*sustainability*

MDPI

*Article*

# Can Energy Efficiency Help in Achieving Carbon-Neutrality Pledges? A Developing Country Perspective Using Dynamic ARDL Simulations

**Md. Emran Hossain [1], Soumen Rej [2], Sourav Mohan Saha [3], Joshua Chukwuma Onwe [4], Nnamdi Nwulu [5], Festus Victor Bekun [6,7,*] and Amjad Taha [8]**

1 Department of Agricultural Finance and Banking, Bangladesh Agricultural University, Mymensingh 2202, Bangladesh; emran49011@bau.edu.bd
2 Vinod Gupta School of Management, Indian Institute of Technology Kharagpur, Kharagpur 721302, West Bengal, India; soumen.rej@iitkgp.ac.in
3 Department of Agricultural Finance, Co-Operatives and Banking, Khulna Agricultural University, Khulna 9100, Bangladesh; sourav@kau.edu.bd
4 Department of Economics and Development Studies, Alex Ekwueme Federal University Ndufu-Alike, Abakaliki P.M.B. 1010, Ebonyi State, Nigeria; joshua.onwe.pg0270@unn.edu.ng
5 Department of Electrical and Electronic Engineering Science, University of Johannesburg, Johannesburg 2006, South Africa; nnwulu@uj.ac.za
6 Faculty of Economics Administrative and Social Sciences, Istanbul Gelisim University, Istanbul 34310, Turkey
7 Adnan Kassar School of Business, Lebanese American University, Beirut 1102-2801, Lebanon
8 Banking and Finance Department, Eastern Mediterranean University, North Cyprus, Via Mersin 10, Famagusta 99628, Turkey; amjad.taha@emu.edu.tr
* Correspondence: fbekun@gelisim.edu.tr

check for updates

**Citation:** Hossain, M.E.; Rej, S.; Saha, S.M.; Onwe, J.C.; Nwulu, N.; Bekun, F.V.; Taha, A. Can Energy Efficiency Help in Achieving Carbon-Neutrality Pledges? A Developing Country Perspective Using Dynamic ARDL Simulations. *Sustainability* **2022**, *14*, 7537. https://doi.org/10.3390/su14137537

Academic Editor: Nicu Bizon

Received: 21 May 2022
Accepted: 15 June 2022
Published: 21 June 2022



**Abstract:** The current research sheds light on the nexus between environmental degradation as proxied by carbon dioxide emissions ($CO_2$), energy efficiency (EE), economic growth, manufacturing value-added (MVA), and the interaction effect of EE and MVA in India. Using yearly data from 1980 to 2019, the current study employs dynamic auto-regressive distribution lag (DARDL) simulations and Fourier Toda and Yamamoto causality techniques. The findings of DARDL reveal that as income and MVA rise, environmental quality decreases, while EE improves environmental conditions in both the long and short run. Surprisingly, the interaction term of EE and MVA has a detrimental influence on environmental quality, meaning that India remains unable to provide energy savings technologies to the manufacturing industry. Furthermore, the environmental Kuznets curve (EKC) hypothesis is well-founded for India, as the long-run income coefficient is smaller than the short-run coefficient, implying that India is in its scale stage of economy, where economic growth is prioritized over environmental quality. The results of the causality technique reveal that $CO_2$ emissions and EE have a bidirectional association. Therefore, policymakers in India should embrace realistic industrialization strategies combined with moderate decarbonization and energy efficiency initiatives under the umbrella of sustainable industrial and economic growth.

**Keywords:** energy efficiency; dynamic ARDL; industrialization; INDCs; Make in India; carbon neutrality

## 1. Introduction

Arising from the recently held United Nations climate change conference COP26, various countries around the world have made various pledges and national commitments to attaining the desired goal of reducing global warming and achieving a clean environment, which is part of the UN's Sustainable Development Goals (SDGs). The recent report by the United Nations [1] on SDGs shows the inability and deficiency of emerging economies in tackling the numerous problems faced with increasing global warming and carbon emission levels. At the moment, developed economies are resorting to possible ways to reduce the effects of greenhouse gas (GHGs) emissions in order to attain a sustainable environmental situation via the drive for clean energy. With COP26 fully ended, countries around the globe have intensified their quest to attain the goals of the conference in the area of energy efficiency. As one of the major players in the world, India has much to do in its quest to achieve the demands of COP26. India is the world's second most populated country and the third largest emitter of GHGs, with 132 tonnes of carbon emissions and equivalent in 2020, although represents a decrease for the first time in over four decades [2]. With a GDP growth rate of 6.7%, India is one of the world's economic powerhouses [3]. Despite a COVID-19-related economic downturn in 2020 and 2021, India is predicted to completely recover by 2025 [4].

However, recently the International Energy Agency (IEA) projected that India leads the global energy stage regarding energy demand. Thus, India is projected to contribute more than any other country to increasing global energy demand between now and 2040 [5]. Such a report from the IEA [6] seemingly poses a threat to the quest of India to attain the prospects of freshwater availability and decreased greenhouse emissions while seriously addressing energy efficiency (EE) and transition [7]. However, following COP26, India remains on track to reduce emissions by 33 to 35% before 2030 [6]. India remains a major hub for industrialization, and the carbon neutrality of various industries is crucial for India as a country in order to continue to chart a course for a low carbon future and EE of its industries, as predicted by the IEA. India is committed to meeting its Intended Nationally Determined Contributions (INDCs) [8] by implementing a successful energy transition from fossil fuels to renewable energy, particularly in the manufacturing and transportation sector. Of course, India's power demand is predicted to rise from 1700 TWh in 2021 to more than 2200 TWh by 2030, and 5000 TWh by 2050 [9], necessitating a major commitment to an EE initiative. Furthermore, India has set a goal of "Make in India" as a key national initiative of the Indian government aimed at facilitating investment, fostering innovation, enhancing skill development, protecting intellectual property, and constructing best-in-class manufacturing infrastructure, all of which demand huge energy supply. Thus, the current research tries to investigate whether India is on track to meet both its INDCs and "Make in India" goals; however, there are significant uncertainties in the areas of closing the global greenhouse gas gap of 1.5 degrees Celsius while achieving carbon neutrality by 2030 [10,11].

Again, India has a pledged to install 40% of total electricity capacity from renewable energy sources before 2030, a projection of 240–300 GW of wind and solar energy installations. Finally, India's targets for forestry intend to create carbon sinks for over three billion tonnes of carbon dioxide before 2030. Compared with the targets set by China and the US, these intentions are ambitious, considering that both China and the US have a more robust economy and a larger share of GDP. In this context, the current study examines the progress of the implementation of the INDC and "Make in India" targets while taking into account carbon neutrality and EE. India's realizations and intentions are a step toward achieving SDG 7, which is to achieve clean and cheap energy [7]. With India's degree of technical growth, it is capable of addressing EE and resolving energy security and pollution challenges. The studies of Murshed at al. [12] and Langlois and Yank [13] have noted that EE can serve as a policy target instrument for developing and developed countries aiming towards carbon neutrality. Previous studies [7,14–18] expects that energy efficiency should lead to dwindling carbon emissions; it is, however, perceived that the degree of impact varies across different levels of development, such that clean energy generation in developed countries shows a convergence sign while developing countries are not able to attain convergence due to absence of structural transformation [19]. Considering this scenario, India stands a chance of achieving self-energy efficiency in terms of its energy needs.

The goal of this article is to look into the impact of EE and manufacturing value added (MVA) in India in the context of the commitment of COP26 to achieve carbon neutrality. This study, among others, intends to explore the INDC pledge and "Make in India" goals using time series data from 1980 to 2019. The current study attempts to add to the existing literature in the following ways. To the best of our knowledge, this is the first study to examine the nexus of EE and MVA on environmental quality in India while taking into account their interacting impacts. Second, the current research aims to re-evaluate the presence of the environmental Kuznets curve (EKC) hypothesis in India throughout the most recent era, that is, 1980 to 2019. Finally, we use the novel dynamic autoregressive distributed lag (DARDL) stimulations technique, which is thought to be more efficient, impartial, and consistent with a small sample group. Fourth, we look at India's two primary goals at the same time, one from an economic standpoint (Make in India) and the other from an environmental standpoint (INDCs). Finally, findings from our study are likely to add to the current literature and expand the frontiers of knowledge among policymakers, both in India and other nations, in the areas of energy efficiency, industrialization, carbon neutrality, economic growth, and environmental quality.

The remainder of the research is organized as follows. The second section provides an overview of the pertinent literature. The theoretical foundations and formulation of the model used in this work are highlighted in Section 3. Section 4 explains the estimating methodologies and data types utilized in the study, whereas Section 5 emphasizes and discusses the resulting empirical findings. Finally, Section 6 concludes the study and discusses its policy implications.

## 2. Review of Related Literature

The goal of literature reviews is to concentrate on previous research addressing the explanatory variables used in the study. Although many studies have looked into the link between the economy and the environment, there appears to be a paucity of specific research on the relationship between EE, MVA, and GHG emissions. We look at three major relationships between the specified variables and $CO_2$ emissions.

### *2.1. Economic Growth and the Environment*

The nexus between economic progress and $CO_2$ emissions has been the central point of discussion in the extant energy literature. Previous research has revealed an inverted U-shaped link between $CO_2$ emissions and economic growth when the quadratic term of income is taken into account. Chen et al. [20] used the data from 2001 to 2015 of 30 OECD countries and found that income is the main reason for escalating $CO_2$ emissions. Balsalobre-Lorente et al. [21] verified the inverted U-shaped connection between $CO_2$ emissions and economic growth for BRICS economies using fully modified ordinary least squares (FMOLS) and dynamic ordinary least square (DOLS). Zhang et al. [22] confirmed that economic growth has a positive impact on environmental degradation in Malaysia by applying wavelet coherence.

However, a few studies have questioned the link between economic development and $CO_2$ emissions Using the Fourier ARDL procedure, Yilanci and Pata [23] found that the EKC hypothesis is invalid for China. In a similar vein, the inverted U-shaped nexus of economic progress and environment was not found to hold for 24 OECD countries [24] and BRICS countries [25]. Other studies that failed to detect the presence of EKC include Lopez-Menendez et al. [26] for 27 economies, Ozcan [27] for 12 Middle East nations, Mrabet and Alsamara [28] for Qatar, Sarkodie and Strezov [29] for USA and Ghana, and more.

### *2.2. Manufacturing Value Added and Environmental Quality*

Several empirical studies have explored the causal linkage between MVA and $CO_2$ emissions. Abbasi et al. [30] found that MVA significantly boosts $CO_2$ emissions in the short term and increases environmental sustainability in the long run. Liu and Bae [31] scrutinized the effect of industrialization on $CO_2$ emissions in China using ARDL and VECM. The study found that MVA increases $CO_2$ emissions and long-run feedback Granger causalities exist. Liu and Hao [32] verified the positive relationship between MVA and $CO_2$ emissions in 69 countries, employing vector error correction model (VECM), FMOLS, and DOLS approaches. Prastiyo and Hardyastuti [33] examined data from 1970 to 2015 in Indonesia and reported a bidirectional causality relationship between $CO_2$ emissions and

MVA. Raza and Hasan [34] estimated the positive impact of Bangladesh's manufacturing sector on $CO_2$ emissions in the period 1980 to 2018. Several studies have reported mixed findings when investigating the relationship between MVA and $CO_2$ emissions. Exploring data for a panel of 56 developing economies adapting EKC and STIRPAT approaches, Avenyo and Tregenna [35] indicated that emissions are higher in medium- and high-technology production than in low-technology manufacturing. Khan [36], using Beta Decoupling Techniques, found that China's primary industries reduced $CO_2$ emissions while a positive relationship persisted for secondary and tertiary industries.

### 2.3. Energy Efficiency and Environmental Quality

Energy efficiency (EE) is regarded as an indispensable solution to control GHG emissions and facilitate countries' efforts to attain SDG 7 and SDG 13 [1]. The role of EE in a better environment has been investigated in a few studies. Improvements in EE have the greatest impact on $CO_2$ emissions reduction in developing countries, according to Mirza et al. [7], while structural adjustments tend to increase $CO_2$ emissions, as developing countries are moving toward industries that create more pollution. Employing asymmetric cointegration analysis and a non-linear autoregressive distributed lag (NARDL) model, Akram et al. [37] reported that positive shocks to EE contribute to long-term $CO_2$ emissions reduction in the MINT nations. Özbuğday and Erbas [38] modeled the long-run effects of EE on $CO_2$ emissions using the CCE estimator for 36 countries, and showed that EE significantly reduces $CO_2$ emissions over time. Akram et al. [39] analyzed the effects of EE on environmental degradation and verified the EKC hypothesis by employing data from 66 developing nations from 1990 to 2014. They found that while EE reduces $CO_2$ emissions at all quantiles, the 90th quantile has the greatest mitigation effect. A study on 30 OECD economies by Tajudeen et al. [40] using both the STSM and LSDVC models showed that improvements in EE were mostly responsible for decreased energy intensity at the group level, whereas at the country level increases in EE played a mixed role. However, several other multi-country and single-country studies have demonstrated a similar impact of EE improvements on $CO_2$ emissions, i.e., in EU countries [41], Nordic countries [42], China [43], Nigeria [44], Sweden [45], and Romania [46].

Through this brief review of the literature, it can be seen that several researchers have identified the nexus between environmental quality and its various determinants using a variety of techniques. However, there is insufficient research explaining the effects of EE and MVA on $CO_2$ emissions. In addition, none of the previous studies have looked into the interaction effect of energy efficiency and MVA in the context of India. Therefore, our study seeks to bridge this gap by employing a novel dynamic ARDL simulation approach to explain the influence of economic growth, MVA, and EE on $CO_2$ emissions in India. Moreover, in the current study we insert the interaction of EE and MVA into the empirical model, which to the best of our knowledge represents the first such approach in any study. The results of this study will allow for determination of the best mix of manufacturing share and EE for long-term environmental quality.

## 3. Theoretical Foundation and Model Specification

This study follows the theoretical framework of the EKC hypothesis first developed in the paper by Kuznets [47]. Environmental economists such as Grossman and Krueger [48] and Panayotou [49] improved on this concept by studying the association between the economy and environmental quality. According to this hypothesis, economic development, as measured by Gross Domestic Product (GDP) per capita, is associated with an increase in environmental deterioration, as measured by the level of certain types of air pollution (emissions), until a point at which the association becomes negative [50]. The particular threshold is thought to describe the level of economic affluence or prosperity that allows economies to subsequently minimize pollution. According to this theoretical paradigm, economic growth can be boosted by energy-intensive economic sectors and activities, which are frequently polluting and destructive to the environment. Economic growth, according to the EKC hypothesis, has three stages, which affect an economy's environmental quality: the scale effect, the structural effect, and composite effects. The initial step consists of the scale effect. The environment initially deteriorates in the first phase, then, after reaching a critical threshold, technological innovation and increasing environmental consciousness begin to enhance environmental quality [51].

Earlier studies have used $CO_2$ emissions data as an indication of environmental harm, designating the dependent variable for the empirical model, despite the fact that it was not bound by any known assumptions. Here, we calculate the impact of per capita income on environmental deterioration as assessed by $CO_2$ emissions as well. We do not employ the square of income per capita in our empirical model due to the possibility of multicollinearity [52]. Although the EKC hypothesis remains valid when short-run income elasticity is larger than long-run elasticity [53]; however, as allowing one regressor may produce a spurious and biased result, other regressors, namely, MVA, EE, and their interaction effects, were included in the model. India's manufacturing sector is a crucial portion of its economy, and occupies 13.10% of the total national GDP [54]. As a result, recent significant growth in the industrial sector may have an impact on the country's environmental quality. The lower energy usage per unit of economic activity is captured by the efficiency component. Therefore, it is crucial to include EE in the model. Moreover, the interaction of MVA and EE is included in the empirical model in order to identify the best mix to promote India's long-term environmental quality. The resulting empirical model can be described as follows:

$$\mathrm{lnnCO_2} = \alpha_0 + \alpha_1\mathrm{lnGDP} + \alpha_2\mathrm{lnMVA} + \alpha_3\mathrm{lnEE} + \alpha_4\mathrm{lnEE} \times \mathrm{lnMVA} + \varepsilon_t \quad (1)$$

where $CO_2$ is carbon dioxide emissions, GDP is GDP per capita, MVA is manufacturing value added, EE is energy efficiency and EE $\times$ MVA is the interaction effect of energy efficiency and MVA.

## 4. Data Definition and Econometric Strategy

### *4.1. Data Description*

The yearly data for India from 1980 to 2019 were used to determine the linkage between EE, MVA, interaction impacts of EE and MVA, and environmental quality. The energy intensity levels of a country can serve as a proxy for the EE variable. The amount of energy used to generate one unit of economic output is defined as EE. As a result, a lower ratio indicates that less energy is used to produce one unit of output, implying higher EE. Following the previous literature, the share of primary electricity consumption (PEC) to GDP was used to assess EE [55]. PEC was used to calculate a country's overall energy demand; this includes energy consumption by industry, losses during energy transformation (for example, from oil or gas to electricity), energy distribution, and end-user consumption (referred as total energy consumption). As a result, it is more justifiable to utilize PEC rather than total energy consumption because total energy consumption only includes end-user usage, overlooking losses during distribution. We assessed the quality of the environment using $CO_2$ emissions quantified in metric tons per capita. GDP per capita in constant 2010 US dollars was used to reflect economic growth, while MVA was reported as a percentage of GDP. The GDP and MVA data used in this study were from the World Development Indicator (WDI) database, while $CO_2$ and PEC data were from the BP Statistical Review of World Energy. Table 1 presents the description and sources of the variables under investigation. In order to standardize the data and eliminate varying units of parameters, we transformed all variables into logarithmic form, as recommended by the literature [56]. Put another way, converting data to logarithms makes it easier to understand coefficients as elasticities [14].

**Table 1.** Variable Specifications.

| Variable | Definition | Source |
|---|---|---|
| $CO_2$ | Carbon dioxide emissions (metric tons per capita) | BP Statistical Review of World Energy |
| GDP | Economic growth (real GDP per capita constant 2010 US$) | World Bank |
| PEC | Primary electricity consumption (exajoules) | BP Statistical Review of World Energy |
| MVA | Manufacturing value-added (% of GDP) | World Bank |
| EE | Energy efficiency level of primary energy (constant 2010 US$/MJ) | Authors' calculation |

### 4.2. Econometric Methodology

Following our investigation of environmental degradation in India, we proceeded to explore the effects of GDP, MVA, EE, and MVA*EE on $CO_2$ emissions using time series data. Before conducting an analysis of time series data, we validated the data with a stationarity check. This study employed Augmented Dickey–Fuller (ADF) [57] and Phillips–Perron (PP) [58] for investigating the unit root properties of the data series.

Upon checking the unit root outcome, cointegration testing must be performed before applying the DARDL simulation method. In order to confirm the existence of a long association among the variables, we conducted *F* bound testing. The following bounds test equation was formed in order to investigate the cointegration among the studied variables:

$$\begin{aligned}\Delta(\mathrm{lnCO_2})_t = {} & \alpha_0 + \alpha_1\mathrm{lnCO}_{2t-1} + \alpha_2\mathrm{lnGDP}_{t-1} + \alpha_3\mathrm{lnMVA}_{t-1} + \alpha_4\mathrm{lnEE}_{t-1} \\ & +\alpha_5\mathrm{lnMVA}*\mathrm{EE}_{t-1} + \sum_{i=1}^{p}\beta_1\Delta\mathrm{lnCO}_{2t-i} + \sum_{i=1}^{p}\beta_2\Delta\mathrm{lnGDP}_{t-i} \\ & + \sum_{i=1}^{p}\beta_3\Delta\mathrm{lnMVA}_{t-i} + \sum_{i=1}^{p}\beta_4\Delta\mathrm{lnEE}_{t-i} + \sum_{i=1}^{p}\beta_5\Delta\mathrm{lnMVA}*\mathrm{EE}_{t-i} \\ & +u_t\end{aligned} \tag{2}$$

where $\Delta$ denotes the change operator, $t - i$ represents the optimal lags chosen using the Akaike information criterion (AIC), $u_t$ represents the error term, and p represents the lag length. Furthermore, $\alpha$ and $\beta$ represent long-run and short-run estimates, respectively.

The null hypothesis for the bounds test was $H_0$: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 0$, which implies that no variables cointegrate, whereas the existence of cointegration was specified by the alternative hypothesis, $H_1$: $\alpha_1 \neq \alpha_2 \neq \alpha_3 \neq \alpha_4 \neq 0$; thus, on the basis of the estimated value of the *F*-statistic, $H_0$ may be rejected or accepted. Furthermore, we compared the *F*-statistic value to the critical values at 1%, 5%, and 10% significance levels. If the *F*-statistic value surpasses the critical values, the long-run association can be ascertained [59].

The dynamic ARDL simulation technique devised by Jordan and Philips [60] was used to estimate the long-run and short-run coefficients. The simulated DARDL approach can generate graphs to predict counterfactual alterations in one explanatory variable and its impact on the response variable while holding the other regressors unchanged. The series should be integrated at I(1) and demonstrate mutual cointegration in order to perform the DARDL technique [60]. This study employed 5000 simulations. The equational form of the dynamic ARDL model, including the error correction factor, is written as:

$$\begin{aligned}\Delta(\mathrm{lnCO_2})_t = {} & \lambda_0 + \theta_0\mathrm{lnCO}_{2t-1} + \beta_1\Delta\mathrm{lnGDP}_t + \theta_1\mathrm{lnGDP}_{t-1} + \beta_2\Delta\mathrm{lnMVA}_t \\ & + \theta_2\mathrm{lnMVA}_{t-1} + \beta_3\Delta\mathrm{lnEE}_t + \theta_3\mathrm{lnEE}_{t-1} + \beta_4\Delta\mathrm{lnMVA}*\mathrm{EE}_t \\ & + \theta_4\mathrm{lnMVA}*\mathrm{EE}_{t-1} + \xi\mathrm{ECT}_{t-1}+u_t\end{aligned} \tag{3}$$

In this research, model stability was checked using several model diagnostic tests, such as cumulative sum (CUSUM) and square of CUSUM plots. The Breusch–Godfrey Lagrange Multiplier (LM) test was used to find serial correlations, whereas the Jarque–

Bera test was used to check for normality. We assessed heteroskedasticity using the Breusch–Pagan–Godfrey tests. The Ramsey reset test was employed to determine whether the model was presented correctly. In addition, we used traditional ARDL, FMOLS, and Canonical Cointegrating Regression (CCR) models to verify the robustness of our dynamic ARDL estimations.

The Toda and Yamamoto (TY) [61] causality method was employed in this investigation to search for causal links between the variables. A preliminary step in the TY causality test is to estimate the vector autoregressive (VAR) model while taking the variables' level values into account. The ideal lag length (ρ) is then added to the series' maximum integration order (dmax) in the projected model and the model is re-calculated. The Granger causality test was enhanced by using Fourier functions to account for structural changes in the data. Fourier functions were introduced to the TY causality test by Nazlioglu et al. [62], who claimed that prior knowledge of the number, date, and type of breaks was not necessary. Equation (5) was generated by combining the Fourier equation with the VAR model in Equation (4). According to Equation (5), the null hypothesis suggests that there is no causality [62]:

$$y_t = \alpha(t) + \vartheta_1 y_{t-1} + \ldots + \vartheta_{\rho+d} y_{t-(\rho+d)} + \varepsilon_t \tag{4}$$

$$y_t = \alpha_0 + \gamma_1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + \vartheta_1 y_{t-1} + \ldots + \vartheta_{\rho+d} y_{t-(\rho+d)} + \varepsilon_t \tag{5}$$

## 5. Results and Discussions

The descriptive statistics for variables in our studies are provided in Table 2. The mean value of lnEE is −2.67, which is the lowest number among the selected variables. It can be seen that lnGDP and lnMVA have mean values of 6.76 and 2.77, respectively, with standard deviations of 0.49 and 0.06, whereas $\ln CO_2$ has a mean value of −0.09 and standard deviation of 0.42. All variables are positively skewed, with the exception of MVA, which is negatively skewed, according to the skewness value. This means that the most $CO_2$, GDP, and EE values are clustered around the left tail of the distribution, whereas the right tail is longer. Table 2 shows the correlation matrix of the variables, and it is clear that there are no concerns with multicollinearity, which is a prime condition for moving further with the regression analysis.

**Table 2.** Descriptive statistics.

| | $\ln CO_2$ | lnGDP | lnMVA | lnEE |
|---|---|---|---|---|
| Mean | −0.09 | 6.76 | 2.77 | −2.67 |
| Median | −0.12 | 6.71 | 2.78 | −2.69 |
| Max. | 0.59 | 7.67 | 2.88 | −2.45 |
| Min. | −0.81 | 6.05 | 2.59 | −2.83 |
| Std. Dev. | 0.42 | 0.49 | 0.06 | 0.11 |
| Skewness | 0.03 | 0.31 | -0.79 | 0.52 |
| Kurtosis | 1.93 | 1.86 | 4.71 | 2.54 |
| Observations | 40 | 40 | 40 | 40 |
| | | **Correlation** | | |
| $\ln CO_2$ | 1.00 | | | |
| lnGDP | 0.89 | 1.00 | | |
| lnMVA | −0.49 | −0.51 | 1.00 | |
| lnEE | 0.76 | 0.84 | −0.51 | 1.00 |

Before delving deeper into the time series analysis, each data series should be tested for stationarity in order to avoid any erroneous outcomes. The results of the stationarity tests are shown in Table 3; we used the traditional ADF and PP tests for this investigation. Table 3 shows that all of the selected variables are non-stationary at the level of the usual ADF and PP tests, except for the interaction of EE and MVA. After I(1), however, the chosen variables become stationary at a 1% significance level. As a result, these findings indicate that there is no unit root problem; thus, the regression model can be run without fear of spurious regression.

**Table 3.** Unit root test.

| Variable | Form | ADF (*t*-Statistics) | | PP (*t*-Statistics) | | Order of Integration |
|---|---|---|---|---|---|---|
| | | Intercept | Trend + Intercept | Intercept | Trend + Intercept | |
| $lnCO_2$ | Level | −0.49 (0.881) | −2.79 (0.211) | −0.48 (0.885) | −1.94 (0.615) | I(1) |
| | First Difference | −2.64 * (0.094) | −3.96 * (0.083) | −6.15 *** (0.000) | −6.08 *** (0.000) | |
| lnGDP | Level | 3.07 (1.000) | −1.28 (0.878) | 7.18 (1.000) | −1.21 (0.895) | I(1) |
| | First Difference | −4.82 *** (0.000) | −6.04 *** (0.000) | −4.82 *** (0.000) | −11.59 *** (0.000) | |
| lnMVA | Level | −0.78 (0.815) | −1.44 (0.833) | −0.99 (0.744) | −1.68 (0.741) | I(1) |
| | First Difference | −4.81 *** (0.000) | −4.88 *** (0.002) | −4.73 *** (0.001) | −4.67 *** (0.003) | |
| lnEE | Level | 0.88 (0.994) | −1.51 (0.811) | 0.81 (0.993) | −1.51 (0.811) | I(1) |
| | First Difference | −6.42 *** (0.000) | −7.08 *** (0.000) | −6.41 *** (0.000) | −7.04 *** (0.000) | |
| lnEE*lnMVA | Level | 1.24 (0.998) | −0.71 (0.966) | 1.48 (0.999) | −0.58 (0.975) | I(0)/I(1) |
| | First Difference | −6.31 *** (0.000) | −7.03 *** (0.000) | −6.42 *** (0.000) | −6.99 *** (0.000) | |

Note: The probability value is shown in parentheses. ***, and * denote a 1%, and 10% level of significance.

To use DARDL regression, it is first necessary to determine whether there is cointegration among the chosen variables. To trace the existence of long-run co-integration, we conducted the ARDL bounds testing approach followed by Pesaran et al. [63]. Table 4 shows the results of the co-integration process. Even at the 1% level of significance, the *F*-statistics generated from the *F*-bounds test are embedded over the critical value of the lower bound I(0) and upper bound I(1). This finding clearly demonstrates that the variables examined in this study move together over the long run. As a consequence, this shows that $CO_2$ emissions and their causes, such as energy efficiency, economic growth, manufacturing value added, and the interaction impact of manufacturing value added and energy efficiency, are co-integrated over the long term.

**Table 4.** *F*-bound test for co-integration.

| Estimated Model | $lnCO_2 = f$ (lnGDP, lnMVA, lnEE, lnEE*lnMVA) | |
|---|---|---|
| Bound test *F*-statistics | 11.46 *** | |
| Critical value | Lower bound I(0) | Upper bound I(1) |
| 1% | 4.4 | 5.72 |
| 2.5% | 3.89 | 5.07 |
| 5% | 3.47 | 4.57 |
| 10% | 3.03 | 4.06 |

Note: *** denotes a 1% level of significance.

The baseline regression of the DARDL simulations approach, shown in Table 5, demonstrates the short-run and long-run linkage between India's economic development, MVA, EE, and the interaction effect of MVA and EE on $CO_2$ emissions. As the results show, GDP per capita stimulates carbon dioxide emission in the both short and long term. With all else constant, $CO_2$ emissions jump 0.637% in regard to a 1% rise in per capita in the long term, whereas $CO_2$ emissions climbed by 0.829% in the short term. However, the elasticity of both lnGDP and ΔlnGDP indicate that India's $CO_2$ emissions are increasing steadily over time. According to estimations, GDP's long-run elasticity is lower than its short-run elasticity, meaning that economic expansion destroys environmental quality more quickly in the short term. This validates the EKC notion in light of Narayan and Narayan [53]. Prior research, such as Rej et al. [64] for India, Awan et al. [65] for ten developing countries, and Agboola et al. [66] for Turkey, has shown similar results, while Rej et al. [67] and Islam et al. [51] have shown contrasting outcomes. The technique utilized, the dependent variable analyzed, and the time span of the study might all account for these discrepancies in results.

**Table 5.** Long-run and short-run coefficients from the dynamic ARDL model.

| Variables | Co-Efficient | Std. Error | *t*-Stat |
|---|---|---|---|
| lnGDP | 0.637 *** | 0.174 | 3.66 |
| ΔlnGDP | 0.829 *** | 0.125 | 6.63 |
| lnMVA | 0.373 ** | 0.179 | 2.08 |
| ΔlnMVA | 0.608 | 0.532 | 1.14 |
| lnEE | −1.489 *** | 0.411 | −3.62 |
| ΔlnEE | −0.254 ** | 0.113 | −2.25 |
| lnEE*lnMVA | 0.208 ** | 0.080 | 2.58 |
| ΔlnEE*lnMVA | 0.045 * | 0.023 | 1.90 |
| Cons. | 4.097 ** | 1.665 | 2.46 |
| ECT (-1) | −0.590 *** | 0.165 | −3.57 |
| $R^2$ | 0.986 | Adjusted $R^2$ | 0.995 |
| *F*-Statistics [Prob.] | 7857.86 [0.000] | Simulation | 5000 |

Note: ***, ** and * denote a 1%, 5%, and 10% level of significance.

Despite the presence of EKC, income causes both short-term and long-term environmental deterioration, illustrating the scale effect. This revelation can be ascribed to a number of factors. India has one of the world's fastest expanding economies, with heavy use of fossil fuels and natural resources making it among the world's greatest emitters of carbon dioxide. In addition, India's economic growth plan relies on carbon-intensive energy resources, resulting in economic gains at the expense of environmental degradation [68]. India's rapid expansion in the industrial sector, based on low labor wages, intensive resource usage, and exports, has essentially reached its limits, resulting in economic and environmental imbalances [3]. However, our results indicate that environmental pollution in India is dwindling over time, as the long-run negative impact is less severe. The Indian government has taken various policy measures to promote an environmentally friendly environment in line with its INDC pledge and the Paris Agreement [68]. Therefore, Indian officials must emphasize and adopt energy-efficient technology in the development process for green growth.

Manufacturing value added (MVA) as a percentage of GDP has a long-term positive and significant relationship with $CO_2$ emissions. In the long run, a 1% increase in MVA raises $CO_2$ emissions by 0.373%, and earlier research findings [30,31] corroborate these findings. However, they negate the outcome of a previous study by Lin et al. [69], which indicated a significant negative relationship between industrialization as a proportion of GDP and emission of $CO_2$. The operation of industry leads to the manufacturing of chemicals, particularly sulphur dioxide ($SO_2$) and nitrogen oxides (NOx), which are particularly toxic when inhaled and can generate acid rain. Furthermore, these particles undergo chemical reactions, resulting in $CO_2$ emissions which wreak havoc on the ecosystem [30]. Manufacturing, on the other hand, is a capital- and resource-intensive sector; however, India, as a highly industrialized country, lacks suitable environmentally friendly investment and infrastructure development initiatives for this sector. Furthermore, capital received in the manufacturing sector does not result in any green investments for the industry's long-term success. MVA, on the other hand, does not have any negative effects on the environment in the short term. This is due to the fact that developments in industrialization and infrastructure do not have an instant impact, as they require time. As time progresses, more land is acquired and more residues are generated by the expanding activities of the industrial sector, which ultimately ends up obliterating the environmental quality.

Interestingly, EE has significant $CO_2$ emission reduction implications: a 1% improvement in energy efficiency decreases $CO_2$ emissions by 1.489% in the long run and 0.254% in the short run, ceteris paribus. This suggests that $CO_2$ emissions are reduced as a result of the methods, technologies, or instruments used in the course of energy activity. These results are consistent with Mirza et al. [7] and Özbuğday and Erbas [12]. Energy efficiency can reduce India's reliance on fossil fuels while improving energy security, energy resource utilization, and industrial performance by lowering operational expenses. Another factor might be that energy efficiency in India's manufacturing, construction, and transportation sectors helps to alleviate $CO_2$ emissions by saving energy. The Indian government's Bureau of Energy Efficiency (BEE), which is part of the Ministry of Power, has initiated a number of measures to enhance EE and thereby reduce $CO_2$ emissions. Beginning in 2006, the BEE has run the Standards and Labelling scheme for equipment and appliances, allowing consumers to make educated decisions regarding energy conservation. In addition, the Energy Conservation Building Code (ECBC) was established in 2007. In 2013, the Indian government announced the National Electric Mobility Mission Plan (NEMMP) 2020. Its purpose is to increase national energy security by promoting the use of hybrid and electric vehicles. An ambitious goal of 6–7 million hybrid and electric car sales per year has been established for 2020 and beyond. The government wants to provide fiscal and monetary incentives to kickstart this fledgling technology, and all of these steps can help India meet its "net-zero" carbon goal by 2070.

However, the coefficient of lnEE*lnMVA is positive and significant in both the short and long run, meaning that the interaction effect of MVA and EE stimulates $CO_2$ emissions in India. This finding provides the further insight that EE measures have not been conducive to manufacturing sector in the pathway of decarbonizing the Indian economic engine. Currently, the Government of India has placed emphasis on attracting capital investment to the energy-intensive homegrown manufacturing sector in order to revitalize domestic manufacturing under the umbrella of the ambitious "Make in India" initiative. Our findings further imply that India is a long way from mandating the kind of strict EE measures in the manufacturing sector that ultimately aid in the reduction of carbon emissions. Our findings suggest that green energy plays a key role in lowering $CO_2$ emissions, and that EE reduces the amount of energy used in the manufacturing process, lowering $CO_2$ emissions [70]. Finally, the error correction term (ECT) value ($-0.590$) is negative and statistically significant, indicating that our model reaches its long-run equilibrium at a rather quick 59% adjustment rate. The $R^2$ (0.986) and adjusted $R^2$ (0.995) values further reveal our empirical model's strong fitness.

While keeping the independent variables unaltered, the DARDL simulations illustrate and predict the real regressor shifts and their influence on the dependent variables. The influence on $CO_2$ emissions of a 1% increase or decrease in explanatory factors such as GDP, MVA, EE, and MVA*EE cab thus be forecasted. Figure 1 shows that a 1% increase or decline in economic growth has a significant short-term influence on $CO_2$ emissions in India. In the long run, however, a positive 1% rise in economic activity in India degrades environmental quality, while a 1% reduction in economic growth curbs $CO_2$ emissions, hence boosting India's environmental quality. Following this, it can be deduced from Figure 2 that a 1% increase or reduction in MVA will have substantial short-term and long-term effects on $CO_2$ emissions in India. Despite the fact that both scenarios have considerable effects on $CO_2$ emissions, according to the findings, environmental sustainability can be achieved with a 1% reduction in MVA. However, because a decrease in manufacturing share might slow economic growth, the Indian government must place a greater emphasis on the environmentally responsible manufacturing sector by adopting energy- and resource-saving technologies.

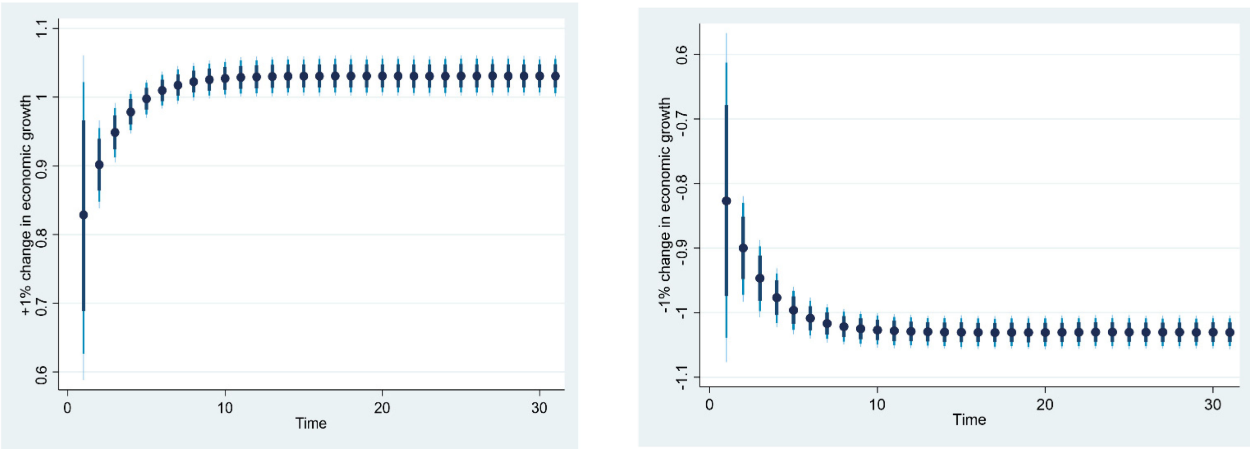



**Figure 1.** Economic growth and environmental quality. The figure signifies a 1% increase or decline in GDP per capita and its effect on $CO_2$ emissions in India. The dots present the forecasted value, whereas the deep blue to light blue lines show the confidence intervals of 75%, 90%, and 95%, respectively. The time in years is represented by the *X*-axis, while the counterfactual change in economic growth is shown by the *Y*-axis.

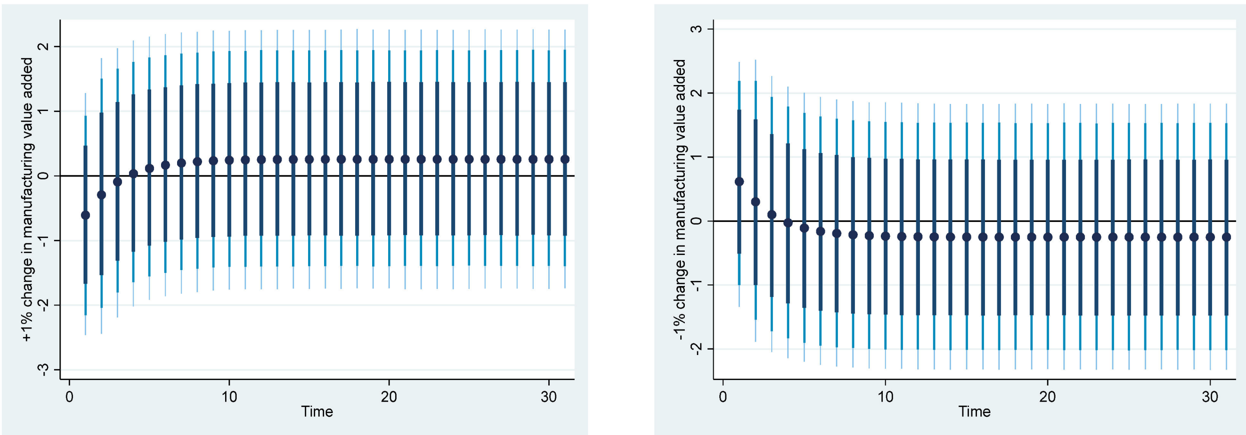



**Figure 2.** MVA and environmental quality. The above figure signifies a 1% increase or decrease in MVA and its effect on $CO_2$ emissions in India. The dots present the forecasted value, whereas the deep blue to light blue lines show the confidence intervals of 75%, 90%, and 95%, respectively. The time in years is represented by the *X*-axis, while the counterfactual change in the manufacturing value added is shown by the *Y*-axis.

In addition, Figure 3 shows that a 1% increase in EE and a 1% decline in EE create substantial changes in India's $CO_2$ emissions in both the short and long run. In the long run, India can achieve a sustainable environment by promoting 1% EE. Although the Indian government has taken various steps to encourage EE, these efforts need to be sustained. This ensures environmental security and, in the long term, maintains a static state. However, a 1% increase or reduction in the interaction of MVA and EE and its influence on $CO_2$ emissions produce intriguing graphs. In either situation, a 1% increase or reduction has a significant impact on environmental quality in both the short and long term. Figure 4a shows that a 1% improvement in both EE and industrial value added can simultaneously raise $CO_2$ emissions in India in a linear fashion from short to long term. In contrast, Figure 4b illustrates that if the interaction of EE and MVA decreases by 1%, the quality of the environment improves with reducing $CO_2$ emissions. As a result, officials should consider the best mix of manufacturing share and EE for long-term environmental quality to ensure that any additional share of the manufacturing sector does not lead to any additional threat to the environment.

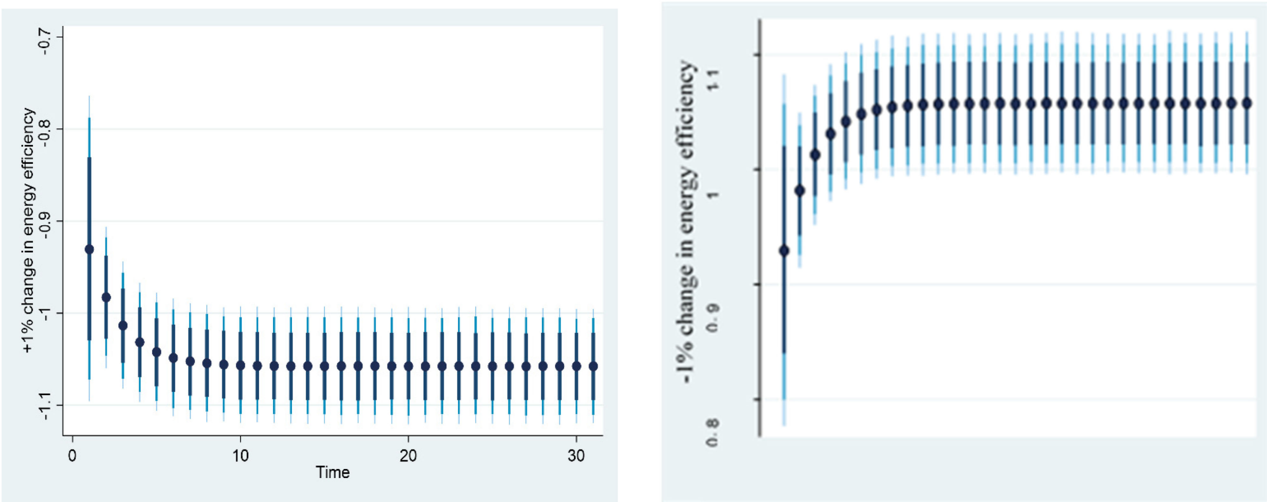
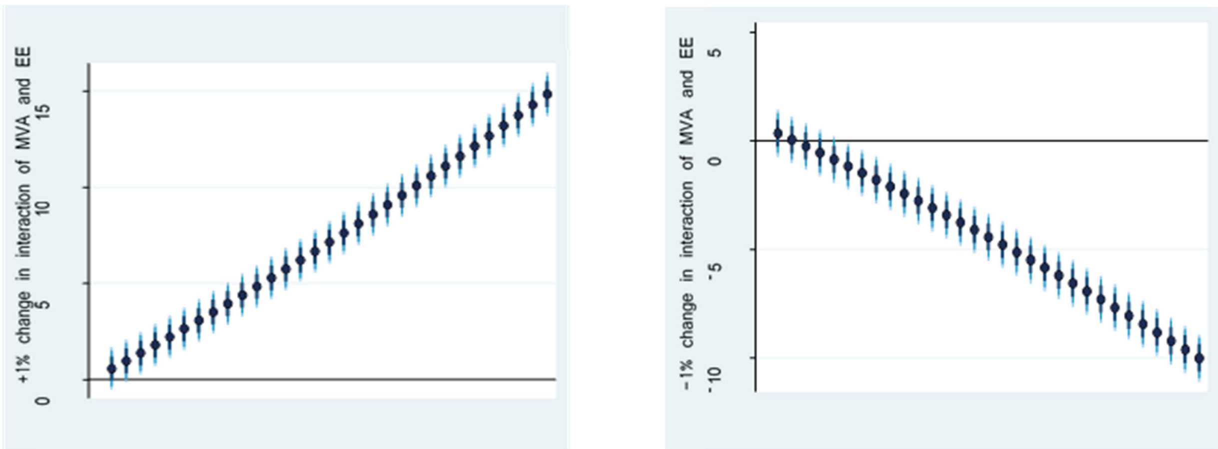



**Figure 3.** EE and environmental quality. The above figure signifies a 1% increase or decrease in EE and its effect on $CO_2$ emission in India. The dots present the forecasted value, whereas the deep blue to light blue lines show the confidence interval of 75%, 90%, and 95%, respectively. The time in years is represented by the *X*-axis, while the counterfactual change in the energy efficiency is shown by the *Y*-axis.




(**a**) (**b**)

**Figure 4.** Interaction effect of MVA and EE on environmental quality. The above diagram (**a**) shows a 1% increase in the interaction of MVA and EE, while (**b**) shows a 1% decrease in the interaction of MVA and EE and its effect on $CO_2$ emissions in India. The dots present the forecasted value, whereas the deep blue to light blue lines show the confidence interval of 75%, 90%, and 95%, respectively. The time in years is represented by the *X*-axis, while the counterfactual change in the interaction term of MVA and EE is shown by the *Y*-axis.

We expanded our investigation by employing multiple diagnostic tests on the time-series data. Table 6 summarizes the findings. To verify the normality and specification of our empirical model, we used the Jarque–Bera normality and Ramsey RESET tests, respectively. According to the results our model is perfectly normal and appropriately defined. In order to identify serial autocorrelation, we used the Breusch–Godfrey LM test, and the results show that our model is devoid of serial autocorrelation. Furthermore, we used the Breusch–Pagan–Godfrey test, which shows that our model is homoscedastic. Finally, we used the CUSUM and CUSUMQ tests to ensure that our model was stable. The generated plots are inside the 95% critical bound, indicating that our econometric model is completely stable, as shown in Figure 5.

**Table 6.** Diagnostic tests for the ARDL model.

| Diagnostic Test | Null Hypothesis | Statistics | Decision |
|---|---|---|---|
| Breusch–Godfrey serial correlation LM test | $H_0$: No auto correlation | *F*-stat: 0.847 Prob: 0.519 | No serial correlation |
| Jarque–Bera test | $H_0$: Normal distribution of error terms | $\chi^2$: 0.699 Prob: 0.705 | Error terms are normally distributed |
| Breusch–Pagan–Godfrey test | $H_0$: Homoskedasticity | *F*-stat: 1.055 Prob: 0.454 | No heteroskedasticity |
| Ramsey RESET test | $H_0$: Model specification is correct | *F*-stat: 2.962 Prob: 0.115 | Model is correctly specified |

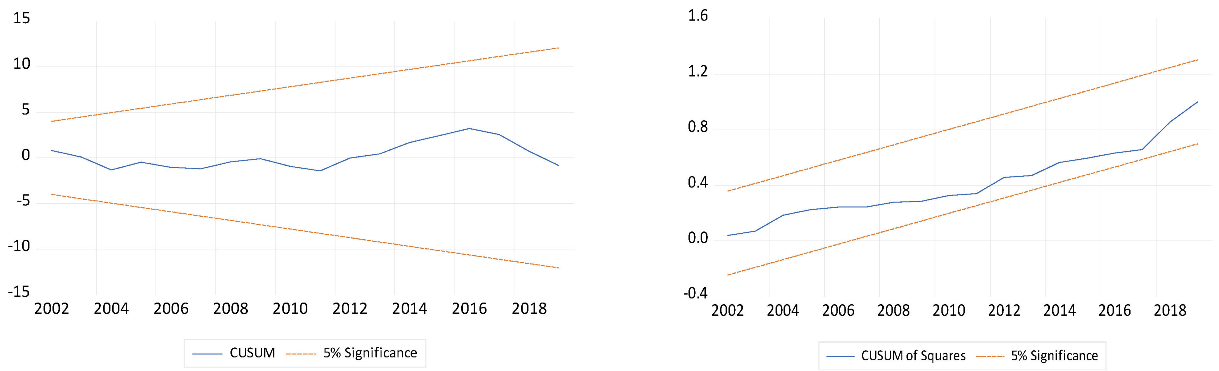



**Figure 5.** Plot of CUSUM and CUSUM of square test.

In our present work, we used the ARDL, FMOLS, and CCR approaches to check the robustness of the DARDL coefficients. The results of these calculations are shown in Table 7. The findings show that the variables' sign and statistical significance levels are compatible with the results of the DARDL estimates, as shown in Table 5. As a result, the DARDL estimations' robustness and accuracy can be validated with absolute assurance.

**Table 7.** Results of ARDL, FMOLS, and CCR.

| Variable | ARDL | | FMOLS | | CCR | |
|---|---|---|---|---|---|---|
| | Coefficient | *t*-Stat. | Coefficient | *t*-Stat. | Coefficient | *t*-Stat. |
| lnGDP | 1.49 *** | 11.76 | 1.03 *** | 130.48 | 1.03 *** | 151.92 |
| lnMVA | 3.01 ** | 2.35 | 3.47 *** | 4.35 | 3.54 *** | 4.87 |
| lnEE | −4.49 *** | −3.15 | −4.76 *** | −5.67 | −4.79 *** | −6.25 |
| lnEE*lnMVA | 1.15 ** | 2.33 | 1.32 *** | 4.32 | 1.32 *** | 4.77 |

Note: *** denotes a 1% level of significance, ** denotes a 5% level of significance.

The findings of the Fourier bootstrap Toda–Yamamoto causality test are shown in Table 8. According to these findings, $CO_2$ emissions and EE have a bidirectional connection, while the significant unidirectional causality runs from: (i) GDP to carbon dioxide emissions; (ii) MVA to GDP; (iii) EE to GDP; (iv) $CO_2$ emissions to MVA; (v) MVA to EE, without any feedback effects. The regression outcomes of GDP, a key factor of $CO_2$ emissions in India, are supported by the unidirectional causality from GDP to $CO_2$ emissions. Rej et al. [64] made a similar discovery, while Alper et al. [71] found a unidirectional causation association between environmental deterioration and economic growth in India. However, the directional relationship between $CO_2$ emissions and EE further highlights the importance of EE to the Indian economy as a measure of curbing the $CO_2$ emissions and improving environmental quality.

**Table 8.** Causality test results.

| | Cumulative Fourier Frequency TY | | | | | TY | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Causal Relation** | **Wald Stat** | **Assym *p*-Value** | **BS *p*-Value** | **Lags** | **Frequency** | **Wald Stat** | **Assym *p*-Value** | **BS *p*-Value** | **Lags** |
| lnMVA → ln$CO_2$ | 8.613 | 0.376 | 0.497 | 8 | 3 | 1.03 | 0.31 | 0.303 | 1 |
| lnEE → ln$CO_2$ | 49.684 | 0.000 *** | 0.017 ** | 8 | 3 | 0.478 | 0.489 | 0.495 | 1 |
| lnGDP → ln$CO_2$ | 36.181 | 0.000 *** | 0.022 ** | 8 | 3 | 0.306 | 0.58 | 0.568 | 1 |
| ln$CO_2$ → lnGDP | 11.618 | 0.169 | 0.351 | 8 | 3 | 0.036 | 0.85 | 0.855 | 1 |
| lnMVA → lnGDP | 23.401 | 0.003 *** | 0.091 * | 8 | 3 | 2.083 | 0.149 | 0.173 | 1 |
| lnEE → lnGDP | 17.971 | 0.021 ** | 0.16 | 8 | 3 | 0.092 | 0.762 | 0.767 | 1 |
| ln$CO_2$ → lnMVA | 33.031 | 0.000 *** | 0.053 * | 8 | 3 | 0.013 | 0.908 | 0.908 | 1 |
| lnGDP → lnMVA | 12.811 | 0.119 | 0.276 | 8 | 3 | 2.339 | 0.126 | 0.133 | 1 |
| lnEE → lnMVA | 8.065 | 0.427 | 0.505 | 8 | 3 | 1.21 | 0.271 | 0.279 | 1 |
| ln$CO_2$ → lnEE | 34.956 | 0.000 *** | 0.043 ** | 8 | 3 | 0.225 | 0.636 | 0.642 | 1 |
| lnGDP → lnEE | 10.149 | 0.255 | 0.381 | 8 | 3 | 0.404 | 0.525 | 0.525 | 1 |
| lnMVA → lnEE | 111.556 | 0.000 *** | 0.001 *** | 8 | 3 | 0.013 | 0.908 | 0.907 | 1 |

NOTE: TY: Toda and Yamamoto Causality test approach. Note: ***, **, and * denote a 1%, 5%, and 10% level of significance. BS: Bootstrapped; Assym: Asymmetric.

## 6. Conclusions and Policy Recommendations

This study was carried out with the premise of attaining India's two seemingly different goals, that is, of reaching its INDC commitment of restricting $CO_2$ emission levels by 33–35% with respect to the emission level in 2005 by 2030 while at the same time accelerating its energy-intensive domestic manufacturing sector as an intrinsic part of the ambitious "Make in India" initiative. This study's aim was to examine whether these two goals complement each other or if they are seemingly divergent in light of the goal of attaining an environmentally friendly economy. In this context, the present study employed a systematic approach to examining the role of EE and MVA on the path to carbon neutralization of the Indian economy over the time period 1980–2019 through the lens of the EKC framework. The interaction term between EE and MVA was augmented within this framework in order to examine whether the goals of "INDC" and "Make in India" can be supportive of each other. We used the recently developed DARDL simulations model to achieve our research objectives. We employed ADF and PP unit root tests to check the stationarity properties of the variables and applied the cumulative Fourier frequency TY approach to unveil the causal association between pairs of variables.

This research provides several fresh insights, and adds to the current body of knowledge in a variety of ways. To begin, this analysis both demonstrates the long-term dynamics among the variables under consideration for the data period 1980–2019 and confirms the existence of the EKC hypothesis for India, as the short-term coefficient of GDP is larger than the long-run coefficient. This study further demonstrates that MVA is associated with the deterioration of environmental quality, posing a serious conflict between the two ambitious goals of "Make in India" and "INDC". Moreover, EE contributes to the reduction of $CO_2$ emissions, qualifying EE as one of the key contributors to the decarbonization pathway. It is expected that the application of EE in the manufacturing sector can help to reduce emissions. However, we found evidence of a positive coefficient of the interaction term, which is an indication of the fact that India is not currently able to furnish the manufacturing sector with EE measures that can aid in the reduction of carbon emissions, which may eradicate the potential conflict between the two developmental goals of "Make in India" and "INDC". Our findings from the cumulative Fourier frequency TY show that a bidirectional relationship exists between $CO_2$ emissions and EE. The unidirectional causality runs from GDP to $CO_2$ emissions, MVA to GDP and EE, $CO_2$ emissions to MVA, and EE to GDP.

In the light of these econometric findings, the resulting policy suggestions for India are as follows: (i) as our research findings imply that energy efficiency measures in the manufacturing sector remain underdeveloped, the Government of India should invest a quantum of capital in the R&D sector and should initiate effective skill-development programs in order to mandate strict energy efficiency measures in the manufacturing sector and aid this sector to become a less polluting or non-polluting sector; (ii) India should endorse strict environmental laws and ensure that all manufacturing industries abide by these laws. This may act as a catalyst toward the decarbonization pathway of the Indian economic growth engine; (iii) As present economic growth is evidenced to not be amenable to environmental sustainability, Indian policymakers should be more focused on enhanced utilization of zero carbon footprint renewable energy sources by initiating strong renewable energy awareness programs and by alerting and educating people about the efficient usage of electricity.

Despite the fact that this study explores an intriguing issue in the context of India's "net-zero" goal, it does have several shortcomings that additional research might solve. Future studies have the opportunity to critically examine the impact of public–private partnerships (PPPs) in energy, particularly renewables, on $CO_2$ emission levels by using disaggregated data in the context of India or other emerging economies. In addition, $CO_2$ emissions may not fully capture environmental deterioration linked to water, forests, biodiversity, sanitation, and other environmental phenomena. As a result, future research should focus on proxies that are more comprehensive, such as ecological footprint. Furthermore, the outcomes of this study might be applied to other nations with comparable macroeconomic characteristics, such as other South Asian countries (Bangladesh, Pakistan, etc.) and other BRICS countries, as the data utilized in this study become more readily available. This study can be expanded and the validity of our assumptions further evaluated by performing similar the analyses in different regions of the globe. Comparable country-specific studies might be carried out to test the credibility of the results recorded in this study if appropriate data are available.

**Author Contributions:** Conceptualization, S.R. and M.E.H.; methodology, M.E.H.; software, M.E.H.; validation, S.M.S., S.R. and M.E.H.; formal analysis, M.E.H.; investigation, M.E.H.; resources, M.E.H.; data curation, S.R.; writing—original draft preparation, M.E.H., S.R., S.M.S. and J.C.O.; writing—review and editing, N.N., A.T. and F.V.B.; visualization, F.V.B.; supervision, F.V.B.; funding acquisition, N.N. and F.V.B. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** Data are freely available https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html, (accessed on 12 April 2022), and https://databank.worldbank.org/source/world-development-indicators, (accessed on 12 April 2022).

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. United Nations. The Sustainable Development Goals Report. 2020. Available online: https://unstats.un.org/sdgs/report/2020/ (accessed on 6 September 2021).
2. Nandi, J. India's $CO_2$ Emissions Fell by 1% in 2019–2020 Financial Year, Hindustan Times, New Delhi, India. 2020. Available online: https://www.hindustantimes.com/india-news/india-s-co2-emissions-fell-by-1-in-2019-20-financial-year/story-kJ2Jus35sKtskGKZk2yhXO.html (accessed on 14 June 2020).
3. World Bank. The World Bank in India. Overview. 2021. Available online: https://www.worldbank.org/en/country/india/overview#1 (accessed on 15 April 2022).

4. IMF. World Economic Outlook World Economic Outlook Update, June 2020: A Crisis like no Other: An Uncertain Recovery, International Monetary Fund, Washington, United States. 2020. Available online: https://www.imf.org/en/Publications/WEO/Issues/2020/06/24/WEOUpdateJune2020 (accessed on 14 December 2020).
5. UNFCCC. India's Intended Nationally Determined Contribution: Working Towards Climate Justice. 2020. Available online: https://www4.unfccc.int/sites/ndcstaging/PublishedDocuments/India%20First/INDIA%20INDC%20TO%20UNFCCC.pdf (accessed on 20 August 2020).
6. IEA. *World Energy Outlook Special Report*; International Energy Agency: Paris, France, 2020. Available online: https://www.iea.org/reports/world-energy-outlook-2020 (accessed on 14 December 2020).
7. Mirza, F.; Sinha, A.; Khan, J.; Kalugina, O.; Muhammad, V. Impact of energy efficiency on $CO_2$ Emissions: Empirical evidence from developing countries. *Gondwana Res.* **2022**, *106*, 64–77. [CrossRef]
8. Goswami, U. India Signals it is Ready to do More to Slow Down Climate Change, The Economic Times, Mumbai, India. 2020. Available online: https://economictimes.indiatimes.com/news/politics-and-nation/india-says-it-will-do-more-to-slow-down-climate-change/articleshow/70813231.cms (accessed on 20 August 2020).
9. IEA. India Energy Outlook 2021, Paris, OECD Publishing. Available online: https://www.iea.org/reports/india-energy-outlook-2021 (accessed on 20 September 2021).
10. Climate Action Tracker. India Country Summary. 2021. Available online: https://climateactiontracker.org/countries/india/ (accessed on 6 September 2021).
11. Abnett, K.; Volcovici, V. Flurry of Emissions Pledges Still not Enough to Meet Global Climate Goals, Reuters, London, United Kingdom. Available online: https://www.reuters.com/business/sustainable-business/flurry-emissions-pledges-still-not-enough-meet-global-climate-goals-2021-08-05/ (accessed on 26 November 2021).
12. Murshed, M.; Khan, S.; Rahman, A.A. Roadmap for achieving energy sustainability in Sub-Saharan Africa: The mediating role of energy use efficiency. *Energy Rep.* **2022**, *8*, 4535–4552. [CrossRef]
13. Langlois, P.; Yank, A. Developing Countries and Energy Efficiency Potential: Strategies for Low-Carbon Development after Paris Agreement. International Partnership for Energy Efficiency Cooperation. 2017. Available online: https://ipeec.org/upload/publication_related_language/pdf/606.pdf (accessed on 2 May 2022).
14. Dahir, M.; Mahi, M. Does energy efficiency improve environmental quality in BRICS countries? Empirical evidence using dynamic panels with heterogeneous slopes. *Environ. Sci. Pollut. Res.* **2022**, *29*, 12027–12042. [CrossRef] [PubMed]
15. Wang, X. Determinants of ecological and carbon footprints to assess the framework of environmental sustainability in BRICS countries: A panel ARDL and causality estimation model. *Environ. Res.* **2021**, *197*, 111111. [CrossRef]
16. Yang, M.; Yu, X. Energy efficiency to mitigate carbon emissions: Strategies of China and the USA. *Mitig. Adapt. Strateg. Glob. Chang.* **2017**, *22*, 1–14. [CrossRef]
17. Rajbhandari, A.; Zhang, F. Does energy efficiency promote economic growth? Evidence from a multicountry and multisectoral panel dataset. *Energy Econ.* **2018**, *69*, 128–139. [CrossRef]
18. Iftikhar, Y.; He, W.; Wang, Z. Energy and $CO_2$ emissions efficiency of major economies: A non-parametric analysis. *J. Clean Prod.* **2016**, *139*, 779–787. [CrossRef]
19. Sinha, A. Inequality of renewable energy generation across OECD countries: A note. *Renew. Sustain. Energy Rev.* **2017**, *79*, 9–14. [CrossRef]
20. Chen, J.; Wang, P.; Cui, L.; Huang, S.; Song, M. Decomposition and decoupling analysis of $CO_2$ emissions in OECD. *Appl. Energy* **2018**, *231*, 937–950. [CrossRef]
21. Balsalobre-Lorente, D.; Driha, O.M.; Bekun, F.V.; Osundina, O.A. Do agricultural activities induce carbon emissions? The BRICS experience. *Environ. Sci. Pollut. Res.* **2019**, *26*, 25218–25234. [CrossRef]
22. Zhang, L.; Li, Z.; Kirikkaleli, D.; Adebayo, T.S.; Adeshola, I.; Akinsola, G.D. Modeling $CO_2$ emissions in Malaysia: An application of Maki cointegration and wavelet coherence tests. *Environ. Sci. Pollut. Res.* **2021**, *28*, 26030–26044. [CrossRef] [PubMed]
23. Yilanci, V.; Pata, U.K. Investigating the EKC hypothesis for China: The role of economic complexity on ecological footprint. *Environ. Sci. Pollut. Res.* **2020**, *27*, 32683–32694. [CrossRef] [PubMed]
24. Destek, M.A.; Sinha, A. Renewable, non-renewable energy consumption, economic growth, trade openness and ecological footprint: Evidence from organisation for economic Co-operation and development countries. *J. Clean. Prod.* **2020**, *242*, 118537. [CrossRef]
25. Isiksal, A.Z. The financial sector expansion effect on renewable electricity production: Case of the BRICS countries. *Environ. Dev. Sustain.* **2021**, *23*, 9029–9051. [CrossRef]
26. López-Menéndez, A.J.; Pérez, R.; Moreno, B. Environmental costs and renewable energy: Re-visiting the Environmental Kuznets Curve. *J. Environ. Manag.* **2014**, *145*, 368–373. [CrossRef]
27. Ozcan, B. The nexus between carbon emissions, energy consumption and economic growth in Middle East countries: A panel data analysis. *Energy Policy* **2013**, *62*, 1138–1147. [CrossRef]
28. Mrabet, Z.; Alsamara, M. Testing the Kuznets Curve hypothesis for Qatar: A comparison between carbon dioxide and ecological footprint. *Renew. Sust. Energ. Rev.* **2017**, *70*, 1366–1375. [CrossRef]
29. Sarkodie, S.A.; Strezov, V. Empirical study of the environmental Kuznets curve and environmental sustainability curve hypothesis for Australia, China, Ghana and USA. *J. Clean. Prod.* **2018**, *201*, 98–110. [CrossRef]

30. Abbasi, K.R.; Hussain, K.; Redulescu, M.; Ozturk, I. Does natural resources depletion and economic growth achieve the carbon neutrality target of the UK? A way forward towards sustainable development. *Resour. Policy* **2021**, *74*, 102341. [CrossRef]
31. Liu, X.; Bae, J. Urbanization and industrialization impact of $CO_2$ emissions in China. *J. Clean. Prod.* **2018**, *172*, 178–186. [CrossRef]
32. Liu, Y.; Hao, Y. The dynamic links between $CO_2$ emissions, energy consumption and economic development in the countries along "the Belt and Road". *Sci. Total Environ.* **2018**, *645*, 674–683. [CrossRef] [PubMed]
33. Prastiyo, S.E.; Hardyastuti, S. How agriculture, manufacture, and urbanization induced carbon emission? The case of Indonesia. *Environ. Sci. Pollut. Res.* **2020**, *27*, 42092–42103. [CrossRef] [PubMed]
34. Raza, M.Y.; Hasan, M.M. Estimating the multiple impacts of technical progress on Bangladesh's manufacturing and industrial sector's $CO_2$ emissions: A quantile regression approach. *Energy Rep.* **2022**, *8*, 2288–2301. [CrossRef]
35. Avenyo, E.K.; Tregenna, F. *The Effects of Technology Intensity in Manufacturing on $CO_2$ Emissions: Evidence from Developing Countries*; Working Paper, No. 846; Economic Research Southern Africa: Cape Town, Southern Africa, 2021.
36. Khan, R. Beta decoupling relationship between $CO_2$ emissions by GDP, energy consumption, electricity production, value-added industries, and population in China. *PLoS ONE* **2021**, *16*, e0249444. [CrossRef] [PubMed]
37. Akram, R.; Umar, M.; Xiaoli, G.; Chen, F. Dynamic linkages between energy efficiency, renewable energy along with economic growth and carbon emission. A case of MINT countries an asymmetric analysis. *Energy Rep.* **2022**, *8*, 2119–2130. [CrossRef]
38. Özbuğday, F.C.; Erbas, B.C. How effective are energy efficiency and renewable energy in curbing $CO_2$ emissions in the long run? A heterogeneous panel data analysis. *Energy* **2015**, *82*, 734–745. [CrossRef]
39. Akram, R.; Chen, F.; Khalid, F.; Ye, Z.; Majeed, M.T. Heterogeneous effects of energy efficiency and renewable energy on carbon emissions: Evidence from developing countries. *J. Clean. Prod.* **2020**, *247*, 119122. [CrossRef]
40. Tajudeen, I.A.; Wossink, A.; Banerjee, P. How significant is energy efficiency to mitigate $CO_2$ emissions? Evidence from OECD countries. *Energy Econ.* **2018**, *72*, 200–221. [CrossRef]
41. Li, M.; Yao-Ping, P.M.; Nazar, R.; Ngozi, A.B.; Shang, M.; Waqas, M. How Does Energy Efficiency Mitigates Carbon Emissions without Reducing Economic Growth in Post COVID-19 Era. *Front. Energy Res.* **2022**, *58*, 832189. [CrossRef]
42. Liimatainen, H.; Arvidsson, N.; Hovi, I.B.; Jensen, T.C.; Nykänen, L. Road freight energy efficiency and $CO_2$ emissions in the Nordic countries. *Res. Transp. Bus. Manag.* **2014**, *12*, 11–19. [CrossRef]
43. Wang, J.; Lv, K.; Bian, Y.; Cheng, Y. Energy efficiency and marginal carbon dioxide emission abatement cost in urban China. *Energy Policy* **2017**, *105*, 246–255. [CrossRef]
44. Tajudeen, I.A. Examining the role of energy efficiency and non-economic factors in energy demand and $CO_2$ emissions in Nigeria: Policy implications. *Energy Policy* **2015**, *86*, 338–350. [CrossRef]
45. Martínez, C.I.P.; Silveira, S. Energy efficiency and $CO_2$ emissions in Swedish manufacturing industries. *Energy Effic.* **2013**, *6*, 117–133. [CrossRef]
46. Emir, F.; Bekun, F.V. Energy intensity, carbon emissions, renewable energy, and economic growth nexus: New insights from Romania. *Energy Environ.* **2019**, *3*, 427–443. [CrossRef]
47. Kuznets, S. Economic growth and income inequality. *Am. Econ. Rev.* **1955**, *45*, 1–28.
48. Grossman, G.M.; Krueger, A.B. Economic growth and the environment. *Q. J. Econ.* **1995**, *110*, 353–377. [CrossRef]
49. Panayotou, T. Demystifying the environmental Kuznets curve: Turning a black box into a policy tool. *Environ. Dev. Econ.* **1997**, *2*, 465–484. [CrossRef]
50. Shafik, N. Economic development and environmental quality: An econometric analysis. *Oxf. Econ. Pap.* **1994**, *46*, 757–773. [CrossRef]
51. Islam, M.S.; Hossain, M.E.; Khan, M.A.; Rana, M.J.; Ema, N.S.; Bekun, F.V. Heading towards sustainable environment: Exploring the dynamic linkage among selected macroeconomic variables and ecological footprint using a novel dynamic ARDL simulations approach. *Environ. Sci. Pollut. Res.* **2022**, *29*, 22260–22279. [CrossRef]
52. Pata, U.K.; Isik, C. Determinants of the load capacity factor in China: A novel dynamic ARDL approach for ecological footprint accounting. *Resour. Policy* **2021**, *74*, 102313. [CrossRef]
53. Narayan, P.K.; Narayan, S. Carbon dioxide emissions and economic growth: Panel data evidence from developing countries. *Energy Policy* **2010**, *38*, 661–666. [CrossRef]
54. World Bank. Manufacturing, Value Added (% of GDP). India. 2022. Available online: https://data.worldbank.org/indicator/NV.IND.MANF.ZS?locations=IN (accessed on 15 April 2022).
55. Baloch, Z.A.; Tan, Q.; Iqbal, N.; Mohsin, M.; Abbas, Q.; Iqbal, W.; Chaudhry, I.S. Trilemma assessment of energy intensity, efficiency, and environmental index: Evidence from BRICS countries. *Environ. Sci. Pollut. Res.* **2020**, *27*, 34337–34347. [CrossRef]
56. Hossain, M.E.; Islam, M.S.; Bandyopadhyay, A.; Awan, A.; Hossain, M.R.; Rej, S. Mexico at the crossroads of natural resource dependence and COP26 pledge: Does technological innovation help? *Resour. Policy* **2022**, *77*, 102710. [CrossRef]
57. Dickey, D.A.; Fuller, W.A. Distribution of the estimators for autoregressive time series with a unit root. *J. Am. Stat. Assoc.* **1979**, *74*, 427–431.
58. Phillips, P.C.; Perron, P. Testing for a unit root in time series regression. *Biometrika* **1988**, *75*, 335–346. [CrossRef]
59. Hossain, M.E.; Islam, M.S.; Sujan, M.H.K.; Tuhin, M.M.; Bekun, F.V. Towards a clean production by exploring the nexus between agricultural ecosystem and environmental degradation using novel dynamic ARDL simulations approach. *Environ. Sci. Pollut. Res.* **2022**, 1–17. [CrossRef]

60. Jordan, S.; Philips, A.Q. Cointegration testing and dynamic simulations of autoregressive distributed lag models. *Stata J.* **2018**, *18*, 902–923. [CrossRef]
61. Toda, H.Y.; Yamamoto, T. Statistical inference in vector autoregressions with possibly integrated processes. *J. Econom.* **1995**, *66*, 225–250. [CrossRef]
62. Nazlioglu, S.; Gormus, N.A.; Soytas, U. Oil prices and real estate investment trusts (REITs): Gradual-shift causality and volatility transmission analysis. *Energy Econ.* **2016**, *60*, 168–175. [CrossRef]
63. Pesaran, M.; Shin, Y.; Smith, R. Bounds testing approaches to the analysis of long-run relationships. *J. Appl. Econ.* **2001**, *16*, 289–326. [CrossRef]
64. Rej, S.; Bandyopadhyay, A.; Mahmood, H.; Murshed, M.; Mahmud, S. The role of liquefied petroleum gas in decarbonizing India: Fresh evidence from wavelet–partial wavelet coherence approach. *Environ. Sci. Pollut. Res.* **2022**, *29*, 35862–35883. [CrossRef]
65. Awan, A.; Abbasi, K.R.; Rej, S.; Bandyopadhyay, A.; Lv, K. The impact of renewable energy, internet use and foreign direct investment on carbon dioxide emissions: A method of moments quantile analysis. *Renew. Energy* **2022**, *189*, 454–466. [CrossRef]
66. Agboola, P.O.; Hossain, M.; Gyamfi, B.A.; Bekun, F.V. Environmental consequences of foreign direct investment influx and conventional energy consumption: Evidence from dynamic ARDL simulation for Turkey. *Environ. Sci. Pollut. Res.* **2022**, 1–14. [CrossRef]
67. Rej, S.; Bandyopadhyay, A.; Murshed, M.; Mahmood, H.; Razzaq, A. Pathways to decarbonization in India: The role of environmentally friendly tourism development. *Environ. Sci. Pollut. Res.* **2022**, 1–22. [CrossRef]
68. Rej, S.; Nag, B. Investigating the role of capital formation to achieve carbon neutrality in India. *Environ. Sci. Pollut. Res.* **2022**, 1–19. [CrossRef]
69. Lin, B.; Omoju, O.E.; Okonkwo, J.U. Impact of industrialisation on $CO_2$ emissions in Nigeria. *Renew. Sust. Energ. Rev.* **2015**, *52*, 1228–1239. [CrossRef]
70. Ponce, P.; Khan, S.A.R. A causal link between renewable energy, energy efficiency, property rights, and $CO_2$ emissions in developed countries: A road map for environmental sustainability. *Environ. Sci. Pollut. Res.* **2021**, *28*, 37804–37817. [CrossRef]
71. Alper, A.E.; Alper, F.O.; Ozayturk, G.; Mike, F. Testing the long-run impact of economic growth, energy consumption, and globalization on ecological footprint: New evidence from Fourier bootstrap ARDL and Fourier bootstrap Toda–Yamamoto test results. *Environ. Sci. Pollut. Res.* **2022**, 1–16. [CrossRef]