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Exploring the impact of economic growth, trade openness and urbanization with evidence from a large developing economy of India towards a sustainable and practical energy policy

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Abstract

Causal relationship among economic growth, urbanization, energy consumption, renewable energy share, trade openness and carbon emissions in the context of a large developing economy of India over the period 1990–2015 is examined in this study. The results support the existence of co-integration among the major variables. Ridge regression is done to model the impact of these variables on carbon emission. Estimated coefficients of economic growth and energy consumption are positive and significant. The major contribution to carbon emission in India comes from total energy consumption (34.12%) and economic growth (12.49%), while renewable energy consumption shows negative impact (− 29.76%). Results support feedback hypothesis among trade and carbon emission. This is revealed that the increase in GDP and trade openness facilitates adoption of renewable and energy-efficient technologies to reduce emission. In view of continued heavy dependence on indigenous fossil fuel coal as the major energy provider, concern should be adoption of ultra-low-emission technology in coal-fired power plants for immediate relief. Development of renewable energy sources coupled with switching to electric mass transport systems and large-scale adoption of energy-efficient green technologies appear as the other most practical and sustainable policy suggestions for a vast economy like India.

Graphic abstract
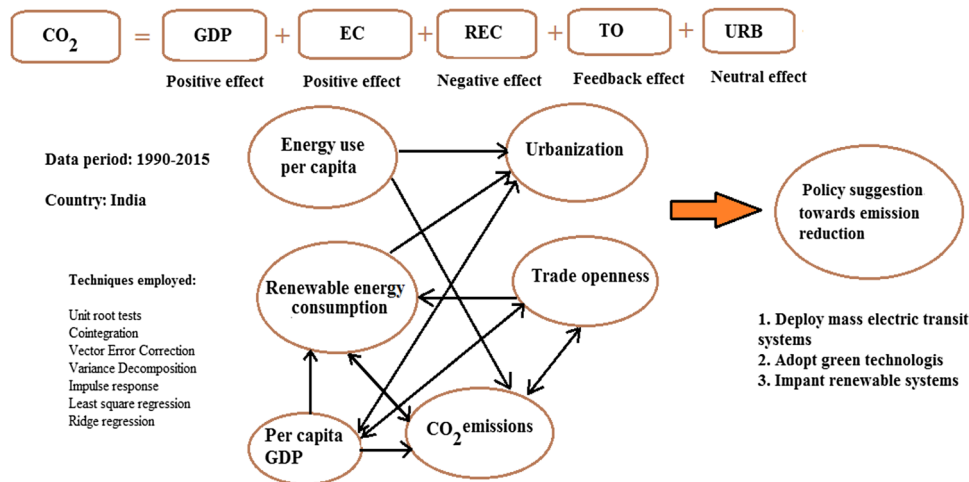
Keywords Carbon emission · Sustainable urbanization · Energy efficiency · Granger causality · Renewable energy

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Abbreviations

EIA   Energy Information Administration
UNPD   United Nations Population Division
WDI   World Development Indicator

VECM	Vector error correction model
ARDL	Autoregressive distributed lag
ASEAN	Association of Southeast Asian Nations
IEA	International Energy Agency
GDP	Per capita growth (Gross Domestic Product)
EC	Energy use per capita
REC	Share of renewable energy use in total final energy consumption
TO	Trade openness
URB	Urbanization
ADF test	Augmented Dickey–Fuller test
PP test	Phillips–Perron test
AR	Autoregression
VAR	Vector autoregression
LR	Likelihood ratio test
FMOLS	Fully modified ordinary least square regression
DOLS	Dynamic ordinary least square regression
EKC	Environmental Kuznets's curve
STIRPAT	Stochastic impacts by regression of population, affluence and technology

Introduction

With structural transformation of the developing economies experiencing fast economic growth, urbanization, trade openness and fossil fuel-based energy consumption, a steady increase in carbon emission contributing to global warming and climate change has been witnessed (Shahbaz 2012; Vance et al. 2015). According to the US Energy Information Administration (EIA), carbon emissions have gone up by 75% within the period from 1980 to 2012. While carbon emission in the developed countries continues to rise, developing economies are expected to experience even 127% higher emission than those in the developed economies by 2040 (EIA 2013). While average worldwide urbanization has crossed 50% in the year 2010, the developing world is expected to reach the 50% level in 2020 and will rise further to 67% by 2050 (UNPD 2007). Simultaneously, value of world trade is found to increase by 450 per cent between 1980 and 2012, as reported by World Development Indicator (WDI 2015). Amidst growing concern for environmental degradation, a good number of studies have revealed a unidirectional causal relationship between urbanization and energy consumption having a significant environmental impact (Martínez-Zarzoso and Maruotti 2011). The presence of bidirectional causality between economic growth and energy use for the period 1971–1999 in the long run and a unidirectional causality running from pollution to economic growth for the period 1971–1999 has been observed in the context of Malaysia using multivariate VECM (vector error correction model)

(Ang 2008). Link between CO_2 emission and energy consumption has also been revealed using Granger causality tests (Pao and Fu 2013). In the bound testing approach to co-integration also, positive correlation between energy consumption and CO_2 emission is well established in the context of some Asian countries (Miao 2017; Raggad 2018). Studies conducted on divergent lines reveal evidence of positive relationship between trade openness, renewable energy consumption and CO_2 emission (Kahia et al. 2019). Using VECM causality approach on a single country like Tunisia, trade openness has been found as one of the principal determinants of carbon emissions in the long run (Farhani et al. 2014). Positive correlation between energy consumption and carbon emissions of selected ASEAN (Association of Southeast Asian Nations) countries both in the short run and in the long run has been observed in some studies (Saboori and Sulaiman 2013).

India was third in the world with CO_2 emissions of 2162 megatons in the year of 2017 according to IEA reports. Per capita carbon emission was, however, 1.8 metric tons; much lower in comparison with global average emissions per capita (4.2 metric tons). But the emission grew steadily over the past decade with an average growth rate of 6%. The energy sector generated highest amount of carbon dioxide emissions (51% of total emissions in India) followed by manufacturing (26%), transport (13.4%) and residential sectors (4%).

Industrialization and radical formulation of supply chain strategies are driving economic growth, accompanied by increasing trade, energy usage and carbon emissions in India. Towards formulation of a sustainable energy policy encompassing the immediate environmental concerns and the nationally determined commitment of target reduction in carbon emission by 2030, it is now absolutely necessary to develop understanding of the temporal changes in emissions from both production and consumption perspectives. Despite a number of studies on causality among the governing parameters of growth–emission nexus in the contexts of several regions, no such comprehensive study accompanying commensurate policy suggestion has been done in the context of India, the largest democracy of the world with high population density, diversity and complexity of socio-politico-economic issues.

The objective of this study is to fill the research gap by examining the impact of economic growth, trade openness and urbanization towards a sustainable energy policy in India during the period of 1990–2015. This research work not only employs vector error correction technique but also variance decomposition and impulse response function, ordinary least square and ridge regression techniques to construct a robust carbon emission model and validate the results. This is done to consolidate policy suggestion through rigorous analysis in the context of a large and growing economy like India.

Literature review

Literature review section is classified into four categories. The first category highlights the relationship among economic growth and carbon emissions in the context of developing countries. Most of these studies obtained either unidirectional relationship or bidirectional relationship among these two variables. Saboori et al. (2012) obtained inverted U relationship in the context of Malaysia in the long run using Granger causality tests. Abid (2015) obtained unidirectional causality running from economic growth towards carbon emission of Tunisia using the same techniques. Roy et al. (2017) obtained similar results in the context of India. Bano et al. (2018) applied ARDL and VEC techniques to examine the causality among economic growth and emissions in the context of Pakistan. A bidirectional relationship has been validated among them using Granger causality test, but no short-run causality exists among the variables.

The second category presents the relationship among energy consumption and carbon emissions in the context of developing countries. Begum et al. (2015) examined the dynamic causality among energy use and carbon emission in Malaysian context. The result reported positive long-run impact of energy consumption on carbon emission. Ahmad et al. (2016) carried out a study in Indian context to determine the causal relationship among energy use and emissions. A bidirectional relationship among these two variables has been reported. Waheed et al. (2019) examined the environmental impact of renewable energy consumption in Pakistan and reported that expansion of renewable energy sector leads to decline in emission. ARDL technique has been used by Bölük and Mert (2015) to investigate the potential of renewable energy resource in reducing emission impact in developing country like Turkey. Coefficient of electricity generated from renewable sources is negative and significant in the long run with respect to carbon emission.

The third category of the literature section focuses on the relationship among trade and emission in the context of developing countries. Trade openness affects the environment in three ways—the first one is the technology effect where the increase in trade openness improves technology leading to decline in carbon emissions. The second one is called scale effect where free trade increases GDP output and subsequently emission. The third one is the composition effect where developing countries are attracted towards pollution intensive firms, leading to an increase in emission. Thus, the technology effect has positive impact on environment, while scale and composition effects degrade the quality of environment. The net effect of trade on emission is ambiguous where the dominance of scale effect and composition effect are greater in comparison with the technology effect (Shahzada et al. 2017). Research study carried out by Boutabba (2014) validated EKC hypothesis among trade and emission in the context of India. The dynamic causal relationship among trade and emission in the context of Turkey has been examined in the study of Ozturk and Acaravci (2013). A unidirectional causality running from emission to trade was reported. Yang and Zhao (2014) confirmed the unidirectional relationship running from trade to emission in the context of India.

Relationship among urbanization and carbon emission variable is also examined in this study. Dietz and Rosa (1997) proposed STIRPAT model which is frequently applied to examine the impact of urbanization on carbon emission. Li and Lin (2015) used the same model to investigate the impact of urbanization on emission variable for countries with different income levels. High-income countries reported the decline of emission with urban growth. Middle-income countries reported an increase in the energy consumption and carbon emission with urban growth. Low-income countries reported an increase in emission despite the reduction in energy consumption. However, the empirical evidence regarding urbanization impact on energy consumption and emission variable is controversial. Some studies suggest that the relationship between urbanization and emission is nonlinear. A threshold method or quadratic term is added to examine the impact of urbanization on environment. An inverted *U* relationship among urbanization and carbon emission is validated suggesting the decrease in emission with urban growth beyond an inflection point (Xu et al. 2015; He et al. 2017).

In the context of developing economy like Malaysia, Shahbaz et al. (2016) examined the impact of urbanization on carbon emission and reported the *U*-shaped relationship among the variables suggesting the growth in emission with further increase in urbanization. Another study by Farhani and Ozturk (2015) in the context of Tunisia suggests that there is a positive influence of urbanization on carbon emission. Thus, it is evident from the previous literature that the relationships between urbanization and carbon emissions are inconclusive and the magnitude of this impact varies upon dataset and estimation methods.

This section summarizes the previous empirical studies describing the relationship among variables considered in this study. Different techniques used to study temporal changes in the determinants of growth–emission nexus are also enlisted here. Although a number of studies are available based on relationship among factors governing carbon emission in developing economy context, no paper has considered so many important aspects together in formulating dynamic model with consolidated policy suggestions.

Model, data and methodology

Data

The study employs a linear logarithmic specification to explore the impacts of energy consumption, economic growth, renewable energy use, trade openness and urbanization on CO_2 emission using the data set of India for the period of 1990–2015. The data have been collected from the World Development Indicators online database and International Energy Agency (WDI 2015; IEA 2017). The variables used are carbon dioxide emissions (CO_2) (measured in terms of metric tons per capita), energy consumption (EC) (measured in terms of kg of oil equivalent per capita), economic growth (GDP) (per capita US dollars at 2011 constant PPP), renewable energy consumption (REC) (obtained from percentage share of renewable energy consumption in total final energy consumption), trade openness (TO) (percentage share of net import and export in GDP) and urbanization (URB) (percentage share of urban people in total population). Table 1 outlines a summary statistics of variables considered for this study.

Methodology

Time series analysis has been employed to conduct a volumetric study for estimating causality among macroeconomic variables. The study begins with unit root test to identify the stationarity of variables. Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) have been employed to test the presence of unit root in variables at original level series, first and second differences, respectively (Perron 1989). Further Johansen co-integration test has been used to determine long-run equilibrium in systems with variables containing unit root. Co-integration incorporates residuals from

vectors in dynamic vector error correction model to prevent the misleading results of vector autoregression (Johansen and Juselius 1990). Error correction model provides the direction of the causal relationship between the variables (Sims 1980). Granger causality measured in time domain presumes the linear interactions among variables. But the reciprocity in the relationship among the variables weakens over time. Therefore, variance decomposition method has been used to compare the relative strength of causality among the variables over various time horizons beyond a selected time period. It specifies the degree up to which predicted error variance of each variable can be explained by the effects of external shocks to each independent variable (Shahbaz 2012). A unit impulse or shock to a variable may cause another variable in the VAR system to respond instantaneously. Impulse response analysis describes the dynamic interactions among variables and measures the speed of adjustment of variables within the system (Yu and Hassan 2008). A stable VAR model is obtained if all roots have modulus equal to or lesser than unity.

Unit root tests

Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) are two popular testing methods used to determine the stationarity of variable series (Perron 1989).

(a)   ADF test

Augmented Dickey–Fuller (ADF) test is an upgraded version of the Dickey–Fuller test meant for higher-order equations, in the presence of autocorrelation of unknown form like ARMA (autoregressive moving average), where the null hypothesis $H_0: \rho = 1$ is tested against alternative hypothesis $H_1: \rho < 1$. ADF test is based on least square estimation of

Table 1 Statistical description of research variables

	CO_2 (metric tons/capita)[b]	EC (kgoe/capita)[b]	GDP ($/capita)[a]	REC (% of energy consumed)[b]	TO (% of import and export/GDP)[a]	URB (% pop)[a]
Mean	1.12	464.09	755.11	48.47	34.73	28.72
Maximum	1.87	693.09	1596.47	58.65	55.79	32.75
Minimum	0.71	351.34	298.22	36.02	15.68	25.55
SD	0.33	96.999	461.40	7.158	13.78	2.219
Coefficient of variation	0.29	0.2090	0.6110	0.148	0.397	0.077
Skewness	0.78	0.8332	0.7145	−0.406	0.204	0.288
Kurtosis	2.48	2.5382	1.1962	1.854	1.487	1.825
Jarque–Bera	2.96	3.2396	3.4849	2.139	2.659	1.853

[a]World Bank Development Indicators (WDI 2015)

[b]International Energy Agency (IEA 2017); variables explained in "Data" section

$$\Delta x_t = (\rho - 1)x_{t-1} + \sum_{j=2}^{k} \Delta_{t-j+1}(\theta_j) + \varepsilon_t \qquad (1)$$

Equation (1) has no constant or process trend.

$$\Delta x_t = \alpha + (\rho - 1)x_{t-1} + \sum_{j=2}^{k} \Delta_{t-j+1}(\theta_j) + \varepsilon_t \qquad (2)$$

Equation (2) has constant but no process trend.

(b) PP test

Phillips–Perron (PP) test provides nonparametric statistical modification of ADF test. The only difference lies between ADF and PP unit root tests is the incorporation of lag terms as regressors in ADF test equation.

$$\Delta x_t = (\rho - 1)x_{t-1} + \varepsilon_t \qquad (3)$$

Equation (4) has no constant or process trend.

$$\Delta x_t = \alpha + (\rho - 1)x_{t-1} + \varepsilon_t \qquad (4)$$

Equation (4) has a constant but no process trend.

Co-integration test

A Johansen co-integration test is used to determine the long-term interrelationship among variables integrated in same order. A number of information criteria like AIC and SIC are used to sort out the lag numbers for the autoregressive model. The number of long-term equilibrium relationships among variables is assessed through this test. It uses trace statistics and maximum. The number of co-integrating vectors r is determined by eigenvalue statistics. If there are n variables having unit roots, then there are at most $n - 1$ co-integrating vectors, and the matrix order becomes $n(n - 1)$. If the rank of the matrix becomes 0, the largest eigenvalue is 0, meaning no co-integrating relationship exists between the variables. If the rank of matrix does not equal to 0, the rank of the matrix is at least one and at least one co-integrating relationship exists between the variables. It is a likelihood ratio (LR) test, and the test statistic is given by

$$LR(r_0, r_0 + 1) = -T \ln(1 - \lambda r_0 + 1) \qquad (5)$$

where λ is the eigenvalue and LR $(r_0, r_0 + 1)$ is the test statistic used for testing null hypothesis H_0: rank of the matrix $= r_0$ against alternate hypothesis H_1: rank of the matrix $= r_0 + 1$.

Trace test examines whether the rank of the matrix is r_0 or not provided alternate hypothesis is $r_0 < \text{rank} \leq p$, where p is the number of possible co-integrating vectors. The test statistic is expressed as

$$LR(r_0, p) = -T \sum_{i=r_0+1}^{p} \ln(1 - \lambda_i) \qquad (6)$$

Causality test and error correction model

In multivariate time series models, vector error correction model (VECM) belongs to a special case of vector autoregression (VAR) technique which is commonly used for the data integrated in same order. Granger representation theorem states that for a co-integrated system, error correction technique prevents the deviation of variables from long-run equilibrium. The error caused due to the last period's deviation from the long-run equilibrium point drives the short-run model dynamics. Both long-term and short-term effects of one time series on another are estimated using VEC technique. In general, an error correction model for CO_2 can be described as

$$\Delta CO_{2t} = \alpha Z_{t-1} + \text{lagged}\left(\Delta CO_{2t}, \Delta EC_t, \Delta GDP_t, \Delta REC_t, \Delta TO_t, \Delta URB_t\right) + \varepsilon_t \qquad (7)$$

Here, Z_{t-1} is the error correction term obtained from the estimates of co-integrating relationship between CO_2 and ε is stationary error term.

Engle and Granger suggested that if the variable series are stationary and co-integrated, it is not appropriate to use classic Granger test; instead, a VEC model must be used (Engle and Granger 1991). Granger causality test may show the presence of causality among variables even if the estimated coefficients of lagged terms are insignificant (Granger 1969). Thus, Eq. (9) can be rewritten as follows:

$$\Delta CO_{2t} = K + \alpha_1 Z t_{-1} + \sum_{j=1}^{m} \theta_1 \Delta CO_{2t-j} + \sum_{j=1}^{m} \tau_1 \Delta EC_{t-j}$$
$$+ \sum_{j=1}^{m} \psi_1 \Delta GDP_{t-j} + \sum_{j=1}^{m} \rho_1 \Delta REC_{t-j} + \sum_{j=1}^{m} \varphi_1 \Delta TO_{t-j}$$
$$+ \sum_{j=1}^{m} \varsigma_1 \Delta URB_{t-j} + \varepsilon_1 t \qquad (8)$$

EC does not have a Granger effect on CO_2 if $\tau_1 = \alpha_1 = 0$; CO_2 emission is not Granger caused by GDP if $\psi_1 = \alpha_1 = 0$; REC does not have Granger effect on CO_2 if $\rho_1 = \alpha_1 = 0$; CO_2 is not Granger caused by TO if $\varphi_1 = \alpha_1 = 0$; URB does not have Granger effect on CO_2 if $\rho_1 = \alpha_1 = 0$. Similar conditions are applicable for the rest of the variables.

Vector decomposition and impulse response

The forecast error variance occurred in each variable as a result of exogenous shocks applied to other variables can

be explained by variance decomposition technique. In order to understand the decomposition technique, one must know laws of variance. For every change in *X*, the response *Y* will keep on changing. The focus of decomposition is on the dependent variable *Y*.

$$2 * \text{Variance}(Y) = \text{Expected}[\text{Variance}(Y/X)] \\ + \text{Variance}[\text{Expected}(Y/X)] \tag{9}$$

The first component is the explained variation due to change in X; the second component is the unexplained variation caused due to change in some different parameters other than *X* or randomness. The decomposition method is applicable for a stochastic dynamic system. The first component as shown in Eq. (9) is divided by the second component to generate a ratio (*F* value) compared to the theoretical *F* ratio which indicates the significant impact of treatment parameters in obtaining a total variance. Cholesky decomposition technique has been used for orthogonal factorization. A shock applied to a variable in the system influences not only the variable itself but also the other endogenous variable through the dynamic lagged VAR system. The effect of an exogenous shock to one of the innovations on endogenous variables can be explained by impulse response functions.

Regression analysis

A linear relationship among the logarithmic series of multiple variables like carbon emission, energy consumption, share of renewable energy, urbanization trade and economic growth is postulated in this study. In OLS (ordinary least square) regression, the error term is presumed to be independent and uniformly distributed with a zero mean and constant variance. FMOLS (fully modified ordinary least square) and DOLS (dynamic ordinary least square) regression techniques are applied in this study to determine the long-run elasticities of variables. OLS is asymptotically biased in nature, and the distribution depends upon undesirable parameters. In order to reduce serial correlation and endogeneity problems, FMOLS and DOLS techniques are introduced by Pedroni (2000, 2001).

Further, ridge regression analysis is performed to suppress multicollinearity effect without omission of a variable and to determine the contribution of each factor on dependent variable. An unbiased $\hat{\beta}$ estimate for an ordinary least square regression (OLS) is

$$\beta^{\wedge} = \left(X^T X\right)^{-1} X^T Y \tag{10}$$

The determinant of the matrix $(X^T X)$ becomes almost zero, signifying the presence of high multicollinearity among *X* variables.

This problem in OLS regression can be reduced by adding small quantity of positive *k* with the $(X^T X)$ matrix along the diagonal elements such that

$$\beta^{\wedge} = \left(X^T X + kI\right)^{-1} X^T Y \tag{11}$$

The variance in ridge regression becomes lesser than that of OLS at $k \geq 0$.

The regression coefficients are multiplied by annual growth rate of each factor to get environmental impact of each variable on carbon emission. The effect of each contributing factor is divided by annual growth rate of carbon emission to get percentage contribution of each factor towards emission (Roy et al. 2017).

Results and discussions

Unit root test results

Both ADF test and PP test are employed to check the stationarity property of the variables in question. The test involves the null hypothesis that there is unit root and the alternative hypothesis is that there is no unit root. Results revealed that all the variable series are non-stationary at level, but stationary at their first differenced form with constant and process trend, except urbanization. This implies that variables (economic growth, trade openness, energy consumption, renewable energy use and carbon dioxide emission) are integrated of order 1 level (Table 2). Both the tests confirm the stationarity property of the variables at their second difference.

Computation based on AR technique study is sensitive with selection of appropriate lag length selection. An autoregressive process with *p* lag length indicates that the current value of a series is controlled by its initial *p* lagged values. The value of *p* is estimated using lag length selection criteria. Following the Akaike information criterion (AIC) and Schwarz information criterion (SIC) criteria in this study, *p* is fixed arbitrarily at 2 to obtain the unknown lag length required to generate the autoregression (AR) process (Table 3).

Co-integration test results

Series may have nonzero means or linear deterministic trends. The asymptotic distribution of sequential modified likelihood ratio (LR) test statistic depends on the assumptions with respect to intercepts and trends displaying the following models:

Table 2 ADF and PP tests

Variables	Equation	Level		1st difference		2nd difference	
		t stat	prob	t stat	prob	t stat	prob
ADF test							
$LNCO_2$	2	1.40	0.998	−4.09	0.0044*	−7.41	0.0000**
LNEC	2	3.12	1.000	−2.69	0.0901*	−6.99	0.0000**
LNGDP	2	0.72	0.990	−5.31	0.0003**	−4.96	0.0007**
LNREC	2	1.38	0.998	−3.84	0.0079**	−7.84	0.0000**
LNTO	2	−1.85	0.349	−4.06	0.0048**	−10.01	0.0000**
LNURB	2	1.52	0.999	−1.25	0.6330	−4.44	0.0021**
PP test							
$LNCO_2$	4	1.46	0.998	−4.08	0.0044**	−13.14	0.0000**
LNEC	4	3.09	1.000	−2.69	0.0901*	−8.42	0.0000**
LNGDP	4	0.68	0.989	−5.32	0.0002**	−15.33	0.0000**
LNREC	4	1.30	0.998	−3.82	0.0082**	−13.40	0.0000**
LNTO	4	−1.79	0.374	−4.15	0.0039**	−12.87	0.0000**
LNURB	4	4.27	1.000	−0.86	0.7824	−4.43	0.0021**

*Stands for the rejection of null hypothesis at 90% significance level

**Stands for the rejection of null hypothesis at 95% significance level

Table 3 VAR lag order selection

Lag	Log L	AIC	SIC
0	268.33	−2.186	−21.57
1	454.73	−34.39	−32.33
2	514.68	−36.39[a]	−32.56[a]

AIC Akaike information criteria, *SC* Schwarz information criteria

[a]Lag order selected = 2

Model 1 assumes no intercept and linear deterministic trends in VSR and in co-integration equation;

Model 2 denotes no intercept and linear trend in the test VAR, and co-integration equation includes intercept only but no linear trend;

Model 3 assumes that only intercepts are present, but there are no linear deterministic trends in both co-integration equation and VAR test;

Model 4 assumes that there is intercept in the VAR without any linear trend, but co-integration equation has both intercept and linear deterministic trend;

Model 5 assumes the presence of both intercept and trend in the VAR as well as in the co-integration relationship.

Johansen co-integration tests confirm the existence of four co-integration equations at none, at most 1, at most 2, at most 3 and at most 5, respectively. Both trace and maximum eigenvalue tests support the presence of co-integration relationship among variables (Table 4).

Causality test and error correction model solutions

According to Engle–Granger representation theorem, if a set of non-stationary variables becomes stationary in their differenced levels and are co-integrated, then they are characterized by vector error correction mechanism

Table 4 Co-integration test results

Hypothesized no. of CE (s)	Eigenvalue	Maximum trace			Maximum eigenvalue		
		Trace stat	0.05 critical	p value**	Max eigenstat	0.05 critical	p value**
None*	0.985	227.327	107.347	0.0000	100.731	43.419	0.0000
At most 1*	0.903	126.596	79.341	0.0000	56.014	37.164	0.0001
At most 2*	0.756	70.583	55.246	0.0013	33.844	30.815	0.0206
At most 3*	0.648	36.739	35.011	0.0323	25.030	24.252	0.0394
At most 4	0.267	11.709	18.398	0.3312	7.459	17.148	0.6626
At most 5*	0.162	4.249	3.841	0.0393	4.249	3.841	0.0393

Unrestricted co-integration rank test (trace and maximum eigenvalue)

*Denotes the rejection of hypothesis at 0.05 level and the presence of four co-integrating equations

**Mckinnon–Hang–Michelis (1999)—p value

(Engle and Granger 1991). The estimated VEC model equation for determining the long-term relationship of CO_2 emission with rest of the variables is provided below.

$$D(LNCO_2) = -1.22\,(LNCO_2(-1) - 0.092 * LNGDP(-1)$$
$$+ 0.802 * LNREC(-1) + 0.141 * LNT(-1)$$
$$+ 0.469 * LNU(-1) - 4.323) - 1.74 * (LNEC(-1)$$
$$+ 0.049 * LNGDP(-1) + 0.814 * LNREC(-1)$$
$$- 0.016 * LNT(-1) - 2.207 * LNU(-1) - 2.266)$$
$$+ 0.98 * D(LNCO_2(-1)) + 0.26 * D(LNEC(-1))$$
$$+ 0.62 * D(LNGDP(-1)) - 0.92 * D(LNREC(-1))$$
$$+ 0.14 * D(LNT(-1)) - 25.7 * D(LNU(-1)) + 0.17$$

The coefficients and *p* values indicating relations and significance of the variables are compiled together in Table 5. Two co-integrating terms are specified while imposing VEC restrictions. The error rectification terms are negative, and one of them is significant in the equation considering CO_2 emission as dependent variable, which confirms the existence of long-run relationship between economic growth, energy consumption, renewable energy and emission.

The impact of energy consumption and economic growth is significant on carbon emission. An increase in 1% energy consumption leads to an increase of 0.26% of carbon emission. Similarly, an increase in 1% GDP leads to 0.62% significant increase in carbon emission. The impact of carbon emission is negative and significant on GDP, but the impact of renewable energy consumption and urbanization is positive and significant on GDP. An impact of trade openness is significant but negative on GDP. Both GDP and urbanization have positive impact on energy consumption. The impact of GDP is positive and significant on both trade and urbanization, respectively. Jarque–Bera statistics reveals that the variables are normal.

The co-integration among the variables implies the possibility of causal relationship between them which may be unidirectional or bidirectional. This relationship among variables is discussed in this study using Granger causality test (Table 6). The results have been obtained using Wald coefficient restriction test which generates the possibility to integrate error correction term into null hypothesis.

Granger causality test suggests that a unidirectional causal relationship exists among energy consumption and urbanization. The test results are similar to the one carried out by Liu (2009). The test report also suggests the existence of unidirectional causality from GDP towards CO_2 emission, similar to the results obtained by Roy et al. (2017). A unidirectional causal relationship also runs from CO_2 emission towards renewable energy consumption (REC), similar to the results obtained by Farhani

Table 5 Vector error correction model solutions

Variables	$\Delta LNCO_2$ Coefficient	$\Delta LNCO_2$ p value	$\Delta LNEC$ Coefficient	$\Delta LNEC$ p value	$\Delta LNGDP$ Coefficient	$\Delta LNGDP$ p value	$\Delta LNREC$ Coefficient	$\Delta LNREC$ p value	$\Delta LNTO$ Coefficient	$\Delta LNTO$ p value	$\Delta LNURB$ Coefficient	$\Delta LNURB$ p value
Coint1	−1.22	0.239	−1.09	0.005**	2.22	0.186	−0.44	0.333	−2.19	0.283	0.009	0.641
Coint2	−1.74	0.047**	−2.68	0.000**	−6.09	0.007**	1.03	0.090*	0.782	0.772	0.016	0.533
$\Delta LNCO_{2t-1}$	0.98	0.158	0.98	0.175	−2.05	0.067*	−0.20	0.508	0.405	0.764	−0.01	0.481
$\Delta LNEC_{t-1}$	0.26	0.046**	0.57	0.114	2.69	0.142	−0.19	0.662	0.231	0.906	−0.02	0.217
$\Delta LNGDP_{t-1}$	0.62	0.034**	0.11	0.015**	0.005	0.976	−0.03	0.508	0.361	0.120	0.28	0.042**
$\Delta LNREC_{t-1}$	−0.92	0.337	1.09	0.212	3.18	0.042**	−0.70	0.090*	−0.07	0.972	−0.01	0.494
ΔLNT_{t-1}	0.14	0.169	−0.01	0.746	−2.14	0.039**	0.013	0.774	−0.27	0.180	−0.00	0.615
ΔLNU_{t-1}	−25.7	0.258	−30.4	0.000**	35.7	0.002**	−3.69	0.708	8.561	0.848	0.992	0.020**
Constant	0.17	0.254	0.20	0.000**	−0.16	0.492	0.02	0.762	0.053	0.856	0.000	0.871
R square	0.6856		0.8179		0.8903		0.6293		0.6773		0.9208	
Jarque–Bera	1.225		2.125		3.814		1.405		0.548		1.639	

* and ** stand for the rejection of null hypothesis at 95% and 90% significance levels, respectively

Table 6 Granger causality test solutions

Null hypothesis	F statistic	Probability
LNEC does not Granger cause $LNCO_2$	3.596	0.0474**
$LNCO_2$ does not Granger cause LNEC	1.597	0.2285
LNGDP does not Granger cause $LNCO_2$	4.937	0.0188**
$LNCO_2$ does not Granger cause LNGDP	0.075	0.9283
LNREC does not Granger cause $LNCO_2$	1.006	0.3842
$LNCO_2$ does not Granger cause LNREC	4.841	0.0200**
LNTO does not Granger cause $LNCO_2$	2.253	0.1324
$LNCO_2$ does not Granger cause LNTO	6.931	0.0055**
LNURB does not Granger cause $LNCO_2$	2.474	0.1109
$LNCO_2$ does not Granger cause LNURB	3.308	0.0584
LNGDP does not Granger cause LNEC	0.927	0.4128
LNEC does not Granger cause LNGDP	0.452	0.6428
LNREC does not Granger cause LNEC	0.213	0.8101
LNEC does not Granger cause LNREC	1.284	0.3000
LNTO does not Granger cause LNEC	0.416	0.6657
LNEC does not Granger cause LNTO	2.489	0.1097
LNURB does not Granger cause LNEC	0.889	0.4274
LNEC does not Granger cause LNURB	4.568	0.0240**
LNREC does not Granger cause LNGDP	0.859	0.439
LNGDP does not Granger cause LNREC	6.628	0.0066**
LNTO does not Granger cause LNGDP	5.925	0.0100**
LNGDP does not Granger cause LNTO	6.219	0.0084**
LNURB does not Granger cause LNGDP	4.836	0.0201**
LNGDP does not Granger cause LNURB	6.174	0.0086**
LNTO does not Granger cause LNREC	5.994	0.0096**
LNREC does not Granger cause LNTO	2.798	0.0861
LNURB does not Granger cause LNREC	2.823	0.0844
LNREC does not Granger cause LNURB	3.596	0.0474**
LNURB does not Granger cause LNTO	3.393	0.0549
LNTO does not Granger cause LNURB	0.038	0.9631

**Stands for the rejection of null hypothesis at 95% significance level

(2013) and between carbon emission and trade openness, similar to the results obtained by Sbia et al. (2014).

Variance decomposition and Impulse response

Forecast error variance decomposition method is used to determine the deviation of the carbon emission attributable to its own shock against shock of other variables concerned. The findings allowing a forecast horizon of 26 years show that 23.73% variance of CO_2 emission is contributed by its own impulsive shock, while shock to renewable energy consumption and trade openness contributes to forecast error variance of CO_2 emission by 36.50% and 21.88%, respectively (Table 7). The impulsive shocks due to the remaining variables such as energy consumption, urbanization and GDP are relatively low (being 2.90%, 3.67% and 11.32% respectively). An impulsive shock of one standard deviation

in the context of CO_2 emission is 8.4% from renewable energy and 29.8% from urbanization. The shock applied to CO_2 emission by trade openness is 65.44% where shock applied to trade openness by urbanization is 35.49%. The findings support robustness of VECM causality analysis.

Impulse response function reflects how the economy reacts over time to exogenous impulses or shocks stemming in other variables concerned. Starting with the response of $LNCO_2$ to each of the six variables, an exogenous shock one standard deviation to $LNCO_2$ itself causes the decline of emission graph up to five periods; after that, there was a slight improvement and the graph gradually tends to a steady state. The response of $LNCO_2$ to $LNCO_2$ is positive in nature. An exogenous shock of one standard deviation to LNEC causes $LNCO_2$ to move towards positive from negative y axis after completion of five periods. An exogenous shock of one standard deviation to LNGDP causes $LNCO_2$ to move towards positive from negative y axis after completion of three periods and finally reaches to a steady state.

The carbon emission trajectory directs to negative axis while applying exogenous shock of one standard deviation to LNTO and LNREC, respectively (Fig. 1). The results provide strong support that response to CO_2 emission down to forecast error resulting in renewable energy consumption is negative and significant, suggesting that renewable energy consumption can be a very important factor in reducing carbon emission level in India.

Regression results

Correlation test results clearly show that all the variables have very high correlation adjuvating multicollinearity (Table 8). OLS has been applied to test the multicollinearity.

The estimated coefficient of the determination of the model is 0.995, and the F test is also significant, with an F-statistic of 804.77 at 0.1% significance level. Both FMOLS and DOLS confirm the existence of linear relationship among economic growth and carbon emission, similar to OLS. Positive influence of energy consumption on carbon emission is affirmed by the three least square techniques (Table 9).

Further, ridge regression is applied with a conservative selection of ridge regression coefficient K for the model to reduce multicollinearity problem of OLS. In the present model, value of K is calculated with a step length of 0.01 changing within (0, 1). The results suggest that all the coefficients are steady with small VIFs when K is 0.05. The model shows a high goodness of fit, with R square value of 0.99, and the F test is highly significant, with F-statistic of 450.661 at 0.01% significance level (Table 10). Results show that estimated coefficients of the variables are significant at 10% level except the variable urbanization. Variables as energy use (non-renewable), GDP and trade openness have

Table 7 Variance decomposition method

Period	SE	LNCO$_2$	LNEC	LNGDP	LNREC	LNTO	LNURB
Variance decomposition of LNCO$_2$							
1	0.033	100	0.00	0.00	0.00	0.00	0.00
5	0.059	62.85	8.55	2.49	20.01	5.14	0.95
10	0.078	41.33	7.54	7.55	29.45	13.86	2.44
15	0.092	32.29	4.13	9.48	33.04	17.99	3.07
20	0.104	27.35	3.42	10.53	35.05	20.23	3.42
26	0.117	23.73	2.90	11.32	36.50	21.88	3.67
Variance decomposition of LNEC							
1	0.012	72.13	27.87	0.00	0.00	0.00	0.00
5	0.039	29.04	13.42	5.06	45.33	5.42	1.73
10	0.057	14.11	7.59	4.24	57.24	13.82	2.98
15	0.069	9.42	6.05	4.11	59.39	17.52	3.51
20	0.081	6.79	5.08	4.06	60.96	19.36	3.75
26	0.084	5.51	4.59	4.02	61.74	20.27	3.87
Variance decomposition of LNGDP							
1	0.053	9.30	0.52	90.18	0.00	0.00	0.00
5	0.209	19.32	2.75	31.59	25.51	16.93	4.07
10	0.404	26.32	4.09	23.47	19.07	22.61	4.44
15	0.533	23.77	4.64	22.51	17.41	24.13	4.53
20	0.635	27.01	4.87	22.16	16.69	24.69	4.57
26	0.739	27.21	4.98	21.94	16.29	24.99	4.58
Variance decomposition of LNREC							
1	0.014	29.98	0.84	0.37	68.82	0.00	0.00
5	0.046	19.86	3.97	3.42	66.75	4.59	1.42
10	0.072	8.40	2.20	5.71	66.07	14.38	3.23
15	0.089	5.42	1.86	6.51	65.12	17.38	3.70
20	0.105	4.01	1.68	6.83	64.86	18.7	3.91
26	0.12	3.06	1.56	7.04	64.69	19.59	4.05
Variance decomposition of LNTO							
1	0.065	31.69	10.53	3.09	38.97	15.72	0.00
5	0.211	63.12	2.94	4.22	23.24	5.20	1.47
10	0.333	65.44	2.76	4.61	19.75	5.77	1.67
15	0.423	66.22	2.89	4.45	18.54	6.14	1.77
20	0.494	66.38	2.92	4.46	18.12	6.29	1.82
26	0.569	66.57	2.94	4.45	17.80	6.38	1.84
Variance decomposition of LNURB							
1	0.000	19.74	10.99	2.10	27.22	35.56	4.38
5	0.004	29.72	16.62	6.31	8.00	35.04	4.29
10	0.006	29.87	18.85	6.28	5.36	35.49	4.14
15	0.008	29.95	19.46	6.19	4.70	35.61	4.08
20	0.009	29.99	19.71	6.16	4.42	35.66	4.06
26	0.011	30.02	19.87	6.14	4.23	35.68	4.05

significant positive influence on carbon emission. Renewable energy consumption has a prominent negative impact on CO$_2$ emission as regression coefficient is negative and statistically significant.

The regression coefficient of urbanization is 0.85, but it is not statistically significant. Excluding the urbanization variable, ridge regression is employed and the estimated coefficient of the determination of the model is 0.989 and the F statistic (566.45) is significant at 0.1% significance level (Table 11). Non-renewable energy consumption is found to have the highest regression coefficient (0.57) followed by trade openness (0.07) and GDP (0.06) (Table 11).

For the period 1990–2015, energy consumption generated from non-renewable energy sources grew at 3.74% per annum,
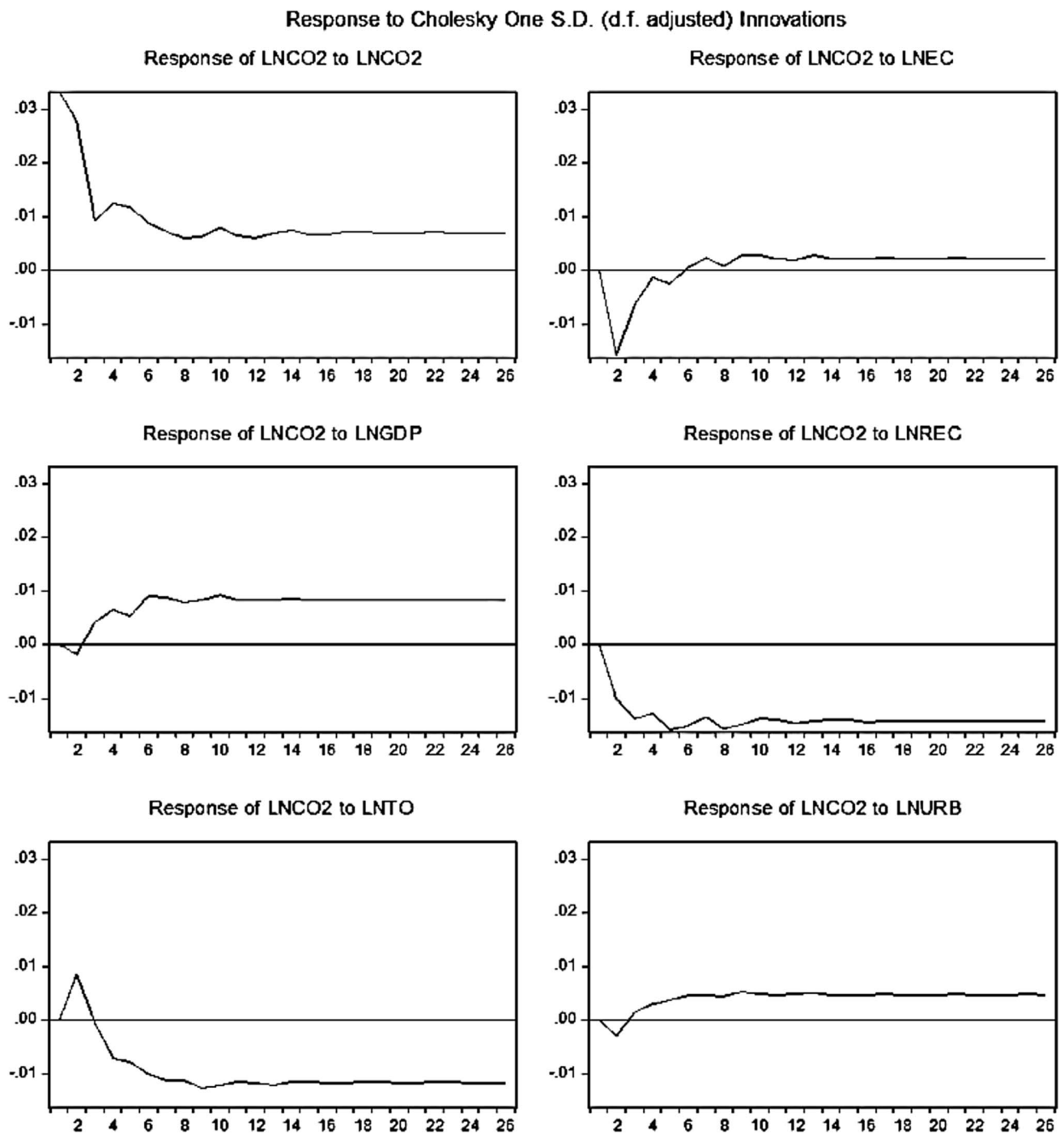
Fig. 1 Impulse response of CO_2 emissions

resulting in 2.13% increase in CO_2 emissions with a contribution degree of 34.12 per cent. GDP growth has the smallest regression coefficient (0.06), but as it grew 13.02% per annum, it causes a 0.781% rise in CO_2 emission with a contribution degree of 12.49%. Trade openness seems to have a contribution degree of 7.28% with the annual growth rate of 6.51% and regression coefficient 0.07. However, renewable energy consumption seems to have a significant negative influence on CO_2 emission. The regression coefficient of the energy consumption from renewable source is 0.64 and it grew at 2.92% per annum, resulting in 1.45% decrease in environmental impact with a contribution degree of 29.76% as reported in Table 12. Major determinants of the increase in carbon emission in India are due to GDP growth, trade openness and

Table 8 Correlation matrix

	LNCO$_2$	LNEC	LNGDP	LNREC	LNTO	LNURB
LNCO$_2$	1.000					
LNEC	0.996**	1.000				
LNGDP	0.974**	0.977**	1.000			
LNREC	− 0.994**	− 0.996**	− 0.979**	1.000		
LNTO	0.907**	0.892**	0.939**	− 0.899**	1.000	
LNURB	0.987**	0.984**	0.982**	− 0.981**	0.944**	1.000

**Significant at 0.01 level (two-tailed)

Table 9 Least square regression solutions

	B	SE	t	Sig.
OLS[a]				
Constant	− 5.02	2.93	− 1.71	.102
LNEC	1.04	0.40	2.57	.018*
LNGDP	0.12	0.50	2.49	.022*
LNREC	− 0.54	0.38	− 1.41	0.17
LNTO	0.08	0.06	1.40	0.18
LNURB	0.39	0.72	0.54	0.59
FMOLS[b]				
Constant	− 4.43	3.05	− 1.45	.163
LNEC	1.12	0.43	2.57	.019*
LNGDP	0.20	0.58	2.46	.024*
LNREC	− 0.65	0.39	− 1.64	.118
LNTO	0.12	0.08	1.62	.122
LNURB	0.31	0.76	0.41	.689
DOLS[c]				
Constant	− 5.02	3.38	− 1.49	.153
LNEC	1.04	0.47	2.23	.037*
LNGDP	0.12	0.57	2.16	.043*
LNREC	− 0.54	0.44	− 1.22	.235
LNTO	0.08	0.07	1.21	.239
LNURB	0.39	0.83	0.47	.643

[a]$R^2 = 0.995$, adjusted $R^2 = 0.994$, F statistics $= 804.77$ (significant), Bias $= 0.0218$

[b]$R^2 = 0.994$, adjusted $R^2 = 0.992$, long-run covariance estimate (Bartlett kernel, Newey–West fixed bandwidth $= 3.000$), Bias $= 0.023$

[c]$R^2 = 0.995$, adjusted $R^2 = 0.994$, long-run covariance estimate (Bartlett kernel, Newey–West fixed bandwidth $= 3.000$), Bias $= 0.0218$

*Denotes variables are significant at 5% level of significance

energy use, resulting in a 3.363% increase in carbon dioxide emission with a contribution degree of 53.89%. However, renewable energy use has a significant negative impact having a 1.86% decrease in carbon emission with a contribution degree of 29.76%.

Table 10 Ridge regression estimates with urbanization as independent variable

Variables	B	SE	T
Constant	− 3.85	.482	− 7.99
LNEC	0.47	.036	13.94
LNGDP	0.04	.039	2.24
LNREC	− 0.55	.051	− 10.82
LNTO	0.02	.024	0.897
LNURB	0.85	.108	7.89
R^2	0.991		
Adjusted R^2	0.989		
F-statistic	450.61		
Bias	0.029		

Table 11 Ridge regression estimates excluding urbanization

Variables	B	SE	T
Constant	− 1.55	.283	− 5.47
LNEC	0.57	.040	14.24
LNGDP	0.06	.017	3.33
LNREC	− 0.64	.049	− 12.97
LNTO	0.07	.026	2.57
R^2	0.989		
Adjusted R^2	0.988		
F-statistic	506.45		
Bias	0.0307		

Discussion

This is expected that fast economic growth along with rise in trade openness in developing countries like India will increase energy consumption which has very serious implications in rise of carbon emission. With the rise in population, urbanization will also increase necessitating more industrialization, transport and other economic activities with increased consumption of energy only. Therefore, massive development of renewable energy sources coupled with use of energy-efficient and green

Table 12 Percentage contributions of the variables to carbon emission, 1990–2015

Variables	Regression coefficient	Growth rate (%)	Effect on emission (%)	% Contribution
$LNCO_2$	–	6.25		
LNEC	0.57	3.74	2.132	34.12
LNGDP	0.06	13.02	0.7812	12.49
LNREC	− 0.64	2.92	− 1.869	− 29.76
LNTO	0.07	6.51	0.455	7.28

CO_2 = Carbon dioxide emission; EC = per capita energy use; GDP = per capita gross domestic product; REC = renewable energy use in total final energy consumption; TO = trade openness; excluded the variable URB (urbanization); LN denotes natural logarithmic data series; effect of variables on change in emission = average annual growth rate X regression coefficient; % contribution of variables towards CO_2 emission = effect of variables on change in emission ÷ Average annual growth rate of CO_2 emission. The carbon emission impact of energy consumption variable is found to be the significant and highest. Energy consumption, GDP per capita and trade openness are major contributing factors to increase carbon dioxide emission with percentage contribution of 53.89% over the period 1990–2015. The impact of renewable energy on emission is significant but negative

technologies seems to be the best options to arrest greenhouse gas emission.

As per the results obtained from this study, economic growth shows positive influence on carbon emissions. The increase in average income causes change in lifestyle, and consumption behaviour of country population significantly influences environmental quality. A hypothesized relationship among environmental quality and economic growth is represented by environmental Kuznets's curve (EKC). It states that environmental quality continues to worsen with the rise in economic growth until the average income reaches an optimal point and environmental impact starts declining. As far as Indian economy is concerned, the emission–growth nexus shows positive trend. With fast economic growth, the country has experienced high growth rate of energy consumption, trade and population which results in a prominent increase in CO_2 emissions. But at the same time, the results show economic growth variable positively influences renewable energy consumption variable. This means the role economic growth is vital in generating resources for expansion of renewable energy sector which serves as an impetus to low-carbon development. Despite the existence of positive relationship among carbon emission and economic growth, it is possible to restrict carbon emission through investment towards successful implantation of renewable and energy-efficient technologies (Kumar et al. 2019, 2020).

The industrial production processes in India are mostly associated with energy consuming conventional unit operations. Emergence of various technologies for conversion of carbon dioxide to methanol or extraction of acids and biofuels from renewable carbon source has opened up a new path towards green production ensuring sustainable business and process intensification (chakrabortty et al. 2019; Pal et al. 2018). Therefore, under environmental regulations, adoption of green technologies should be encouraged in all possible ways. Such technologies are known as sustainable technologies as they pass the litmus test of process intensification that approves only technologies serving the long-term interests of the people, the planet and the profit for the industry. Drastically reduced is the consumption of energy in such industries in producing high-purity products at relatively low price (Pal and Dey 2013; Dekonda et al. 2014; Pal et al. 2015; Pal and Nayak 2015). Some of these new and green technologies as referred here use membrane-based downstream separation and purification techniques culminating in very compact and extremely simplified plant configurations. For example, in a conventional lactic acid production plant, a large number of unit operations like ordinary filtration, evaporation, crystallization, carbon adsorption, acid hydrolysis, etc. are involved for the production of lactic acid. But in a membrane-based new technology, as referred here, this production can be carried out in just three steps (viz., fermenter unit, a microfiltration and a nanofiltration unit employing membranes). As no phase change is involved in membrane-based separation, energy consumption is drastically reduced. The cited literature shows (Pal and Dey 2013) that energy consumption in a membrane-based technology for production of lactic acid is only one-fifth the energy required in a conventional lactic acid production plant.

Trade openness and industrialization also enable implantation of energy-efficient technologies to reduce carbon emission. Patronizing green technologies and renewable energy systems with emphasis on carbon sequestration will thus definitely contribute to reduce carbon emission (Table 12).

Conclusions and policy suggestions

The results suggest an increase in GDP, and large-scale trade in the long run facilitates the adoption of renewable and energy-efficient technologies to reduce emission. This paper not only employs Vector error correction and Granger tests, but also variance decomposition and impulse response function, OLS and ridge regression techniques to construct a robust carbon emission model and validate the results. Such a vast analysis has not been shown in previous publications. With economic growth, urbanization, rise in population and trade openness, Indian economy has witnessed a fast rise in carbon emission at the rate of 6.25% per annum during the period 1990–2015. The empirical evidence reveals that energy consumption, GDP and trade

openness are major contributing factors to increase carbon dioxide emission in India having a 53.89% contribution to change in environmental impact over the period 1990–2015. Energy use largely from non-renewable energy source is the most important factor having a significant positive environmental impact (34.12%). By applying Granger causality test, the study shows that there exists a bidirectional causality between trade and economic growth, urbanization and economic growth, trade and renewable energy consumption and unidirectional causality running from economic growth to carbon emission, energy consumption to carbon emission, economic growth to renewable energy and carbon emission to trade, respectively. Thus, the causality test suggests large-scale trade in the long run allows the implantation of renewable and energy-efficient technologies to reduce emission. In view of continued heavy dependence on indigenous fossil fuel coal for major energy source even for the foreseeable future, it is imperative to develop more efficient, ultra-low-emission technologies for coal-fired power plants. These technologies include newly designed pulverized coal combustion systems with supercritical steam cycle technology, fluidized bed combustion and integrated gasification combined cycle provided with carbon capture and storage facilities. In addition to this, development of renewable energy sources coupled with massive switching to electric mass transport and large-scale adoption of energy-efficient green technologies appear as most practical policy suggestions for a big economy like India.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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