Wada, Isah

Article

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The Nexus of Anthropogenic Climate Change, Primary Energy Consumption and Dynamic Economic Change in India

Isah Wada*

Department of Economics, Faculty of Economics and Administrative Sciences, Cyprus International University, Haspolat, via mersin 10 Turkey. *Email: iwada@ciu.edu.tr

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ABSTRACT

The empirical connection between anthropogenic climate changes, aggregate production index, primary energy consumption, population dynamics, capital formation, and real per capita income in India is investigated in this study. The equilibrium long-run relationship among the studied variables and their causality are analysed using the theoretical framework of Cobb Douglas's production function. The study used a time series data set from 1965 to 2018 as part of a novel bound testing methodology strongly backed up by the classical cointegration techniques. As a result, the model's short-and long-run relationships are estimated. The estimation reveals long-run equilibrium convergence between anthropogenic climate change and the remaining exogenous factors empirically examined. Consequently, the aggregated production index, real domestic investment, and real economic growth have both short-run and long-run positive impact in the estimated model. The findings revealed further that primary energy use is the leading cause of anthropogenic climate change, causing changes to real domestic investment and population. A significant policy recommendation, among others, is a faster transition to cleaner energy to combat anthropogenic climate change, owing to India's extremely high energy intensity power sector with massive primary energy consumption.

Keywords: Anthropogenic Climate Change, Equilibrium Convergence, Modified causality, Primary Energy Consumption, Production Function
JEL Classifications: C51, Q13, P18, P28, Q43

1. INTRODUCTION

According to United Nation High-level Panel on Threats, Challenges and Change (2004) climate change has seen an alarming and dramatic increase in its impact throughout the years and human actions are now being blamed for the massive climatic shift that is being observed around the world. There is a well-established empirical consensus that global warming is a direct outcome of anthropogenic effects (Friedlingstein et al. 2019). Thus, as the human economic enterprise becomes vast, the growth of human civilization and the evolution of measuring science serve to reveal the mass of stored carbon dioxide in the earth's atmosphere. As a result, the dynamic pattern and growth in global greenhouse emission is thought to be a fundamental driver of atmospheric climate change. The Greenhouse emission, notably carbon dioxide emissions (CO_2)are harmful to the earth's atmosphere and are traced to forest reserves and ocean bodies, in addition to the earth's atmosphere.

As a key contributor to global emissions acceleration, this research focuses on the anthropogenic impact of CO_2 a proxy for climate change-and the resulting economic structural changes in India. This stems from the necessity to promote and ensure high environmental quality for both living and non-living organisms while pursuing high economic growth and structural change. In general, when countries increase output production, they intensify natural resource exploitation, resulting in huge depletion for future generations. Meanwhile, the degradation of the natural environment is exacerbated by the exploited resource. Even more so, real output expansion necessitates primary energy demand adversely impacting environmental quality (Ozturk, 2015; Wada et al, 2020). As a result, the the Grossman and Krueger (1991) environment Kuznets hypothesis is frequently used to study whether this process becomes more intense as economies grow and develop (Wada et al. 2021). Previous research has looked into the environment Kuznets hypothesis in greater depth and reached a variety of empirical conclusions (Begum et al, 2015; Ali et al. 2016; Sinha and Shahbaz, 2018; Abokyi et al. 2019; Shahbaz and Sinha, 2019; and Yao et al, 2019). Furthermore, studies rely on Kraft and Kraft (1978)'s important contribution in structuring policy recommendations on the strength of the empirical relationship between economic growth, energy, and environmental quality (Wada, 2017). The study research question in this regard is: Does economic expansion have a negative influence on environmental quality due to the dynamic nexus of energy use and production?

A plethora of academic studies have attempted to resolve the research question on the output production nexus with primary energy consumption and resource usage in the existing literature. Particularly since fossil fuels continue to dominate the energy mix in many countries, accounting for around 80% of total energy consumption. This realization implies that primary energy consumption is intimately linked to greenhouse gas emissions and, as a result, climate change (Rüstemolu, 2022). The emission of CO_2 is intensifying as heavy industrial activity and manufacturing take firm hold in many economies. As the goal of achieving net-zero emissions by 2050 approaches, the question of decarbonizing CO_2 emissions from economic growth and/or the need to pursue a lower economic growth ambition takes centre stage.

To begin, there have been numerous empirical findings on the environmental impacts of anthropogenic climate change in the literature. Studies that explicitly regard human activities as having less of an impact on global climate change are at the other end of the spectrum. This study concludes that anthropogenic CO_2 emissions and temperature changes are insignificant, especially when other CO_2 emitting sources are taken into account. Others argue that humans are at the root of anthropogenic climate change and global warming. Lenaerts et al. (2021) used more recent evidence to consider output growth as the historic cause of global greenhouse gas emissions and environmental degradation. This emphasizes the role of human activities in the climate debate, casting doubt on the continued focus on economic growth.

More recently, the focus is shifting toward greener growth theories, which propose the right policy mix and technological drive to boost output growth while reducing pollution. Dell et al. (2014)'s research also demonstrates how anthropogenic effects are emphasized in the climate debate when accounting for extreme temperature changes and atmospheric weather patterns. Since Stern (2004)'s work, studies have begun to look more deeply into anthropogenic climate change, with a particular focus on the economic growth dynamic impacts. There are many important factors in the explanation of climate change's impact on economic growth, according to Dell et al. (2007). Especially, through the channels of primary energy consumption (Katircioglu, 2014), industrial and manufacturing production, population expansion, and increased domestic investment in capital accumulation, output growth increases concern for environmental quality. As a result, the dynamic relationship between economic growth, energy consumption, and environmental degradation continues to inspire researchers, influencing energy and environmental policy in a variety of ways.

Our observation reveals a scarcity of studies for India on our topic, despite the fact that, as of 2018, India has the world's third largest primary energy consumption, trailing only China and the United States (US) (US EIA, 2020). This will continue to rise as the country's output level rises in tandem with the country's population growth and dynamic economic modernization. For example, the gross domestic product (GDP) adjusted for inflation reached about 8.2% from 2011 to 2016, before falling to 5.0% in 2019 (EIA, 2020). And thus, primary fuel consumption has increased by nearly 916 tons per million equivalent of oil between 1990 and 2018. Coal accounts for 45% of the country's energy matrix, followed by petroleum liquids (26%), biomass traditional waste (20%), and natural gas (around 6%). Renewables make up a small percentage of the total. The country aims to increase its natural gas market share to nearly 15% by 2030, while also attempting to reduce pollution of the atmosphere by stemming the tide of unclean fuel combustion. As it expands its potential capacity, India's energy sector is also undergoing a massive shift away from biomass waste fuel and toward clean energy, such as wind, solar, and hydro. In 2030, the country aims to produce 40% of its energy from non-carbon fuels. India, on the other hand, is a major CO_2 emitter due to its heavy reliance on coal. With an emission growth of about 1.8% in 2019, the country is now the third largest CO_2 emitter in the world, behind China and the United States. With a population of around 1.38 billion people, India ranks 140th in terms of CO_2 emissions per person, while the United States and China are ranked 14th and 48th, respectively. This makes India's efforts to reduce emissions and contribute to a global temperature reduction of 2°C (3.6°Fahrenheit) commendable (Climate action tracker, 2021). Despite these efforts, anthropogenic effects such as direct carbon fuel combustion, traditional biomass, and automobile exhaust continue to be a major source of pollution in India.

The study's novelty stems from the theoretical framework used in the analysis of the empirical relationship of the selected variables, as well as the ease with which the econometric estimation technique is applied. The study takes into account dynamic breaks in the estimation data structure and uses the dynamic Autoregressive distributed lag (ARDL) regression model for the empirical analysis. This method works with non-stationary and mixed time series integration orders, and it's great for separating the short-run and long-run dynamic effects in the estimated model. To support the Pesaran et al. (2001) ARDL-bounds approach in examining long-run equilibrium relations for the selected variables, the study draws inspiration from Johansen's (1995) cointegration technique for robustness. Lastly, we used the idea of component analysis to derive a much more robust series aggregating industrial and manufacturing value add in production for the India economy. The remaining part of the research follow thus. Section 2 details India CO_2 emission. Section 3% the data and methodological approach. Section 4 highlights the results obtained and discussion, and section 5 concludes the study.

1.1. India CO_2 Emission Brief Account

India has a far-reaching and overbearing reliance on its coal sector (MoEFCC, 2018). And with its energy demand forecasted to more than double as its decades of industrialization unfold, energy generation from the coal-fired power plant is yet to peak. Coal has been the most energy reliable source for India, even though there exists an opportunity for renewable energy. Coal ensures the energy security of the country and is a veritable source of national revenue. The country operates the largest coal mining operation in the world receiving about 40,000 Indian rupees (INR) yearly for royalties' related income (Coal India, 2020). And coal production remains very significant for the livelihood of millions in the country. However, with the anthropogenic effects of coal production, the inevitability of it eventually phasing out seem imminent. For instance, there exist a significant correlation between annual death records and increasing emission level in India and the enormous ash produced by the coal-fired power plant contributes to very severe and challenging health conditions. These arises from the unavoidable water body and vegetation pollution to heat trapped CO_2 emission from coal combustion and irresponsible ash waste disposal. Thus, the anthropogenic effects of CO_2 emission are growing very significantly at about equal or more pace than the primary energy consumption and output expansion for India.

Hence, the evidence suggests that India does not yet have a credible "net zero" target for emission reduction. The estimates show that by 2030 India's emission of greenhouses gases would reach 3.84–4.02GtCO2e (Climate Action Tracker, 2021). Although the country's climate target for 2030 remains in progress, it is yet to transfer its nationally facilitated documents to the United Nations Framework Convention on Climate Change (UNFCC). Therefore, CO_2 emission in India records 948.5 million tonnes mostly from carbon-fuel, namely: coal–1.67 billion tonnes (Bts), oil–672.91 million tonnes (Mts), gas–128.68 Mt; cement production-143.66 Mts and flaring–1.58 Mts. It has had 51.94 Bts of cumulative emission from 1858 to 2019 (Ritchie and Roser, 2021). The country's global emission share is 7.18% as of 2019 with an annual change of about 25.13 Mts of emission.

In terms of sectoral emission, the data shows that India emission from electric power generation and heating is 1.11 Bts, the manufacture and constructing industry–533.80 Mts, transportation–265.30 Mts, changes in land usage and forest–118.73 Mts, industrial sector–110.60, building–109.20 Mts, combustion of applied fuels–57.30 Mts and escaped (fugitive) emission–1.48 Mts.

Although India's renewable sector policies are ambitious with a 175 GW expansion plan, it is still producing at 98.9 GW of installed capacity. The realization of its renewable sector ambition can usher in a regime of cleaner energy, low wind and solar energy prices, and the decommissioning of the coal production power plant. Therefore to cut its emission level in general, India must address its emissions-intensity target in line with its commitment to the Paris agreement. The country's intensity target for its emission level remains yet unsatisfactory. Subsequently, the country's climate commitment and policy frameworks are inconsistently off-target toward emission reduction and the realization of net-zero ambition. As a result more needs to be done for the commitment of 33-35% emission intensity reduction by 2030 and the goal of stimulating electricity power capacity expansion for non-carbon fuel to 40%. And the planned emission reduction via 2.5–3 $GtCO_2e$ carbon-sinking thorough regenerating forestry and tree covering would mean additional sacrifice.

Finally, as India realized a 6.8 GW of its coal installed capacity–totalling around 50% energy generation (India Energy Outlook, 2020), and retires old coal production pipelines, it seems committed to its energy decarbonisation efforts.

2. DATA AND METHODS

2.1. Data

With the exception of primary energy consumption-PEC the study uses available time series annual economic data from 1965 to 2018 culled from World Bank development indicators. The PEC data comes from the "Our World in Data" data bank, which is based on BP World Energy Review statistics. The rest of the study data are carbon dioxide emission in metric tons per thousand (kt)– CO_2; Industry value added in constant 2010 United State Dollars (USD)-IDV and Manufacturing value-added constant 2010 USD–MVA (thereafter, aggregate production index, using the principal component analysis); Primary energy consumption in TeraWatt Hour(s) (TWh)–PE; Population total–PT; Gross fixed capital formation in constant 2010 USD–GFCF; Gross domestic product per capita in constant 2010 USD-GPK and Squared GDP per capita in constant 2010 USD-GPK^2. We use CO_2 emission as a proxy for anthropogenic climate change effects because it is the leading anthropogenic type greenhouse effect affecting the balance of the earth's radiation resulting in human-caused climate predicaments. It is defined as India's total carbon dioxide emission from both carbon-based fuels, biomass, and heavy industrial production activities.

The aggregate production series is defined according to the 'international standard industrial classification (ISIC)' reported by the World Bank to include value add from production and manufacturing activities. The primary energy consumption data (PEC) are mostly fuels with commercial viability such as coal energy, crude oil, natural gas including nuclear energy, and modern stocks of renewable. The population variable (PT) counts the entire residents of the country devoid of their citizenship background or status legally. The data on Gross fixed capital formation (GFCF) refers to the real domestic investment in fixed assets-such as the improvement of land, purchases of factories, plants, machinery, and equipment. It also covers investment in the construction of national infrastructure, the building of commercial and industrial complexes. The variable on real GDP per capita is obtained by dividing India's gross domestic product by the mid-year total population value. Theoretically, it indicates the level of prosperity or per-head income of the citizens in India.

2.2. Methodology

We use a robust theoretical framework derived from Cobb-Douglas' production constant return model, such as; $Y_t = f(A_t,$

K_t, L_t) to model the dynamic functional relationship for our study variables. Where Y denotes output growth, A denotes technological advancement, K denotes capital accumulation, and L denotes labor growth. Since real output growth is thought to play a significant role in anthropogenic climate change, we use CO_2 as a proxy for man-made climate change, with $CO_2 = Y_t = f(A_t, K_t, L_t)$. We included the net value of the industrial and manufacturing sector to account for the impact of technological progress on output expansion because technological progress causes higher real output growth through significant value addition in production. We construct a new dynamic series for the net effect of industrial and manufacturing value add using the methodical approach of component analysis.

Hence to explain the Kuznets hypothesis within an anthropogenic climate change-output growth model given the specified relationship, the natural logarithm of squared GDP per capita is incorporated into the theoretical model such that;

$$LnCO_{2t} = \beta_0 + \beta_1 LnAPI_t + \beta_2 LnPEC_t + \beta_3 LnPT_t + \beta_4 LnGFCF_t + \beta_5 LnGPK_t + \beta_6 (LnGPK_t)^2 + \varepsilon_t \quad (1)$$

Therefore when $\beta_5 > 0$ and $B_6 < 0$ with significant estimates, the EKC hypothesis is confirmed.

Equation (1) also captures the equilibrium long-run nexus of the selected variables; where the variables are in natural logarithm at given time *t* and *LnCO2* is the Carbon dioxide emission variable-a proxy for Anthropogenic climate change, *LnAPI* is the aggregate of production value-added from real industrial and manufacturing activities, *LNPEC* is Primary energy consumption, *LNP* is the Population (total) variable, *LNGFCF* is utilized as a proxy for real domestic investment, *LNGPK* is real *GDP* per capita and $(LnGPK)^2$ is the Squared real *GDP* per capita. As a result, estimating an error correction model of the form in equation (2) reveals the speed with which our dynamic model transitions from short-run to long-run equilibrium.

$$\Delta LnCO_{2t} = \beta_0 + \sum_{i=0}^{v} \beta_1 \Delta LnC0_{2t-i} + \sum_{i=0}^{r} \beta_2 \Delta LnAPI_{t-i} + \sum_{i=0}^{r} \beta_3 \Delta LnPEC_{t-i} + \sum_{i=0}^{r} \beta_4 \Delta LnPT_{t-i} + \sum_{i=0}^{r} \beta_5 \Delta LnGFCF_{t-i} + \sum_{i=0}^{r} \beta_6 \Delta LnGPK_{t-i} + \sum_{i=0}^{r} \beta_7 \Delta (LnGPK_{t-i})^2 + \tau_1 \varepsilon_{t-1} + u_t \quad (2)$$

2.3. Non-stationary Test

Perron's (1989) influential work demonstrates the value of examining structural breaks for time series data. The evidence shows that structural shifts and regime changes have a significant impact on time series data (Greene, 2008). The Perron (1989) test approach is derived from the generalized ADF specification with the following break in both mean and trend terms:

$$\Delta Z_t = \varphi Z_{t-1} + \sum_{r=1}^{v-1} \gamma Z_{t-r} + \mu_t + u_t \quad (3)$$

Where $\mu_t = \mu_0 + \mu_0{}^l b_{tTN} + \mu_1 + \mu_1{}^l (t - T_N) b_{tTN}$ gives the likely deterministic value, hence a constant as $\mu_0 \neq 0$ and conversely a trend term for $\mu_1 . \neq 0$. This method is widely panned because it considers the break to be exogenous. We use the unit root test when there are endogenous breaks to avoid any confusion. As a result, Zivot and Andrews (2002) (hereafter ZA [2002]) is considered. The result of the unit root test is presented in Table 1. The result shows that the series are integrated of order 1–*I*(1), hence the null hypothesis of unit root is rejected. This suggests that the dynamic Autoregressive distributed lag (ARDL) model, which is admissible in cases of I(O), I(I), or jointly cointegrated, is a good fit for our empirical analysis.

2.4. Cointegration Test

The cointegration relationship (Engle and Granger, 1987) is defined by weighted cointegrated vectors resulting from the linear association of series, I(1) or I(0), giving rise to the empirical long-run equilibrium relation. Assuming a single cointegration vector of a standard regression model having *p*+1 time series of dimension $Y_{t1} X_{t1}{}'$ vector, the cointegration equation takes the form:

$$Q_t = \gamma_t{}' \beta + A_{it}{}' \theta_1 + U_{it} \quad (4)$$

where $A_t = (A_{it}{}' A_{2t}{}')^1$ is the trend regression directly derived from the equation with accompanying stochastic specification generated by set of system equation.

2.5. Dynamic ARDL Bounds Testing

The ARDL is a time series specification with linear regressors that are related both contemporaneously and across lagged values. We estimate the conditional error correction with unrestricted parameter using the ARDL methodological framework, which is based on the long-run equilibrium nexus of the selected variable. As a result, the following is the ARDL unrestricted conditional error correction (UCEC) model:

$$\Delta LnCO_{2t} = \beta_0 + \sum_{i=1}^{v} \beta_1 \Delta LnC0_{2t-i} + \sum_{i=1}^{v} \beta_2 \Delta LnAPI_{t-i} + \sum_{i=1}^{v} \beta_3 \Delta LnPEC_{t-i} + \sum_{i=1}^{v} \beta_4 \Delta LnPT_{t-i} + \sum_{i=0}^{r} \beta_5 \Delta LnGFCF_{t-i} + \sum_{i=0}^{r} \beta_6 \Delta LnGPK_{t-i} + \sum_{i=0}^{r} \beta_7 \Delta LnGPK_{t-i}{}^2 + \delta_1 LnC0_{2t-i} + \delta_2 LnAPI_{t-i} + \delta_3 LnPEC_{t-i} + \delta_4 LnPT_{t-i} + \delta_5 LnGFCF_{t-i} + \delta_6 LnGPK_{t-i} + \delta_7 LnGPK_{t-i}{}^2 + \varepsilon_t \quad (5)$$

where Δ is the differencing operating term and ε_t is the serially independent and identical random error with finite zero mean and covariance form matrix. Therefore by estimating the specified *UCEC* model, the dynamic long-run equilibrium is established using both the F-and t-test statistic. Consequently, the null and alternate hypothesis of long-run equilibrium relationship involves examining the following;

$$H_0 = \delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = 0$$

$$H_1 = \delta_0 \neq \delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq \delta_5 \neq \delta_6 \neq \delta_7 \neq 0$$

The rejection of H_0 confirms the existence of a valid equilibrium long-run relationship and motivates the estimation of the equilibrium adjusting speed from the short-run to the long-run.

Table 1: The Zivot and Andrews (2002) unit root test with a structural break

	$LNCO_2$	LNAPI	LNPEC	LNPT	LNGFCF	LNGPK	$LNGPK^2$
Z_I	−4.0271	−4.0517	−3.9495	−3.9669	−3.0721	−1.9088	0.9914
	(1998[4])	(2006[4])	(1988[3])	(1992[4])	(2004[0])	(1979[4])	(1979[4])
Z_T	−3.7027	−3.0470	−2.8056	−4.1606*	−3.2333	−1.7295	−0.7714
	(2003[4])	(1992[4])	(1996[3])	(2001[4])	(1985[0])	(1980[4])	(1980[4])
Z_B	−4.406	−3.0260	−3.7586	−4.0747	−3.1853	−2.1007	−1. 1438
	(2001[4])	(1991[4])	(1988[3])	(2000[4])	(1984[0])	(1979[4])	(1979[4])
ΔZ_I	−9.2099***	−5.8322***	−5.6204***	−9.4421***	−9.1585***	−6.5029***	−6.2857***
	(1990[0])	(2008[2])	(1992[1])	(1977[1])	(2008[0])	(1985[4])	(1979[4])
ΔZ_T	−8.7371***	−5.8348***	−5.3556***	−6.3503***	−9.0197***	−6.1773***	−5.9827***
	(1984[0])	(2007[2])	(1989[1])	(2007[10])	(2007[0])	(2008[4])	(2004[4])
ΔZ_B	−9.6352***	−6.0672***	−5.5788***	−6.9577***	−9.1531***	−6.2124***	−6.0232***
	(1990[0])	(2004[2])	(1992[1])	(1979[1])	(2005[0])	(1985[4])	(2004[4])
	Reject	Reject	Reject	Reject	Reject	Reject	Reject

The test series are presented in natural logarithm. Carbon dioxide emission variable is $LNCO_2$, LNAPI: Aggregate production Index, LNPEC: Primary energy consumption (TWh), LNPT: Population, total, LNGFCF: Gross fixed capital formation (constant 2010 USD), LNGPK *GDP* per capita (constant 2010 USD), $LNGPK^2$: Squared *GDP* per capita (constant 2010 USD), RGDP: Real gross domestic product. ZAI is unit root test with intercept only, ZAT: Unit root with trend only, ZAB: Unit root with intercept and trend. Test break dates are in ( ) and the maximum lag selected in [ ]. *, ** and *** 1%, 5% and 10% significant level for the test hypothesis rejection

2.6. Granger Causality

The current study follows the conventional approach to Granger causality testing within the dynamic Vector Autoregressive model (VAR). Additionally, the approach of Dolado and Lütkepohl (1996), following the VAR augmented framework, where the VAR true lag is modified by adding an extra singular lag $r + 1$ before performing the test on the lags of the first coefficient of r is proposed. Similarly, to the Toda and Yamamoto (1995) test framework preliminary pre-testing is entirely unnecessary when implementing the Dolado and Lütkepohl (1996) Granger non-causality test. Thus, consider the VAR(q) model;

$$X_t = \pi + G_1 X_{t-1} + \ldots + G_q X_{t-q} + \varepsilon_t \tag{6}$$

where, X_t π and ε_t~(0,ω) are vectors of m dimension and G_v is the m*m matrix parameter associated with lag V. And thus, the h^{th} X_t element do not Granger cause gth element of X_t element by the non-rejection of the null hypothesis;

H_0 = grow, h column of element G_q is zero for $q = 1\ldots r$

The hypothesis is tested using the modified version of the Wald test within the described VAR augmented model.

3. RESULTS AND DISCUSSION

Table 1 presents the results of the Zivot and Andrews (2002) structural break unit root test for three different scenarios: Trend and intercept break; trend break only; and intercept breakpoint. The test is run on the natural logarithm series, and the results are displayed along with the break date and selected lag. The result refutes the null hypothesis of a unit root, such that after first differencing, the series becomes stationary.

The maximum eigenvalue and trace statistic for the cointergration test are shown in Table 2, which were obtained by estimating an unrestricted cointegration equation with 52 adjusted observations within a linearly deterministic trend model. As a result, at the 5% level, the Johansen unrestricted cointegration rank test for the trace statistic reveals three significant cointegrating equation(s).

Table 2: The Johansen cointegration test

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized		Trace	0.05	
No. of CE (s)	Eigenvalue	Statistic	Critical value	Prob.**
None*	0.790457	198.6672	125.6154	0.0000
At most 1*	0.547432	117.4001	95.75366	0.0007
At most 2*	0.432083	76.17362	69.81889	0.0142
At most 3	0.334126	46.75305	47.85613	0.0632
At most 4	0.212688	25.60701	29.79707	0.1409
At most 5	0.193216	13.17221	15.49471	0.1086
At most 6	0.037876	2.007837	3.841465	0.1565
Unrestricted cointegration rank test (maximum eigenvalue)				
Hypothesized		Max-eigen	0.05	
No. of CE (s)	Eigenvalue	Statistic	Critical value	Prob.**
None*	0.790457	81.26708	46.23142	0.0000
At most 1*	0.547432	41.22647	40.07757	0.0369
At most 2	0.432083	29.42057	33.87687	0.1553
At most 3	0.334126	21.14603	27.58434	0.2675
At most 4	0.212688	12.43480	21.13162	0.5054
At most 5	0.193216	11.16438	14.26460	0.1462
At most 6	0.037876	2.007837	3.841465	0.1565

52 observations included in estimation after adjustments. The Trend assumption is based on a linear deterministic trend. Trace test indicates 3 cointegration equation (s) at the 0.05 level. Max-eigenvalue test indicates 2 cointegration equation (s) at the 0.05 level. *denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-Haug-Michelis (1999) P-values

Furthermore, the maximum eigenvalue rank statistic at 5% yields two cointegrating equations. Consequently, the null hypothesis is rejected in both cases, indicating a very stable long-run relationship between the variables.

Additionally, the result of the ARDL bounds test for level relationship is reported in Table 3 with the test critical value derived from Narayan (2005) F-statistic and Pesaran et al. (2001) t-ratios.

The test decision criterion is to reject the null hypothesis for critical values beyond the upper bound and fail to reject for values below the lower bound. The test is presented for three different cases: restricting the determining trend term (F_{IV}), unrestricting the determining trend term (F_V), and completely omitting the

Table 3: The bounds test for long-run equilibrium

P (K=6)	Deterministic trend			Without deterministic trend		Decision
	FIV	*FV*	*tV*	*FIII*	*tIII*	*H0*
2	1.760994^X	1.899332^X	–2.274369^X	2.007201^X	–2.256617^X	Reject
3	2.093645^X	2.390281^X	–2.988575^X	2.052672^X	–2.793759^Y	
4	3.776766^Z	4.306198^Z	–4.684394^Z	4.434155^Z	–5.087835^Z	

P denotes lag length based on the appropriate information criteria. F_{IV} is F-statistic with unrestricted intercept and restricted trend, F_V is F-statistic with unrestricted intercept and trend, and F_{III} is F-statistic with intercept and no trend. t_V and t_{III} are t-ratios with and without deterministic trends. x: Denote value below the lower bound, y: Values between; and z: Values above. K denotes the number of regressors

Table 4: Dynamic ARDL estimates

A. Long-run	Coefficient	SE	t-Statistic	Prob.
LNAPI	−0.197257***	0.006969	−28.30436	0.0000
LNPEC	0.592067***	0.012489	47.40816	0.0000
LNPT	1.507530***	0.033317	45.24812	0.0000
LNGFCF	−0.044868***	0.006014	−7.461069	0.0000
LNGPK	−2.015082***	0.067552	−29.83016	0.0000
LNGPK²	0.174444***	0.003749	46.53588	0.0000
EC=LNC0$_2$ – (–0.1973*LNAPI+0.5921*LNPEC+1.5075*LNPT –0.0449 * LNGFCF –2.0151*LNGPK+0.1744 * LNGPK^2				
B. Short−run	**Coefficient**	**SE**	**t-Statistic**	**Prob.**
C	−12.35681***	2.978093	−4.149236	0.0002
$\Delta LNCO_{2t-1}$	0.310130	0.184713	1.678989	0.1026
$\Delta LNCO_{2t-2}$	0.600359***	0.151573	3.960848	0.0004
$\Delta LNCO_{2t-3}$	0.370857**	0.139308	2.662137	0.0119
$\Delta LNAPI$	−0.123828	0.094599	−1.308980	0.1996
$\Delta LNPEC$	0.659721***	0.145809	4.524552	0.0001
$\Delta LNPT$	−7.972564**	2.939936	−2.711815	0.0105
$\Delta LNGFCF$	−0.070395	0.060434	−1.164827	0.2524
$\Delta LNGPK$	−1.298545	1.943906	−0.668008	0.5088
$\Delta LNGPK^2$	0.117483	0.158078	0.743196	0.4626
ε_{t-1}	−0.804916***	0.193858	−4.152092	0.0002
C. Diagnostic test	**Statistic (probability)**			
B-G LM Test	0.471975 (0.6282)			
ARCH	0.745888 (0.3922)			
J-B	8.5102 (0.2709)			
Q-statistic [10]	8.5102 (0.579)			
Q-squared [10]	10.977 (0.947)			

***Indicate significance at 1%; **Significance at 5% and *Significance at 10%

determining trend (F_{III}). The result presented in Table 4 **(**Panel A**)** confirms a long-run stable equilibrium relationship for the specified ARDL correction model.

3.1. Estimates of the Long-run

In the long run, a 1% increase in aggregate production index ($LnAPI_t$=–0.197257; P < 0.01) causes anthropogenic climate change to decline by about 0.197257%. This implies that India has the long-term capacity to reduce the extreme impact of climate change in their country through significant efficiency and expansion of total production value add. The long-run effect of Indian primary energy consumption is estimated to be inelastic and positive ($LnPEC_t$=0.592067; P < 0.01). The result shows that an increase in India's energy consumption by 1% causes anthropogenic climate change to increase by nearly 0.591967%. Awodumi and Adewuyi (2020) also evidenced similar finding in their study.

The estimates of India's total population are empirically estimated to be positive and elastic ($LnPT_t$=1.507530; P < 0.01) over the long-run horizon. Thus, we argue that non-emitted capita levels expand due to dynamic changes in the total population. Thus, as the population number expands rapidly, this bears effect on climate change. Scovronick et al. (2017) empirical evidence support this findings, demonstrating how a growing population in the face of climate change increases economic burden.

GFCF is estimated to be highly significant and inelastic ($LnGFCF_t$=–0.044868; P < 0.01) meaning that an increase in domestic investment reduces the anthropogenic climate change effect by 0.044868% over the long run. Thus, according to 'UNFCCC: Investment and financial flows to address to address climate change', policies that encourage domestic private sector investment to acquire modern production assets typically reduces climate change effects.

Our finding also shows that changes in real income ($LnGPK_t$ = –2.015082; P < 0.01) have a profound diminishing effect on the anthropogenic climate in India. Thus, a 1% increase in real per capita GDP exerts a statistically significant negative impact on anthropogenic change climate. Berg et al. (2021), reported mixed finding in their research for the crossed section of countries examined.

To investigate the *EKC* hypothesis for India within the specified model, the signs of both $LnGPK_t$ and the squared real per capita GDP ($LnGPK_t^2$) is examined. ($LnGPK_t$ = –2.015082; P < 0.01) has a negative sign and ($LnGPK_t^2$) has a significantly positive sign ($LnGPK_t^2$ = 0.174444; P < 0.01). Consequently, the evidence reveals that the estimated coefficient $\beta_6 < 0$ and $\beta_7 > 0$ yields a typical U-curve relationship for India. Hence, the necessary condition for the inversion of the U-curve is empirically refuted in the long run. Thus, the evidence reveal that the EKC is not validated for India. However, the study of Sinha and Shahbaz (2018) found EKC in India amidst CO_2 emission-renewable energy nexus.

3.2. Short-run Estimates

Table 4 (Panel B) reports the short-run finding. The dynamic short-run adjusting equilibrium term (ε_{t-1}) is found to be negative and statistically significant (ε_{t-1} = –0.804916; P < 0.01). Thus, given the endogenous and exogenous variable estimated, the specified model adjusts consistently at a rate of 80.5 percent annually toward stable long-run equilibrium for India. The short-run model indicates that past lags of anthropogenic climate change ($\Delta lnCO_{2t-2}$ = 0.600359 P < 0.01 and $\Delta lnCO_{2t-3}$= 0.370857 P < 0.05) have increasingly statistically significant positive impact on the observed current levels of anthropogenic climate effects. Furthermore, the estimate of primary energy consumption is found to be positive and statistically significant ($\Delta lnPEC_t$ = 0.659721; P < 0.01). Also, the population variable short-run elasticity estimates is negative and

Figure 1: CUSUM plot

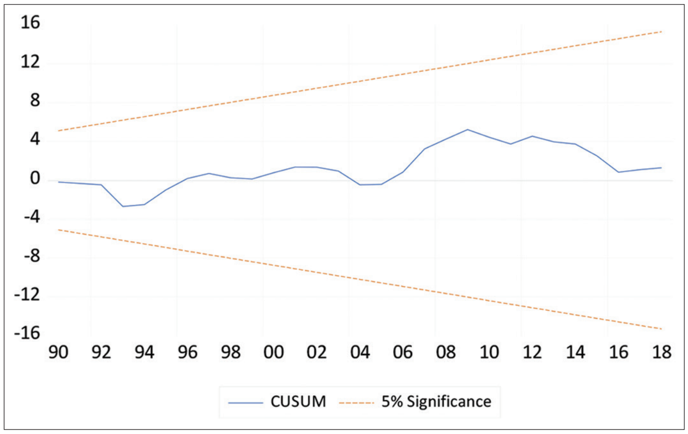
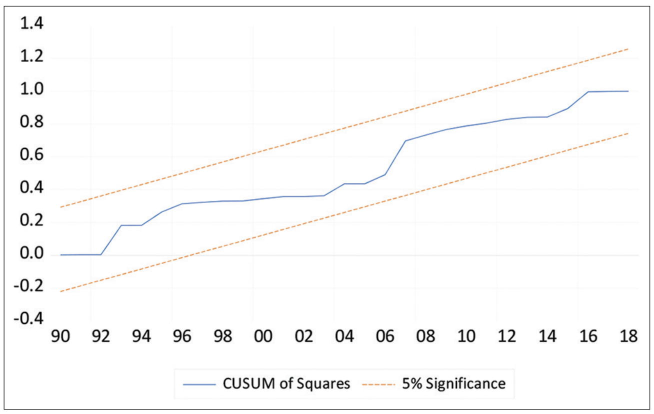


Figure 2: Plot of CUSUM square



highly elastics. This estimate is statistically significant ($\Delta \ln PT_t = -7.972564$; $P < 0.05$). Hence, population growth and climate change move in opposite directions in short run. Moreover, the estimates of $\Delta \ln API_t$ and $\Delta \ln GFCF_t$ are found to statistically insignificant in the short run.

Lastly, neither the real per capita income nor the squared real per capita income estimates ($\Delta \ln GPK_t = -1.298545$; $\Delta \ln GPK_t^2 = 0.117483$) are statistically significant in the short run. However, the result shows that the short-run environmental Kuznets hypothesis yield a typical U shape for India within our estimated model.

3.3. Diagnostic Test

The ARDL model diagnostics is presented in Table 4 (Panel C). Overall, the test shows that the model is well specified-thus no problem of misspecification. Hence, the error distribution satisfies the Gaussian assumption with no higher-order serial correlation and heteroskedasticity detected.

As proposed by Brown et al. (1975), we perform cumulative (CUSUM) and cumulative sum squared (CUMSUMSQ) test to verify the model stability. The plot of the CUMSUM in Figure 1 and CUMSUMSQ, Figure 2, is presented at a significant level of 5%. Since the all plots are within the bounds of the test critical value, the stability of the estimated model is confirmed.

Table 5: Modified pairwise granger causality tests

Causality	F-statistic	Prob.	Decision
LnAPI≠LnCO$_2$	0.53704	0.6594	Reject
LnCO$_2$≠LnAPI	1.56582	0.2111	Rejec
LnPEC≠LnCO$_2$	0.37712	0.7699	Reject
LnCO$_2$→LnPEC	2.78762	0.0517	Do not reject
LnPT≠LnCO$_2$	1.37421	0.2631	Reject
LnCO$_2$≠LnPT	1.18886	0.3250	Reject
LnGFCF≠LnCO$_2$	0.14137	0.9346	Reject
LnCO$_2$→LnGFCF	2.25175	0.0956	Do not reject
LnGFCF≠LnCO$_2$	0.29165	0.8312	Reject
LnCO$_2$≠LnGPK	1.28706	0.2907	Reject
LnGPK^2≠LnCO$_2$	0.27835	0.8407	Reject
LnCO$_2$≠LnGPK^2	1.09795	0.3601	Reject
LnPEC≠LnAPI	0.64020	0.5932	Reject
LnIPV≠LnPEC	0.20139	0.8949	Reject
LnPT≠LnAPI	2.02984	0.1235	Reject
LnAPI→LnPT	4.66282	0.0065	Do not reject
LnGFCF≠LnAPI	0.8626	0.4677	Reject
LnAPI→LnGFCF	3.85636	0.0156	Do not reject
LnGPK≠LnIPV	0.42656	0.7349	Reject
LnAPI≠LnGPK	1.41513	0.2511	Reject
LnGPK^2≠LnAPI	0.46744	0.7065	Reject
LnAPI≠LnGPK^2	1.40235	0.2548	Reject
LnPT→LnPEC	3.87746	0.0152	Do not reject
LnPEC≠LnPT	0.17891	0.9101	Reject
LnGFCF≠LnPEC	0.65410	0.5847	Reject
LnPEC≠LnGFCF	1.56255	0.2119	Reject
LnGPK≠LnPEC	0.49213	0.6896	Reject
LnPEC≠LnGPK	1.50260	0.2271	Reject
LnGPK^2≠LnPEC	0.49355	0.6886	Reject
LnPEC≠LnGPK^2	1.32991	0.2768	Reject
LnGFCF↔LnPT	3.98019	0.0136	Do not reject
LnPT↔LnGFCF	2.49794	0.0720	Do not reject
LnGPK↔LnPT	5.32683	0.0032	Do not reject
LnPT↔LnGPK	2.40478	0.0801	Do not reject
LnGPK^2→LnPT	4.39639	0.0086	Do not reject
LnPT≠LnGPK^2	1.7861	0.1637	Reject
LnGPK≠LnGFCF	2.98127	0.0415	Do not reject
LnGFCF≠LnGPK	1.09527	0.3612	Reject
LnGPK^2→LnGFCF	3.44249	0.0246	Do not reject
LnGFCF≠LnGPK^2	1.03190	0.3878	Reject
LnGPK^2≠LnGPK	0.67867	0.5698	Reject
LnGPK≠LnGPK^2	0.70488	0.5542	Reject

3.4. Granger Causality Test

Table 5 report the results of the pairwise modified Granger causality. The result indicates that the estimated model contains two significant bi-directional relationships (*LnGFCF ↔ LnPT; LnGPK ↔ LnPT*). The first is a bidirectional causality between India's real domestic investment and total population, and the second is a causality between GDP per capita and total population.

The causality model also reveals eight statistically significant unidirectional relationships, the first of which is the relationship between anthropogenic climate change and primary energy consumption. Then, anthropogenic climate change moves in lockstep with real domestic investment and anthropogenic climate change causes real domestic investment.

Furthermore, the relationship between the aggregate production index and population is one-way, and the production index causes real domestic investment. There is also one-way causal relationship between India's population and primary energy consumption.

More so, the squared real GDP per capita and population move in the same direction. Furthermore, real GDP per capita squared has a one-way causal relationship with real domestic investment and real per capita GDP and real domestic investment are causally linked.

4. CONCLUSIONS

Despite being recognized as making a significant contribution to the Paris Agreement on climate change, there are concerns about India's commitment to the 2050 "net zero" target of emission reduction. The nation must reach the ideal balance of greenhouse gas production and subtractions from the atmosphere in order to meet the 2050 target. For any ambitious drive to achieve the "net zero" 2050 goal, India's operation of the world's largest coal mining operation represents a significant setback. This puts even more pressure on the ambitious target of reducing emission intensity from its level in 2005 to about 35% in 2030. With about 2.62 billion tonnes of CO_2 emissions in 2019 and a sizable primary energy consumption, India is without a doubt the third-largest worldwide emitter.

Therefore, we found empirical justification for conducting these studies given that India is reputed to be among the world's worst polluters, with its energy sector alone accounting for 51.7% of carbon fuel in 2016 and a significant 22.0% industrial combusting emission, as well as transport 10.7%, building 7.5%, and non-combustion emission 8.8%.

There is light at the end of the tunnel for India as it has reduced its GDP emission intensity by 21% since 2020 and strives to generate 40% of its electricity without the use of fossil fuels. According to empirical evidence, reducing energy intensity significantly aid reduction of emissions (Rüstemolu and Andrés, 2016).

In light of the many challenges ahead, the relationship between anthropogenic climate change, aggregate production value add, primary energy consumption, population, real domestic investment, and per capita income for India is critically analysed. The break date in anthropogenic climate change with both intercept and trend of 1990 corresponds to the period marking the released document of the international protocol on climate change assessment (IPCCC) This was followed by a call for a globalize climate change treaty by the IPCC leading to the 1992 UNFCCC.

Thus of note, we found that primary energy consumption in India significantly accelerates anthropogenic climate change. Hence, considering the uni-directional causality of anthropogenic climate change and primary energy consumption ($CO_2 \rightarrow PEC$), primary energy consumption is an important determinant of anthropogenic climate change. Therefore, emission reduction must be accompanied by a reduction in the production and consumption of carbon-based fuels. Furthermore, the one-way causality of the population to primary energy consumption ($P \rightarrow PEC$), meant that the growing population in India further cause the consumption of primary fuels to expand. As a result, a population policy should help to reduce primary energy consumption, which has a huge impact on anthropogenic climate change. These findings are supported by the impulse responses and decomposition of the forecasts error variances[1]. For instance, the changes in real GDP per capita help explain the enormity of carbon fuel consumption variations. Thus, 24.00314% of real GDP forecast errors at period 10 are explained by exogenous shock to primary energy consumption. Thus, primary energy consumption shock significantly explains large variation in the error variance of a population, real domestic investment, real GDP per capita, and squared GDP per capita. These implies that fossil-based fuels not only contributes to anthropogenic climate change in India, it also causes changes in real domestic investment and population growth.

The Indian government must therefore seriously pursue a policy aimed at population control as a result of the growing pressure its population is putting on primary energy production and consumption. Reducing population growth also means consuming less fossil-based energy. Real income and population growth are two important emission propellers, so following income adjustment policy requires caution and accurate evaluation. A national population control strategy will make sure that a rise in real income leads to lessened anthropogenic climate change effects. Furthermore, policies that support modern technological advancement and efficient production must be supported in order to increase total production value additions sustainably. Lastly, because the power sector uses so much energy, switching to cleaner renewable energy sources becomes more and more important.

REFERENCES

Abokyi, E., Appiah-Konadu, P., Abokyi, F., Oteng-Abayie, E.F. (2019), Industrial growth and emissions of CO_2 in Ghana: The role of financial development and fossil fuel consumption. Energy Reports, 5, 1339-1353.

Ali, W., Abdullah, A., Azam, M. (2016), The dynamic linkage between technological innovation and carbon dioxide emissions in Malaysia: An autoregressive distributed lagged bound approach. International Journal of Energy Economics and Policy, 6(3), 389-400.

Awodumi, O., Adewuyi, A. (2020), The role of non-renewable energy consumption in economic growth and carbon emission: Evidence from oil producing economies in Africa. Energy Strategy Reviews, 27, 100434.

Begum, R.A., Sohag, K., Abdullah, S.M.S., Jaafar, M. (2015), CO_2 emissions, energy consumption, economic and population growth in Malaysia. Renewable and Sustainable Energy Reviews, 41, 594-601.

Brown, R. L., Durbin, J. and Evans, J. M. (1975), Techniques for testing the constancy of regression relations over time, Journal of Royal Statistical Society B, 37, 149–72.

Climate Action Tracker. (2021), Climate Action Tracker. Available from: https://www.climateactiontracker.org [Last accessed on 2021 Dec 20].

Coal India. (2020), Kolkata: Coal India Limited. Available from: https://www.coalindia.in/#carouselexampleindicators [Last accessed on 2021 Dec 25].

Dell, M., Jones, B.F., Olken, B.A. (2014), What do we learn from the weather? The new climate-economy literature. Journal of Economic Literature, 52(3), 740-798.

Dolado, J.J., Lütkepohl, H. (1996), Making wald tests work for cointegrated VAR systems. Econometric Reviews, 15(4), 369-386.

Engle, R.F., Granger, C.W. (1987), Co-integration and error correction:

1 For brevity, the results are not presented here but are available upon request.

Representation, estimation, and testing. Econometrica, 55(2), 251-276.

Friedlingstein, P., Jones, M.W., O'Sullivan, M., Andrew, R.M., Hauck, J., Peters, G.P., Peters, W., Pongratz, J., Sitch, S., Le Quéré, C., Bakker, D.C.E., Canadell, J.G., Ciais, P., Jackson, R.P., Anthoni1, ., Barbero, L., Bastos, A., Bastrikov, V., Becker, M., Bopp, L., Buitenhuis, E., Chandra, N., Chevallier, E.F., Chini, L.P., Currie, K.I., Feely, R.A., Gehlen, M., Gilfillan, D., Gkritzalis, T., Goll, D.S., Gruber, N., Gutekunst, S., Harris, I., Haverd, V., Houghton, R.A., Hurtt, G., Ilyina, T., Jain, A.K., Joetzjer, E., Kaplan, J.O., Kato, E., Goldewijk, K., Korsbakken, J.I., Landschützer, P., Lauvset, S.K., Lefèvre, N., Lenton, A., Lienert, S., Lombardozzi, D., Marland, G., McGuire, P.C., Melton, J.R., Metzl, N., Munro, D.R., Nabel, J.E.M., Nakaoka, S.I., Neill, C., Omar, A.M., Ono, T., Peregon, A., Pierrot, D., Poulter, B., Rehder, G., Resplandy, L., Robertson, E.R., Rödenbeck, C., Séférian, R., Schwinger, J., Smith, N., Tans, P.P., Tian, T., Tilbrook, B., Tubiello, F.N., Van der Werf, G.R., Wiltshire, A.J., Zaehle, S. (2019), Global carbon budget. Earth System Science Data, 11(4), 1783-1838.

Greene, W.H. (2008), Econometric Analysis. Harlow: Pearson Prentice Hall.

Grossman, G.M., Krueger, A.B. (1991), Environmental Impacts of a North American free Trade Agreement. NBER Working Papers. Massachusetts: National Bureau of Economic Research, Inc.

High-level Panel on Threats, Challenges and Change. (2004), A More Secure World: Our Shared Responsibility: Report of the Secretary-general's High-level Panel on Threats, Challenges and Change (PDF). New York: United Nations.

India Energy Outlook. (2020), India Energy Outlook. Available from: https://www.iea.org/reports/india-2020 [Last accessed on 2020 Dec 18].

Katircioglu, S.T. (2014), International tourism, energy consumption, and environmental pollution: The case of Turkey. Renewable and Sustainable Energy Reviews, 36, 180-187.

Kraft, J., Kraft, A. (1978), On the relationship between energy and GNP. The Journal of Energy and Development, 3(2), 401-403.

Kuznet, S. (1955), Towards theory of economic growth. In: Lakachman, R., editor. National Policy for Economic Welfare at Home and Abroad. Garden City, NY: Doubleday.

Lenaerts, K., Tagliapietra, S., Wolff, G.B. (2021), Can Climate Change be Tackled without Ditching Economic Growth? Working Paper 10/2021, Belgium: Bruegel Think Tank.

MoEFCC. (2018), Second Biennial Update Report to the United Nations Framework Convention on Climate Change. India: Ministry of Environment, Forest and Climate Change, Government of India.

Narayan, P.K., (2005), The Saving and Investment Nexus for China: Evidence from Cointegration Tests. Applied Economics, 37, 1979-1990.

Ozturk, I., (2015), Sustainability in the food-energy-water nexus: Evidence from BRICS (Brazil, the Russian Federation, India, China, and South Africa) countries. Energy, Netherland: Elsevier, 93, 999–1010.

Perron, P. (1989), The great crash, the oil price shock, and the unit root hypothesis. Econometrica, 57(6), 1361-1401.

Pesaran, H.H., Shin, Y. (1998), Generalized impulse response analysis in linear multivariate models. Economic Letters, 58(1), 17-29.

Rüstemoğlu, H. (2021), Analysis of the drivers of CO_2 emissions and ecological footprint growth in Australia. Energy Efficiency, 15(1), 1.

Rüstemoğlu, H., Andrés, A.R. (2016), Determinants of CO_2 emissions in Brazil and Russia between 1992 and 2011: A decomposition analysis. Environmental Science and Policy, 58, 95-106.

Scovronick, N., Budolfson, M.B., Dennig, F., Fleurbaey, M., Siebert, A., Socolow, R.H., Spears, D., Wagner, F. (2017), Impact of population growth and population ethics on climate change mitigation policy. Proceedings of the National Academy of Sciences, 114(46), 12338-12343.

Shahbaz, M., Sinha, A. (2019), Environmental Kuznets curve for CO_2 emissions: A literature survey. Journal of Economic Studies, 46(1), 106-168.

Sinha, A., Shahbaz, M., (2018), Estimation of environmental Kuznets curve for CO_2 emission: Role of renewable energy generation in India. Renewable Energy, 119, 703-711.

Stern, D. I., (2004), The rise and fall of the environmental Kuznets curve. World development, 32, 1419-1439.

Toda, H.Y., Yamamoto, T. (1995), Statistical inference in vector autoregressions with possibly integrated processes. Journal of Econometrics, 66(1-2), 225-250.

United Nations Framework Convention on Climate Change UNFCCC. Investment and Financial Flows to Address Climate Change. New York: United Nations Framework Convention on Climate Change. Available from: https://www.unfccc.int/resource/docs/publications/financial_flows.pdf

United state Energy Information Agency. (2020), Analysis-Energy Sector Highlights. United States: United State Energy Information Agency. Available from: https://www.eia.gov/international/overview/country/IND [Last accessed on 2021 Nov 25].

Wada, I. (2017), Dynamic causality in energy production and output growth in Nigeria revisited: ARDL bounds test approach. Energy Sources Part B Economics Planning and Policy, 12(11), 945-951.

Wada, I., Faizulayev, A., Khademolomoom, A. H., and Alzubi, A., (2020), Energy use, real output-growth, fdi, energy-intensity and co2 emission; the case of Kazakhstan. Journal of Public Affairs, 22(1)

Wada, I., Faizulayev, A., Bekun, F.V. (2021), Exploring the Role of Conventional Energy Consumption on Environmental Quality in Brazil: Evidence from Cointegration and Conditional Causality. Gondwana Research, 98, 244-256.

World Bank Development Indicators. (2021), Data and Research. World Bank Development Indicators. Available from: https://www.databank.worldbank.org/source/world-development-indicators [Last accessed on 2021 Dec 30].

Yao, S., Zhang, S., Zhang, X. (2019), Renewable energy, carbon emission and economic growth: A revised environmental Kuznets curve perspective. Journal of Cleaner Production, 235, 1338-1352.

Zivot, E., Andrews, D.W.K. (2002), Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. Journal of Business Economics and Statistics, 20(1), 25-44.