Energy Reports 8 (2022) 2793–2805

Contents lists available at ScienceDirect

Energy Reports

journal homepage: www.elsevier.com/locate/egyr

Research paper

Reduction of CO_2 emissions: The role of renewable energy, technological innovation and export quality

Mohammad Mafizur Rahman [a], Khosrul Alam [b,*], Eswaran Velayutham [a]

[a] School of Business, University of Southern Queensland, Australia
[b] Department of Economics, Bangabandhu Sheikh Mujibur Rahman Science and Technology University, Gopalganj 8100, Bangladesh

ARTICLE INFO

Article history:
Received 14 September 2021
Received in revised form 21 January 2022
Accepted 27 January 2022
Available online xxxx

JEL classification:
C23
F18
O30
Q20
Q53

Keywords:
CO_2 emissions
Renewable energy
Technological innovation
Export quality
NARDL approach

ABSTRACT

In the 22 well-developed countries of the world, the level of CO_2 emissions has been reducing over the years despite positive economic growth. This study therefore attempts to explore the role of contributory factors for CO_2 emissions reduction in these countries. Selecting the data period of 1990–2018, our chosen independent variables are gross domestic product (GDP), square of the gross domestic product (GDP^2), renewable energy, technological innovation and export quality. Adopting a panel non-linear autoregressive distributed lag (NARDL) approach, a pooled mean group (PMG) estimation technique is used to explore the asymmetric linkages between CO_2 emissions and these independent variables. The panel heterogeneous causality test is used to examine the direction of causality. The estimated results have confirmed the existence of environmental Kuznets curve (EKC) hypothesis; and renewable energy and export quality are found as contributory factors for the reduction of CO_2 emissions. Positive stimuli of technological innovation measured by research and development expenditure and export quality index reduce, whereas the negative shocks or counter incentives of these variables increase CO_2 emissions. In regards to causal relationship, bidirectional causality is found between renewable energy and CO_2 emissions, technological innovation and CO_2 emissions, GDP and renewable energy, and renewable energy and technological innovation. In addition, a unidirectional causality is also revealed from GDP to CO_2 emissions, export quality and technological innovation, and from technological innovation to export quality. Policy recommendations are made following the findings.

1. Introduction

The notions of climate change and global warming are widely noted as the prime concerns for the survival of the living beings on the planet. As the environmental and economic activities have coexisted since the inception of the earth's history, the developmental actions have gradually but profoundly exacerbate the environment by increasing CO_2 emissions. Because of the lack of proper policy initiatives, the earth is now facing the adverse consequences of environmental vulnerabilities and degradation, which hail misery for the lives of humans, animals, and plants throughout the world. Therefore, reducing CO_2 emissions as a way to construct a green and sustainable earth has become a desirable goal for contemporary researchers by considering various contributory factors like renewable energy, technological innovation, export quality, and economic growth. Moreover, the United Nations has proposed Sustainable Development Goals (SDGs) to be achieved by 2030, which emphasize the need for the inexpensive and clean energy, comprehensive and sustainable economic growth, technological innovation, as ways to combat climate change on an urgent basis (Goal-7, 8, 9, and 13 of SDGs, UNDP, 2015).

Against this backdrop, this study has targeted 22 well-developed countries (see Section 3.1) of the world that are experiencing positive economic growth, despite the continuous reduction of the level of CO_2 emissions over the years. Together, these well-developed countries have a geographical area of 21,136,725.57 square kilometres and a total population of 831.00 million, where the total GDP is US$38,954,194.15 million (WDI, 2020), which is 44.42% of the world's GDP. The total change in real GDP (GDP at constant 2010 US$) of these countries during 2000–2018 is 38.54% indicating a tremendously progressive economic growth; whereas the total change in CO_2 emissions over the period of 2000–2018 is −14.96%, exhibiting a diminishing trend (WDI, 2020; IEA, 2020). In this study, we intend to explore the issue of CO_2 emissions reduction. Thus, our study is a

* Corresponding author.
E-mail addresses: mafiz.rahman@usq.edu.au (M.M. Rahman), alam.khosrul@gmail.com (K. Alam), Eswaran.Velayutham@usq.edu.au (E. Velayutham).

https://doi.org/10.1016/j.egyr.2022.01.200

comprehensive effort to investigate the world's survival and global sustainability by combating CO_2 emissions.

The significant contributions of this study are: (i) to the best of our knowledge, this is the first and unique study in the literature that explores the contributory elements for CO_2 reduction in the 22 well-developed economies of the world where CO_2 emissions have been decreasing despite positive economic growth for a long time; (ii) this study has used the most up-to-date and complete data over the period of 29 years (1990–2018); (iii) the robust results are attained by adopting various well-equipped econometric techniques i.e. the Pedroni and Kao test, the panel non-linear autoregressive distributed lag (NARDL) approach of pooled mean group (PMG), and the panel heterogeneous causality test (details are in Section 3.2); (iv) detailed policy suggestions, based on the findings, are provided for the researchers and policy makers to reduce CO_2 emissions for environmental sustainability by taking note of comprehensive policies on renewable energy (energy from a source that is not depleted when used), economic growth, technological innovation (creation and/or use of improved technology), and export quality (measured by index number — higher value indicates higher quality of export products).

The confounding nexus between CO_2 emissions and the related contributing factors is unveiled in contemporary literature with diverse methodologies, data periods, and geographical locations. In the present study, we will scrutinize the past literature as under.

In exploring the nexus between CO_2 emissions and renewable energy use, some researchers found the renewable energy to be significant synergist for reducing CO_2 emissions (See Bilgili et al., 2016; Jebli et al., 2016; Bekun et al., 2019; Adams and Acheampong, 2019, among others). In contrast, some other researchers found insignificant or no association between them (see Charfeddine and Kahia, 2019; Nathaniel and Iheonu, 2019; Rahman and Vu, 2020, for example). Bilgili et al. (2016), Jebli et al. (2016) and Bekun et al. (2019) found that renewable energy diminishes CO_2 emissions in the context of 17 OECD countries covering data of 1977–2010, and employing panel fully modified ordinary least square (FMOLS) and panel dynamic ordinary least square (DOLS) models, 25 OECD countries covering 1980–2010 and conducting panel FMOLS and panel DOLS models, and 16 EU countries covering 1996–2014 and applying Panel Pooled Mean Group-Autoregressive Auto regressive distributive lag model (PMG-ARDL model), respectively. Likewise, Inglesi-Lotz and Dogan (2018), Hanif (2018), and Adams and Acheampong (2019) found negative link between CO_2 emissions and renewable energy for 10 major electricity generating countries covering 1980–2011 by using panel estimation techniques, 34 emerging countries from 1955–2015 by using a system generalized method of moment (GMM), and 46 Sub-Saharan African countries from 1980–2015 by adopting an instrumental variable GMM, respectively. Similar findings are also derived by, Dogan and Seker (2016) for top renewable energy using countries, Bhattacharya et al. (2017) for 85 developed and developing countries, Kahia et al. (2019) for 12 MENA countries Liu et al. (2017) for 4 ASEAN countries, Zoundi (2017) for selected 25 African countries, Danish et al. (2017) for Pakistan, Sinha and Shahbaz (2018) for India, and Chen et al. (2019) for China, Rahman and Alam (2021) for Bangladesh. In contrast, Charfeddine and Kahia (2019) found that renewable energy consumption has a weak influence on CO_2 emissions in the case of 24 MENA countries for the data of 1980–2015 where panel vector autoregressive (PVAR) model is employed. In the same way, Nathaniel and Iheonu (2019), Pata (2018), and Rahman and Vu (2020) obtained an insignificant link for 19 African countries, Turkey, and Canada, respectively. Saidi and Omri (2020) found bidirectional causality between CO_2 emissions and renewable energy in the short-run but no causal link between them in the long-run in the case of 15 major renewable energy-using countries. Thus, the indefinite influence of renewable energy on CO_2 emissions requires further exploration.

The nexus between CO_2 emissions and economic growth is found to validate and establish the Environmental Kuznets Curve (EKC) hypothesis, a non-linear inverted U-shaped curve, which denotes the positive link between them at the earlier stage of development of an economy but a negative association after a certain level of income. The EKC hypothesis is endorsed by various researchers (see Dogan and Seker, 2016; Bilgili et al., 2016; Jebli et al., 2016; Hanif, 2018, among others) however, many of the researchers got no significant authentication regarding this (see Adams and Acheampong, 2019; Zoundi, 2017, for example). Dogan and Seker (2016) had the support of the EKC hypothesis in the case of the top renewable energy consuming countries from the FMOLS and DOLS methods. Corresponding identification has also been endorsed by Bilgili et al. (2016) for 17 OECD, Jebli et al. (2016) for 25 OECD, Apergis and Ozturk (2015) for 14 Asian countries, Hanif (2018) for 34 Sub-Saharan African countries, Sinha and Shahbaz (2018) for India, Pata (2018) for Turkey, Danish et al. (2017) for Pakistan, Ahmad et al. (2017) for Croatia, Chen et al. (2019) for China and Alam et al. (2016) for Indonesia, Brazil, and China. In contrast, Erdoğan et al. (2020), and Adams and Acheampong (2019) revealed no evidence of the EKC hypothesis for 14 G20 countries from 1971–2017, and 46 sub-Saharan African countries from 1980–2015, respectively. Similar findings were also identified by Rahman et al. (2021) for Newly Industrialized countries, Zoundi (2017) for 25 African countries, Liu et al. (2017) for 4 ASEAN countries, Alshehry and Belloumi (2017) for Saudi Arabia, and Alam et al. (2016) for India. Without considering the EKC hypothesis, some researchers also tried to establish a link between CO_2 emissions and economic growth. For example, a positive nexus was found by Rahman and Vu (2020) for Australia and Canada, Rahman (2020a,b) for the top 10 electricity consuming countries, Kahia et al. (2019) for 12 MENA countries, Bekun et al. (2019) for 16 EU countries, and Rahman and Alam (2021), Kashem and Rahman (2019) for Bangladesh. A contrasting (negative) association between CO_2 emissions and economic growth was also found by Rahman (2020a) for India for the data period of 1971–2011 where ARDL bounds testing model is used. Rahman (2017) found unidirectional causality running from economic growth to CO_2 emissions for 11 Asian populous countries; whereas Rahman et al. (2020), Saidi and Omri (2020), and Saidi and Rahman (2020) observed the bidirectional causal link between CO_2 emissions and economic growth for 5 south Asian countries, 15 major renewable energy-using countries, and 4 out of 5 OPEC countries, respectively. Rahman and Kashem (2017), and Mbarek et al. (2018) also obtained a short and long run nexus between economic growth (industrial production) and CO_2 emissions in Bangladesh for the period of 1972–2011 by using Granger causality test and ARDL bounds testing model, and Tunisia covering the period 1990–2015 by employing Granger causality test and VECM model, correspondingly. Therefore, these indeterminate influences assert for more investigation of economic growth on CO_2 emissions for better policy forming.

The conundrum nexus is also witnessed between CO_2 emissions and technological innovations (research & development expenditure) in much contemporary literature (see Shahbaz et al., 2020; Yu and Du, 2019; Khan et al., 2020; Ganda, 2019; Irandoust, 2016, among others). Shahbaz et al. (2020) and Yu and Du (2019) found that technological innovations had a negative influence on CO_2 emissions for China during 1984–2018 where bootstrapping autoregressive distributed lag modelling (BARDL) was employed, and during 1997–2015 where stochastic impacts by regression on population, affluence, and technology (STIRPAT) model was used, respectively. A similar identification was also revealed by Ibrahiem (2020) for Egypt, Su et al. (2020) for the USA, Khan et al. (2020) for G7 countries, Kumail et al. (2020) for Pakistan, Erdoğan et al. (2020) for 14 countries in the G20 countries, Salman et al. (2019) for 7 ASEAN countries, Ganda (2019) for OECD countries, Ahmad et al. (2019) for 26 OECD, Aldakhil et al. (2019) for South Asia, Lee and Min (2015) for Japanese manufacturing firms, Apergis et al. (2013) for Germany, France and the U.K, and Fernández et al. (2018) for 15 European countries and the USA. In contrast, Chen and Lee (2020) found that technological innovation not significantly alleviate on CO2 emissions globally in the case of 96 countries, except group-based countries covering the data of 1996–2018 by utilizing spatial econometric models. Similarly, Irandoust (2016) found no causality between technological innovation and CO_2 emissions in 4 Nordic countries. Churchill et al. (2019) also found a time-varying nexus between research and development expenditure and CO_2 emissions in the G7 countries. Petrović and Lobanov (2020) found that the long-run effect of research and development expenditure on CO_2 emissions was negative, but the country-specific nexus was found both to be positive and negative for 16 OECD countries for the data period of 1981–2014. Hence, the identification of the future role of technological innovation on CO_2 emissions urged for time-demanded policy build-up.

The mingled nexus between CO_2 emissions and export quality is also prevalent in the literature. For example, Fang et al. (2019) and Dogan et al. (2020) showed the positive impact of the quality of exports on CO_2 emissions for 82 developing economies using the data of 1970–2014, and 63 developed and developing countries covering data of 1971–2014, respectively. However, Gozgor and Can (2017) and Murshed and Dao (2020) found that export quality was negatively associated with CO_2 emissions for China for the period 1971–2010, and 5 South Asian economies for the period of 1972–2014, respectively. In the case of export diversification, the positive link between export diversification and CO_2 emissions has been obtained by Mania (2020) for 98 developed and developing countries using data period of 1995–2013 and applying system GMM and Pooled Mean Group (PMG) estimation methods, and Wang et al. (2020) for G-7 countries covering data of 1990–2017 and using ARDL and AMG approaches. On the contrary, the opposite link between export diversification and CO_2 emissions was ascertained by Shahzad et al. (2020) for 63 developed and developing countries, Wu et al. (2019) for China, and Apergis et al. (2018) for 19 developed economies. So, more identification of the influence of export quality on CO_2 emissions is necessary for the policy makers.

The aforementioned literature depicted an unresolved nexus between CO_2 emissions and renewable energy use, economic growth, technological innovation, and export quality, which is not conducive to articulate effective unanimous policy efforts on reducing CO_2 emissions. Moreover, the consideration of the mentioned contributory factors of CO_2 emissions is not collectively found in the existing literature, especially in the context of 22 well-developed countries. Thus, our present study is an earnest attempt to fill the existing literary gaps, which will be supportive to provide reliable and unequivocal policy implications for environmental sustainability. The summary of the literature review is listed in Table 1.

This research is organized in the following order: following the introduction Section 2 describes the data and methodology; Section 3 reports and discusses the empirical results; and Section 4 concludes this research, along with policy implications.

2. Data and methodology

2.1. Panel data set and variable selection

We have selected 22 well-developed countries[1] where the level of carbon emissions has been reducing over the years, specifically since 2000, despite the positive economic growth.[2] We assume that renewable energy and shocks of technological innovation and export quality might contribute to the difference in the reduction of carbon emissions. While we are testing the Environmental Kuznets Curve (EKC) hypothesis, our focus is to explore the role of renewable energy, asymmetric technological innovation and export quality shocks in the reduction of carbon emissions in these countries. We have collected the data of carbon emissions per capita (CO_2) measured kiloton, gross domestic product (GDP) per capita, (proxy for economic growth), renewable energy consumption as a % of total final energy consumption (REN), research and development expenditure as % of GDP (RDE) (proxy for technological innovation) and export quality index (EQI) for the period 1990–2018.[3] Except for the export quality index data, all other data were collected from the World Development Indicator (WDI, 2020), World Bank. Export quality index data were collected from the International Monetary Fund database (IMF, 2020).

The justification for selecting these variables is based on both theoretical and conceptual ideas and past literature. Renewable energy plays significant role on CO_2 emissions (See Bekun et al., 2019; Adams and Acheampong, 2019; Rahman and Vu, 2020, among others) The inclusion of the economic growth variable is considered in the context of the environmental Kuznets curve (EKC) hypothesis, where economic growth increases CO_2 emissions at the primary stage of development, but after a certain stage it reduces CO2 emissions (Dogan and Seker, 2016; Hanif, 2018). The technological innovation (proxy of the research and development expenditure) creates environmentally efficient technologies to reduce CO_2 emissions, although there may be some disagreement (Shahbaz et al., 2020; Khan et al., 2020) (a). Following the studies of Yu and Du (2019), Chen and Lee (2020) and Lin and Zhu (2019) we have used research and development expenditure as a proxy for technological innovation. Export quality has a significant effect on CO_2 emissions, (Murshed and Dao, 2020; Dogan et al., 2020).

2.2. Econometric approaches

We have used several econometric approaches for our panel data study. We have performed the cross-sectional dependence (CD) tests first as CD is a main concern in a study of panel data. Then, we have employed unit-root tests to verify the stationary of the variables followed by a co-integration test to find any long-term relationships among the studied variables. We have adopted a nonlinear autoregressive distributed lag (NARDL) to see the asymmetric linkage between the selected variables in the studied countries. Finally, a panel heterogeneous causality test is used to test the short-run causalities among the variables.

This study follows several investigative procedures, which are shown in the following flow chart in Fig. 1.

[1] The countries are: Australia, Austria, Belgium, Bulgaria, Czech Republic, Denmark, Finland, France, Germany, Hungary, Ireland, Netherlands, Portugal, Romania, Slovakia, Spain, Sweden, Switzerland, Ukraine, United Kingdom, United States, and Uzbekistan.

[2] Sources: https://www.ecosystemmarketplace.com/articles/21-countries-reducing-carbon-emissions-growing-gdp/; and https://www.environment.gov.au/system/files/resources/6686d48f-3f9c-448d-a1b7-7e410fe4f376/files/nggi-quarterly-update-mar-2019.pdf

[3] A five-year moving average was used to fill up any missing data.

Table 1
Summary of the findings of past empirical studies.

Author(s)	Time span	Area(s) of study	Methodology	Findings
Bilgili et al. (2016)	1977–2010	17 OECD	FMOLS, DOLS	Renewable energy reduces CO_2 emissions; supported EKC hypothesis
Jebli et al. (2016)	1980–2010	25 OECD	FMOLS, DOLS, Granger causality	Renewable energy reduces CO_2 emissions; supported EKC hypothesis
Bekun et al. (2019)	1996–2014	16 EU countries	PMG-ARDL, Panel causality	Renewable energy reduces CO_2 emissions; positive nexus between CO2 emissions and economic growth is found
Inglesi-Lotz and Dogan (2018)	1980–2011	10 major electricity generating	Panel causality	Renewable energy reduces CO_2 emissions;
Hanif (2018)	1995–2015	34 emerging	System GMM	Renewable energy reduces CO_2 emissions; supported EKC hypothesis
Adams and Acheampong (2019)	1980–2015	46 Sub-Saharan African countries	IV-GMM	Renewable energy reduces CO_2 emissions; EKC hypothesis is not supported
Dogan and Seker (2016)	1985–2011	23 top renewable energy using countries	FMOLS, DOLS	Renewable energy reduces CO_2 emissions; supported EKC hypothesis
Bhattacharya et al. (2017)	1991–2012	85 developed and developing countries	System GMM, FMOLS	Renewable energy reduces CO_2 emissions;
Kahia et al. (2019)	1980–2012	12 MENA countries	Panel VAR, Granger causality	Renewable energy reduces CO2 emissions; Positive nexus between CO2 emissions and economic growth is found
Liu et al. (2017)	1970–2013	4 ASEAN countries	Panel estimation, Granger causality	Renewable energy reduces CO_2 emissions; EKC hypothesis is not supported
Zoundi (2017)	1980–2012	25 selected African countries	Panel cointegration test	Renewable energy reduces CO_2 emissions; EKC hypothesis is not supported
Danish et al. (2017)	1970–2012	Pakistan	ARDL, Granger causality	Renewable energy reduces CO_2 emissions; supported EKC hypothesis
Sinha and Shahbaz (2018)	1971–2015	India	ARDL	Renewable energy reduces CO_2 emissions; supported EKC hypothesis
Chen et al. (2019)	1980–2014	China	ARDL, VECM	Renewable energy reduces CO_2 emissions; supported EKC hypothesis
Rahman and Alam (2021)	1973–2014	Bangladesh	ARDL, Toda-Yamamoto Granger causality	Renewable energy reduces CO_2 emissions; positive nexus between CO2 emissions and economic growth is found
Charfeddine and Kahia (2019)	1980–2015	24 MENA countries	Panel VAR	Renewable energy consumption has a weak influence on CO_2 emissions
Nathaniel and Iheonu (2019);	1990–2014	19 African countries	Augmented Mean Group (AMG)	Insignificant link of renewable energy consumption on CO_2 emissions is revealed.
Pata (2018);	1974–2014	Turkey	ARDL, FMOLS	Insignificant link of renewable energy consumption on CO_2 emissions is revealed; supported EKC hypothesis
Rahman and Vu (2020)	1960–2015	Australia and Canada	ARDL, VECM Granger causality	Insignificant link of renewable energy consumption on CO2 emissions is revealed; Positive nexus between CO2 emissions and economic growth is found
Saidi and Omri (2020)	1990–2014	15 major renewable energy-using countries	FMOLS, VECM	Short-run causality exists but no long-run causality between renewable energy consumption and CO_2 emissions is found; Bidirectional causal link between CO2 emissions and economic growth exists
Apergis and Ozturk (2015)	1990–2011	14 Asian countries;	GMM	EKC hypothesis is supported
Ahmad et al. (2017)	1992Q1–2011Q1	Croatia	ARDL, VECM	EKC hypothesis is supported
Alam et al. (2016)	1970–2012	Indonesia, Brazil, and China; India	ARDL	EKC hypothesis is supported; EKC hypothesis is not supported
Erdoğan et al. (2020)	1971–2017	14 G20 countries	Panel estimation	EKC hypothesis is not supported; Technological innovations have a negative influence on CO2 emissions
Rahman and Alam (2021)	1979–2017	Newly Industrialized countries	FMOLS, DOLS, PMG	EKC hypothesis is not supported
Alshehry and Belloumi (2017)	1971–2011	Saudi Arabia	ARDL, Granger causality	EKC hypothesis is not supported
Rahman (2020a,b)	1971–2013	top 10 electricity consuming countries	FMOLS, DOLS, Dumitrescu and Hurlin causality	Positive nexus between CO2 emissions and economic growth is found
Kashem and Rahman (2019)	1972–2015	Bangladesh	Johansen co-integration, Granger causality	Positive nexus between CO2 emissions and economic growth is found
Rahman (2020a)	1971–2011	India	ARDL, Granger causality	Negative association between CO2 emissions and economic growth is shown
Rahman (2017)	1960–2014	11 Asian populous countries	FMOLS, DOLS, Granger causality	Unidirectional causality running from economic growth to CO2 emissions is found

(continued on next page)

Table 1 (*continued*).

Author(s)	Time span	Area(s) of study	Methodology	Findings
Rahman et al. (2020)	1990–2017	5 south Asian countries	Panel co-integration, Granger causality	Bidirectional causal link between CO2 emissions and economic growth exists
Saidi and Rahman (2020)	1990–2014	4 out of 5 OPEC countries	FMOLS, DOLS	Bidirectional causal link between CO2 emissions and economic growth exists
Rahman and Kashem (2017)	1972–2011	Bangladesh	ARDL, Granger causality	Short and long run nexus between economic growth (industrial production) and CO2 emissions is found
Mbarek et al. (2018)	1990–2015	Tunisia	VECM, Granger causality test	Short and long run nexus between economic growth (industrial production) and CO2 emissions is found
Shahbaz et al. (2020)	1984–2018	China	Bootstrapping ARDL	Technological innovations have a negative influence on CO2 emissions
Yu and Du (2019)	1997–2015	China	Logistic equation	Technological innovations have a negative influence on CO2 emissions
Ibrahiem (2020)	1971–2014	Egypt	ARDL, FMOLS, DOLS, Toda-Yamamoto Granger causality	Technological innovations have a negative influence on CO2 emissions
Su et al. (2020)	1990–2017	USA	ARDL, DOLS	Technological innovations have a negative influence on CO2 emissions
Khan et al. (2020)	1990Q1–2017Q2	G7 countries	FMOLS, DOLS, CCR, frequency domain causality test	Technological innovations have a negative influence on CO2 emissions
Kumail et al. (2020)	1990–2017	Pakistan	ARDL, Bayer and Hanck cointegration	Technological innovations have a negative influence on CO2 emissions
Salman et al. (2019)	1990–2017	7 ASEAN countries	Panel quantile regression	Technological innovations have a negative influence on CO2 emissions
Ganda (2019)	2000–2014	26 OECD	system-GMM	Technological innovations have a negative influence on CO2 emissions
Ahmad et al. (2019)	1990–2014	26 OECD	Multiple empirical analyses	Technological innovations have a negative influence on CO2 emissions
Aldakhil et al. (2019)	1975–2016	South Asia	Robust least square regression	Technological innovations have a negative influence on CO2 emissions
Lee and Min (2015)	2001–2010	Japanese manufacturing firms	Panel estimation	Technological innovations have a negative influence on CO2 emissions
Apergis et al. (2013)	1998–2011	Germany, France, and U.K	Threshold autoregressive model	Technological innovations have a negative influence on CO2 emissions
Fernández et al. (2018)	1990–2013	15 European countries and the USA	OLS	Technological innovations have a negative influence on CO2 emissions
Chen and Lee (2020)	1996–2018	96 countries	Spatial econometric models	Technological innovation does not significantly alleviate CO2 emissions
Irandoust (2016)	1975–2012	4 Nordic countries	VAR, Granger causality	No causality between technological innovation and CO2 emissions is found
Churchill et al. (2019)	1870–2014	G7 countries	Panel cointegration, CCEMG	Time-varying nexus between research and development expenditure and CO2 emissions exists
Petrović and Lobanov (2020)	1981–2014	16 OECD countries	long-run regression models	Long-run effect of research and development expenditure on CO2 emissions was negative, but the country-specific nexus was found both to be positive and negative
Fang et al. (2019)	1970–2014	82 developing economies	Paneldata estimation technique	Positive impact of the quality of exports on CO2 emissions is exhibited
Dogan et al. (2020)	1971–2014	63 developed and developing countries	Panel quintile estimators	Positive impact of the quality of exports on CO2 emissions is exhibited
Gozgor and Can (2017)	1971–2010	China	ARDL	Export quality was negatively associated with CO2 emissions
Murshed and Dao (2020)	1972–2014	5 South Asian economies	Panel data econometric analyses	Positive link between export diversification and CO2 emissions is revealed
Mania (2020)	1995–2013	98 developed and developing countries	System GMM, PMG	Positive link between export diversification and CO2 emissions is revealed
Wang et al. (2020)	1990–2017	G-7 countries	ARDL, AMG	Positive link between export diversification and CO2 emissions is revealed
Shahzad et al. (2020)	1971–2014	63 developed and developing countries	Unrestricted fixed effects and system GMM	Negative link between export diversification and CO2 emissions is found
Wu et al. (2019)	2014	China	IMED| CGE model	Negative link between export diversification and CO2 emissions is found
Apergis et al. (2018)	1962–2010	19 developed economies	Panel cointegration, Panel quantile regression	Negative link between export diversification and CO2 emissions is found

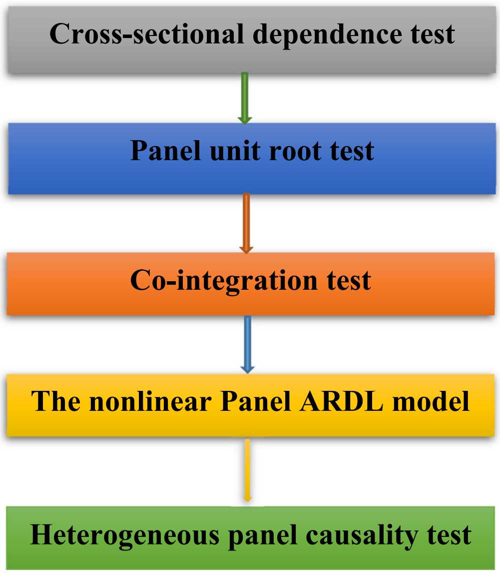

Fig. 1. Flow chart of the investigative procedures used in this study.

2.2.1. Cross-sectional dependence

Our sample countries have a similar pattern in terms of economic growth and CO_2 emissions. It is observed that carbon emissions are reducing while GDP growth is increasing in the selected countries (Aden, 2016). These countries might have similar economic and institutional attributes that may cause cross-sectional dependency. Therefore, investigation for the presence of cross-sectional dependency is more important in panel data sets. Four tests have been widely used: Breusch and Pagan (1980) BP Lagrange Multiplier (LM) test, Pesaran (2004) scaled LM test, Baltagi et al. (2012) biased-corrected scaled LM test, and Pesaran (2004) CD test to verify cross-sectional dependency.

The following panel data model for testing cross-sectional dependence was introduced by Breusch and Pagan (1980).

$$CD_{BP} = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{p_{ij}}^{2} \tag{1}$$

where CD_{BP} is cross-sectional dependence of Breusch and Pagan (1980), $\widehat{p_{ij}}^{2}$ represents the pairwise cross-sectional correlation coefficient of residuals, T is the time and N indicates cross-sectional dimensions of the panel.

Pesaran (2004) develops the following LM statistics to overcome to the disadvantages of Breusch and Pagan (1980) test.

$$CD_{LM} = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(\widehat{p_{ij}}^{2} - 1\right) \tag{2}$$

where CD_{LM} is cross-sectional dependence of Pesaran (2004), $\widehat{p_{ij}}^{2}$ represents the pairwise cross-sectional correlation coefficient of residuals, T is the time and N indicates cross-sectional dimensions of the panel.

Baltagi et al. (2012) develop a simple asymptotic bias correction for the scaled LM test statistics as follows:

$$CD_{BC} = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (\widehat{p_{ij}}^{2} - 1) - \frac{N}{2\,(T-1)} \tag{3}$$

where CD_{BC} is cross-sectional dependence of Baltagi et al. (2012), $\widehat{p_{ij}}^{2}$ represents the pairwise cross-sectional correlation coefficient of residuals, T is the time and N indicates cross-sectional dimensions of the panel.

Pesaran (2004) recommends that if the cross-sectional size is larger than the time dimension the following test statistic can be used instead.

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{p_{ij}}^{2} \tag{4}$$

where CD is cross-sectional dependence of Pesaran (2004), $\widehat{p_{ij}}^{2}$ represents the pairwise cross-sectional correlation coefficient of residuals, T is the time and N indicates cross-sectional dimensions of the panel.

The null hypothesis of the Pesaran CD tests is H_0 : no cross-sectional dependence. The alternative hypothesis of this test is H_1 : cross-sectional dependence.

2.2.2. Panel unit root test

We used first- and second-generation unit root tests, namely Breitung (2001), Levin et al. (2002), Im et al. (2003) and Pesaran (2007) to check the stationarity of the variables. The null hypothesis is: all variables contain a unit root.

Breitung (2001) considers the following equation:

$$y_{it} = \sum_{k=1}^{p+1} \beta_{ik} X_{it-k} + \varepsilon_{it} \tag{5}$$

Where we assume that the alternative hypothesis is panel series is stationary. Breitung (2001) uses the below transformed vectors Yi* = Ayi = [yit* . . . yiT*] and X1* = Axi = xiT*] to construct the following test statistic:

$$\lambda_B = \frac{\sum_{i=1}^{N} \sigma_1^{-2} Y_i^{*'} X_i^{*'}}{\sqrt{\sum_{i=1}^{n} \sigma_1^{-2} A_i^{*'} A' X_i^{*'}}} \tag{6}$$

The above equation shown to have standard normal distribution.

Im et al. (2003) test adapts the same null and alternative hypotheses as of the Breitung (1999).

Levin et al. (2002) propose the following adjusted t-statistic equation:

$$t_p^* = \frac{t_p}{\sigma_T^*} - NT\hat{S}_N \left(\frac{\hat{\sigma}_{\hat{p}}}{\hat{\sigma}_{\hat{\varepsilon}}^{2}}\right) \left(\frac{\mu_T^*}{\sigma_T^*}\right) \tag{7}$$

Where $\mu\dot{T}$ and $\sigma\dot{T}$ indicate mean and standard deviation adjustment factors. $\hat{S}_N$ equals to $(1/N) \sum_{i=1}^{N} \hat{\sigma}_{yi}/\hat{\sigma}\varepsilon j$, where $\hat{\sigma}_{yi}$ indicates a kernel estimator of long run variance for the country i.

Im et al. (2003) propose the t-bar test using the following equation.

$$t - bar = \sqrt{N\,(t_{\alpha} - k_t)}/\sqrt{v_t} \tag{8}$$

where N represents the panel size, t_{α} denotes the average of the individual ADF t- statistics for the cross-sectional unit, with and without a trend, and k_t and v_t are estimates of the mean and variance of each $t_{\alpha i}$ statistics, respectively.

Pesaran (2007) constructs a panel unit root test with cross-sectional dependence, and adopts the below cross-sectional augmented Dickey–Fuller (CADF) regression:

$$\Delta y_{it} = \alpha_i + p_i \bar{y}_{t-1} + \sum_{j=0}^{k} \gamma_{ij} \Delta \bar{y}_{it-1} + \sum_{j=0}^{k} \delta_{ij} y_{it-1} + \varepsilon_{it} \tag{9}$$

where $\bar{y}_{t-1}$ and $\Delta\bar{y}_{it-1}$ represent, respectively, the cross-sectional averages of lagged levels and first differences individual series. Once running the CADF statistics, the cross-sectionally augmented (Im et al., 2003) (CIPS) statistic is be obtained as follows:

$$CIPS = \left(\frac{1}{N}\right)\sum_{i=1}^{N} t_i\,(N,T) \tag{10}$$

2.2.3. Co-integration test

Pedroni (1999, 2004) proposes residual-based two typed co-integration tests, namely panel tests and group tests. The panel test of the within dimension method comprises of four statistics: panel v-statistic, panel rho-statistic, panel PP-statistic and panel ADF-statistic. The group tests of the between dimension method contain three statistics: group rho statistic, group PP-statistic and group ADF-statistic. All these statistics are asymptotically distributed as standard normal, which are based on the estimated residuals resulting from the following long-run model:

$$Y_{it} = \propto_i + \lambda_i + \sum_{j=1}^{m} \beta_{ji} X_{jit} + \varepsilon_{it} \tag{11}$$

where X and Y are expected to be integrated of order one in levels. Parameters α_i and β_i are individual and time effects that might be set zero if it is possible.

The structure of the estimated residuals is shown below:

$$\varepsilon_{it} = p_i \varepsilon_{it-1} + u_{it} \tag{12}$$

where ε_{it} is residual, p_i is panel statistic test and u_{it} is adjustment term.

The null hypothesis of Pedroni's (1999, 2004)'s co-integration test is: there is no co-integration among the variables. The current study uses the following panel co-integration regression where four within-dimension based and three between-dimension based statistics will be compared with the maximum likelihood-based panel co-integration statistics. Pedroni (1999, 2004) adopts the following cointegration system for panel data:

$$Y_{it} = \propto_i + \beta X_{it} + \varepsilon_{it} \tag{13}$$

where X and Y are expected to be integrated of order one in levels. ε_{it} is residual.

2.2.4. The nonlinear panel ARDL model

A nonlinear autoregressive distributed lag (NARDL) method is an asymmetric extension to the well-known ARDL model of Pesaran et al. (1999, 2001). This model is constructed in this current study following Shin et al. (2014) in panel format to consider both long-run and short-run asymmetries in our variables of interest. Jareño et al. (2020) and Arize et al. (2017) state that the NARDL approach has some advantages over other estimation techniques. This approach is not inclined to omitted lag bias. NARDL approach is suitable irrespective of the stationary properties of the variables. This approach produces both estimates of short and long-run nonlinearities simultaneously through the positive and negative partial sum of decomposition of the regression. We assume the asymmetric response of carbon emissions to changes in technological innovation (research and development) and export quality. Shin et al. (2014) suggest that asymmetric relationship is performed by decomposing the exogenous variables. A positive and negative partial sum of ΔRDE^+ and ΔRDE^- and ΔEQI^+ and ΔEQI^- is supposed to capture upward and downward fluctuations of technological innovation and export quality. As a result, positive and negative shocks of technological innovation and export quality might affect carbon emissions differently. Investment in technological innovation and research and development is believed to reduce carbon emissions. The decomposition of technological innovation can be created as follows:

$$\left.\begin{aligned} RDE^+_{i,t} &= \sum_{j=1}^{t} \Delta RDE^+_{i,j} + \sum_{j=1}^{t} \max(\Delta RDE^+_{i,j}, 0) \\ RDE^-_{i,t} &= \sum_{j=1}^{t} \Delta RDE^-_{i,j} + \sum_{j=1}^{t} \min(\Delta RDE^-_{i,j}, 0) \end{aligned}\right\} \tag{14}$$

where of ΔRDE^+ and ΔRDE^- are computed as positive and negative shocks of technological innovation.

The decomposition of the export quality can be created as follows:

$$\left.\begin{aligned} EQI^+_{i,t} &= \sum_{j=1}^{t} \Delta EQI^+_{i,j} + \sum_{j=1}^{t} \max(\Delta EQI^+_{i,j}, 0) \\ EQI^-_{i,t} &= \sum_{j=1}^{t} \Delta EQI^-_{i,j} + \sum_{j=1}^{t} \min(\Delta EQI^-_{i,j}, 0) \end{aligned}\right\} \tag{15}$$

where of ΔEQI^+ and ΔEQI^- indicate positive and negative shocks of export quality.

The following equation represents a nonlinear panel ARDL model that incorporates the short-run and long-run asymmetric relationship between carbon emissions and our explanatory variables:

$$\begin{aligned} \Delta CO_{2it} &= \mu_i + \gamma_j^i CO_{2it-1} + \gamma_j^i GDP_{it-1} + \gamma_j^i GDP^2_{it-1} + \gamma_j^i REN_{it-1} + \\ &+ \gamma_j^i RDE^+_{it-1} + \gamma_j^i RDE^-_{it-1} + \gamma_j^i EQI^+_{it-1} + \gamma_j^i EQI^-_{it-1} \\ &+ \sum_{j=1}^{p1} \delta_{1ij} \Delta CO_{2it-1} + \sum_{j=1}^{p2} \delta_{2ij} \Delta GDP_{it-1} + \sum_{j=1}^{p3} \delta_{3ij} \Delta GDP^2_{it-1} \\ &+ \sum_{j=1}^{p4} \delta_{4ij} \Delta REN_{it-1} + \sum_{j=1}^{p6} (\delta^+_{5ij} \Delta RDE^+_{it-1} + \delta^-_{5ij} \Delta RDE^-_{it-1}) \\ &+ \sum_{j=1}^{p6} (\delta^+_{6ij} \Delta EQI^+_{it-1} + \delta^-_{6ij} \Delta EQI^-_{it-1}) + \varepsilon_{it} \end{aligned} \tag{16}$$

where γ and δ represent the long-term and short-term coefficients, respectively. CO_2 is per capita carbon emissions measured in metric tons. GDP and GDP^2 are per capita gross domestic product and square of per capita gross domestic product. REN is renewable energy consumption as a % of total final energy consumption. TEI^+ and TEI^- indicate the positive and negative shock of research and development expenditure as % of GDP (proxy for technological innovation), respectively and EQI^+ and EQI^- denote the positive and negative shocks of the export quality index, respectively. Export quality index data were collected from the International Monetary Fund database (IMF, 2020). The asymmetric error correction version of the above equation can be written as follows:

$$\begin{aligned} \Delta CO_{2it} &= \tau_i + \sum_{j=1}^{p1} \delta_{1ij} \Delta CO_{2it-1} + \sum_{j=1}^{p2} \delta_{2ij} \Delta GDP_{it-1} \\ &+ \sum_{j=1}^{p3} \delta_{3ij} \Delta GDP^2_{it-1} + \sum_{j=1}^{p4} \delta_{4ij} \Delta REN_{it-1} \\ &+ \sum_{j=1}^{p5} (\delta^+_{5ij} \Delta RDE^+_{it-1} + \delta^-_{5ij} \Delta RDE^-_{it-1}) \\ &+ \sum_{j=1}^{p6} (\delta^+_{6ij} \Delta EQI^+_{it-1} + \delta^-_{6ij} \Delta EQI^-_{it-1}) + ect_{it} + \varepsilon_{it} \end{aligned} \tag{17}$$

where, CO_2, GDP, REN, TEI^+, TEI^-, EQI^+ and EQI^- represent carbon emissions per capita, gross domestic product per capita,

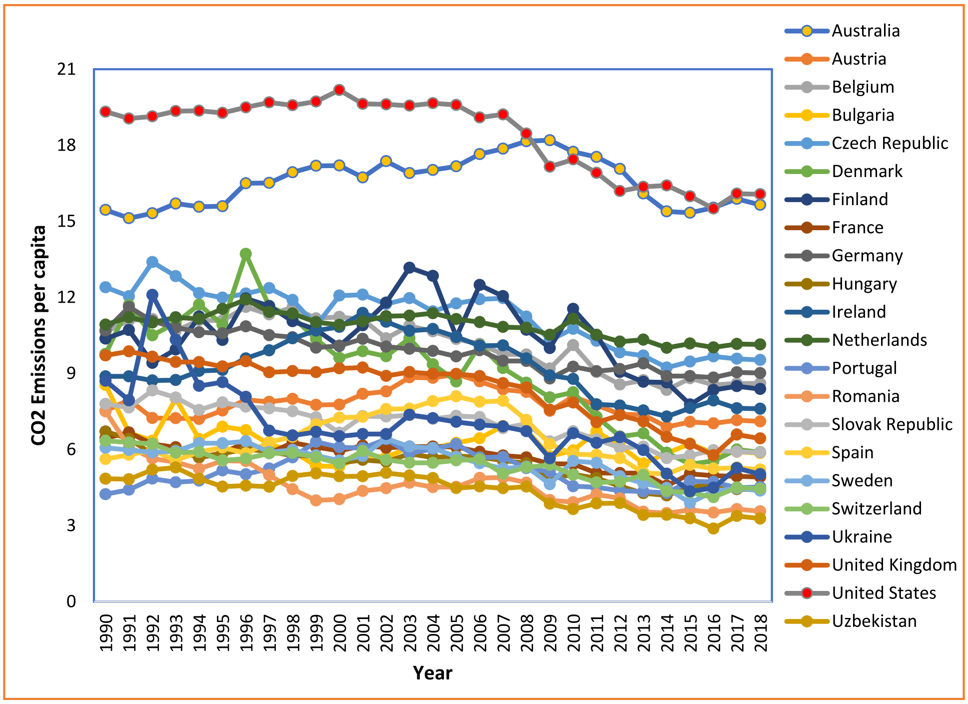

Fig. 2. Trend of CO_2 Emissions per capita (kiloton).

renewable energy consumption as a % of total final energy consumption, positive shock of technological innovation, negative shock of technological innovation, positive shock of the export quality index and negative shock of export quality index, respectively. ect_{it} is the asymmetric error correction term that offers the speed of adjustment to the long-run equilibrium and the associated coefficient explains how long it needs to reach in the long-run equilibrium in the presence of shocks in the short run.

2.2.5. Heterogeneous panel causality test

Dumitrescu and Hurlin (2012) developed panel causality in heterogeneous panel data models. This model has some benefits over other panel causality tests (Aydin, 2019; Dumitrescu and Hurlin, 2012). For example, this test incorporates cross-sectional dependency, and the time and the size of the cross-section relative to each other are irrelevant. Two different distributions are presented in this test: the asymptotic and the semi-asymptotic. The asymptotic distribution is applied when T is larger than N; the semi-asymptotic distribution is used if N is larger than T. The following model detects the causality in panel data:

$$y_{it} = \propto_i + + \sum_{j=1}^{J} \lambda_{i\,i}^{J} y_{i,t-J} + \sum_{j=1}^{J} \beta_{i\,i}^{J} x_{i,t-J} + \varepsilon_{i,t} \quad (18)$$

Where $x_{\mathrm{i,t}}$ and $y_{\mathrm{i,t}}$ denote the observations of two stationary variables for the individual i in period t. j shows the lag length, $\lambda_i^{(J)}$ represents autoregressive parameter while $\beta_i^{(J)}$ is the regression coefficient that varies within the groups. It is assumed that lag order J is to be equal for all individuals with a balanced panel. This test is a fixed type of test that yields a fixed coefficient model. It allows heterogeneity maintaining normal distribution. The null hypothesis of no causal relationship and the alternative hypothesis for testing causal relationship are noted below:

$H_o : \beta_{\mathrm{i}} = 0 \forall_{\mathrm{I}} = 1, \ldots, N$

$H_1 : \beta_{\mathrm{i}} = 0 \forall_{\mathrm{I}} = 1, \ldots, N_1$

$\beta_{\mathrm{i}} \pm 0 \forall_{\mathrm{I}} = N_1 + 1, N_1 + 2, \ldots, N$

Table 2
Descriptive statistics.

	CO_2	GDP	REN	RDE	EQI
Mean	2.041	10.018	2.051	1.644	0.975
Median	1.998	10.482	2.145	1.611	0.989
Maximum	3.005	11.280	3.975	3.908	1.045
Minimum	1.059	6.774	−0.509	0.130	0.757
Std. Dev.	0.408	1.056	1.055	0.923	0.051
Skewness	0.350	−1.340	−0.354	0.314	−1.482
Kurtosis	2.527	3.932	2.269	2.052	4.954
Jarque–Bera	19.005	213.884	27.551	34.358	335.089
Probability	0.000	0.000	0.000	0.000	0.000
Observations	**638**	**638**	**638**	**638**	**638**

Note: All the variables are transformed into the natural logarithm form except TEI and EQI.

Here, N_1 shows the unknown parameter but it satisfies the condition $0 \leq N_1/N < 1$. Under any situation, the ratio of N_1/N should be certainly inferior to 1, because if N_{i}= N, this indicates no causal link for any of the cross-section in the panel. That is, the null hypothesis of this test is not rejected. Alternatively, if $N_1 = 0$, this indicates s the causal link for all the individuals in the panel.

3. Empirical results

3.1. Descriptive statistics

Table 2 shows the descriptive statistics for the dependent and independent variables. The mean (median) values of the natural logarithm of carbon emissions, GDP and renewable energy are 2.041 (1.998), 10.018 (10.482) and 2.051 (2.145), respectively. The mean of technological innovation and export quality index are 1.644 and 0.975, respectively.

Figs. 2 compares carbon emissions per capita during 1990–2018 period. CO_2 emissions are measured as metric tons per capita downloaded from the World Development Indicator (WDI, 2020), World Bank. The United States and Australia have the highest carbon emissions per capita in selected 22 developed

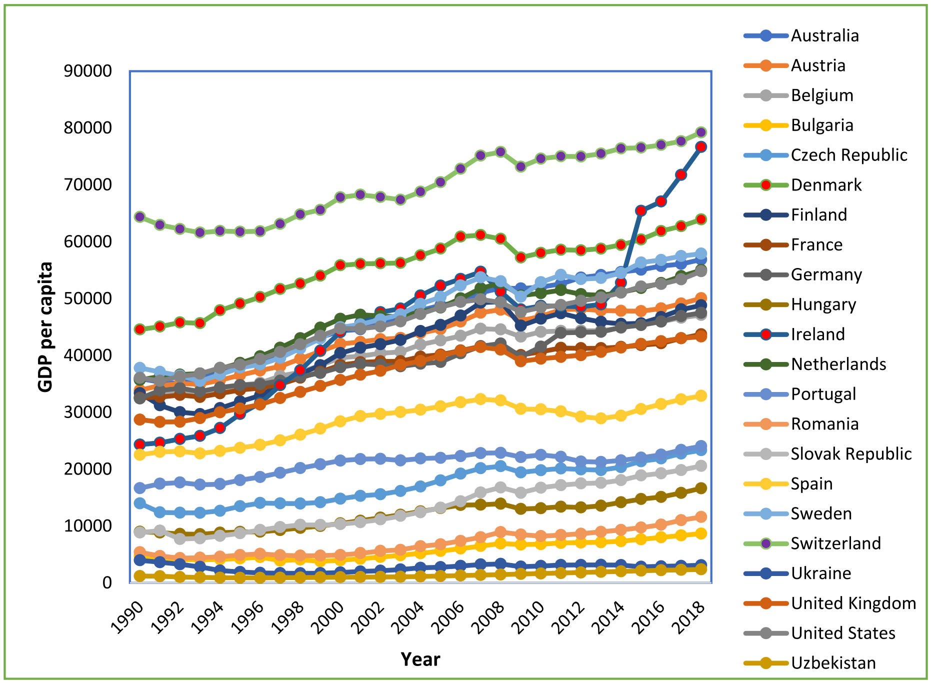

Fig. 3. Trend of GDP Per Capita (constant US$).

Table 3
Cross-sectional dependence test results.

Test	CO_2	GDP	REN	RDE	EQI
Breusch–Pagan LM	3316.32***	5374.69***	4427.46***	2519.68***	2186.15***
Pesaran scaled LM	143.54***	239.31***	195.24***	106.48***	90.96***
Bias-corrected scaled LM	143.15***	238.91***	194.84***	106.09***	90.57***
Pesaran CD	52.43***	71.71***	63.66***	18.18***	32.91***

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

countries. On the other hand, Romania and Uzbekistan have the lowest per capita CO_2 emissions among the selected countries. Fig. 3 compares GDP per capita in the selected developed nations. Switzerland and Denmark have the highest GDP per capita during 1990–2018 periods. Uzbekistan and Ukraine have the lowest GDP per capita among the selected countries.

3.2. Cross-sectional dependence test results

Table 3 reports the results of cross-sectional dependence tests. The associated p-values of CO_2, GDP, REN, RDE and EQI are significant at the 1% level accepting the null hypothesis of cross-sectional dependence for all variables.

3.3. Unit root test results

The results of panel unit root tests are shown in Table 4. The panel unit root test results provide that evidence of a mixed order of integration, suggesting that the variable is either stationary at the level or becomes stationary after the first difference. The mixed order of variables indicates that this study should adopt a panel ARDL approach proposed by Pesaran et al. (1999) to investigate the long-run link between carbon emissions, economic growth, renewable energy, technological innovation and export quality.

3.4. Co-integration test results

This study investigates the possible long-run relationship between variables using panel co-integration tests proposed by Pedroni (1999, 2004). Table 5 shows the results of the panel cointegration test. Six out of eleven estimates in the Pedroni test are significant at the 1% level, confirming that the variables are co-integrated in the long run. It is suggested that the null hypothesis of no-co-integration is rejected, accepting the alternative hypothesis of co-integration among the variables.

Table 4
Unit root test results.

	CO_2	GDP	REN	RDE	EQI
			Level		
Breitung	−1.27	−1.54*	−0.84	0.13	−3.60***
LLC	1.42	−3.10***	−0.75	1.88	−3.17***
IPS	3.48	2.44	3.50	3.51	−2.59***
Pesaran (2007)	−0.91	−0.24	−2.41***	4.04	−1.749**
			First difference		
Breitung	−7.05***	−3.64***	−7.64***	−7.58***	−12.15***
LLC	−10.89***	−9.18***	−10.30***	−8.31***	−14.62***
IPS	−14.46***	−9.96***	−11.52***	−10.91***	−16.11***
Pesaran (2007)	−2.491***	−4.126***	−4.089***	−0.824	−2.274***

Note: ***, and **denote significance level at 1% and 5%, respectively.

3.5. Panel NARDL estimation results

We run the nonlinear model using Eq. (16) with both the panel mean group (PMG) and mean group (MG) estimation. We employ the Hausman test to choose the more correct estimation technique between PMG and MG. The Hausman specification test reported in Table 6 shows the non-rejection of the null hypothesis

Table 5
Pedroni and Kao panel co-integration test results.

Pedroni co-integration test				
Estimates	Statistic	Prob.	Weighted statistics	Prob.
Alternative hypothesis: common AR coefficients (within-dimension)				
Panel v-Statistic	0.38	0.35	0.89	0.19
Panel rho-Statistic	−0.27	0.39	0.08	0.53
Panel PP-Statistic	−9.30***	0.00	−8.19***	0.00
Panel ADF-Statistic	−4.49***	0.00	−2.69***	0.00
	Statistic		Prob.	
Alternative hypothesis: individual AR coefficients (between-dimension)				
Group rho-Statistic	1.59		0.94	
Group PP-Statistic	−11.80***		0.00	
Group ADF-Statistic	−3.50***		0.00	

Note: ***and ** denote significance level at 1% and 5% respectively.

suggesting that the PMG estimation is more efficient than the MG estimation. Table 6 reports the results of the PMG estimation indicating the long-run coefficients in Panel A and the short-run coefficients in Panel B. The results show that the long-run elasticities of carbon emissions with respect to GDP and GDP^2 are positive and negative, respectively; the results are significant supporting the Environmental Kuznets Curve (EKC) hypothesis.

The long-run coefficient of renewable energy is negatively associated with the carbon emissions and the coefficient is statistically significant at 1% level, implying that the carbon emissions are reduced with the increased use of renewable energy in these selected countries. In terms of the asymmetric impact of technological innovation on the carbon emissions, the results from Panel A of Table 6 show that negative shocks on technological innovation (RDE^-) (the negative changes in research and development expenditure as % of GDP) have a significant and positive effect on the carbon emissions in the long-run; however, the impact of positive technological innovation shocks (RDE^+) (the positive changes in research and development expenditure as % of GDP) on the carbon emissions provide insignificant negative associations. These results suggest that any negative shock on technological innovation (negative changes in research and development expenditure as % of GDP) lead to an increase in carbon emissions. We have found an interesting result on the nonlinearity of the long-run association between the export quality index and carbon emissions. In the long run, the positive shocks in the export quality are negatively linked with carbon emissions, implying that an increase in the export quality substantially decreases carbon emissions. On the other hand, the impact of negative shocks in export quality on carbon emissions is positive and significant at the 1% level indicating that the reduction in export quality has increased carbon emissions considerably in the long run in the selected sample countries.

Turning to the nonlinear short-run effects, Panel B of Table 6 confirms that we have found no evidence for the EKC hypothesis in the selected sample. The impact of renewable energy on carbon emissions is negative and significant, implying that renewable energy supports reducing carbon emissions not only in the long-term but also in the short run. However, no significant impact of technological innovation and export quality is found on carbon emissions in the short-run. The coefficient of the error-correction term (ECT) is negative, which is also statistically significant at a 1% level, with a coefficient equal to −0.3704. This value indicates that the rate of adjustment towards the long-run equilibrium is approximately 37% per year. The significance and the negative signs of the ECT suggest that adjustment of the variables towards long-run dynamics is assured.

Table 6
Panel NARDL results.

Panel A: Long-run coefficients	
GDP	0.7868**
	(2.55)
GDP^2	−0.0377**
	(−2.27)
REN	−0.1198***
	(−9.96)
RDE^+	−0.0085
	(−0.58)
RDE-	0.0724**
	(2.51)
EQI^+	−1.5163***
	(−3.07)
EQI^-	1.0981***
	(2.65)
Panel B: Short-run coefficients	
ECT	−0.3704***
	(−5.63)
ΔGDP	−5.3705
	(−0.86)
ΔGDP^2	0.2919
	(0.94)
ΔREN	−0.1422**
	(−2.10)
ΔRDE^+	0.0154
	(0.28)
ΔRDE^-	−0.0782
	(−0.77)
ΔEQI^+	−0.1108
	(−0.23)
ΔEQI-	0.4683
	(0.83)
Constant	−0.6311***
	(−5.44)
Hausman test	4.58 (0.7109)
No of obs.	616
Log likelihood	1254.828

3.6. Heterogeneous panel causality test results

Table 7 reports the results of the Dumitrescu and Hurlin (2012) panel causality test. In the short-run, this study has found bidirectional causal links between renewable energy and carbon emissions (REN $\leftrightarrow$ CO_2), between technological innovation and carbon emissions, (RDE $\leftrightarrow$ CO_2), between renewable energy and economic growth (REN $\leftrightarrow$ GDP), and between technological innovation and renewable energy (RDE $\leftrightarrow$ REN). We have also found a unidirectional causality from economic growth to carbon emissions (GDP$\rightarrow$ CO_2), from carbon emissions to export quality ($CO_2$$\rightarrow$ EQI), from economic growth to technological innovation

Table 7
Results of Dumitrescu and Hurlin (2012) panel causality test.

Null hypothesis:	W-Stat.	Prob.	
GDP does not cause CO_2	5.103***	0.000	GDP→ CO2 (unidirectional causality)
CO_2 does not cause GDP	2.839	0.218	
REN does not cause CO_2	11.246***	0.000	REN ↔ CO2 (bidirectional causality)
CO_2 does not cause REN	4.328***	0.000	
RDE does not cause CO_2	4.479***	0.000	RDE ↔ CO2 (bidirectional causality)
CO_2 does not cause RDE	4.733***	0.000	
EQI does not cause CO_2	2.610	0.429	CO2→ EQI (unidirectional causality)
CO_2 does not cause EQI	4.468***	0.000	
REN does not cause _GDP	3.776***	0.002	REN ↔ GDP (bidirectional causality)
GDP does not cause REN	8.884***	0.000	
RDE does not cause GDP	2.318	0.820	GDP→ RDE (unidirectional causality)
GDP does not cause RDE	5.525***	0.000	
EQI does not cause GDP	2.773	0.269	GDP→ EQI (unidirectional causality)
GDP does not cause EQI	5.218***	0.000	
RDE does not cause REN	3.669***	0.005	RDE ↔ REN (bidirectional causality)
REN does not cause RDE	5.871***	0.000	
EQI does not cause REN	2.661	0.374	REN→ EQI (unidirectional causality)
REN does not cause EQI	4.782***	0.000	
EQI does not cause RDE	2.905	0.174	RDE→ EQI (unidirectional causality)
RDE does not cause EQI	3.217**	0.050	

Note: ***, and ** denote significance level at 1% and 5%, respectively.

(GDP→ RDE), from economic growth to export quality (GDP→ EQI), from renewable energy to export quality (REN→ EQI), and from technological innovation to export quality (RDE→ EQI).

4. Conclusion and policy implications

This study explores the role of contributory factors for CO_2 emissions reduction in the 22 well-developed countries of the world. Selecting the data period of 1990–2018, our chosen independent variables are GDP, GDP^2, renewable energy, technological innovation and export quality. Adopting a panel non-linear autoregressive distributed lag (NARDL) approach, the pooled mean group (PMG) estimation technique is used to explore the asymmetric linkages between CO_2 emissions and these independent variables. The panel heterogeneous causality test is used to examine the direction of causality. The obtained results confirm the existence of the environmental Kuznets curve (EKC) hypothesis, and renewable energy and export quality are revealed as the contributor for CO_2 emissions reduction. Negative shocks of technological innovation increase CO_2 emissions, and a bidirectional causality is found between renewable energy and CO_2 emissions, technological innovation and CO_2 emissions, GDP and renewable energy, and renewable energy and technological innovation. A unidirectional causality is also exhibited from GDP to CO_2 emissions, export quality and technological innovation, and from technological innovation to export quality. All the findings are consistent theoretically, which has empirical implications as well. The policy implication of our study is: the sustainable economic growth, utilization of renewable energy, more investment in technological innovation, and improved export quality are required to ensure the reduction of CO_2 emissions in the studied countries as well as in other countries. The following specific recommendations will be helpful in this regard:

i. *Sustainable economic growth* Economic growth increases CO_2 emissions, but at higher level of growth, the reduction of CO_2 emissions is also evident due to taking care of environmental issues. Therefore, the implementation of inclusive economic growth and developmental activities without harming the environment is dominantly crucial for lowering CO_2 emissions. Green growth, green technology adoption, green urbanization, and green industrialization, will all be effective and conducive to ensuring sustainable economic growth. In this perspective, a suitable and efficient policy initiative is necessary.

ii. *Utilization of renewable energy* Renewable energy declines CO_2 emissions significantly. Therefore, in terms of energy usage, fossil fuel or non-renewable energy should be cut down and the utilization of renewable energy should be prioritized to reduce CO_2 emissions. In this regard, more investment is needed to increase the sources of renewable energy by patronizing solar and wind power, and by offering encouragement and incentives for using energy efficient technologies and appliances among the masses. For this, a proper energy policy should be formulated and implemented.

iii. *More investment on technological innovation*: The positive stimulus of technological innovation reduces but negative shock increases CO_2 emissions. Therefore, technological innovation by increasing more expenditure on scientific research and development will help to introduce more environmentally and energy efficient technologies and equipment, which in turn will reduce CO_2 emissions. Suitable policy initiatives for more investment on technological innovation are required on a priority basis.

iv. *Improvement of export quality*: Positive incentive of export quality diminishes whereas negative shock raises the CO_2 emissions. Hence, the improved export quality by emphasizing cleaner, efficient and environmentally friendly production techniques for manufacturing items promisingly contributes to reducing CO_2 emissions. In this perspective, comprehensive and wide-ranging policy efforts regarding the upgrading of export quality will really be helpful for improving environmental quality in these countries without sacrificing the desired economic growth.

Funding

The Study received no funding.

CRediT authorship contribution statement

Mohammad Mafizur Rahman: Study plan, Conceptual and methodological development, Variable selection, Data collection, Econometric estimation, and data and result analysis, Writing abstract, Writing main sections of the paper, Polishing and editing, and improving the quality of the manuscript, Overall supervising. **Khosrul Alam:** Literature review, Writing introductory sections, conclusion and mention policy implications, helping to complete the paper. **Eswaran Velayutham:** Methodological development, Data collection, Econometric estimation, and data and result analysis, Helping to complete the paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and material

May be provided by the corresponding author upon request.

References

Adams, S., Acheampong, A.O., 2019. Reducing carbon emissions: The role of renewable energy and democracy. J. Cleaner Prod. 240, 118245.

Aden, N., 2016. The Roads to Decoupling: 21 Countries Are Reducing Carbon Emissions While Growing GDP. World Resources Institute. https://www.wri.org/insights/roads-decoupling-21-countries-are-reducing-carbon-emissions-while-growing-gdp.

Ahmad, N., Du, L., Lu, J., Wang, J., Li, H.-Z., Hashmi, M.Z., 2017. Modelling the CO2 emissions and economic growth in Croatia: Is there any environmental Kuznets curve? Energy 123, 164–172.

Ahmad, M., Khan, Z., Rahman, Z.U., Khattak, S.I., Khan, Z.U., 2019. Can innovation shocks determine CO2 emissions (CO2e) in the OECD economies? A new perspective. Econ. Innov. New Technol. http://dx.doi.org/10.1080/10438599.2019.1684643.

Alam, M.M., Murad, M.W., Noman, A.H.M., Ozturk, I., 2016. Relationships among carbon emissions, economic growth, energy consumption and population growth: Testing Environmental Kuznets Curve hypothesis for Brazil, China, India and Indonesia. Ecol. Indic. 70, 466–479.

Aldakhil, A.M., Zaheer, A., Younas, S., Nassani, A.A., Abro, M.M.Q., Zaman, K., 2019. Efficiently managing green information and communication technologies, high-technology exports, and research and development expenditures: A case study. J. Cleaner Prod. 240, 118164.

Alshehry, A.S., Belloumi, M., 2017. Study of the environmental kuznets curve for transport carbon dioxide emissions in Saudi Arabia. Renew. Sustain. Energy Rev. 75, 1339–1347.

Apergis, N., Can, M., Gozgor, G., Lau, C.K.M., 2018. Effects of export concentration on CO2 emissions in developed countries: an empirical analysis. Environ. Sci. Pollut. Res. 25, 14106–14116.

Apergis, N., Eleftheriou, S., Payne, J.E., 2013. The relationship between international financial reporting standards, carbon emissions, and R & D expenditures: Evidence from European manufacturing firms. Ecol. Econom. 88, 57–66.

Apergis, N., Ozturk, I., 2015. Testing Environmental Kuznets Curve hypothesis in Asian countries. Ecol. Indic. 52, 16–22.

Arize, A.C., Malindretos, J., Igwe, E.U., 2017. Do exchange rate changes improve the trade balance: An asymmetric nonlinear cointegration approach. Int. Rev. Econ. Finance 49, 313–326.

Aydin, M., 2019. Renewable and non-renewable electricity consumption–economic growth nexus: evidence from OECD countries. Renew. Energy 136, 599–606.

Baltagi, B.H., Feng, Q., Kao, C., 2012. A Lagrange multiplier test for cross-sectional dependence in a fixed effects panel data model. J. Econometrics 170, 164–177.

Bekun, F.V., Alola, A.A., Sarkodie, S.A., 2019. Toward a sustainable environment: Nexus between CO2 emissions, resource rent, renewable and nonrenewable energy in 16-EU countries. Sci. Total Environ. 657, 1023–1029.

Bhattacharya, M., Churchill, S.A., Paramati, S.R., 2017. The dynamic impact of renewable energy and institutions on economic output and CO2 emissions across regions. Renew. Energy 111, 157–167.

Bilgili, F., Koçak, E., Bulut, Ü., 2016. The dynamic impact of renewable energy consumption on CO2 emissions: A revisited Environmental Kuznets Curve approach. Renew. Sustain. Energy Rev. 54, 838–845.

Breitung, J., 1999. The local power of some unit root tests for panel data.

Breitung, J., 2001. The Local Power of Some Unit Root Tests for Panel Data. Nonstationary Panels, Panel Cointegration, and Dynamic Panels. Emerald Group Publishing Limited.

Breusch, T.S., Pagan, A.R., 1980. The Lagrange multiplier test and its applications to model specification in econometrics. Rev. Econom. Stud. 47, 239–253.

Charfeddine, L., Kahia, M., 2019. Impact of renewable energy consumption and financial development on CO2 emissions and economic growth in the MENA region: A panel vector autoregressive (PVAR) analysis. Renew. Energy 139, 198–213.

Chen, Y., Lee, C.-C., 2020. Does technological innovation reduce CO2 emissions? Cross-country evidence. J. Cleaner Prod. 263, 121550.

Chen, Y., Wang, Z., Zhong, Z., 2019. Co2 emissions, economic growth, renewable and non-renewable energy production and foreign trade in China. Renew. Energy 131, 208–216.

Churchill, S.A., Inekwe, J., Smyth, R., Zhang, X., 2019. R & D intensity and carbon emissions in the G7: 1870–2014. Energy Econ. 80, 30–37.

Danish, Zhang, B., Wang, B., Wang, Z., 2017. Role of renewable energy and non-renewable energy consumption on EKC: Evidence from Pakistan. J. Cleaner Prod. 156, 855–864.

Dogan, B., Madaleno, M., Tiwari, A.K., Hammoudeh, S., 2020. Impacts of export quality on environmental degradation: does income matter? Environ. Sci. Pollut. Res. 27, 13735–13772.

Dogan, E., Seker, F., 2016. The influence of real output, renewable and non-renewable energy, trade and financial development on carbon emissions in the top renewable energy countries. Renew. Sustain. Energy Rev. 60, 1074–1085.

Dumitrescu, E.-I., Hurlin, C., 2012. Testing for granger non-causality in heterogeneous panels. Econ. Model. 29, 1450–1460.

Erdoğan, S., Yıldırım, S., Yıldırım, D.Ç., Gedikli, A., 2020. The effects of innovation on sectoral carbon emissions: Evidence from G20 countries. J. Environ. Manag. 267, 110637.

Fang, J., Gozgor, G., Lu, Z., Wu, W., 2019. Effects of the export product quality on carbon dioxide emissions: evidence from developing economies. Environ. Sci. Pollut. Res. 26, 12181–12193.

Fernández, Y.F., López, M.A.F., Blanco, B.O., 2018. Innovation for sustainability: The impact of R & D spending on CO2 emissions. J. Cleaner Prod. 172, 3459–3467.

Ganda, F., 2019. The impact of innovation and technology investments on carbon emissions in selected organisation for economic co-operation and development countries. J. Cleaner Prod. 217, 469–483.

Gozgor, G., Can, M., 2017. Does export product quality matter for CO2 emissions? Evidence from China. Environ. Sci. Pollut. Res. 24, 2866–2875.

Hanif, I., 2018. Impact of economic growth, nonrenewable and renewable energy consumption, and urbanization on carbon emissions in Sub-Saharan Africa. Environ. Sci. Pollut. Res. 25, 15057–15067.

Ibrahiem, D.M., 2020. Do technological innovations and financial development improve environmental quality in Egypt? Environ. Sci. Pollut. Res. 27, 10869–10881.

IEA, 2020. IEA Atlas of Energy. Source: http://energyatlas.iea.org/#!/tellmap/1378539487/0.

Im, K.S., Pesaran, M.H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. J. Econometrics 115, 53–74.

IMF, 2020. International Monetary Fund. URL https://www.imf.org/en/Data.

Inglesi-Lotz, R., Dogan, E., 2018. The role of renewable versus non-renewable energy to the level of CO2 emissions a panel analysis of sub- Saharan Africa's Big 10 electricity generators. Renew. Energy 123, 36–43.

Irandoust, M., 2016. The renewable energy-growth nexus with carbon emissions and technological innovation: Evidence from the Nordic countries. Ecol. Indic. 69, 118–125.

Jareño, F., De La O González, M., Tolentino, M., Sierra, K., 2020. Bitcoin and gold price returns: A quantile regression and NARDL analysis. Resour. Policy 67, 101666.

Jebli, M.B., Youssef, S.M., Ozturk, I., 2016. Testing environmental kuznets curve hypothesis: The role of renewable and non-renewable energy consumption and trade in OECD countries. Ecol. Indic. 60, 824–831.

Kahia, M., Ben Jebli, M., Belloumi, M., 2019. Analysis of the impact of renewable energy consumption and economic growth on carbon dioxide emissions in 12 MENA countries. Clean Technol. Environ. Policy 21, 871–885.

Kashem, M.A., Rahman, M.M., 2019. CO_2 emissions and development Indicators: a causality analysis for Bangladesh. Environ. Processes 6, 433–455.

Khan, Z., Ali, M., Kirikkaleli, D., Wahab, S., Jiao, Z., 2020. The impact of technological innovation and public–private partnership investment on sustainable environment in China: Consumption-based carbon emissions analysis. Sustain. Dev. 28 (5), 1317–1330.

Kumail, T., Ali, W., Sadiq, F., Wu, D., Aburumman, A., 2020. Dynamic linkages between tourism, technology and CO2 emissions in Pakistan. Anatolia 31 (3), 436–448.

Lee, K.-H., Min, B., 2015. Green R & D for eco-innovation and its impact on carbon emissions and firm performance. J. Cleaner Prod. 108 (A), 534–542.

Levin, A., Lin, C.-F., James Chu, C.-S., 2002. Unit root tests in panel data: asymptotic and finite-sample properties. J. Econometrics 108, 1–24.

Lin, B., Zhu, J., 2019. Determinants of renewable energy technological innovation in China under CO2 emissions constraint. J. Environ. Manag. 247, 662–671.

Liu, X., Zhang, S., Bae, J., 2017. The impact of renewable energy and agriculture on carbon dioxide emissions: Investigating the environmental Kuznets curve in four selected ASEAN countries. J. Cleaner Prod. 164, 1239–1247.
Mania, E., 2020. Export diversification and CO2 emissions: An augmented environmental Kuznets curve. J. Int. Dev. 32 (2), 168–185.
Mbarek, M.B., Saidi, K., Rahman, M.M., 2018. Renewable and non-renewable energy consumption, environmental degradation and economic growth in Tunisia. Qual. Quant. 52, 1105–1119.
Murshed, M., Dao, N.T.T., 2020. Revisiting the CO2 emission-induced EKC hypothesis in South Asia: the role of Export Quality Improvement. GeoJournal http://dx.doi.org/10.1007/s10708-020-10270-9.
Nathaniel, S.P., Iheonu, C.O., 2019. Carbon dioxide abatement in Africa: The role of renewable and non-renewable energy consumption. Sci. Total Environ. 679, 337–345.
Pata, U.K., 2018. Renewable energy consumption, urbanization, financial development, income and CO2 emissions in Turkey: Testing EKC hypothesis with structural breaks. J. Cleaner Prod. 187, 770–779.
Pedroni, P., 1999. Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxford Bull. Econ. Stat. 61, 653–670.
Pedroni, P., 2004. Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. Econom. Theory 20, 597–625.
Pesaran, M.H., 2004. General diagnostic tests for cross section dependence in panels.
Pesaran, M.H., 2007. A simple panel unit root test in the presence of cross-section dependence. J. Appl. Econometrics 22, 265–312.
Pesaran, M.H., Shin, Y., Smith, R.P., 1999. Pooled mean group estimation of dynamic heterogeneous panels. J. Amer. Statist. Assoc. 94, 621–634.
Pesaran, M.H., Shin, Y., Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. J. Appl. Econometrics 16, 289–326.
Petrović, P., Lobanov, M.M., 2020. The impact of R & D expenditures on CO2 emissions: Evidence from sixteen OECD countries. J. Cleaner Prod. 248, 119187.
Rahman, M.M., 2017. Do population density, economic growth, energy use and exports adversely affect environmental quality in Asian populous countries? Renew. Sustain. Energy Rev. 77, 506–514.
Rahman, M.M., 2020a. Environmental degradation: The role of electricity consumption, economic growth and globalisation. J. Environ. Manag. 253, 109742.
Rahman, M.M., 2020b. Exploring the effects of economic growth, population density and international trade on energy consumption and environmental quality in India. Int. J. Energy Sect. Manag. 14 (6), Online published on 21 April.
Rahman, M.M., Alam, K., 2021. Clean energy, population density, urbanization and environmental pollution nexus: Evidence from Bangladesh. Renew. Energy 172, 1063–1072. http://dx.doi.org/10.1016/j.renene.2021.03.103.
Rahman, M.M., Kashem, M.A., 2017. Carbon emissions, energy consumption and industrial growth in Bangladesh: Empirical evidence from ARDL cointegration and granger causality analysis. Energy Policy 110, 600–608.
Rahman, M.M., Nepal, R., Alam, K., 2021. Impacts of human capital, exports, economic growth and energy consumption on CO2 emissions of a cross-sectionally dependent panel: Evidence from the newly industrialized countries (NICs). Environ. Sci. Policy 121, 24–36. http://dx.doi.org/10.1016/j.envsci.2021.03.017.
Rahman, M.M., Saidi, K., Mbarek, M.B., 2020. Economic growth in south Asia: the role of CO2 emissions, population density and trade openness. Heliyon 6 (5), e03903.
Rahman, M.M., Vu, X.B., 2020. The nexus between renewable energy, economic growth, trade, urbanisation and environmental quality: A comparative study for Australia and Canada. Renew. Energy 155, 617–627.
Saidi, K., Omri, A., 2020. The impact of renewable energy on carbon emissions and economic growth in 15 major renewable energy-consuming countries. Environ. Res. 186, 109567.
Saidi, K., Rahman, M.M., 2020. The link between environmental quality, economic growth, and energy use: new evidence from five OPEC countries. Environ. Syst. Decis. http://dx.doi.org/10.1007/s10669-020-09762-3.
Salman, M., Long, X., Dauda, L., Mensah, C.N., Muhammad, S., 2019. Different impacts of export and import on carbon emissions across 7 ASEAN countries: A panel quantile regression approach. Sci. Total Environ. 686, 1019–1029.
Shahbaz, M., Raghutla, C., Song, M., Zameer, H., Jiao, Z., 2020. Public–private partnerships investment in energy as new determinant of CO2 emissions: The role of technological innovations in China. Energy Econ. 86, 104664.
Shahzad, U., Ferraz, D., Doğan, B., Rebelatto, D., Aparecida Do Nascimento Rebelatto, D., 2020. Export product diversification and CO2 emissions: Contextual evidences from developing and developed economies. J. Cleaner Prod. 276, 124146. http://dx.doi.org/10.1016/j.jclepro.2020.124146.
Shin, Y., Yu, B., Greenwood-Nimmo, M., 2014. Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In: Festschrift in Honor of Peter Schmidt. Springer.
Sinha, A., Shahbaz, M., 2018. Estimation of Environmental Kuznets Curve for CO2 emission: Role of renewable energy generation in India. Renew. Energy 119, 703–711.
Su, C.-W., Naqvi, B., Shao, X.-F., Li, J.-P., Jiao, Z., 2020. Trade and technological innovation: The catalysts for climate change and way forward for COP21. J. Environ. Manag. 269, 110774.
UNDP, 2015. Sustainable Development Goals. Retrieved from: https://www.undp.org/content/undp/en/home/sustainable-development-goals.html.
Wang, L., Chang, H.L., Rizvi, S.K.A., Sari, A., 2020. Are eco-innovation and export diversification mutually exclusive to control carbon emissions in G-7 countries? J. Environ. Manag. 270, 110829. http://dx.doi.org/10.1016/j.jenvman.2020.110829.
WDI, 2020. World Development Indicators, World Bank. Source: http://datatopics.worldbank.org/world-development-indicators/.
Wu, R., Dai, H., Geng, Y., Xie, Y., Tian, X., 2019. Impacts of export restructuring on national economy and CO2 emissions: A general equilibrium analysis for China. Appl. Energy 248, 64–78.
Yu, Y., Du, Y., 2019. Impact of technological innovation on CO2 emissions and emissions trend prediction on 'New Normal' economy in China. Atmos. Pollut. Res. 10 (1), 152–161.
Zoundi, Z., 2017. CO2 emissions, renewable energy and the Environmental Kuznets Curve, a panel cointegration approach. Renew. Sustain. Energy Rev. 72, 1067–1075.