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## **RESEARCH ARTICLE**

# Energy transition and environmental guality prospects in leading emerging economies: The role of environmental-related technological innovation

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### Abstract

The world has witnessed a significant rise in greenhouse gas emissions since the end of the 20th century as several economies begin to emerge into industrial hubs and manufacturing giants across the globe. Thus, in the wake of global interest in clean energy development and campaign for sustainable climate and ecosystem, the role of the emerging countries in the debate is unarguably vital and demanding. Importantly, this study seeks to examine the commitment of the leading emerging countries (E7) of Brazil, China, India, Indonesia, Mexico, Russia, and Turkey to energy transition and carbon-neutral 2050. We employ the cross-sectionally augmented autoregressive distributed lag approach that accounts for potential country-specific factors to examine the role of environmental-related technological innovations (ERT) in achieving climate neutrality in the E7 over the period from 1992 to 2018. Notably, the findings revealed that a 1 percent increase in ERT yields ~0.33% (short-run) and  $\sim$  0.17% (long-run) reductions in carbon emission, thus suggesting that the E7 economies could be heading toward environmental sustainability with the application of ERT. Additionally, the result revealed that the application of ERT in the energy utilization profile significantly reduced the undesirable impact of primary energy utilization. However, the result showed that such an impact is not enough to trigger a transition to environmentally desirable cleaner energy that could mitigate carbon emissions. This is because the larger share of the E7 countries' primary energy utilization is from conventional and/or non-renewable energy sources. The environmental Kuznets curve hypothesis is also validated.

#### KEYWORDS

economic growth, emerging economies, energy utilization, environmental sustainability, innovation, technology

#### INTRODUCTION 1

From a historical perspective, advanced economies mainly the United States of America (US) and those in Europe (precisely Western Europe) have dominated the major point of discussion about greenhouse gas (GHG) emissions mitigation following the early industrial revolutions (Alola, Adebayo, et al., 2021; Alola, Akadiri, et al., 2021; Allen, 2009; Friedrich & Damassa, 2014; Kasa, 1973).

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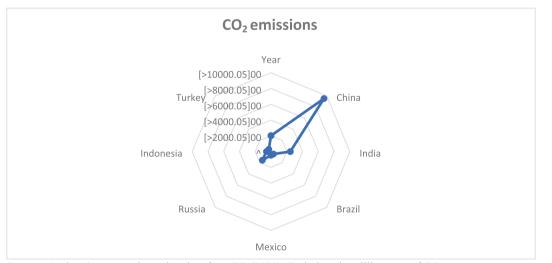
However, the world has seen a dramatic change in emissions trajectory and the composition of major emitting economies toward the end of the 20th century until date. This change occurs as many other economies begin to emerge into industrial hubs and manufacturing giants across the globe. Some of the countries in this category have been classified into various groups. As a prominent group of countries, the world's Emerging seven (E7) economies consisting of China, India, Brazil, Mexico, Russia, Indonesia, and Turkey are increasing gaining more attention in the subject of global climate change (Alola & Nwulu, 2021; Etokakpan et al., 2021; Huang et al., 2021; Zoaka et al., 2022).

Based on available reliable data, emissions levels have greatly increased among the E7 economies over the last few decades and this bloc of countries is arguably the largest contributor to the global emissions in recent times. Countries like China have emerged as the topemitting nation accounting for over 27% of total emissions as of 2017 according to the United Nation Emission Gap Report (UNEP, 2018). Jiang et al. (2022), noted that greenhouse gasses (GHGs) have been a major challenge to global environmental sustainability, and energyrelated carbon emissions, in particular, stand out as a major concern in countries like China. Other countries among the E7 also contribute to a significant chunk of the global carbon emissions for instance about 7.1% of the total greenhouse gas (GHG) emissions were attributed to India. In the South and Central America region, Brazil accounts for the highest emissions with about 35.02% of the region's total carbon dioxide emissions (British Petroleum, 2020). Emission is also fast growing in Turkey, Indonesia, Russia, and Mexico as seen in Figure 1. As of 2018, China leads in emission among these countries followed by India, Russia, Indonesia, Mexico, Brazil, and Turkey, respectively, and carbon emission level is yet to peak in most of these economies.

On the other hand, the literature is currently replete with the dangers of unabated emissions of anthropogenic CO<sub>2</sub> and other greenhouse gases (GHGs) emissions (IPCC, 2007,<sup>1</sup>; Jolly et al., 2015;

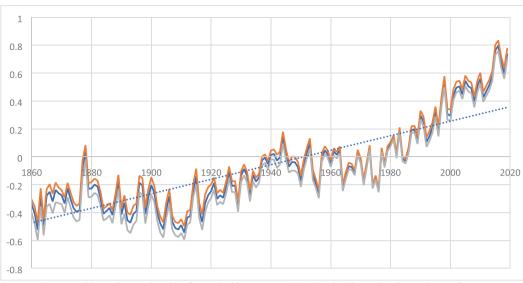
Anderson & Bows, 2011; Alola, Adebayo, et al., 2021; Alola, Akadiri, et al., 2021). Besides, growing emissions levels have been identified as a major factor contributing to rising levels of environmental disasters with predictions of more dangers ahead if nothing is done to curtail cumulative emissions in the meantime (IPCC, 2021; UNEP, 2021). Furthermore, Mora et al. (2018) noted that an approximate 584.4 GtC (gigatons of CO<sub>2</sub>) was emitted from human activities including the burning of fossil fuel, industrial activities, and land use between 1860 and 2014. This was also estimated to have resulted in about 0.9 °C of global warming as the global average temperature has maintained an upward trend over the decades as seen in Figure 2.

Therefore, in the wake of the rising potential dangers of climate change and environmental disaster vis-à-vis increasing GHG emission levels, the impact of innovative technology on carbon emission levels and its significance for achieving the global zero-carbon target is gradually attracting the attention of researchers. At the moment, the bulk of the research relating to the environmental impacts of innovation has addressed countries in the OECD bloc and a couple of Asian economies (Álvarez-Herránz et al., 2017; Amin et al., 2020; Godil et al., 2021; Shahbaz, Raghutla, et al., 2020). However, there is the concern that countries in some of these blocs may not necessarily be at the same tier of economic progress or development. To the best of the authors' knowledge, none of the existing studies has addressed the innovation-emission nexus for the specific case of the E7 economies except for the most recent study by Tao et al. (2021). However, just like most studies on other blocs mainly considered the innovation-emission nexus, their study also did not examine whether the expected desirables environmental impact of innovation holds in the E7 when interacting the level of innovations with the weights of the overall energy use per capita among these countries. This aspect is however very crucial when considering the guest for wealth creation as seen in the push to maintain economic growth which is a major trait among all economies and most especially for emerging



Source: Authors' computation using data from BP (2020). Emissions in million tons of CO<sub>2</sub>.

FIGURE 1 CO<sub>2</sub> emission in the E7 (end of 2018). Authors' computation using data from British Petroleum (2020). Emissions in million tons of CO<sub>2</sub>. [Colour figure can be viewed at wileyonlinelibrary.com]



**Source:** Computed by authors using data from Ritchie & Roser, (2020). The blue color shows the median temperature anomaly (1961-1990) average, while the dotted line is the trendline. The orange and grey lines are for upper and lower confidence intervals respectively. The horizontal axis is for average temperature (°C) and years are on the horizontal axis.

**FIGURE 2** Global average temperature trend (1860–2018). Computed by authors using data from Ritchie and Roser (2020). The blue color shows the median temperature anomaly (1961–1990) average, while the dotted line is the trendline. The orange and gray lines are for upper and lower confidence intervals, respectively. The horizontal axis is for average temperature (°C) and years are on the horizontal axis. [Colour figure can be viewed at wileyonlinelibrary.com]

economies. As such, the present study aims to contribute to the developing literature relating to the emerging economies in the following ways;

- a. Firstly, by examining the impacts of technological innovations on carbon emission levels while juxtaposing the roles of energy usage in the case of the E7 economies.
- Secondly, to examine how the interaction between innovation and energy use influence the environmental quality of the E7 Economies.
- c. Thirdly, within an income-sustainability framework, the study further aims to examine the EKC conjecture for the E7 countries when technological innovation is being accounted for.

Following the introduction as the first chapter, the other part of this study has been subsequently structured into four sections with the review of the literature in Section 2 while providing the details about the methods of data analysis in Section 3. Subsequently, the discussion of findings comes up in Section 4, and Section 5 wraps up the study with policy matters.

## 2 | THEORETICAL AND EMPIRICAL UNDERPINNING

The theoretical underpinnings behind this study are the environmental Kuznets curve (EKC) conjecture (Kuznets, 1955) and the Jevons technological innovation paradox (Jevons, 2001). On the aspect of

economic growth-environment nexus, the EKC conjecture argues that although the environment may be in jeopardy of pollution at an initial rate of economic growth, the detrimental environmental effects of growth will later clear out at a growth peak after which higher growth would only produce a cleaner environment (Balsalobre-Lorente et al., 2022; Onifade, 2022). To compensate for the initial pollution levels at a higher stage of income according to the EKC conjecture, important factors such as technological innovation among others, have to be integrated into the environment-income nexus.

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It is a conventional belief that technological innovations can enhance environmental sustainability, especially from the perspective of improvement in energy efficiency. However, William Stanley Jevons in 1865 (Jevons, 2001) in his seminar work demonstrated that energy efficiency (through innovations) may not really enhance sustainability as often expected through a reduction in aggregate energy consumption or resource use, on the contrary, it would rather increase consumptions. This view has been popularly regarded as the Jevons paradox and the paradox has been a long-held environmental point of discussion among economists. Inter alia, Bunker (1996) argued that large-scale economic production activities for profit-seeking in a typical economy where the focus is on growth can lead to an increase in overall energy use, even in the presence of potential higher energy efficiency that is achievable through energy technological innovations. Hence, the question of what roles technological innovations play in environmental sustainability may not necessarily follow a straightforward answer especially when the issues bordering on energy use and the quest for economic growth are accounted for.

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### TABLE 1 Summary of empirical studies

|   |                       | The country(s)              |                                  |  |
|---|-----------------------|-----------------------------|----------------------------------|--|
| The author(s)                             | Scope of study        | examined                    | Empirical methods                | Summary of the findings and conclusion   |
| Technological innovation and CO           | $O_2$ emissions       |                             |                                  |  |
| Álvarez-Herránz et al.<br>(2017)          | 1990-2014             | 28 OECD<br>members          | V-lag distribution model         | Innovations help to mitigate $CO_2$ emissions  |
| Godil et al. (2021)                       | 1990-2018             | China                       | QARDL methods                    | Innovations help to mitigate CO <sub>2</sub> emissions in the transport sector   |
| Jahanger et al. (2022)                    | 1990-2016             | 73 developing countries     | PMG-ARDL                         | Technological innovations reduce the negative<br>environmental consequences of resource<br>utilization                             |
| Erdogan (2021)                            | 1992-2018             | BRICS Countries             | DCCE                             | Innovations help to mitigate $CO_2$ emissions from the building sector   |
| Amin et al. (2020)                        | 1985-2019             | Asian Countries             | VECM and FMOLS                   | Innovations help to mitigate CO <sub>2</sub> emissions<br>but energy use induces it  |
| Shahbaz, Nasir, et al.<br>(2020)          | 1984-2018             | China                       | BARDL                            | Innovations help to mitigate $\mathrm{CO}_2$ emissions   |
| Baloch et al. (2021)                      | 1996-2016             | <b>BRICS</b> Countries      | DOLS and FMOLS                   | Innovations help to mitigate CO <sub>2</sub> emissions   |
| Chen et al. (2020)                        | 1996-2018             | 96 nations                  | GNS model                        | Innovations have no significant contribution toward reducing CO <sub>2</sub> emissions   |
| Wang and Zhu (2020)                       | 2001-2017             | China                       | POLS                             | Fossil energy innovations induce CO <sub>2</sub><br>emissions while innovation in renewable<br>mitigates CO <sub>2</sub> emissions |
| Su et al. (2021)                          | 1990 to 2018          | BRICS Countries             | Driscoll-Kraay regression        | Innovations increase the level of CO <sub>2</sub> emissions  |
| Fan and Hossain (2018)                    | 1974-2016             | China & India               | ARDL and causality               | Both innovation and $\mbox{CO}_2$ induce growth in the case of China   |
| Growth, energy use and CO <sub>2</sub> em | nissions              |                             |                                  |  |
| Shahbaz, Raghutla, et al.<br>(2020)       | 1870-2017             | The UK                      | Bootstrapping bounds test method | Energy consumption in the UK increases CO <sub>2</sub><br>emissions levels   |
| Apergis and Payne (2014)                  | 1980-2011             | 25 OECD<br>members          | FMOLS                            | A rise in economic growth level increases the growth of carbon emissions   |
| Leitão and Balsalobre-<br>Lorente (2021)  | 1990-2018             | EU-28                       | DOLS and Granger<br>causality    | Energy consumption (renewable) helps to reduce $CO_2$ emissions in the EU  |
| Gyamfi et al. ( <mark>2021</mark> )       | 1990-2018             | G7 nations                  | AMG and QR                       | Energy consumption increases pollution levels.   |
| Alola (2019)                              | 1990(Q1)-<br>2018(Q2) | The USA                     | Dynamic ARDL                     | Both economic growth and energy use trigger<br>carbon emission levels  |
| Dogan and Aslan (2017)                    | 1995-2011             | EU Countries                | FMOLS and DOLS                   | Economic growth reduces emissions but<br>energy consumptions do not  |
| Ozturk and Acaravci (2016)                | 1980-2006             | Island of Malta &<br>Cyprus | ARDL and causality test          | CO <sub>2</sub> emissions and energy use trigger<br>economic growth  |
| Shahbaz et al. (2016)                     | 1970(Q1)-<br>2011(Q4) | Malaysia                    | ARDL                             | Energy use increases emission intensity and<br>economic growth triggers CO <sub>2</sub> emissions                                  |
| Bekun et al. (2021)                       | 1995-2016             | The E7 countries            | CCEMG and AMG                    | A rise in energy use triggers growth in CO <sub>2</sub><br>emissions levels  |
| Sarkodie and Owusu (2017)                 | 1971 to 2013          | Ghana                       | Linear regression method         | Energy consumption and economic growth<br>increase the level of CO <sub>2</sub> emissions  |
| Adebayo et al. (2021)                     | 1965-2019             | South Korea                 | FMOLS, ARDL, and DOLS            | Economic growth is induced by CO <sub>2</sub> emissions levels   |
| Anwar et al. (2021)                       | 1990-2014             | Asian Countries             | FMOLS and DOLS                   | Energy consumption (renewable) helps to<br>reduce CO <sub>2</sub> emissions but economic growth<br>triggers emissions              |

*Note*: DCCE: UK, United Kingdom; EU, European Union, dynamic common correlated effect; FMOLS, Fully Modified OLS; DOLS, dynamic OLS; QR, quantile regression; AMG, Augmented Mean Group; CCEMG, common correlated effects mean group; POLS, panel ordinary least squares; ARDL, autoregressive distributed lag; OLS, ordinary least squares; GNS, generalized nesting spatial model; BARDL, bootstrapping ARDL.

Clement (2011) examined state-level carbon emissions levels in the United States between 1963 and 1997 while exploring the Jevons paradox within the context of environmental advantages of innovations. His findings show that there are only a few environmental gains from improvements in technology due to capitalism and its political economy. The study showed that although the carbon intensity of all the American states decreased by nearly 30% in the United States between 1963 and 1997, however, there was an increase in total carbon emissions in the country within the same period. The study of York and McGee (2016) also revealed similar results that buttressed Jevons's argument. They studied a panel of selected countries and their finding showed that there is a higher tendency to have higher energy consumption and CO<sub>2</sub> emission from nations with a higher level of energy efficiency. In other words, carbon emission has the tendency to rise in countries with more innovative capacity to improve energy efficiency. This is because the environmental deficits of increased energy consumption rates such as carbon emission due to energy innovation can outweigh the benefits of the increased energy usage itself. Therefore, technological innovations may not really enhance solutions to environmental challenges, especially given the insatiable quest for economic growth that is often propelled by higher energy demand on the ambient of fossil energy consumption. Hence, the validity of the EKC phenomenon also needs to be well scrutinized by accounting for the impact of innovation.

### 2.1 | Review of empirical studies

Some empirical studies have examined how technological innovation impacts the sustainability of the environment amidst economic growth trends and energy use in different countries and the results have often varied across studies. A vast majority of extant studies have captured environmental quality by the level of carbon emissions. Table 1 contains a list of extant empirical studies in two subdivisions. The first part summarizes the findings of the impact of innovative technologies on carbon emission levels, while the second part summarizes the effects of economic growth and energy usage on emissions levels.

### 3 | DATA AND EMPIRICAL METHOD

The summarized details of the data used for the empirical analysis are provided in Table 2. The analysis covers observations from the E7 countries between 1992 and 2018. The dataset used did not cover the pre-1992 periods due to restrictions in data availability on technological innovation for some of the countries, especially Turkey and Indonesia.

### 3.1 | Empirical model

Equation (1) was structured as a baseline model for exploring the roles of technological innovation and energy use in the environmental quality of the E7 Economies. An interaction term between technological innovation proxy and energy use was also incorporated into the model to assess its influence within the framework of the economic growth recorded among the rapidly emerging seven countries.

In the functional Equation (1), the squared values of the amount of carbon emission ( $Y^2$ ) were introduced to reflect the impact of income expansion to assess whether or not the EKC hypothesis holds in the income-environment nexus when technological innovation is accounted for in agreement with extant studies (Baloch et al., 2021; Gyamfi et al., 2021; Su et al., 2021). Having incorporated technological innovation and energy use proxies to observe their impacts, the variable *IVEPC* denotes the interaction between these two variables of interest in the model. All the variables were utilized in natural logarithm form and the empirical procedures have been detailed in the subsequent subheadings of the methodological section.

### 3.2 | Empirical procedures

The analytical approach in this study opens with a critical examination of the datasets for an understanding of their properties. Such critical examinations position researchers for making a well-informed decision

#### TABLE 2 Description of variables

| Proxies                  | Abbreviations   | Information  | Data origin                        |
|--------------------------|-----------------|--|------------------------------------|
| Carbon emissions         | CO <sub>2</sub> | Countries' level of carbon dioxide emissions (presented<br>in million tons)      | British Petroleum (2020)           |
| Income                   | Y               | The countries' real GDP per capita (current US\$)                                | World Development Indicator (2020) |
| Technological innovation | INOV            | Comprises of countries' patents in environment-related technologies (% of total) | OECD (2021)                        |
| Energy consumption       | EPC             | Total primary energy consumption per capita                                      | British Petroleum (2020)           |

Source: Authors' compilation.

Abbreviations: GDP, Gross Domestic Product; BP. British Petroleum; OECD. Organization of Economic Cooperation and Development.

about choices of the right techniques and methodologies vis-à-vis compatibility of approaches with individual data features and variable characteristics. Given the prevailing interconnectivity among economies around the globe that often results in the transfer of economic shocks, similar trends, and patterns among other issues between countries, an examination of likely cross-sectional dependency (CD) in errors among the heterogeneous dataset becomes essential. Chudik and Pesaran (2015) emphasized the significance of paying attention to this test as it is crucial for obtaining robust results while choosing the appropriate heterogeneous panel data estimators. To this end, the study combines the Breusch and Pagan (1980) LM techniques with the duo of Pesaran (2015) LM techniques and Pesaran (2007) CD tests to ascertain the presence of CD. The cruciality of the test has been further reinforced in some empirical research (Adebayo et al., 2022; Erdoğan et al., 2022; Gyamfi et al., 2021; Gyamfi et al., 2022; Onifade, Gyamfi, et al., 2021). The findings relating to the tests affirm the presence of CD (see Section 4 for the full results).

Given the valid insights on the presence of CD, the stationarity test to be adopted for variables and corresponding cointegration examinations must be capable of addressing the CD challenge. As such, the IPS and CIPS techniques were applied in exploring the stationarity properties of the variables. These unit root methodologies are useful for observing variation within panels and the techniques also provide essential features for observing the second-order generation in a typical panel analysis. The equational expression of the CIPS procedures is given in Equation (2), while the corresponding test statistics estimator is presented in Equation (3).

$$\Delta CA_{i,t} = \Phi_i + \Phi_i Z_{i,t-1} + \Phi_i CA_{i\bar{t}-1} + \sum_{1=0}^{p} \Phi i I \Delta CA_{t-1} + \sum_{i=0}^{p} \Phi i I \Delta CA_{i,t1}$$
$$+ \mu_{it}, \qquad (2)$$

$$CIPS_{2007} = N^{-1} \sum_{i=0}^{n} CDFi.$$
 (3)

In Equation (3), the CDF reflects the cross-sectional dependent augmented Dickey-Fuller (CADF), while the cross-sectional (CD) averages are captured by  $CA_{it-1}$  and  $\Delta CA_{i,t1}$ . Moving on, considering the CD properties of the dataset and having utilized a unit root technique that caters to this panel characteristic, the corresponding cointegrating technique to be adopted needs to also take into cognizance the CD challenge in the sample observation. Therefore, the usual first-generation panel, long-run relationship tests could produce misleading evidence for rejecting a null hypothesis under the cointegration analysis. Hence, the Westerlund (2007) secondgeneration cointegration technique was applied to bypass the CD limitation and subsequently ensure accuracy with regard to the validity of the decision on the null hypothesis of no cointegration between panel observations. This cointegration method is modeled after an error adjustment process as depicted in Equation (4) to ascertain long-run relationships between variables vis-à-vis the estimated group statistics (Gt, G $\alpha$ ,) as well as panel statistics (Pt, P $\alpha$ ).

$$\Delta \mathbf{Y}_{it} = \beta_i \mathbf{D}_t + \psi_i \mathbf{Y}_{it-1} + \lambda_i \mathbf{X}_{it-1} + \sum_{j=1}^{p_i} \psi_{ij} \Delta \mathbf{Y}_{i,t-j} + \sum_{j=0}^{p_i} \gamma_{ij} \Delta \mathbf{X}_{i,t-j} + \varepsilon_{it}.$$
(4)

In Equation (4),  $(\psi_i)$  captures the error adjustment process while the  $\beta_t$ captures the vector of parameters. On the other hand, there is a possibility of varying the deterministic representations  $(D_t)$  of the analysis. For instance, a model can be specified with no deterministic term such that  $D_t = 0$ , or there could be specification with just the constant term alone such that  $D_t = 1$ , and both the constant and trend can be captured in the model such that  $D_t = (1, t)$ . The Westerlund (2007) cointegration method stands to be a well-patronized approach in the related literature (Baloch et al., 2021; Bekun et al., 2021) due to its suitability in dealing with matters such as the CD limitations in panel analysis.

#### Long-run and short-run estimations 3.2.1

Considering the outcomes of the preliminary tests, the cross-sectionally augmented autoregressive distributed lag (CS-ARDL) model of Chudik and Pesaran (2015) was adopted for the coefficient analysis. Given the cointegration and unit root evidence that are presented in the results discussion section (Section 4), the panel ARDL approach of Pesaran et al. (1999) could ordinarily be applied, however, Chudik and Pesaran (2015) stressed the disadvantage of doing that, especially in the circumstance where CD characterized the panel sample observation. In such a situation, the CS-ARDL becomes more useful as it utilizes both the mean group (MG) estimator as well as the pooled mean group PMG estimator. The CS-ARDL approach also produces both long-run and short-run estimates, while adjusting the related prediction errors thereby taking care of long-term correlations in panel observation that are characterized by heterogeneous effects. Besides, the approach becomes more useful given the nature of the study's sample observation with relatively small T where variables are characterized with a mixed integration order { (0) or I(1)} (Chudik et al., 2016; Erülgen et al., 2020).

$$\Delta \mathbf{Y}_{it} = \delta_i \left\{ \mathbf{Y}_{i(t-1)} - \vartheta_i \mathbf{X}_{it} \right\} + \sum_{j=1}^{p-1} \beta_{ij} \Delta \mathbf{Y}_{i(t-j)} + \sum_{j=0}^{q-1} \pi_{ij} \Delta \mathbf{X}_{i(t-j)} + \varphi_i + \varepsilon_{it} \quad (5)$$

In the error adjustment procedure of a simplified panel ARDL model, as shown in Equation (5), the adjustment term is represented by  $\{Y_{i(t-1)} - \vartheta_i X_{it}\}$  while  $\vartheta_i$  represent the long-run relationship vector. On the other hand, the  $\delta_i$  coefficient denotes the expected groupspecific correction speed which ought to be negative and significant to uphold its validness while the corresponding short-run estimates are captured by the  $\beta_{ii}$  and  $\pi_{ii}$  parameters. The traditional panel ARDL still retains its validity regardless of the cointegration order but the estimates become unreliable if errors are cross-sectionally correlated. Thus, to bypass this setback, the panel CS-ARDL augments the model with the cross-sectional averages of the explanatory variables, the dependent variables, and a combination of their lag values to effectively correct the cross-sectional correlation in the error component.

### TABLE 3 Statistical properties of the variables

Sustainable Development

| E7 countries | CO <sub>2</sub> emissions | Technological innovation | Energy consumption | Economic growt |
|--------------|---------------------------|--------------------------|--------------------|----------------|
| China        |                           |                          |                    |                |
| Mean         | 3.729844                  | 0.884412                 | 1.714709           | 3.310544       |
| Maxi         | 3.978049                  | 1.003461                 | 1.978185           | 3.998986       |
| Mini         | 3.411824                  | 0.564666                 | 1.420179           | 2.564027       |
| Std. Dev.    | 0.210854                  | 0.096611                 | 0.203265           | 0.467329       |
| India        |                           |                          |                    |                |
| Mean         | 3.098936                  | 0.827484                 | 1.180111           | 2.879789       |
| Maxi         | 3.389609                  | 1.050766                 | 1.391285           | 3.300360       |
| Mini         | 2.826904                  | 0.447158                 | 1.001982           | 2.478796       |
| Std. Dev.    | 0.178365                  | 0.159288                 | 0.123285           | 0.277843       |
| Brazil       |                           |                          |                    |                |
| Mean         | 2.532210                  | 0.911235                 | 1.692408           | 3.771047       |
| Maxi         | 2.702241                  | 1.161667                 | 1.786483           | 4.122072       |
| Mini         | 2.335096                  | 0.382017                 | 1.577101           | 3.414459       |
| Std. Dev.    | 0.106036                  | 0.220362                 | 0.063615           | 0.233778       |
| Mexico       |                           |                          |                    |                |
| Mean         | 2.588779                  | 0.946789                 | 1.782952           | 3.876469       |
| Maxi         | 2.678469                  | 1.170555                 | 1.820915           | 4.038577       |
| Mini         | 2.447141                  | 0.416641                 | 1.738009           | 3.594196       |
| Std. Dev.    | 0.078104                  | 0.191694                 | 0.027311           | 0.130574       |
| Russia       |                           |                          |                    |                |
| Mean         | 3.188598                  | 1.030554                 | 2.282383           | 3.715925       |
| Maxi         | 3.316508                  | 1.192846                 | 2.364279           | 4.203431       |
| Mini         | 3.159880                  | 0.912753                 | 2.230459           | 3.124099       |
| Std. Dev.    | 0.035995                  | 0.061286                 | 0.030637           | 0.343500       |
| Indonesia    |                           |                          |                    |                |
| Mean         | 2.518847                  | 0.927612                 | 1.344231           | 3.197972       |
| Maxi         | 2.763967                  | 1.311966                 | 1.487555           | 3.590380       |
| Mini         | 2.205565                  | 0.365488                 | 1.143253           | 2.666469       |
| Std. Dev.    | 0.169072                  | 0.251092                 | 0.103408           | 0.295841       |
| Turkey       |                           |                          |                    |                |
| Mean         | 2.372414                  | 0.870992                 | 1.740040           | 3.792023       |
| Maxi         | 2.598909                  | 1.329805                 | 1.895211           | 4.100880       |
| Mini         | 2.157550                  | 0.580925                 | 1.587141           | 3.356090       |
| Std. Dev.    | 0.134117                  | 0.146548                 | 0.092809           | 0.251901       |

Source: Computed by Author.

Note: Std Dev. denotes standard deviation, while Maxi and Mini denote the maximum and the minimum values in that order.

Hence, the augmented representation of the model for the CS-ARDL is given in Equation (6).

$$\Delta Y_{it} = \delta_i \left\{ Y_{i(t-1)} - \vartheta_i X_{it} + \alpha_i^{-1} n_i \overline{Y}_t + \alpha_i^{-1} Y_i \overline{X}_t \right\} + \sum_{j=1}^{p-1} \beta_{ij} \Delta Y_{i(t-j)}$$
$$+ \sum_{j=0}^{q-1} \pi_{ij} \Delta X_{i(t-j)} + \sum_{j=0}^{p-1} \lambda_{ik} \Delta \overline{Y}_{i(t-j)} + \sum_{j=0}^{q-1} Y_{ik} \Delta \overline{X}_{i(t-j)} + \varphi_i + \varepsilon_{it} \quad (6)$$

In Equation (6), the cross-sectional average of the variables  $Y_{it}$  and  $X_{it}$  are denoted by  $\overline{Y}_t$  and  $\overline{X}_t$ , respectively, while the level components

of the cross-sectional averages are utilized in capturing the longrun equilibrium interactions as encapsulated in the bracket. The pace of equilibrium correction is denoted by  $\delta_i$ , while  $\vartheta_i$  captures the needed long-run estimates. The results of the estimates were provided in the discussion section. From there, the estimates from the panel PMG-ARDL approach of Pesaran et al. (1999) were also reported for sensitivity checks and comparative analysis before finalizing the analysis with a granger causality report following the Dumitrescu and Hurlin (2012) causality approach. 8

Correlation evidence

TABLE 4

| Variables         | LnCO <sub>2</sub> | LnY       | LnY <sup>2</sup> | LnINOV    | LnEPC     | LnIVEPC |
|-------------------|-------------------|-----------|------------------|-----------|-----------|---------|
| LnCO <sub>2</sub> | 1                 |           |                  |           |           |         |
| p-value           | -                 |           |                  |           |           |         |
| LnY               | -0.1506**         | 1         |                  |           |           |         |
| p-value           | (0.0385)          | -         |                  |           |           |         |
| LnY <sup>2</sup>  | -0.1481**         | 0.9979*** | 1                |           |           |         |
| p-value           | (0.0419)          | (0.0000)  | -                |           |           |         |
| LnINOV            | 0.0884            | 0.3078*** | 0.3070           | 1         |           |         |
| p-value           | (0.2262)          | (0.0000)  | (0.0000)         | -         |           |         |
| LnEPC             | 0.2295***         | 0.7152*** | 0.7076***        | 0.3281    | 1         |         |
| p-value           | (0.0015)          | (0.0000)  | (0.0000)         | (0.0000)  | -         |         |
| LnIVEPC           | 0.2170***         | 0.6214*** | 0.6187***        | 0.7718*** | 0.8448*** | 1       |
| p-value           | (0.0027)          | (0.0000)  | (0.0000)         | (0.0000)  | (0.0000)  | -       |

Source: Computed by author.

\*\*\*Statistical relevance of value at the 1% level.

\*\*Statistical relevance of values at the 5% level.

#### TABLE 5 Cross-sectional dependency result

| Technique(s)      | Breusch and Pagan (1980) LM test | Pesaran (2007) CD test | Pesaran (2015) LM test |
|-------------------|----------------------------------|------------------------|------------------------|
| Equation (1)      | 426.83***                        | 20.58***               | 62.62***               |
| Estimated P-value | (0.0000)                         | (0.0000)               | (0.0000)               |

\*\*\*Statistical relevance of value at the 1% level.

### 4 | FINDINGS AND DISCUSSION

A summary of the descriptive statistics for individual country variables and a sample correlation matrix for the panel observations heralded the presentation of data and empirical discussion as seen in Tables 3 and 4 respectively. The highest level of average carbon emissions throughout the study is recorded in China followed by Russia, India, Mexico, Brazil, Indonesia, and Turkey, respectively. China also takes the lead in the amount of energy consumption on average over the sample period. As for the correlation among the variables, economic growth and energy use are positively correlated with carbon emission while no significant correlation can be seen between emission and energy innovations. The correlation output partly reveals just a handful of information which is certainly not sufficient as it does not show the true magnitude of impacts of these variables on the emission level. Hence, some other vital preliminary analyses were conducted to take into cognizance the nature of the data set.

Further results from the preliminary evaluations confirmed that the dataset for the study suffers from cross-sectional dependence (CD) as seen in Table 5. All the test statistics lend credence to the presence of CD and as such, the unit-root test conducted also took cognizance of this crucial issue. In Table 6, the findings from the CDcompactible unit root tests (CIPS and IPS) reveal that all data are differenced stationary [I(1)] datasets except for the technology innovation data set and the interaction term that are stationary at the level which implies that they are I(0) proxies. This result necessitates that long-run estimators that are compatible for mixed order of integration among variables must be applied if there is evidence of cointegration among the variables. As such, following the confirmation of the long-run relationship among variables by both panel and group statistics of the Westerlund (2007) approach in Table 6, the study adopted the CS-ARDL panel estimator to examine the long-run coefficients as reported in Table 7.

### 4.1 | Coefficient and causality estimates

The output of the empirical results from the CS-ARDL model provides critical information that is apt for policy directives for the E7 economies unlike the results from the PMG techniques that are unreliable due to the challenges of CD that have been established in the preliminary analysis. Hence, following the CS-ARDL estimates in Table 7, the results reveal that both energy consumption and economic growth (real income levels) occur as significant drivers of environmental pollution in the E7 countries. According to the estimates, a percent rise in energy consumption level and economic growth levels induce pollution from  $CO_2$  emissions by 0.51% and 0.68%, respectively. The observed impacts of these two variables reflect the destructive

#### TABLE 6 Unit root and cointegration results

|  | CIPS approach           | $\begin{tabular}{c} & & & & & \\ \hline & & & & & \\ \hline & & & & & \\ \hline & & & &$ |               |                                  |            |           |
|--|-------------------------|--|---------------|----------------------------------|------------|-----------|
|  | Intercept and trend     |  |               |                                  |            |           |
|  | D <sub>t</sub> = (1, t) |  |               |                                  |            |           |
| List of variables For level analysis Analysis at the first difference    |                         | e For l  | evel analysis | Analysis at the first difference |            |           |
| LnCO <sub>2</sub>  | -2.203 -3.991***        |  | -2.0          | )462                             | -4.6616*** |           |
| LnY  | -3.044** -4.984***      |  | -1.6          | 5719                             | -4.2803*** |           |
| LnY <sup>2</sup>   | -2.674 -4.834***        |  | -1.6984       |                                  | -4.1915*** |           |
| Ln <i>INOV</i>   | -5.005***               | -6.059***  | -4.6          | 623***                           | -7.7833*** |           |
| LnEPC  | -2.011                  | -3.521***  | -2.0          | 0420                             | -4.3389*** |           |
| Ln <i>IVEPC</i>  | -4.868***               | -5.877***  | -4.4          | 1028***                          | -7.6138*** |           |
| Westerlund cointeg   | ration                  |  |               |                                  |            |           |
| Model 1  |                         |  | Group         |                                  | Panel      |           |
| $LnCO_2 = f(LnY)$ , $(LnY^2)$ , $(LnINOV)$ , $(LnEPC)$ , and $(LnIVEPC)$ |                         |  | Gτ            | Gα                               | Ρτ         | Ρα        |
| Statistics   |                         |  | -1.718***     | -1.906 ***                       | -4.309***  | -4.577*** |
| Robust <i>p</i> -value   |                         |  | 0.0000        | 0.0000                           | 0.0000     | 0.0000    |

Source: Computed by author.

\*\*\*Statistical relevance of value at the 1% level.

\*\*Statistical relevance of value at the 5% level.

#### TABLE 7 Long- and short-run coefficient estimates

|   | Long-run coefficients  |         |               | Country-specific ECT (PMG) |              |            |          |
|---|------------------------|---------|---------------|----------------------------|--------------|------------|----------|
| List of variables CO <sub>2</sub> (explained) | CS-ARDL Estimates      | P-value | PMG Estimates | P-value                    | E7 countries | Estimates  | P-values |
| LnY   | 0.6869***              | 0.0005  | 1.3738***     | 0.0000                     | China        | -0.0764*** | 0.0000   |
| LnY <sup>2</sup>                              | -0.0976***             | 0.0003  | -0.2549***    | 0.0000                     | India        | -0.4774*** | 0.0001   |
| LnINOV  | -0.1733**              | 0.0430  | -0.2313       | 0.3626                     | Brazil       | -0.0055*** | 0.0017   |
| LnEPC   | 0.5107***              | 0.0000  | 1.4496***     | 0.0000                     | Mexico       | -0.0135*** | 0.0000   |
| LnIVEPC                                       | 0.0963**               | 0.0310  | 0.2335        | 0.2552                     | Russia       | 0.0115     | 0.0000   |
|   | Short-run coefficients |         |               |                            | Indonesia    | -0.0153*** | 0.0000   |
| ECT   | -0.9753***             | 0.0000  | -0.0834       | 0.2116                     | Turkey       | -0.0075*** | 0.0004   |
| ΔLnY  | 1.2936***              | 0.0002  | 0.1049        | 0.6954                     |              |            |          |
| $\Delta LnY^2$                                | -0.1848***             | 0.0001  | -0.0131       | 0.7089                     |              |            |          |
| ΔLnINOV                                       | -0.3340**              | 0.0420  | -0.1153       | 0.3702                     |              |            |          |
| ∆LnEPC  | 1.0064***              | 0.0000  | 0.9599***     | 0.0000                     |              |            |          |
| ∆LnIVEPC                                      | 0.1863**               | 0.0310  | 0.0462        | 0.5517                     |              |            |          |
| С   | -1.9753***             | 0.0000  | -0.0413       | 0.1829                     |              |            |          |
| No. regressors                                | 5                      |         | 5             |                            |              |            |          |
| No. Observations                              | 175                    |         | 175           |                            |              |            |          |
| No. group                                     | 7                      |         | 7             |                            |              |            |          |

Source: Computed by author.

\*\*\*Statistical relevance of values at the 1% level.

\*\*Statistical relevance of value at the 5% level.

consequences of the environmentally detrimental economic growth push among the E7 countries. The upward trend in the level of economic growth is anchored on increased energy demands that are

essentially sustained by fossil fuel usage which is known to constitute the largest chunk of the total primary energy consumption in the emerging seven (E7) economies. The observed environmentally

TABLE 8 Panel causality evidence

|                   | ZDar-Stat         |           |           |           |  |
|-------------------|-------------------|-----------|-----------|-----------|--|
| Variables         | LnCO <sub>2</sub> | LnY       | LnINOV    | LnEPC     | Causality scheme                                       |
| LnCO <sub>2</sub> | -                 | 6.8921*** | 5.2775*** | 7.7935*** | $LnCO_2 \rightarrow LnY, LnINOV, LnEPC$                |
| LnY               | 2.4578**          | -         | 3.5610*** | 3.2986*** | $LnY \rightarrow LnCO_2, LnINOV, LnEPC$                |
| LnINOV            | 1.0329            | -0.3135   | -         | 2.6499*** | $\text{Ln}\text{INOV} \rightarrow \text{Ln}\text{EPC}$ |
| LnEPC             | 3.4722***         | 5.1593*** | 4.8878*** | -         | $LnEPC \rightarrow LnCO_2, LnY, LnINOV$                |
|                   |                   |           |           |           |  |

Source: Computed by author.

\*\*\*Statistical relevance of value at the 1% level.

Zhar stat

\*\*Statistical relevance of value at the 5% level.

destructive impacts of economic growth and energy consumption, in the long run, are also consistent with the short-run estimates from the model. Also, there is a two-way causality between energy consumption, economic growth, and carbon emissions among these countries as seen in Table 8. The overall results resonate with some empirical information on the nexus among these variables as obtainable in some extant empirical studies, howbeit, some of the studies were in different climes and used other techniques (Alola, 2019; Sarkodie & Owusu, 2017; Shahbaz et al., 2016). The current findings further buttress the empirically substantiated arguments in support of the need for the E7 nations to address their energy portfolios such that the proportion of conventional energy use in total primary energy consumption is reduced to the barest minimal. In this regard, going by several empirical results on the roles of renewables in improving environmental quality as seen in the extant literature (Erdoğan et al., 2021; Onifade, Alola, et al., 2021; Usman & Balsalobre-Lorente, 2022), more investments in renewable energy would help to further position the E7 economies on the expected environmental sustainability path.

On the other hand, technological innovations produced some succoring shreds of evidence for environmental sustainability among the E7 countries. The estimated CS-ARDL model shows that a percent growth in technological innovation reduces emissions levels by 0.17% in the long run. This nexus is also validated in the short-run dynamics although with a much higher magnitude compared to what is obtainable in the long-run dynamics. This is an indicator for policymakers and authorities in the E7 to leverage on the instrumentality of technological innovation for environmental gains. The results complement a couple of studies in the literature on the beneficial roles of innovation in combating environmental menace (Amin et al., 2020; Shahbaz, Raghutla, et al., 2020; Tao et al., 2021).

However, on the aspect of the impacts of the interaction between innovation and energy consumption, the empirical analysis produced contrary evidence for upholding the innovationenvironmental sustainability nexus as a percent rise in the interaction of these variables significantly induces pollution from  $CO_2$  emission by around 0.096%. Although this magnitude is relatively low compared to the impacts of other variables, it, however, portends crucial information about the E7 economies. A possible explanation for this result among the emerging seven (E7) countries is that the environmental gains from innovations tend to be significantly undermined or at least overwhelmed by the magnitude of the impacts of the unsustainable energy portfolios that features environmentally detrimental energy sources as the largest share of the overall total primary energy consumption. Another important point is that the innovation being witnessed among the E7 countries vis-à-vis the energy required to actualize their desired economic growth target has perhaps mainly accelerated higher rates of overall energy use rather than creating a reduction in energy intensity via higher efficiency as expected. Thus, the scenario at play partly aligns with the arguments of Jevons (Jevons, 2001) that innovations may not enhance overall environmental sustainability as expected by a reduction in energy consumption on a broad scale, even though it can reduce carbon emissions levels. Besides, looking at the granger causality in Table 8, it can be further observed that the only directional causality from innovations relates to energy consumption and the latter variable has witnessed exponential growth in the E7 countries over the last couple of decades (British Petroleum, 2020).

Lastly, while a detrimental impact of economic growth was confirmed in the study in terms of environmental sustainability, there is also evidence that this detrimental effect is expected to be neutralized by income expansion as seen by the significant negative impact of the income square coefficient in the CS-ARDL model. This result thus approves the EKC conjecture for the E7 countries within the incomesustainability framework when technological innovation is accounted for thereby lending credence to some evidence in support of the EKC validity in emerging economies (Baloch et al., 2021). In the results in Table 7, there is no evidence that the system will adjust to equilibrium under the PMG approach as the overall coefficient estimate for the ECT was found to be statistically insignificant despite the possibility of equilibrium adjustment in the country-specific short-run subcategory. This finding further reveals the shortcomings of the PMG technique in the presence of cross-sectional dependency. On the other hand, the CS-ARDL estimates reveal that there will be a significant adjustment to equilibrium for the system following the significant negative value of the ECT (-0.9753). In a nutshell, the use of the lagged cross-sectional averages in the CS-ARDL technique proved to be a better option to the PMG approach as it has taken care of any cross-correlation in residuals owing to identified common factors among observations.

## 5 | CONCLUSION AND POLICY REFLECTION

The impacts of technological innovation and energy use on the environmental quality of the E7 economies have been explored in this study. While doing so, the interaction between the variables was also incorporated into the model to assess its influence among the E7 economies using data covering 1992–2018. The result confirmed the EKC conjecture and suggested that innovation cushions pollutant emissions in the E7 economies. Both energy consumption and economic growth were found to be an adversary to the sustainability of the environment in these emerging economies. Furthermore, while innovation cushions pollutant emissions among the countries, its desirable environmental impacts become unnoticeable when interacting with the level of energy consumption among these economies. A major explanation for this development lies in the overwhelming share of conventional energy use in the overall energy portfolios of the E7 economies. As such, the gains from innovations can be said to be undermined in the E7. The causality results also provided some corroborative evidence for the estimates and these inform useful policy directives for the E7 economies and other emerging economies at large.

### 5.1 | Policy

Considering that the environmental-related technological innovation shows a mitigation impact on carbon emission, more responsibility is bestowed on the emerging economies to ensure technology and innovation-driven investments. Moreover, because environmentalrelated technological innovation has the potential of moderating the role of primary energy utilization on carbon emission, this further suggests that more intervention should be geared toward energyspecific technologies and innovations. By so doing, more desirable outcomes about the mitigation of carbon emissions could be attained over time, especially with the right attitude toward environmental responsibility.

In concrete terms, the authorities of the E7 nations can take advantage of diverse approaches to exploiting the environmental benefits of innovations including the adoption of a public-private partnership model in funding and promoting research and development (R&D) projects about environmental protection. The authorities of the E7 economies should also prioritize adequate funding and supports for established research institutions, technical and tertiary institutions, and other ingenious establishments that are saddled with specific environmental targets. Furthermore, there is a need for the E7 nations to address their energy portfolios such that the proportion of conventional energy use in total primary energy consumption is reduced to the barest minimum. In this regard, the authorities of the E7 should be committed to providing adequate investment supports for innovative technologies, especially renewable energy technologies to rightly position the E7 economies on the expected environmental sustainability path.

## 5.2 | Limitations and the future research directions

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The current study adopts novel approaches for the empirical analysis from the case of the E7 economies thus providing a solid foundation for more investigations to be conducted in other blocs. However, while the roles of energy use were aggregated in total primary energy consumption in the current study, future studies can extend the established framework to examine the roles of disaggregated energy use (individual energy types) within the innovation-environmental nexus analysis for the E7 countries or other blocs.

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#### AVAILABILITY OF DATA AND MATERIALS

The data for this present study are sourced from the database of the World Development Indicators (https://data.worldbank.org), the British Petroleum (BP) Statistical Review of World Energy data (http:// www.bp.com/statisticalreview) and the Organization of Economic Cooperation and Development (OECD) (https://data.oecd.org/ envpolicy/patents-on-environment-technologies).

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### CONFLICT OF INTEREST

I wish to disclose here that there are no potential conflicts of interest at any level of this study.

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### ENDNOTE

<sup>1</sup> IPCC is the Intergovernmental Panel on Climate Change.

### REFERENCES

- Adebayo, T. S., Awosusi, A. A., Kirikkaleli, D., Akinsola, G. D., & Mwamba, M. N. (2021). Can CO<sub>2</sub> emissions and energy consumption determine the economic performance of South Korea? A time series analysis. *Environmental Science and Pollution Research*, 28(29), 38969-38984.
- Adebayo, T. S., Onifade, S. T., Alola, A. A., & Muoneke, O. B. (2022). Does it take international integration of natural resources to ascend the ladder of environmental quality in the newly industrialized countries? *Resources Policy*, 76, 102616. https://doi.org/10.1016/j.resourpol.2022.102616
- Allen, R. C. (2009). The British industrial revolution in global perspective. Cambridge University Press.
- Alola, A. A. (2019). Carbon emissions and the trilemma of trade policy, migration policy and health care in the US. *Carbon Management*, 10(2), 209–218.
- Alola, A. A., Adebayo, T. S., & Onifade, S. T. (2021). Examining the dynamics of ecological footprint in China with spectral granger causality and

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quantile-on-quantile approaches. *International Journal of Sustainable Development & World Ecology, 29*(3), 263-276. https://doi.org/10. 1080/13504509.2021.1990158

- Alola, A. A., Akadiri, S. S., & Usman, O. (2021). Domestic material consumption and greenhouse gas emissions in the EU-28 countries: Implications for environmental sustainability targets. *Sustainable Development*, 29(2), 388–397.
- Alola, A. A., & Nwulu, N. (2021). Income vs. economic freedom threshold and energy utilities in Russia: An environmental quality variableness? *Environmental Science and Pollution Research*, 28(26), 35297–35304.
- Álvarez-Herránz, A., Balsalobre, D., Cantos, J. M., & Shahbaz, M. (2017). Energy innovations-GHG emissions nexus: Fresh empirical evidence from OECD countries. *Energy Policy*, 101, 90–100.
- Amin, A., Aziz, B., & Liu, X. H. (2020). The relationship between urbanization, technology innovation, trade openness, and CO<sub>2</sub> emissions: Evidence from a panel of Asian countries. *Environmental Science and Pollution Research*, 27(28), 35349–35363.
- Anderson, K., & Bows, A. (2011). Beyond 'dangerous' climate change: Emission scenarios for a new world. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 369(1934), 20–44.
- Anwar, A., Sinha, A., Sharif, A., Siddique, M., Irshad, S., Anwar, W., & Malik, S. (2021). The nexus between urbanization, renewable energy consumption, financial development, and CO<sub>2</sub> emissions: Evidence from selected Asian countries. *Environment, Development and Sustainability*, 24(5), 6556-6576.
- Apergis, N., & Payne, J. E. (2014). The causal dynamics between renewable energy, real GDP, emissions and oil prices: Evidence from OECD countries. *Applied Economics*, 46(36), 4519–4525.
- Baloch, M. A., Danish, & Qiu, Y. (2021). Does energy innovation play a role in achieving sustainable development goals in BRICS countries? *Environmental Technology*, 1–10.
- Balsalobre-Lorente, D., Ibáñez-Luzón, L., Usman, M., & Shahbaz, M. (2022). The environmental Kuznets curve, based on the economic complexity, and the pollution haven hypothesis in PIIGS countries. *Renewable Energy*, 185, 1441–1455.
- Bekun, F. V., Gyamfi, B. A., Onifade, S. T., & Agboola, M. O. (2021). Beyond the environmental Kuznets curve in E7 economies: Accounting for the combined impacts of institutional quality and renewables. *Journal of Cleaner Production*, 314, 127924. https://doi.org/10.1016/j.jclepro. 2021.127924
- Breusch, T. S., & Pagan, A. R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies*, 47(1), 239–253.
- British Petroleum. (2020). Statistical Review of World Energy June 2020. Available at: http://www.bp.com/statisticalreview. Accessed May 2021
- Bunker, S. (1996). Raw materials and the global economy: Oversights and distortions in industrial ecology. Society & Natural Resources, 9, 419–429.
- Chudik, A., Mohaddes, K., Pesaran, M. H., & Raissi, M. (2016). Long-run effects in large heterogeneous panel data models with cross-sectionally correlated errors. Emerald Group Publishing Limited. https://doi.org/ 10.1108/S0731-905320160000036013
- Chudik, A., & Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, 188(2), 393–420. https://doi. org/10.1016/j.jeconom.2015.03.007
- Chen, Y., & Lee, C. C. (2020). Does technological innovation reduce CO2 emissions? Cross-country evidence. *Journal of Cleaner Production*, 263, 121550.
- Clement, M. T. (2011). The Jevons paradox and anthropogenic global warming: A panel analysis of state-level carbon emissions in the United States, 1963–1997. Society & Natural Resources, 24(9), 951–961.

- Dogan, E., & Aslan, A. (2017). Exploring the relationship among CO<sub>2</sub> emissions, real GDP, energy consumption and tourism in the EU and candidate countries: Evidence from panel models robust to heterogeneity and cross-sectional dependence. *Renewable and Sustainable Energy Reviews*, 77, 239–245.
- Dumitrescu, E., & Hurlin, C. (2012). Testing for granger non-causality in heterogeneous panels. *Economic Modelling*, 29(4), 1450–1460. https:// doi.org/10.1016/j.econmod.2012.02.014
- Erdogan, S. (2021). Dynamic nexus between technological innovation and buildings Sector's carbon emission in BRICS countries. *Journal of Envi*ronmental Management, 293, 112780.
- Onifade, S. T., Erdoğan, S., Alagöz, M., & Bekun, F. V. (2021). Renewables as a pathway to environmental sustainability targets in the era of trade liberalization: Empirical evidence from Turkey and the Caspian countries. Environmental Science and Pollution Research, 28(31), 41633-41674. https://doi.org/10.1007/s11356-021-13684-1
- Erdoğan, S., Onifade, S. T., Altuntaş, M., & Bekun, F. V. (2022). Synthesizing urbanization and carbon emissions in Africa: How viable is environmental sustainability amid the quest for economic growth in a globalized world? Environmental Science and Pollution Research, 29(16), 24348-24361. https://doi.org/10.1007/s11356-022-18829-4
- Erülgen, A., Rjoub, H., & Adalıer, A. (2020). Bank characteristics effect on capital structure: Evidence from PMG and CS-ARDL. *Journal of Risk* and Financial Management, 13(12), 310.
- Etokakpan, M. U., Akadiri, S. S., & Alola, A. A. (2021). Natural gas consumption-economic output and environmental sustainability target in China: An N-shaped hypothesis inference. *Environmental Science* and Pollution Research, 28(28), 37741–37753.
- Fan, H., & Hossain, M. I. (2018). Technological innovation, trade openness, CO<sub>2</sub> emission and economic growth: Comparative analysis between China and India. International Journal of Energy Economics and Policy, 8(6), 240.
- Friedrich, J., & Damassa, T. (2014). The history of carbon dioxide emissions. Avialable at. https://www.wri.org/insights/history-carbondioxide-emissions#fnref:1
- Godil, D. I., Yu, Z., Sharif, A., Usman, R., & Khan, S. A. R. (2021). Investigate the role of technology innovation and renewable energy in reducing transport sector CO<sub>2</sub> emission in China: A path toward sustainable development. Sustainable Development, 29(4), 694-707.
- Gyamfi, B. A., Bekun, F. V., Balsalobre-Lorente, D., Onifade, S. T., & Ampomah, A. B. (2022). Beyond the environmental Kuznets curve: Do combined impacts of air transport and rail transport matter for environmental sustainability amidst energy use in E7 economies? *Environment, Development and Sustainability*, 1-19. https://doi.org/10.1007/ s10668-021-01944-6
- Gyamfi, B. A., Onifade, S. T., Nwani, C., & Bekun, F. V. (2021). Accounting for the combined impacts of natural resources rent, income level, and energy consumption on environmental quality of G7 economies: A panel quantile regression approach. *Environmental Science and Pollution Research*, 29(2), 2806-2818. https://doi.org/10.1007/s11356-021-15756-8
- Huang, Y., Xue, L., & Khan, Z. (2021). What abates carbon emissions in China: Examining the impact of renewable energy and green investment. Sustainable Development, 29(5), 823–834.
- IPCC (2007). Summary for policymakers. In Climate change 2007: The physical science basis. Contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change. Cambridge University Press.
- IPCC (2021). Summary for policymakers. In V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. B. R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, & B. Zhou (Eds.), Climate change 2021: The physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change. Cambridge University Press.
- Jahanger, A., Usman, M., Murshed, M., Mahmood, H., & Balsalobre-Lorente, D. (2022). The linkages between natural resources, human

capital, globalization, economic growth, financial development, and ecological footprint: The moderating role of technological innovations. *Resources Policy*, *76*, 102569.

- Jevons, W. S. (2001). Of the economy of fuel. Organization & Environment, 14(1), 99–104.
- Jiang, T., Yu, Y., Jahanger, A., & Balsalobre-Lorente, D. (2022). Structural emissions reduction of China's power and heating industry under the goal of" double carbon": A perspective from input-output analysis. *Sustainable Production and Consumption*, 31, 346–356.
- Jolly, W. M., Cochrane, M. A., Freeborn, P. H., Holden, Z. A., Brown, T. J., Williamson, G. J., & Bowman, D. M. (2015). Climate-induced variations in global wildfire danger from 1979 to 2013. *Nature Communications*, 6(1), 1–11.
- Kasa, S. (1973). Industrial revolutions and environmental problems. Confluence, 1941, 70.
- Kuznets, S. (1955). Economic growth and income inequality. The American Economic Review, 45(1), 1–28.
- Leitão, N. C., & Balsalobre-Lorente, D. (2021). The effects of tourism, economic growth and renewable energy on carbon dioxide emissions. In In strategies in sustainable tourism, economic growth and clean energy (pp. 67–87). Springer.
- Mora, C., Rollins, R. L., Taladay, K., Kantar, M. B., Chock, M. K., Shimada, M., & Franklin, E. C. (2018). Bitcoin emissions alone could push global warming above 2 C. *Nature Climate Change*, 8(11), 931–933.
- OECD (2021). Patents in environment-related technologies. Organization for Economic Co-operation and Development. Available at https:// data.oecd.org/envpolicy/patents-on-environment-technologies.htm Accessed November 2021
- Onifade, S. T. (2022). Retrospecting on resource abundance in leading oilproducing African countries: How valid is the environmental Kuznets curve (EKC) hypothesis in a sectoral composition framework? *Environmental Science and Pollution Research*. https://doi.org/10.1007/ s11356-022-19575-3
- Onifade, S. T., Alola, A. A., Erdoğan, S., & Acet, H. (2021). Environmental aspect of energy transition and urbanization in the OPEC member states. Environmental Science and Pollution Research, 28(14), 17158– 17169. https://doi.org/10.1007/s11356-020-12181-1
- Onifade, S. T., Gyamfi, B. A., Ilham, H., & Bekun, F. V. (2021). Re-examining the roles of economic globalization on environmental degradation in the E7 economies: Are human capital, urbanization, and Total natural resources essential components? *Resources Policy*. https://doi.org/10. 1016/j.resourpol.2021.102435
- Ozturk, I., & Acaravci, A. (2016). Energy consumption, CO<sub>2</sub> emissions, economic growth, and foreign trade relationship in Cyprus and Malta. *Energy Sources, Part B: Economics, Planning, and Policy*, 11(4), 321–327.
- Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross section dependence. *Journal of Applied Econometrics*, 22(2), 265–312.
- Pesaran, M. H. (2015). Testing weak cross-sectional dependence in large panels. *Economic Review*, 34(6–10), 1089–1117.
- Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, 94(446), 621–634.
- Ritchie, H., & Roser, M. (2020). CO<sub>2</sub> and greenhouse gas emissions: Our world in data.https://ourworldindata.org/grapher/temperatureanomaly?time=1850.2019&country=~Global

Sarkodie, S., & Owusu, P. A. (2017). Recent evidence of the relationship between carbon dioxide emissions, energy use, GDP, and population in Ghana: A linear regression approach. *Energy Sources, Part B: Economics, Planning, and Policy*, 12(6), 495–503.

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- Shahbaz, M., Loganathan, N., Muzaffar, A. T., Ahmed, K., & Jabran, M. A. (2016). How urbanization affects CO2 emissions in Malaysia? The application of STIRPAT model. *Renewable and Sustainable Energy Reviews*, 57, 83–93.
- Shahbaz, M., Nasir, M. A., Hille, E., & Mahalik, M. K. (2020). UK's net-zero carbon emissions target: Investigating the potential role of economic growth, financial development, and R&D expenditures based on historical data (1870–2017). Technological Forecasting and Social Change, 161, 120255.
- Shahbaz, M., Raghutla, C., Song, M., Zameer, H., & Jiao, Z. (2020). Publicprivate partnerships investment in energy as new determinant of CO2 emissions: The role of technological innovations in China. *Energy Economics*, 86, 104664.
- Su, C. W., Xie, Y., Shahab, S., Faisal, C., Nadeem, M., Hafeez, M., & Qamri, G. M. (2021). Towards achieving sustainable development: Role of technology innovation, technology adoption and CO<sub>2</sub> emission for BRICS. International Journal of Environmental Research and Public Health, 18(1), 277.
- Tao, R., Umar, M., Naseer, A., & Razi, U. (2021). The dynamic effect of ecoinnovation and environmental taxes on carbon neutrality target in emerging seven (E7) economies. *Journal of Environmental Management*, 299, 113525.
- UNEP. (2018). *The emissions gap report 2018*. United Nations Environment Programme.
- UNEP (2021). United Nations Environment Program: Emissions Gap Report. The Heat Is On – A World of Climate Promises Not Yet Delivered. Nairobi. Retrieved November 1, 2021 from www.unep.org/ resources/emissions-gap-report-2021.
- Usman, M., & Balsalobre-Lorente, D. (2022). Environmental concern in the era of industrialization: Can financial development, renewable energy and natural resources alleviate some load? *Energy Policy*, 162, 112780.
- Wang, Z., & Zhu, Y. (2020). Do energy technology innovations contribute to CO2 emissions abatement? A spatial perspective. *Science of the Total Environment*, 726, 138574.
- Westerlund, J. (2007). Testing for error correction in panel data. Oxford Bulletin of Economics and Statistics, 69(6), 709-748.
- World Development Indicators. (2020). Available at: https://data. worldbank.org/indicator. Accessed December 2020
- York, R., & McGee, J. A. (2016). Understanding the Jevons paradox. Environmental. Sociology, 2(1), 77–87.
- Zoaka, J. D., Ekwueme, D. C., Güngör, H., & Alola, A. A. (2022). Will financial development and clean energy utilization rejuvenate the environment in BRICS economies? *Business Strategy and the Environment*.

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Development, 1–13. https://doi.org/10.1002/sd.2346