLS (DOLS) and Pedroni's (2001) fully modified OLS (FMOLS) for the functions of economic development, household final consumption expenditure, electricity consumption and carbon emissions are reported in Tables 4a-4d. In Tables 4a-4d, the t-statistics are reported in parenthesis and statistical significance are denoted at 1% and 5% by *** and **, respectively. The results of Table 4a show that both panel DOLS and panel FMOLS report consistent estimates of energy consumption, trade openness and urbanization, strongly suggesting their positive influence on economic development. The elasticity of energy consumption on economic development ranges 0.88-1.62 and this generic positive influence of energy consumption is consistent with Narayan and Smyth (2008).

Table 4a: The Long Run Determinants of GDP with Panel OLS, Panel DOLS and Panel FMOLS

	Panel OLS	*Panel DOLS*	*Panel FMOLS*
Constant	-1.637*** -4.462		
Energy Consumption EC	1.619*** 16.204	0.726*** 5.947	0.882*** 12.220
Trade Openness TO	0.042** 2.307	0.096*** 2.812	0.059*** 3.993
Urbanization URB	-0.377*** -7.327	0.661** 2.368	0.706** 4.850
Adjusted R^2	0.97	-5.34	-7.45

The results of Table 4b show consistent estimates of economic development in all three OLS models, suggesting that the economic development positively influences household final consumption expenditure.

Table 4b: The Long Run Determinants of HFC with Panel OLS, Panel Dynamic OLS and Panel FMOLS

	Panel OLS	*Panel DOLS*	*Panel FMOLS*
Constant	2.248***		
	14.405		
Economic Development GDP	0.852***	0.658***	0.769***
	29.972	2.832	7.906
Trade Openness TO	0.038***	-0.009	-0.040
	3.151	0.130	1.547
Urbanization URB	-0.528***	0.245	0.182
	-17.772	0.686	0.873
Adjusted R^2	0.98	-32.91	0.23

The statistically significant consistent coefficient estimates of urbanization in all three OLS models as reported in Table 4c suggest that the electricity consumption is positively determined by the population migration from rural to urban areas.

Table 4c: The Long Run Determinants of EPC with Panel OLS, Panel DOLS and Panel FMOLS

	Panel OLS	*Panel DOLS*	*Panel FMOLS*
Constant	-6.236***		
	8.413		
Household Final Consumption HFC	0.637***	0.055	0.568
	5.617	0.119	1.396
Trade Openness TO	0.131***	0.148	-0.164
	2.851	1.315	1.957
Urbanization URB	2.111***	2.799***	4.621***
	18.835	2.856	5.679
Adjusted R^2	0.97	-12.86	-108.95

The consistent estimate of electricity consumption on carbon emissions in all three OLS models as reported in Table 4d suggests that the electricity consumption positively influences the carbon emissions and is consistent with that of Lean and Smyth (2010). This positive influence is consistent with the fact that coal and natural gas are widely used in electricity and heat production in India which is a major contributor of CO_2 emissions in the region.

4.4. Panel VECM Causality Analysis

Table 5 reports the panel VECM causality results which show significant negative coefficient of the lagged error correction term ECT_{t-1} i.e, γ for causal functions of GDP, HFC and EPC, suggesting the restoring of economic development, household final consumption and

Table 4d: The Long Run Determinants of CEEHP with Panel OLS, Panel DOLS and Panel FMOLS

	Panel OLS	*Panel DOLS*	*PanelFMOLS*
Constant	-5.638*** 16.027		
Electricity Consumption EPC	1.269*** 20.595	1.215*** 7.208	1.246*** 13.318
Trade Openness TO	-0.005 0.183	0.045 0.516	-0.054 1.466
Urbanization URB	-0.854*** 4.710	-1.536** 2.108	-0.769 1.404
Adjusted R^2	0.98	-22.26	-4.04

electricity consumption from temporary deviation to their equilibrium at the magnitude of γ in each period. The magnitude of the γ in these three cointegrating functions indicates that the household final consumption comes to the equilibrium at the fastest while economic development at the slowest.

The significant positive estimates of EC and TO suggest that both energy consumption and trade openness positively determine GDP. The positive causal effect of energy consumption is consistent with that of Narayan and Smyth (2008). The significant positive coefficients of GDP in HFC function and that of EPC in CEEHP function support our conjecture that household final consumption expenditure is a positive function of economic development and carbon emissions is a positive function of electricity consumption.

The short run estimates in all four functions confirm insignificant effect of urbanization on economic development, household final consumption, electricity consumption and finally carbon emissions. Further, the estimates also confirm both short run and long run effect of

Table 5: Panel VECM Estimates

Dependent Variable	*Short Run Causality*						*Long Run Causality*
	ΔEC	*ΔGDP*	*ΔHFC*	*ΔEPC*	*ΔTO*	*ΔURB*	*γECT*
ΔGDP	0.211 2.090**				0.039 2.319**	0.799 1.60	-0.005 4.250***
ΔHFC		0.362** 2.629			0.029 1.164	0.096 0.148	-0.042*** 3.735
ΔEPC			-0.144 1.333		0.050 1.500	1.012 1.100	-0.031*** 4.842
ΔCEEHP				0.288** 2.038	-0.009 0.185	2.170 1.424	-0.021 0.021

Δ denotes first difference.

the energy consumption on economic development which in turn has similar effect on household final consumption. Furthermore, the household final consumption determines electricity consumption only in the long run whereas electricity consumption determines carbon emissions only in short run. The effect of electricity consumption on carbon emissions is consistent with that of Shahbaz *et al.* (2014) with their Bangladesh evidence and Lean and Smyth (2010) with their ASEAN evidence.

4.5. Pair wise Panel Granger Causality Analysis

Table 6 reports the Dumitrescu Hurlin (2012) pair wise Panel Causality estimates using the optimum lag length 3 suggested by the AIC. The estimates show that CO_2 emissions from electricity and heat production CEEHP Granger causes household final consumption HFC because of their significant p-value at less than 1%. This may be attributed to the fact the CO_2 emissions may precede the household final consumption, if a bulk of the emissions arise from electricity consumption used in deriving household final consumption. This is supported by the rejection of null hypothesis that EPC does not homogeneously cause CEEHP and by the evidence of Lean and Smyth (2010) and Shahbaz *et al.* (2014).

Table 6: Pairwise Panel Causality Results of Dumitrescu Hurlin (2012)

Null Hypothesis:	*W-Statistics*	*Zbar- Statistics*	*Probability*
HFC does not homogeneously cause CEEHP	4.25	0.65	0.52
CEEHP does not homogeneously cause HFC	7.77	2.81	0.00
EPC does not homogeneously cause CEEHP	11.58	5.14	0.00
CEEHP does not homogeneously cause EPC	2.84	-0.21	0.83
GDP does not homogeneously cause CEEHP	4.09	0.55	0.58
CEEHP does not homogeneously cause GDP	4.09	0.55	0.58
EC does not homogeneously cause CEEHP	6.91	2.28	0.02
CEEHP does not homogeneously cause EC	1.75	-0.89	0.37
EPC does not homogeneously cause HFC	7.25	2.49	0.01
HFC does not homogeneously cause EPC	7.84	2.85	0.00
GDP does not homogeneously cause HFC	11.97	5.38	0.00
HFC does not homogeneously cause GDP	2.21	-0.60	0.55
EC does not homogeneously cause HFC	8.37	3.17	0.00
HFC does not homogeneously cause EC	5.08	1.16	0.25
GDP does not homogeneously cause EPC	5.70	1.54	0.12
EPC does not homogeneously cause GDP	3.61	0.26	0.80
EC does not homogeneously cause EPC	3.90	0.43	0.67
EPC does not homogeneously cause EC	6.25	1.88	0.06
EC does not homogeneously cause GDP	3.12	-0.05	0.96
GDP does not homogeneously cause EC	4.72	0.93	0.35

The included lag is 3.

The bidirectional causalities between EPC and HFC support our conjecture that household final consumption HFC positively influences usage of electricity intensive household appliances and that electricity consumption in production function raises the GDP which, in turn, influences household final consumption. The estimates also reject the null of no causality from energy consumption EC to HFC. The effect of household final consumption is consistent with that of Park and Heo (2007) and Dai *et al.* (2012) who report drastically rising of both direct and indirect energy requirements and carbon emissions resulting from rising income and is further supported by the rejection of the null hypothesis that 'GDP does not homogeneously cause HFC'. The pair wise causal relation reinforces the individual estimates of cointegration regression and VECM by reporting the direction of causation.

To estimate the response of each variable to innovations in other variables, and also to predict longevity of the shock, we report the generalized impulse response IR Figure 1 of Koop *et al.* (1996) and Pesaran and Shin (1998) which unlike other standard approach is insensitive to the ordering of variables in the VAR system and hence overcomes the orthogonality problem inherent in traditional out-of-sample Granger causality tests. Figure 1 depicts the responses of electricity consumption and carbon emissions to the generalized one standard deviation innovative shocks of household final consumption expenditure HFC, economic development GDP, trade openness TO and urbanization URB. The figure depicts that both the electricity consumption and the carbon emissions have similar response to the generalized one standard deviation innovative shocks of HFC and GDP. In particular, their responses are negative to the innovative shocks of HFC but positive to that of GDP. This supports our conjecture and regression estimates that household final consumption influences electricity consumption. The responses of carbon emissions to both the trade openness and urbanization do not follow any significant trend, suggesting carbon emissions may not respond to the shocks of these variables.

4.6. Innovative Accounting Approach IAA

Table 7 reports the results of one-standard deviation accumulated forecast variance decomposition generated by own innovations of each of the five key endogenous variables with respect to other four endogenous variables based on a 10-year forecasting horizon. The variance generated by other four endogenous variables are not reported for precision. It is worth mentioning here that, at the 5-year forecasting horizon, CO_2 emissions from electricity and heat production CEEHP generates about 92% of one standard deviation accumulated forecast variance by its own innovations, whereas it is 90% for electricity consumption EPC. The one standard deviation accumulated forecast variance generated by own innovations by household final consumption HFC, GDP and energy consumption EC are 76%, 73% and 65%, respectively. The response to the own innovative shocks in the 10-year-long horizon declines by 7% from 90% to 83% for EPC and 16% from 92% to 76% for CO_2 emissions. In the long-run, the decline is strongly significant for HFC which declines by nearly 30% in 5 years.

The variance generated by own innovative shocks of GDP exceptionally contradicts with the evidence that, instead of declining, it increases by 3% from 73% to 76% and more interestingly, it actually remains nearly stagnant. This suggests that forecast variance in GDP is definitely influenced by innovations in other factors. The findings thus suggest that electricity consumption will be least impacted whilst household final consumption will be most impacted by the innovative shocks of rest of the four endogenous variables.

Table 7: Variance Decomposition of five dependent variables for the Indian Subcontinent: 1972-2014

Period	*CEEHP*	*HFC*	*EPC*	*GDP*	*EC*
1	100.00	99.92	98.07	75.14	80.92
2	98.94	93.72	94.68	69.24	74.35
3	97.43	88.61	93.17	70.40	70.79
4	94.98	83.01	91.89	71.70	67.95
5	91.97	76.71	90.37	73.05	65.52
6	88.68	70.29	88.84	74.16	63.25
7	85.40	64.06	87.33	75.06	61.12
8	82.27	58.22	85.88	75.76	59.10
9	79.38	52.84	84.50	76.30	57.18
10	76.75	47.96	83.19	76.70	55.35

5. CONCLUSION

The findings of this study report a chain of causalities from energy consumption to carbon emissions through economic development, household final consumption expenditure and electricity consumption after controlling the effect of urbanization and trade openness. The chain causation is documented in the order that energy consumption causes economic development which causes household final consumption expenditure and household final consumption expenditure causes electricity consumption which ultimately causes carbon emissions. The socioeconomic development reported in the Indian subcontinent as a rising trend over period and our findings conclude that economic development led higher living standard influences consumption of more electricity intensive appliances and thereby contributes to environmental degradation through CO_2 emissions from electricity and heat production. It has specifically identified the carbon emissions averaging 230 kg per capita per annum caused by electricity and heat production.

The findings confirm both short-term and long-term causalities between energy consumption and economic development and between household final consumption and economic development. Further, the findings document long run causality from household final consumption to electricity consumption and short-run causality from electricity consumption to CO_2 emissions from electricity and heat production. The pair wise results further report bidirectional causality between household final consumption and electricity consumption but unidirectional causality from economic development to household final consumption and from electricity consumption to carbon emissions.

The results of this study thus empirically provide evidence of a chain of integrated nexuses, such as, between energy consumption and economic development; between economic development and household final consumption; between household final consumption and electricity consumption; and electricity consumption and CO_2 emissions. This chain of integrated nexuses and causalities are expected to contribute to the ecological economics through specifically documenting the contribution of household final consumption led household electricity consumption to the environmental degradation. The findings provide policymakers in the region with a better carbon emission mapping which help them formulate sustainable socioeconomic development policies targeting electricity production and consumption. Hence, our findings have policy implications and recommend policy interventions by the respective country for ecofriendly socioeconomic development through promoting renewable solar electricity production for household consumption in the Indian subcontinent.

Notes

1. With only 3.67% of world total GDP at current prices in 2016 USD. The GDP growth averages 6.65% with world average 2.44% in 2016: The World Development Indicator of World Bank, 2016.
2. *https://www.globalcarbonproject.org/*
3. The carbon emissions data is consistently available from 1972 to only 2014 (in 2019) for all three economies, viz. Bangladesh, India, and Pakistan. Per capita carbon emissions from electricity and heat production is derived as a product of per capita carbon emission and carbon emissions from electricity and heat production as % of total emissions.
4. Breitung (2000) is actually based on panel based Augmented Dickey-Fuller (ADF) unit root process which restricts ρ to be identical across cross-sectional units, while allowing the first difference lag terms to vary across cross-sectional units.
5. Here for precision, instead of specifying pair of endogenous functions, only four VECM models are specified and their estimates are reported.

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