



# Trade-environment nexus in OIC countries: fresh insights from environmental Kuznets curve using GHG emissions and ecological footprint

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## Abstract

Being closely correlated with income and economic growth, trade openness impacts the environmental quality through different means. The study analyzes the robustness of the environmental Kuznets curve (EKC) hypothesis in OIC countries by examining the extent to which trade openness influence environmental quality through different environmental indicators for the period 1991 to 2018. A new methodology dynamic common correlated effects (DCCE) is applied to resolve the issue of cross-sectional dependence (CSD). We have used greenhouse gas (GHG) emissions, carbon dioxide (CO<sub>2</sub>), methane (CH<sub>4</sub>) and nitrous oxide (N<sub>2</sub>O) along with ecological footprint as indicators of environmental quality. Results of DCCE estimation identify a negative association of trade openness with CO<sub>2</sub>, N<sub>2</sub>O, and CH<sub>4</sub>, while the positive relationship with the ecological footprint in overall OIC countries and higher income OIC countries. On the other hand, trade openness has a positive association with all environmental indicators in lower income OIC countries. Our findings confirm that inverted-U-shaped EKC exists in all groups of OIC countries when CO<sub>2</sub>, CH<sub>4</sub>, and ecological footprint are used as environmental indicators. However, a U-shaped EKC exists in overall OIC countries and lower income OIC countries when N<sub>2</sub>O is used. Eventually, it is recommended that if OIC countries continue trade openness policies and energy sector reforms and maintain sustainable use of biocapacity; then, they will be able to combat environmental issues with the increase in income.

**Keywords** GHG emissions · Ecological footprint · Trade openness · Environment · Environmental Kuznets curve (EKC) · Cross-sectional dependence (CSD) · DCCE estimation

**JEL classification** F18 · Q56 · Q57

## Introduction

Today, the world is in favor of trade openness because open economies grow faster (Sachs and Warner 1995), are more productive (Kim and Lin 2009), and have higher per capita GDP (Antweiler et al. 2001) than closed economies. Trade openness

may have a negative or positive effect on the environment due to technique, scale, comparative advantage, and composition effects (Grossman and Krueger 1991; Antweiler et al. 2001; Ling et al. 2015; Sahu and Kamboj 2019). Furthermore, trade openness also influences environmental quality via economic growth (Baek and Kim 2011; Ali et al. 2016; Destek et al. 2018). During the growth process, environmental quality first degrades and then begins to improve after reaching a certain threshold. This inverse U-shaped GDP-pollution pattern is also called the environmental Kuznets curve (EKC)<sup>1</sup> (Grossman and Krueger 1991, 1995; Antweiler et al. 2001). Generally, the negative impact of economic growth on environmental quality at the initial phase of development is due to the scale effect of trade openness and increased energy consumption. However, it would have a

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<sup>1</sup> This relationship resembles the inverse-U-shaped GDP-income inequality pattern defined by Kuznets (1955).

positive impact on the environment at the subsequent stage due to technique and/or composition effect (Mrabet and Alsamara 2017; Lan 2017; Destek et al. 2018). In scale effect, the environmental quality degrades due to more economic activities (transportation, industrial production, and deforestation) and energy consumption because, at the early stage of development, more attention is given to growth instead of environmental quality. Afterwards, when income level increases in the second stage of development under technique effect, people demand cleaner environment to attain a higher living standard (Grossman and Krueger 1991; Antweiler et al. 2001; Mahalik et al. 2018; Sarkodie and Strezov 2019). For this regard, production of goods based on dirty technology is replaced with cleaner technology, or with the services sector, having a positive effect on the environment called composition effect (Antweiler et al. 2001; Lin 2017; Uddin et al. 2017). Trade openness helps to improve environmental quality if the technical effect dominates the scale effect and composition effect (Antweiler et al. 2001). Moreover, trade openness can improve environmental quality through capital-labor channels and when environmental regulation is greater than capital-labor effect (Copeland and Taylor 1994; Managi et al. 2009).

Trade openness, innovations, and global movements of a capital encourage vector of green growth and especially adequate instruments to fight climate change and pollution (Meschi and Taymaz 2017; Song et al. 2019; Lv and Xu 2019). The EKC hypothesis has been a central point of the environment since trade openness became more extensive in the world (Antweiler et al. 2001; Mrabet and Alsamara 2017; Shahbaz et al. 2017). Trade openness also invites FDI in the country (Salman et al. 2018; Udeagha and Ngepah 2019; Ali et al. 2020). Proponents of free trade suggested that international trade will lead to enhance world income, but the intensive trade also has some environmental consequences which may outweigh the benefits from trade (Nemati et al. 2019; Mrabet and Alsamara 2017; Ali et al. 2020). Comparative advantage is the hallmark of free trade, but it can lead to further environmental degradation (Tsai 1999; Wei et al. 2019). According to the pollution haven hypothesis (PHH), due to trade openness and comparative advantage, the dirty industrial production migrates from more developed countries, with strict environmental standards, to the less developed economies, with the lax regulations (Copeland and Taylor 1994; Cole 2004). The comparative advantage effect on environmental quality depends on the combined effect of the overall composition of trade in an economy (Ling et al. 2015). Due to the complex nature of the relationship between trade openness and economic growth, it is hard to pinpoint the paths that underlie the trade-growth-environment nexus (Kellenberg and Mobarak 2008). It may be inappropriate to generalize EKC patterns for all countries since the process of development is likely to differ among them (De Bruyn et al. 1998). Despite this fact, however, the EKC provides a useful

link on how trade openness may influence pollution through growth (Uddin et al. 2017; Alola et al. 2019).

Most of the studies used greenhouse gas (GHG) emissions like carbon dioxide (CO<sub>2</sub>), sulfur dioxide (SO<sub>2</sub>), methane (CH<sub>4</sub>), sulfur hexafluoride (SF<sub>6</sub>), and nitrous oxide (N<sub>2</sub>O) as indicators of environmental quality (Frankel and Rose 2005; Apergis 2016; Dogan and Seker 2016; Apergis et al. 2017). Another indicator which is now widely recognized as a new measurement tool for the sustainable ecological system is known as ‘ecological footprint’ (Wiedmann and Barrett 2010; Galli 2015; Solis-Guzman and Marrero 2015; Ali et al. 2020). The ecological footprint is the best device to deal with the biological and ecological capacity of the earth for environmental sustainability (Aydin et al. 2019; Ali et al. 2020). Natural resources (minerals, water, lands, and forests) are dissipated due to industrial and human actions. If only emissions are selected as the indicators of environmental quality, then economic and human activities are neglected which will be hazardous for the sustainable ecosystem (Sarkodie 2018; Aydin et al. 2019; Li et al. 2019; Dogan et al. 2019).

One of the least studied regions in terms of EKC is Organization of Islamic Cooperation (OIC) countries, consisting of fifty-seven economies, comprising the Muslim community and incorporates a considerable proportion of the underdeveloped countries. OIC countries have 23.8% population of the world (SESRIC 2018). Due to globalization and trade openness, the industrial production of OIC countries is expanding which leads to more consumption of energy and natural resources which increases pollution (Mirjalili and Motaghian Fard 2019; Nekooei et al. 2015; Ali et al. 2020). Many countries adopted the Paris agreement to deal with environmental issues and agreed to make arrangements to mitigate the world temperature by reducing GHG emissions. This agreement is endorsed by 196 countries, but only 166 countries have ratified it in which 43 are OIC countries (SESRIC 2018). Moreover, environmental scarcities and degradation of natural resources can create socio-economic disputes in OIC countries (Tolba and Saab 2008; Gholipour and Farzanegan 2018).

The present study seeks to evaluate the trade-environment nexus and their role in EKC for OIC countries. Although many researchers have discussed the impact of trade openness on the environment in different countries, but in case of OIC countries, the comprehensive literature on the subject are very limited (Konac 2004; Ali et al. 2020). Currently, no study is available, which has evaluated the trade-environment nexus in the context of EKC in OIC countries. So, this research makes a contribution to the current literature through different means as consistent with the abovementioned discussion: (i) it is a first study which elaborates the trade-environment nexus with reference to EKC in OIC countries, (ii) unlike past empirical studies, this study uses a new technique called ‘dynamic common correlated effects (DCCE)’ which can deal with several methodological issues of the panel data like heterogeneity and cross-sectional dependence

(CSD). The DCCE technique calculates dynamic common correlated effects by considering heterogeneous slopes and assuming that the variables can be represented by a common factor, (iii) a great majority of EKC literature use only CO<sub>2</sub> emissions as a proxy for environmental quality which is an insufficient measure to capture environmental effects. Policymakers can be misleading when CO<sub>2</sub> emissions are used exclusively as a proxy for environmental quality. So, more inclusive environmental variables are used to obtain robust findings. So, this study addresses the environmental issues in a modern context by considering three GHG emissions, i.e., carbon dioxide (CO<sub>2</sub>), methane (CH<sub>4</sub>), and nitrous oxide (N<sub>2</sub>O) along with a new proxy of environmental quality called ecological footprint, (iv) one of the largely ignored variables in the existing literature of EKC is trade openness. So, trade openness is added in our models to avoid specification bias. (v) The examination of the OIC countries is of interest to governments, researchers, and policymakers, since having accounted for almost 25.0% of the world total population, OIC countries are responsible for only 8.2% of global production and 10.2% of world's trade, and having a higher level of air pollution than non-OIC developing nations (SESRI 2018); (vi) it provides valuable suggestions based on the findings, which will open the routes for future research on the trade-environment nexus and its implications in OIC countries.

To this end, this paper evaluated the trade-environment nexus to test the EKC hypothesis in OIC countries by using various environmental indicators. A novel technique 'dynamic common correlated effects (DCCE)' is applied. Our findings confirm that inverted-U-shaped EKC exists in all groups of OIC countries when CO<sub>2</sub>, CH<sub>4</sub>, and ecological footprint are used as environmental indicators. However, a U-shaped EKC is found in overall OIC countries and lower income OIC countries when N<sub>2</sub>O is used. As a policy recommendation, OIC countries should continue trade openness policies and energy sector reforms and maintain sustainable use of biocapacity. The rest of the paper is structured as follows: [Literature review](#) section presents the review of empirical literature related to the trade-environment nexus and EKC. [Data and methodology](#) section introduces data and methodology. [Results and discussion](#) section yields results and discussion. Conclusion and policy recommendations are given in the [Concluding remarks and recommendations](#) section.

## Literature review

The empirical research about the trade-environment nexus commenced with the presentation of EKC, which has been famous since the early 1990s. In pioneer studies, the effects of GDP and trade openness were observed by Grossman and Krueger (1991) for NAFTA,<sup>2</sup> which made a foundation for

the further expedition of the EKC hypothesis. Shafik and Bandyopadhyay (1992) explored the empirical evidence of EKC through the growth-environment nexus. Despite many studies, the conflicting results have kept this area interesting for further investigation and research. For example, Frankel and Rose (2005) by using CO<sub>2</sub> and SO<sub>2</sub>, while Shahbaz et al. (2015), Apergis and Ozturk (2015), Ertugrul et al. (2016), and Mutascu (2018) by using CO<sub>2</sub> emissions discovered a significant and positive impact of trade openness on pollution. Moreover, some empirical studies, for example, Kellenberg and Mobarak (2008) and Saleem et al. (2019), had observed mixed evidence about the trade-environment nexus by using various environmental indicators (CO<sub>2</sub>, SO<sub>2</sub>, NO<sub>2</sub>, and VOCs<sup>3</sup>). On the other side, using the EKC hypothesis, the outcomes of Shafik (1994), Mukhopadhyay and Chakraborty (2005), Soytaş et al. (2007), Bernard and Mandal (2016), and Al-Mulali et al. (2015) could not find the trade-environment nexus, and the studies by Kathuria (2018) and Jobert et al. (2019) using the PHH also could not observe the link between trade openness and environment.

Antweiler et al. (2001) observed the trade-environment nexus under, i.e., technique, scale, and composition effect. The net impact of these three components originates the EKC. It was found that the environment improved if the strength of the technique effect was more than the scale effect and composition effect. Cole (2004) explained trade-environment nexus and validated PHH in OECD countries. Similarly, the relationship between trade openness and the environment was re-evaluated by Managi et al. (2009) for two GHG emissions (SO<sub>2</sub> and CO<sub>2</sub>) in case of OECD and non-OECD economies, and similar outcomes were found as of Cole (2004). The changes in EKC pattern due to changes in trade was observed by Antweiler et al. (2001), Lindmark (2002), Cole (2004), Ali et al. (2016), Lan (2017), and Pata (2019). However, it is observed that if the growth of a country come through trade openness, then the level of pollution increases with economic growth (Copeland and Taylor 2005; Chang 2012; Shahbaz et al. 2013; Jebli and Youssef 2015; Ahmed et al. 2016; Lin 2017) and eventually, this scale effect is offset by the technological change due to change in preferences of individuals (Kozul-Wright and Fortunato 2012; Meschi and Taymaz 2017; Song et al. 2019). Apergis and Ozturk (2015) validated EKC for 14 countries of Asia by using CO<sub>2</sub> emissions. After applying the GMM method, an inverse-U-shaped association was found between GDP and environmental degradation. Zambrano-Monserrate and Fernandez (2017) validated the EKC hypothesis in Germany by using N<sub>2</sub>O emissions. It was found that per capita GDP increased due to technique effect, and the quadratic

<sup>2</sup> North American Free Trade Agreement

<sup>3</sup> VOCs (volatile organic compounds) are released from burning fuel such as coal, gasoline, wood, cigarettes, air fresheners, and pesticides. They easily become vapors or gases.

association between income and N<sub>2</sub>O emissions was also indicated. Similarly, Dogan and Turkekul (2016) evaluated the impact of energy consumption, GDP, and trade openness on CO<sub>2</sub> emissions in the USA for the year 1960–2010. Energy consumption has positive while trade openness had a negative impact on CO<sub>2</sub> emissions. EKC hypothesis was also validated.

Some recent studies have utilized a new indicator for environmental quality named ecological footprint rather than greenhouse gas (GHG) emissions. Mrabet and Alsamara (2017) explored the trade-environment nexus using ecological footprint and CO<sub>2</sub> emissions in Qatar for the year 1980 to 2011. The ARDL model indicated that trade openness had a positive relationship with environmental indicators. Trade openness had improved environmental quality because the technical effect dominated the scale effect and composition effect. EKC is validated by using the ecological footprint but not in the case of CO<sub>2</sub> emissions. Uddin et al. (2017) observed the GDP-trade-ecological footprint nexus through DOLS method and found a positive association between GDP and ecological footprint while trade openness had a negative impact on ecological footprint. In another study, Aydin et al. (2019) observed the asymmetric relationship between GDP and pollution in 26 countries of the European Union by taking ecological footprint. The findings of the PSTR model indicated that environmental pressure increased with economic growth but did not decrease with further growth, and EKC did not prevail. On the other hand, Destek et al. (2018) analyzed the relationship between GDP, trade openness, and ecological footprint in European Union countries. Trade openness was negatively associated with the ecological footprint, and an inverse U-shaped relationship was found between real GDP and environmental degradation, which supported EKC. In another study, Dogan et al. (2019) validated the EKC for Indonesia, Mexico, Turkey, and Nigeria by using ecological footprint. Augmented EKC model indicated that exports, financial development, urbanization, and the consumption of fossil fuel energy were the main determinants of anthropogenic pressure on environmental degradation.

Only two studies are found regarding environmental quality in OIC countries. In the first study, Konac (2004) defined how trade openness and different environmental indicators were used to achieve sustainable development in OIC countries according to OIC plan of Action of 1994. It was argued that human activities like unsustainable use of agricultural land, poor irrigation practices, frequent use of heavy machinery, deforestation, removal of natural vegetation, and natural disasters were the main factors of land degradation (Konac 2004). An organic relationship was found between development and environmental protection as they both need and could harm each other. In the second study, Ali et al. (2020) observed the association between trade openness, foreign direct investment, and institutional performance on

environmental quality by taking ecological footprint for OIC countries. Five different indicators are used to construct the institutional performance index. It was observed that openness, foreign direct investment, and urbanization decreased environmental quality while institutional performance improved environmental quality in OIC countries.

The empirical review suggested that many studies analyzed the trade-environment nexus in the EKC context for different group of countries, but in the case of OIC, only limited studies exist.<sup>4</sup> The review of previous studies also claims that cross-sectional dependence (CSD) may occur in the trade-environment relationship due to unobserved factors. It leaves space for doing comprehensive empirical research to find the role of trade-environment nexus in the validation of the EKC hypothesis by considering the issue of CSD. Furthermore, it would be beneficial to investigate this issue in terms of a particular region, i.e., OIC countries.

## Data and methodology

In order to evaluate the trade-environment nexus under EKC hypothesis in OIC countries, we have used three pollutants, i.e., carbon dioxide (CO<sub>2</sub>), nitrous oxide (N<sub>2</sub>O), and methane (CH<sub>4</sub>) along with ecological footprint as dependent variables in 4 different models. The independent variables are GDP, GDP square, energy consumption, trade openness, and urbanization. The reason for choosing these indicators as environmental indicators is that these pollutants have a large share in GHG emissions. CO<sub>2</sub> emissions have the largest share in GHG emissions followed by CH<sub>4</sub> and N<sub>2</sub>O. CO<sub>2</sub> emissions are mainly generated from energy consumption, industrial production, and transportation (SESRI 2018). N<sub>2</sub>O emissions are generated from agricultural production (Aneja et al. 2019) while CH<sub>4</sub> emissions are emitted during the production of oil, coal, and natural gas (Wang et al. 2020; Yusuf et al. 2020). The ecological footprint is a new indicator of environmental quality which can reflect the biological and ecological capacity of the country.

Generally, GHG emissions include N<sub>2</sub>O, CO<sub>2</sub>, CH<sub>4</sub>, and F-gases.<sup>5</sup> Figure 1 shows that the level of GHG emissions in OIC countries was 3.3 thousand MtCO<sub>2</sub>e<sup>6</sup> in 1990, while in 2017, it is 7.0 thousand MtCO<sub>2</sub>e (World Resources Institute 2018). Among OIC countries, Iran has the highest level of CO<sub>2</sub> emissions followed by Indonesia, Turkey, and Kazakhstan (see Appendix Table 9).

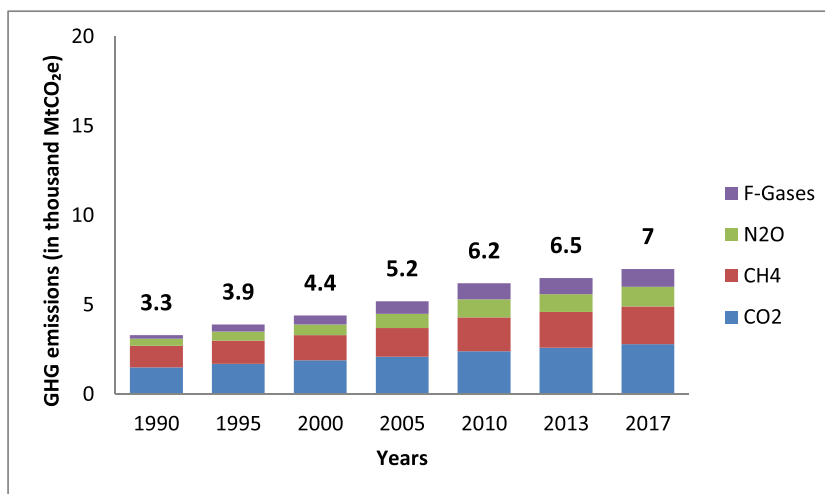
Figure 2 depicts that the ecological footprint in OIC countries has been growing from 32 million global hectares in 1992

<sup>4</sup> See Konac (2004) and Ali et al. (2020)

<sup>5</sup> Fluorinated gases, i.e., perfluorocarbons, sulfur hexafluoride, and hydrofluorocarbons.

<sup>6</sup> Metric tons of carbon dioxide equivalent

**Fig. 1** GHG emissions in OIC countries. Source: SESRIC Economic Outlook of OIC Countries (various issues)



to 52 million global hectares in 2010 and 60 million global hectares in 2016. Indonesia has the highest level of ecological footprint in OIC countries followed by Turkey, Iran, and Nigeria (see Appendix Table 9).

There are 57 OIC countries, but due to non-availability of data for some countries, we have selected 49 countries. World Bank classified the countries of the world into four income groups according to their per capita GDP; low-income, lower middle-income, upper middle-income, and high-income countries. For our analysis, following by the study of Farooq et al. (2020), we have divided OIC countries into three groups. In first group, we place all OIC countries (hereinafter we call it overall OIC countries). We put low-income and lower-middle income OIC countries in second group (hereinafter denoted as lower income OIC countries) and in the third group, we place upper middle-income and high-income OIC countries (hereinafter referred to as higher-income OIC countries). So, in this way, we have divided OIC countries into three groups; overall OIC countries, lower income OIC countries, and higher income OIC countries (see Appendix Table 10).

We have used a panel data set for the year 1991 to 2018. Some missing values in the data are calculated through

multiple imputation method (Rubin 1976, 1996). This method improves the data quality and inferences validity by providing stable imputations of missing data (Hassan et al. 2020). In previous studies, various types of methodologies like GMM, fixed effect, and random effect models have been used for panel data estimation. But these conventional methodologies ignore the issue of heterogeneity and assume homogeneity in data, and only permit to change the intercepts of cross-sectional units. Therefore, now there is a need to be more focused on the issue of cross-sectional dependence (CSD).

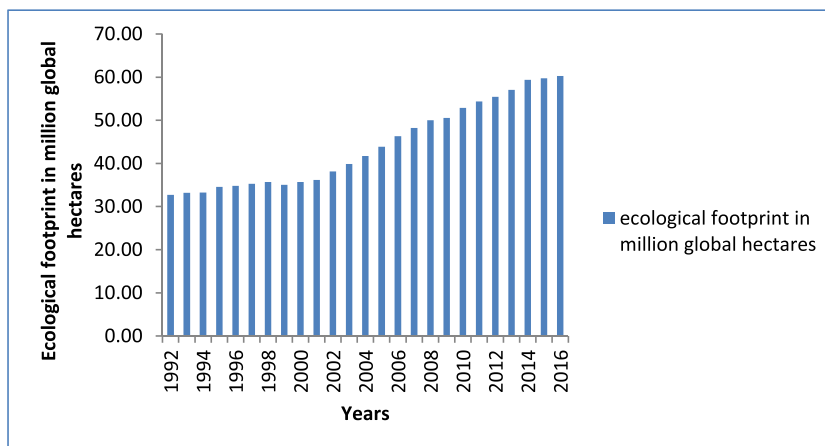
### Cross-sectional dependence tests

Lagrange multiplier (LM) test is widely used to examine the CSD in the panel data. This test is initially developed by Breusch and Pagan (1980).

A standardized form of LM test of Breusch and Pagan (1980) is as follows:

$$LM_{BP} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}^2$$

**Fig. 2** Ecological footprint in OIC countries. Source: Global Footprint Network



where  $\hat{\rho}_{ij}^2$  shows the sample estimate of the pair-wise correlation coefficients. LM test of Breusch and Pagan (1980) is suitable in case of sufficiently large  $T$  and relatively small  $N$ . This test becomes inappropriate if the mean of average pair-wise correlation is close to zero (Pesaran 2004). Thus, to overcome the shortcomings of the  $LM_{BP}$  test, Pesaran (2004) introduced another test statistics on the base of scaled version of the LM test. This test can be applicable even with large  $N$  and small  $T$ .

$$\text{Scaled LM Test} = \sqrt{\left(\frac{1}{N(N-1)}\right)} \left[ \sum_{i=1}^{N-1} \sum_{j=i+1}^N (T\rho_{ij}^2 - 1) \right].$$

This test is likely to exhibit substantial size distortions with large  $N$  and small  $T$ . To overcome this issue, Pesaran (2004) proposed another cross-sectional dependence test which can also be suitable with large  $N$  and small  $T$ .

$$CD = \sqrt{\left(\frac{2T}{N(N-1)}\right)} \left[ \sum_{i=1}^{N-1} \sum_{j=i+1}^N \rho_{ij} \right].$$

With  $T \rightarrow \infty$  and  $N \rightarrow \infty$ , the  $CD$  test has an asymptotic standard normal distribution under the null hypothesis. This test is based on a scaled average of the pair-wise correlation coefficients rather than their squares which are used in the LM test. This test gives robust outcomes in case of heterogeneous dynamic models and including multiple breaks in slope coefficients.

Baltagi et al. (2012) modified the LM test by using accurate mean and variance of the LM statistics, which is formulated as follows:

$$LM_{adj} = \sqrt{\left(\frac{2T}{N(N-1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \rho_{ij} \frac{(T-k)\rho_{ij}^2 - \mu_{Tij}}{\sqrt{\nu_{Tij}^2}},$$

where  $\mu_{Tij}$  and  $\nu_{Tij}^2$  are the exact mean and variance of  $(T-k)\rho_{ij}^2$  tabulated by Baltagi et al. (2012).

### Panel unit root test (CIPS-test)

CIPS panel unit root test is a 2nd-generation unit root test which is considered superior than 1st-generation unit root tests. The 1st-generation unit root tests used by many studies like Levin et al. (2002) and Im et al. (2003) and Maddala and Wu (1999) have mainly assumed cross-sectional independence and homogeneity. If the analyzed variables are not cross-sectionally independent and homogeneous, the 1st-generation tests likely produce inefficient results. On the other hand, the 2nd-generation panel unit root test (CIPS-test) developed by Choi (2006) and Pesaran (2007) give more certain outcomes because it can effectively control for CSD and heterogeneity.

### Westerlund error-correction-based panel cointegration test

Westerlund (2007) error-correction-based cointegration test is used to check the cointegration among variables and is most suitable in case of CSD. This test also has the capability of dealing short time period and structural breaks (Persyn and Westerlund 2008). In order to evaluate the null hypothesis of no cointegration, Westerlund (2007) proposed four statistics which are classified into two categories, i.e., group mean-based tests (Group- $\alpha$ , Group- $T$ ) and panel-based tests (Panel- $\alpha$ , Panel- $T$ ). For individual cross-sectional units, panel-based tests calculate the whole panel-based error-correction term, while the group mean-based tests estimate the weighted sum of the error-correction term. These tests examine the cointegration in a panel series by checking the mechanism of error-correction for both individual cross-sections and the whole panel.

### Slope homogeneity test

Slope homogeneity test is used to check the presence of cross-sectional heterogeneity in the data. The null hypothesis for slope homogeneity test is that slope coefficients are homogeneous (no heterogeneity) against the alternative hypothesis of no homogeneity (heterogeneity).

Initially, Swamy (1970) developed a test for slope homogeneity which required fixed  $N$  relative to  $T$ . Later on, Pesaran et al. (2008) modified this test which is suitable if  $(N, T) \rightarrow \infty$  by assuming that error terms has a normal distribution.

Pesaran et al. (2008) test of slope homogeneity is modeled as follows:

$$\tilde{S} = \sum_{i=1}^N \left( \beta_i - \tilde{\beta}_{WFE} \right)' \frac{x_i' M_\tau x_i}{\tilde{\sigma}_i^2} \left( \beta_i - \tilde{\beta}_{WFE} \right).$$

Here,  $\beta_i$  and  $\tilde{\beta}_{WFE}$  indicate pooled OLS coefficient and weighted fixed effect pooled estimator respectively.  $M_\tau$  represents an identity matrix while  $\tilde{\sigma}_i^2$  denotes an estimate of variance. The following formula can be used to calculate the standard dispersion statistic:

$$\bar{\Delta} = \sqrt{N} \left( \frac{N^{-1} \tilde{S} - k}{\sqrt{2k}} \right).$$

$\Delta$  test consists of standard and asymptotically normal distribution under the null hypothesis of  $(N, T) \rightarrow \infty$  and  $\sqrt{N/T} \rightarrow \infty$ . The biased-adjusted version of the  $\bar{\Delta}$  test is represented as follows:

$$\bar{\Delta}_{adj} = \sqrt{N} \left( \frac{N^{-1} \tilde{S} - E(\bar{z}_{it})}{\sqrt{\text{var}(\bar{z}_{it})}} \right),$$

where the variance and mean are denoted by  $\text{var}(\bar{z}_{it}) = 2k(T-k-1) / T + 1$  and  $E(\bar{z}_{it}) = k$ , respectively.

The slope homogeneity test is critical because it determines whether the coefficients of the countries in the long run are homogeneous or heterogeneous. Due to strong CSD, it is possible that each country may have similar dynamics in the processes of opening up trade. If the panel data is heterogeneous, assuming slope homogeneity can result in inaccurate outcomes (Breitung 2005). So, the slope homogeneity test is helpful to identify the presence of cross-sectional heterogeneity while analyzing the empirical outcomes.

### Dynamic common correlated effects (DCCE)

Many studies argued that CSD exists among countries due to economic shocks and unobserved components as a result of trade openness and globalization. In this era of modernization, due to the trade openness, economic changes in other countries have significantly affected each country. (Dogan et al. 2017; Ozcan and Ozturk 2016, 2019; Arain et al. 2019; Dogan et al. 2020). A new technique dynamic common correlated effects (DCCE) by Chudik and Pesaran (2015) is helpful to deal such issue of CSD. This technique considers that CSD is caused by an unobserved single common factor and the variables can be represented by this common factor. The DCCE methodology is developed on the basis of pooled mean group (PMG) estimation developed by Pesaran et al. (1996), mean group (MG) estimation presented by Pesaran and Smith (1995), and common correlated effects (CCE) estimation by Pesaran (2006). The CCE approach includes cross-sectional averages of both independent and dependent variables in regression to obtain unobserved common factors. Although CCE technique is robust to cointegration, nonstationarity, serial correlation, and breaks, but it is not suitable for dynamic panels because the lag of dependent variable in this approach is not considered strictly exogenous (Chudik and Pesaran 2015).

On the other hand, in DCCE methodology, the estimator becomes more consistent by including additional lags of cross-sectional means. Ditzen (2019) modified the DCCE approach of Chudik and Pesaran (2015) by claiming that both short-run and long-run results can be estimated for heterogeneous panels. The DCCE technique deals with five critical problems which are not considered by other old techniques. First, this methodology comprehends the issue of CSD by taking logs and averages of all cross-sectional units. The second issue is heterogeneity in the parameters, which can be resolved with the properties of mean group (MG) estimation

included in the DCCE approach. Third, it estimates dynamic common correlated effects by considering heterogeneity and assuming that the variables can be represented by a common factor. Fourth, the DCCE approach can also be used for a small sample size by implementing the command of Jackknife<sup>7</sup> correction (Chudik and Pesaran 2015; Ditzen 2016, 2019). In the last, this technique can also be applied when there are structural breaks (Kapetanios et al. 2011) and unbalanced panel data (Ditzen 2016).

Our empirical models are based on the studies of Grossman and Krueger (1991) and Destek et al. (2018) who recognize the role of trade openness while validating EKC hypothesis. Along with trade openness and GDP, we have also incorporated other important determinants of environmental quality, i.e., energy consumption and urbanization to avoid omitted variable bias. The DCCE approach can easily deal with the heterogeneity and CSD issue in data by considering heterogeneous slopes in which the parameters vary across cross-sections.

Based on abovementioned specifications, DCCE equation can be written as follows:

$$Y_{it} = \alpha_i Y_{it-1} + \delta_i X_{it} + \sum_{p=0}^{P_T} \gamma_{xip} \bar{X}_{t-p} + \sum_{p=0}^{P_T} \gamma_{yip} \bar{Y}_{t-p} + \mu_{it}. \quad (1)$$

Here,  $i$  and  $t$  depict cross-sectional and time dimensions, respectively.  $Y_{it}$  denotes the dependent variable.  $Y_{it-1}$  is lag of dependent variable, which is used as an independent variable.  $X_{it}$  is the set of other independent variables.  $\gamma_{xip}$  and  $\gamma_{yip}$  are unobserved common factors.  $P_T$  denotes the lag of cross-sectional averages.  $\mu_{it}$  represents the error term.

### Model specification

Suppose EI is an environmental indicator (i.e., CO<sub>2</sub>, SO<sub>2</sub>, and ecological footprint) and GDP (Gross Domestic Product) is an indicator of economic growth. Then, following the studies of Grossman and Krueger (1991), Sinha et al. (2018), and Özcan and Öztürk (2019), a basic U-shaped/inverted-U-shaped EKC model can be written as follows:

$$EI = a_0 + a_1 GDP + a_2 GDP^2 + \mu. \quad (2)$$

From Eq. (2), we obtain the following specifications, which denote specific functional forms:

- $a_1 = a_2 = 0$ , no growth-pollution association
- $a_1 > 0, a_2 = 0$ , linearly increasing growth-pollution association
- $a_1 < 0, a_2 = 0$ , linearly decreasing growth-pollution association

<sup>7</sup> In STATA, Jackknife command is useful to calculate robust standard errors and robust variance estimates. It is also helpful in case of small data size. Most STATA commands can be used with jackknife.

$a_1 > 0$ ,  $a_2 < 0$ , inverted-U-shaped growth-pollution association

$a_1 < 0$ ,  $a_2 > 0$ , U-shaped/monotonically increasing growth-pollution association.

To check the validity conditions of EKC, Eq. (2) should be differentiated with respect to GDP:

$$\frac{dEI}{dGDP} = a_1 + 2a_2GDP. \quad (3)$$

Now, taking the 2nd derivative of Eq. (3):

$$\frac{d^2EI}{dGDP^2} = 2a_2. \quad (4)$$

Here,

$a_2 < 0$ , implies the presence of local maxima, thereby indicating the existence of inverted-U-shaped EKC.

$a_2 > 0$ , implies the existence of local minima, thereby indicating the presence of U-shaped EKC.

The threshold point (turning point) of EKC is obtained by setting the 1st derivation (as shown in Eq. 3) equal to zero and solved for GDP.

$$a_1 + 2a_2GDP = 0, \quad (5)$$

$$GDP^* = \frac{-a_1}{2a_2}. \quad (6)$$

Here,  $GDP^*$  denotes a threshold (turning) point of GDP.

The basic EKC model described in Eq. 2 is further extended into the following 4 models by including additional variables and underlying EKC hypothesis. We have used various proxies for environmental quality as dependent variables followed by the studies of Managi et al. (2009), Mrabet and Alsamara (2017), Mahmood et al. (2019), and Aydin et al. (2019).

$$\begin{aligned} LNCO_{2it} = & \alpha_i LNCO_{2it-1} + \delta_i X_{it} + \sum_{p=0}^{p_r} \gamma_{xip} \bar{X}_{t-p} \\ & + \sum_{p=0}^{p_r} \gamma_{yip} \bar{X}_{t-p} + \mu_{it}, \text{ (Model 1)} \end{aligned}$$

$$\begin{aligned} LNN_2O_{it} = & \alpha_i LNN_2O_{it-1} + \delta_i X_{it} + \sum_{p=0}^{p_r} \gamma_{xip} \bar{X}_{t-p} \\ & + \sum_{p=0}^{p_r} \gamma_{yip} \bar{X}_{t-p} + e_{it}, \text{ (Model 2)} \end{aligned}$$

$$\begin{aligned} LNCH_{4it} = & \alpha_i LNCH_{4it-1} + \delta_i X_{it} + \sum_{p=0}^{p_r} \gamma_{xip} \bar{X}_{t-p} \\ & + \sum_{p=0}^{p_r} \gamma_{yip} \bar{X}_{t-p} + \varepsilon_{it}, \text{ (Model 3)} \end{aligned}$$

$$\begin{aligned} LNECF_{it} = & \alpha_i LNECF_{it-1} + \delta_i X_{it} + \sum_{p=0}^{p_r} \gamma_{xip} \bar{X}_{t-p} \\ & + \sum_{p=0}^{p_r} \gamma_{yip} \bar{X}_{t-p} + \nu_{it}. \text{ (Model 4)} \end{aligned}$$

In above equations,  $LNCO_2$  (log of  $CO_2$  emissions) in Model 1,  $LNN_2O$  (log of  $N_2O$  emissions) in Model 2,  $LNCH_4$  (log of methane emissions) in Model 3, and  $LNECF$  (log of ecological footprint) in Model 4 are dependent variables representing proxies for environmental quality, and their lags are used as independent variables. All other independent variables (log of GDP, log of GDP square, log of trade openness, log of energy consumption, and log of urbanization) are represented by  $X_{it}$ .  $\mu_{it}$ ,  $e_{it}$ ,  $\varepsilon_{it}$ , and  $\nu_{it}$  are error terms of models 1, 2, 3, and 4 respectively.

Table 1 gives a detail description of the variables and their sources.

## Results and discussion

Table 2 shows the descriptive statistics of data which summarizes the important features of the data.  $CO_2$ ,  $N_2O$ ,  $CH_4$ , ECF, GDP, ENC, TOP, and URB represents  $CO_2$  emissions,  $N_2O$  emissions,  $CH_4$  emissions, ecological footprint, GDP per capita, energy consumption, trade openness, and urbanization, respectively.

CD test (Pesaran 2004) and scaled LM test developed by Pesaran (2004) and biased-corrected scaled LM test developed by Baltagi et al. (2012) are applied to test the existence of CSD as demonstrated in Table 3. Results of tests are helpful not only to determine the appropriate methodology but also crucial to determine the application of 2nd-generation panel unit root tests that are more suitable in case of CSD.

The 2nd-generation unit root test, which is also called CIPS-test (Pesaran 2007), is shown in Table 4. This test assumes CSD among the variables. All the variables are stationary at the level and 1st difference and none of them is stationary at the 2nd difference. The findings of CIPS unit root test confirm that  $LNN_2O$ ,  $LNCH_4$ ,  $LNECF$ ,  $LNTOP$ ,  $LNENC$ , and  $LNURB$  are stationary at level, while  $LNCO_2$ ,  $LNGDP$ , and  $LNGDP^2$  are stationary at 1st difference.

The traditional cointegration test like Pedroni (1999) may be ambiguous as it can ignore some critical issues like CSD, serial correlation, heteroskedasticity, and structural breaks in data (Westerlund 2007; Arain et al. 2019; Ali et al. 2020). On the other hand, an advanced test of 2nd-generation Westerlund (2007) error-correction-based panel cointegration test considers all these issues, and its results are more reliable. We have applied Westerlund cointegration test as shown in Table 5.



**Table 1** Description of variables and data sources

Variables	Description	Unit of measurement	Data sources
LNCO <sub>2</sub>	Log of CO <sub>2</sub> emissions	metric tons per capita	World Bank
LNN <sub>2</sub> O	Log of nitrous oxide emissions	Thousand metric tons of CO <sub>2</sub> equivalent	World Bank
LNCH <sub>4</sub>	Log of methane emissions	kt of CO <sub>2</sub> equivalent	World Bank
LNECF	Log of ecological footprint	Global hectares (gha)	Global Footprint Network
LNENC	Log of energy consumption	Thousand metric ton of oil equivalent	World Bank
LNGDP	Log of GDP per capita	Constant 2010 US\$	World Bank
LNURB	Log of urbanization	Total persons living in urban areas	World Bank
LNTOP	Log of trade openness	Volume of imports plus volume of exports (constant 2010 US\$)	World Bank

The values of all test statistics (Group- $\alpha$ , Group- $\tau$ , Panel- $\alpha$ , and Panel- $\tau$ ) of Westerlund (2007) cointegration test are significant on the basis of robust  $p$  values. So the null hypothesis of no cointegration is rejected, and it is verified that there is a long-run association among the variables. Our results of Westerlund cointegration test are consistent with the findings of Arain et al. (2019), Ali et al. (2020), and Meo et al. (2020) who also found a long-run association among the variables by applying the Westerlund (2007) cointegration test.

Table 6 shows the results of slope homogeneity test (Pesaran et al. 2008). The null hypothesis for slope homogeneity test is that slope coefficients are homogenous (no heterogeneity) against the alternative hypothesis of no homogeneity (heterogeneity). The  $t$ -statistics values of slope homogeneity test ( $\bar{\Delta}$ ) and its biased-adjusted version ( $\bar{\Delta}_{adj}$ ) provide us enough evidence to reject the null hypothesis of slope homogeneity and accept the alternative hypothesis of country-specific heterogeneity in our all 4 models.

Table 7 shows the results of DCCE estimation of overall OIC countries, and Table 8 indicates the DCCE estimates of lower income and higher income OIC countries. All the independent variables of our models show a significant association

with the lag terms of dependent variables (L.LNCO<sub>2</sub>, L.LNN<sub>2</sub>O, L.LNCH<sub>4</sub>, and L.LNECF). The long-run and short-run estimates of DCCE demonstrate a positive and significant association of per capita GDP with all environmental indicators except in Model 2, where it shows a negative and significant association with N<sub>2</sub>O emissions in overall OIC countries and lower-income OIC countries while the positive association with N<sub>2</sub>O emissions in higher-income OIC countries. The negative association between per capita GDP and N<sub>2</sub>O emissions in overall and lower-income OIC countries is aligning with the study of Bilgili et al. (2016). The positive relationship between per capita GDP and the environmental indicators (CO<sub>2</sub>, CH<sub>4</sub>, and ecological footprint) is consistent with Shahbaz et al. (2013), Jebli and Youssef (2015), Ahmed et al. (2016), Lin (2017), and Uddin et al. (2017). As discussed before, this positive impact of per capita GDP on environmental indicators is true in the initial phase of development in OIC countries due to the scale effect of trade openness and increased energy consumption. In scale effect, the environmental quality degrades due to more economic activities (transportation, industrial production, and deforestation) and energy consumption because, at the early stage of development, more

**Table 2** Descriptive statistics of variables

	CO <sub>2</sub>	N <sub>2</sub> O	CH <sub>4</sub>	ECF	GDP	ENC	TOP	URB
Mean	5.39	13,535.26	37,837.57	57,886,498	7246.17	1,234,397	57,200,000,000	16,640,874
Median	2.61	4478.44	12,691.30	22,253,592	2746.83	12,017.61	20,800,000,000	6,949,061
Minimum	0.08	71.75	945.68	1,245,639	339.14	1210.80	96,688,254	243,702
Maximum	44.64	369,900.3	912,858	389,000,000	72,444.08	37,712,280	615,000,000,000	128,000,000
Skewness	2.14	6.08	5.78	1.97	2.65	4.89	2.99	2.28
Std.Dev.	7.51	29,192.30	68,507.20	72,409,720	10,000.18	6,041,469	90,200,000,000	22,042,052
Kurtosis	7.35	54.86	57.20	6.96	11.79	25.36	13.16	9.03
Observations	1372	1372	1372	1372	1372	1372	1372	1372

\* and \*\* shows 1% and 5% level of significance, respectively

**Table 3** Panel unit root tests for CSD

Variables	CD test		Scaled LM test		Bias-corrected scaled LM	
	Statistic	Probability	Statistic	Probability	Statistic	Probability
LNCO <sub>2</sub>	31.74	0.00*	129.28	0.00*	128.32	0.00*
LNN <sub>2</sub> O	27.85	0.00*	130.30	0.00*	129.21	0.00*
LNCH <sub>4</sub>	80.71	0.00*	221.23	0.00*	220.16	0.00*
LNECF	26.69	0.01*	104.02	0.00*	103.12	0.00*
LNGDP	58.76	0.00*	265.48	0.00*	264.63	0.00*
LNGDP <sup>2</sup>	58.76	0.00*	265.48	0.00*	264.63	0.00*
LNTOP	16.02	0.00*	80.17	0.00*	78.29	0.00*
LNENC	67.85	0.00*	196.55	0.00*	195.91	0.00*
LNURB	143.57	0.00*	531.52	0.00*	530.64	0.00*

\* and \*\* shows 1% and 5% level of significance, respectively

attention is given to growth instead of environmental quality. The long-run elasticities of per capita GDP and per capita GDP square for environmental indicators (CO<sub>2</sub>, CH<sub>4</sub>, and ecological footprint) are less than short-run elasticities in all groups of OIC countries (overall, lower income, and higher income OIC countries).

Trade openness indicates a negative and significant association with all GHG emissions in overall OIC countries and higher-income OIC countries, which shows that environmental quality improves with increase in trade openness. This finding is consistent with the studies of Uddin et al. (2017) and Destek et al. (2018). The possible reason for the negative association between trade openness and GHG emissions in OIC countries is may be due to the domination of technical effect on scale effect and composition effect as defined by Antweiler et al. (2001). The negative impact of trade openness on environmental indicators in higher-income OIC countries is also consistent with the pollution haven hypothesis which advocates that due to trade openness foreign firms bring advance and cleaner technology to host economies which will improve environmental quality (Wang et al. 2013). However,

trade openness shows positive linkage with all environmental indicators in lower income OIC countries which demonstrates that the environmental quality deteriorates with the increase in GHG emissions and ecological footprint. This finding is aligning with pollution haven hypothesis (PHH) which states that lower income countries have loose environmental regulations, and the environmental quality in these economies degrades in the result of increased industrial activities due to trade openness (Copeland and Taylor 1994; Baek and Koo 2009). However, trade openness has a positive relationship with the ecological footprint in all groups of OIC countries, which demonstrates that environmental quality decreases with increase in trade openness when the ecological footprint is used as an environmental indicator. This finding is consistent with Baek and Koo (2009), Lin (2017), Shahbaz et al. (2017), and Ali et al. (2020). Ecological footprint consists of many factors, i.e., carbon footprint, biocapacity, cropland, grazing lands, fishing grounds, and forest products (Global Footprint Network 2018). These factors represent the biological and ecological capacity of the countries, which is severely affected by industrial and human activities due to trade openness (Sarkodie 2018; Aydin et al. 2019). This is one of the main possible reasons for this positive association between trade openness and ecological footprint.

Both short-run and long-run estimates of our models indicate that the impact of the square of per capita GDP on CO<sub>2</sub>, CH<sub>4</sub>, and ecological footprint is negative and significant in all groups of OIC countries (overall, lower income, and higher income OIC countries). The negative and significant signs of the coefficients of a square of per capita GDP with CO<sub>2</sub>, CH<sub>4</sub>, and ecological footprint show the presence of EKC in OIC countries. These observations of EKC is aligning with the studies of Antweiler et al. (2001), Destek et al. (2018), Song et al. (2019), and Sharif et al. (2019). In other words, there exists EKC or inverse-U-shaped association between per capita GDP and environmental indicators when we take

**Table 4** Results of panel unit root test (CIPS-test)

	Level	1st difference
LNCO <sub>2</sub>	-1.88	-6.16*
LNN <sub>2</sub> O	-2.31**	-4.09*
LNCH <sub>4</sub>	-2.59*	-5.11*
LNECF	-2.75*	-5.22*
LNGDP	-1.91	-5.66*
LNGDP <sup>2</sup>	-1.91	-5.66*
LNTOP	-2.57*	-5.18*
LNENC	-2.35**	-4.57*
LNURB	-2.21*	-4.02*

\* and \*\* refer to the levels of significance at 1% and 5% respectively

**Table 5** Westerlund error-correction-based panel cointegration test

$H_0$ : no cointegration	Model 1		Model 2		Model 3		Model 4	
	Stat.	Robust $p$ value	Stat.	Robust $p$ value	Stat.	Robust $p$ value	Stat.	Robust $p$ value
Group- $\alpha$	-3.04*	0.00	-3.27*	0.00	-1.37	0.00	-4.28*	0.00
Group- $\tau$	-3.03**	0.02	-3.64*	0.00	-3.81*	0.00	-4.22*	0.00
Panel- $\alpha$	-3.19*	0.00	-2.53	0.00	-3.03*	0.00	-3.95**	0.02
Panel- $\tau$	-7.42*	0.00	-5.79**	0.02	-8.03*	0.00	-3.59*	0.00

\* and \*\* refer to the level of significance at 1% and 5% respectively

CO<sub>2</sub>, CH<sub>4</sub>, and ecological footprint as dependent variables. According to the theory of Grossman and Krueger (1991) and Antweiler et al. (2001), after the first stage of development where income is positively correlated with environmental indicators, the second stage begins with the negative linkage of income with environmental indicators due to technique and/or composition effect. In this stage of development, people demand a cleaner environment to attain a higher living standard. In OIC countries, under scale effect, the environmental quality degrades due to energy consumption and economic activities, because at the early stage of development, more attention is given to growth instead of environmental quality. Afterwards, when the income level increases in the second stage of development under technique effect, people demand a cleaner environment to attain a higher living standard. Moreover, the production of goods based on dirty technology is replaced with cleaner technology, or with the services sector, called the composition effect, which leads to a positive impact on environmental quality in OIC countries.

A square of per capita GDP and N<sub>2</sub>O has a positive and insignificant relationship in short-run while positive and significant association in long-run in overall OIC countries and lower income OIC countries. The possible reason for the positive association between per capita GDP square and N<sub>2</sub>O emissions in overall and low-income OIC countries in long-run is that N<sub>2</sub>O emissions generate mainly from agricultural production<sup>8</sup> which significantly contributes to the economic activity of OIC countries. In the second stage of economic development, unlike other emissions, N<sub>2</sub>O increases with the increase in per capita GDP due to increased agricultural activities. So, instead of inverted-U-shaped relationship, a U-shaped association is found between per capita GDP and N<sub>2</sub>O, thus showing no evidence of EKC in overall OIC countries and lower-income OIC countries. This outcome is consistent with the findings of Destek and Sarkodie (2019) and Saleem et al. (2019). On the other hand, a square of per capita GDP and N<sub>2</sub>O has a negative and significant relationship with N<sub>2</sub>O emissions in higher income OIC countries which indicate the existence of EKC in these countries. Unlike lower-income

OIC countries, higher-income OIC countries (i.e., Qatar, Kuwait, Saudi Arabia, and the United Arab Emirates) are less dependent on the agriculture sector, and more rely on other sectors like petroleum and services sector. Due to this reason, when the income level increases in the second stage of development, N<sub>2</sub>O emissions decreases due to the reduction of agricultural activities. Moreover, the long-run elasticities of per capita GDP and per capita GDP square for N<sub>2</sub>O emissions are more than short-run elasticities in all groups of OIC countries (overall, lower income, and higher income OIC countries).

For the EKC curve, we have calculated the turning points<sup>9</sup> of per capita GDP (where pollution is maximized) for different income groups of OIC countries. The turning point of EKC for per capita GDP in case of ecological footprint is above than the turning points for CO<sub>2</sub>, N<sub>2</sub>O and CH<sub>4</sub> emissions in all income groups of OIC countries in both short-run and long-run. The ecological footprint consists of many components like biocapacity, carbon footprint, cropland, fishing grounds, grazing lands, and forest products. When income level increases, these components degrade environmental quality due to increased economic activities and the turning point (threshold level of per capita income) after which environmental quality begins to improve comes after the threshold points of other environmental indicators. This finding is consistent with the study of Mrabet and Alsamara (2017). The long-run turning point of EKC using ecological footprint is at the per capita income of US\$1248.87, US\$906.87, and US\$8103.08 for overall OIC countries, lower income OIC countries, and higher income OIC countries, respectively. However, not all the OIC countries have reached this level by 2018, especially low-income OIC countries like Benin, Chad, Togo, Uganda, Gambia, Guinea, and Niger, due to their per capita income which is below this threshold level. Similarly, all higher-income OIC countries cannot reach their threshold point; some of them perform more poorly than others, especially non-oil exporters. The turning point of EKC for per capita GDP in case of CO<sub>2</sub> emissions is below

<sup>8</sup> For instance, see Aneja et al. (2019)

<sup>9</sup> Formula for calculating the turning point of EKC is defined in eq. 5 of model specification.

**Table 6** Results of slope homogeneity test

	$\bar{\Delta}$	$\bar{\Delta}_{adj}$
Model 1	5.63*	6.12*
Model 2	8.18*	9.14*
Model 3	5.31*	5.99*
Model 4	5.42*	6.07*

\* and \*\* refer to the levels of significance at 1% and 5% respectively

than the turning points for N<sub>2</sub>O, CH<sub>4</sub>, and ecological footprint in all income groups of OIC countries in both short-run and long-run. Using N<sub>2</sub>O emissions, U-shaped curve is found instead of inverted-U-shaped EKC in case of overall OIC countries and lower-income OIC countries with long-run turning points of US\$ 290.14 and US\$368.70, respectively. The previous studies by Raymond (2004), Mrabet and Alsamara (2017), Sinha et al. (2018), and Mahmood et al. (2019) also assessed the turning points by defining the validity conditions of EKC.

**Table 7** Dynamic common correlated effects (DCCE) estimation (overall OIC countries)

		Overall OIC countries			
Regressors		Model 1 (LNCO <sub>2</sub> ) Coefficient	Model 2 (LNN <sub>2</sub> O) Coefficient	Model 3 (LNCH <sub>4</sub> ) Coefficient	Model 4 (LNECF) Coefficient
Short-run estimates	D.LNGDP	0.810** (0.02)	-0.638* (0.00)	0.720* (0.00)	0.990* (0.01)
	D.LNGDP <sup>2</sup>	-0.062** (0.02)	0.056 (0.22)	-0.053* (0.00)	-0.071* (0.00)
	D.LN <sub>TOP</sub>	-0.360* (0.00)	-0.110* (0.00)	-0.280* (0.00)	0.190* (0.00)
	D.LN <sub>ENC</sub>	0.201* (0.00)	0.210* (0.00)	0.121** (0.02)	0.170* (0.00)
	D.LN <sub>URB</sub>	0.900*** (0.06)	0.854** (0.02)	0.210 (0.19)	0.360 (0.23)
Turning Point (constant 2010 US\$)		685.39	295.89	888.91	1064.22
Long-run estimates	L.LNCO <sub>2</sub>	-0.750** (0.04)	-	-	-
	L.LNN <sub>2</sub> O	----	-0.800* (0.01)	. ----	-
	L.LNCH <sub>4</sub>	-	-	-0.720* (0.00)	-
	L.LNECF	----	-	----	-0.700* (0.01)
	LNGDP	0.790** (0.03)	-0.647* (0.00)	0.682* (0.00)	0.970* (0.00)
	LNGDP <sup>2</sup>	-0.058** (0.02)	. 0.057*** (0.00)	-0.050* (0.00)	-0.068* (0.00)
	LNTOP	-0.470* (0.01)	-0.180** (0.02)	-0.360* (0.00)	0.240* (0.01)
	LN <sub>ENC</sub>	0.370* (0.00)	0.310* (0.01)	0.350** (0.02)	0.205* (0.00)
	LN <sub>URB</sub>	1.100*** (0.06)	0.770* (0.01)	0.206** (0.05)	0.347 (0.30)
	Turning point (constant 2010 US\$)		906.87	290.14	915.98

\*, \*\*, and \*\*\* refer to the levels of significance at 1%, 5%, and 10% respectively. (.) shows the probability value. We have taken 2 cross-sectional lags in DCCE estimation command

**Table 8** Dynamic common correlated effects (DCCE) estimation (lower income and higher income OIC countries)

Regressors		Lower-income OIC countries				Higher-income OIC countries			
		Model 1 (LNCO <sub>2</sub> ) Coefficient	Model 2 (LNN <sub>2</sub> O) Coefficient	Model 3 (LNCH <sub>4</sub> ) Coefficient	Model 4 (LNECF) Coefficient	Model 1 (LNCO <sub>2</sub> ) Coefficient	Model 2 (LNN <sub>2</sub> O) Coefficient	Model 3 (LNCH <sub>4</sub> ) Coefficient	Model 4 (LNECF) Coefficient
Short-run estimates	D.LNGDP	0.690** (0.02)	- 0.610* (0.00)	0.555* (0.00)	0.910* (0.01)	0.988** (0.02)	0.870* (0.00)	1.05* (0.00)	0.920* (0.01)
	D.LNGDP <sup>2</sup>	-0.051** (0.02)	0.060** (0.12)	-0.042* (0.00)	-0.067* (0.00)	-0.062** (0.02)	-0.05 (0.11)	-0.067** (0.00)	-0.051* (0.00)
	D.LNTOPI	0.230* (0.00)	0.090* (0.00)	0.193* (0.00)	0.140* (0.00)	-0.230* (0.00)	-0.126* (0.00)	-0.258* (0.00)	0.164* (0.00)
	D.LNENC	0.255* (0.00)	0.241* (0.00)	0.100** (0.02)	0.152* (0.00)	0.244* (0.00)	0.222* (0.00)	0.125** (0.02)	0.173* (0.00)
	D.LNURB	0.880*** (0.06)	0.800** (0.02)	0.151 (0.19)	0.254 (0.23)	0.950*** (0.06)	0.752** (0.02)	0.120 (0.11)	0.422 (0.23)
	Turning Point (constant 2010 US\$)	862.64	383.75	735.09	888.91	2540.20	6002.91	2540.20	8266.77
Long-run estimates	L.LNCO <sub>2</sub>	-0.850** (0.02)	-	-	-	-0.800** (0.04)	-	-	-
	L.LNN <sub>2</sub> O	-	-0.800* (0.01)	-	-	-	-0.750* (0.01)	-	-
	L.LNCH <sub>4</sub>	-	-	-0.720* (0.00)	-	-	-	-0.651* (0.00)	-
	L.LNECF	-	-	-	-0.700* (0.01)	-	-	-	-0.600* (0.01)
	LNGDP	0.680** (0.03)	-0.722* (0.00)	0.501* (0.00)	0.886* (0.00)	0.970** (0.03)	0.900* (0.00)	0.994* (0.00)	0.900* (0.00)
	LNGDP <sup>2</sup>	-0.050** (0.02)	0.061*** (0.06)	-0.040* (0.00)	-0.065* (0.00)	-0.060** (0.02)	-0.051** (0.03)	-0.063* (0.00)	-0.050* (0.00)
	LNTOP	0.180* (0.01)	0.121** (0.02)	0.170* (0.00)	0.162* (0.01)	-0.200* (0.01)	-0.141** (0.02)	-0.280* (0.00)	0.202* (0.01)
	LNENC	0.220* (0.00)	0.213* (0.01)	0.084** (0.02)	0.130* (0.00)	0.363* (0.00)	0.325* (0.01)	0.372** (0.02)	0.240* (0.00)
	LNURB	1.050*** (0.06)	0.702* (0.01)	0.120** (0.05)	0.200 (0.20)	1.150*** (0.06)	0.793* (0.01)	0.200** (0.04)	0.310 (0.13)
	Turning Point (constant 2010 US\$)	897.84	368.70	523.21	906.87	3229.23	6768.26	2643.87	8103.08

\*, \*\*, and \*\*\* refer to the levels of significance at 1%, 5%, and 10% respectively. () shows the probability value. We have taken 2 cross-sectional lags in DCCE estimation command

Energy consumption indicates a significant and positive association with all the indicators of environmental quality in short-run as well as long-run in all groups of OIC countries, which demonstrates that extensive use of energy will worsen environmental quality. This finding is consistent with the studies of Shahbaz et al. (2013), Shahbaz et al. (2015), Ali et al. (2016), and Saleem et al. (2019). Urbanization also shows a positive association with all the environmental indicators which clarify that a rapid increase in urban population will lead to the degradation of environmental quality in OIC countries. The positive association between urbanization and environment is aligning with the findings of Sharif and Raza (2016), Ali et al. (2016) and Ali et al. (2020).

### Concluding remarks and recommendations

In this study, we have explored the trade-environment nexus to validate the EKC hypothesis in OIC countries. GHG emissions; CO<sub>2</sub>, CH<sub>4</sub>, and N<sub>2</sub>O along with ecological footprint have been used as indicators of environmental quality. Various CSD tests are applied, which illustrate that CSD is present in the data. Slope homogeneity test confirms that the slope coefficients are heterogeneous. We have applied a novel methodology dynamic common correlated effects (DCCE) to deal with the problem of CSD. DCCE estimation identifies the existence of EKC in OIC countries. The EKC exists in all our models except for N<sub>2</sub>O emissions in overall OIC countries and lower-income OIC countries.

**Table 9** List of OIC countries with GHG emissions and ecological footprint

Country	CO <sub>2</sub> emissions(kt)	N <sub>2</sub> O emissions (thousand metric tons of CO <sub>2</sub> equivalent)	CH <sub>4</sub> emissions (kt of CO <sub>2</sub> equivalent)	Ecological footprint (in million global hectares)
Indonesia	464,176.2	93,138.9	223,315.7	441
Turkey	345,981.5	35,611.7	78,852.9	267
Iran	649,480.7	25,191.2	121,298.1	256
Nigeria	96,280.7	36,184.6	89,781.9	202
Saudi Arabia	601,047	6517.4	62,903.4	201
Egypt	201,894	25,110.1	51,976.7	173
Pakistan	166,298.5	30,651.2	158,336.6	161
Bangladesh	73,189.6	26,682.8	105,141.6	137
Malaysia	242,821.4	15,310.2	34,270.6	122
Kazakhstan	248,314.6	17,821.7	71,350.4	99
Algeria	145,400.2	6382.1	48,527.1	97
UAE	211,369.5	2412.9	26,119.5	82
Iraq	168,443.6	5007.1	24,351.1	64
Uzbekistan	105,213.6	13,191.5	47,333.3	60
Morocco	59,863.7	6007.2	12,012.4	60
Sudan	15,364.7	84,959.1	96,531.4	48.3
Uganda	5229.1	14,931.7	21,160.8	44.1
Qatar	107,853.8	339.1	41,124	37
Kuwait	95,408	704.2	12,690.6	34.8
Niger	2126.8	2195.3	6857.7	34.3
Cameroon	7003.9	13,900.2	18,516.3	32.3
Turkmenistan	68,422.5	4923.8	22,008.5	30.1
Oman	61,169.2	1146.2	16,857.6	29.9
Mali	1411.7	10,892.1	18,041.5	28.3
Cote d'Ivoire	11,045	10,034.1	16,265.6	28
Syria	30,703.7	6000.7	12,782.8	25.5
Afghanistan	9809.2	–	13,763.1	25.2
Tunisia	28,829.9	2962.6	7647.1	25
Libya	56,996.1	1465.6	18,494.9	23.5
Mozambique	8426.7	2261.3	9967.7	23.5
Burkina Faso	2849.2	7366.4	14,957.1	22.5
Chad	729.7	14,862.8	18,363.8	21.9
Azerbaijan	37,487.7	2672.5	19,955.3	20.2
Lebanon	24,070.1	462.4	1149.7	19.7
Jordan	26,450.1	604.5	2114.7	19.7
Guinea	2449.5	21,254.4	28,653.7	19.3
Yemen	22,698.7	3671.9	8939.9	18.5
Senegal	8855.8	6561.6	9927.6	17.6
Benin	6318.2	4866.6	6982.5	15.4
Somalia	608.7	16,205.8	4923.2	13.9
Bahrain	31,338.1	131.2	3378.5	12.3
Mauritania	2709.9	2347.6	6081.5	9.96
Kyrgyzstan	9607.5	4291.1	1567.1	9.86
Sierra Leone	1309.1	1604.7	3352.1	8.80

**Table 9** (continued)

Country	CO <sub>2</sub> emissions(kt)	N <sub>2</sub> O emissions (thousand metric tons of CO <sub>2</sub> equivalent)	CH <sub>4</sub> emissions (kt of CO <sub>2</sub> equivalent)	Ecological footprint (in million global hectares)
Tajikistan	5188.8	5407.5	1848.1	8.28
Togo	2621.9	3048.6	5342.6	8.03
Albania	5716.8	1146.1	2644.2	5.88
Gabon	5192.4	837.8	3893.9	4.54
Mauritius	4228.1	311.3	170.3	4.45
Guinea-Bissau	271.3	989.6	1420.6	2.69
Guyana	2009.5	2122.8	2124.1	2.62
Djibouti	722.3	634.0	256.9	2.26
Gambia	513.3	499.8	1039.2	2.04
Brunei	9108.8	342.3	4539.3	1.79
Suriname	1991.1	273.2	709.3	1.66
Comoros	154.1	283.7	59.4	0.98
Palestine	–	–	–	–

Source: Global Footprint Network 2018; World Bank 2018

The validation of EKC in our models encourages the ultimate improvement in environmental quality in OIC countries. Following EKC hypothesis, the empirical outcomes of this study recommend that per capita GDP has a self-correcting mechanism, where degradation of the environment due to scale effect (high energy consumption) may be improved subsequently due to technique effect (income effect). Moreover, the findings also reveal that the policy of trade openness should be continued as it improves the environment and supports economic growth in the long-run path especially in higher income OIC countries where it is helpful for obtaining the composite effect and comparative advantages. Based on the findings, the OIC countries should divert the investment inflows and trade-induced technical changes towards sustainable development goals (SDGs) by using relevant policy instruments. Moreover, trade openness is increasing pollution in lower income OIC countries. So these countries should make strict environmental regulations to control industrial activities. Pollution charges and fines should be imposed on the industries, which create more pollution. These pollution charges can be used to support the activities of the government to control environmental quality.

The composition effect of the energy sector is considered as the key underlying factor for environmental quality. Energy consumption increases the pollution level in OIC countries. So, as a policy perspective, energy sector reforms are also necessary to improve the environmental quality in OIC

countries. Governments of OIC countries should give more attention to renewable energy rather than conventional sources of energy. The EKC hypothesis is not proved in the case of N<sub>2</sub>O emissions in overall and lower-income OIC countries. Most OIC countries (especially lower income countries) are agriculture-based, and N<sub>2</sub>O emissions are mainly generated from agriculture activities. The joint behavior between economic growth and N<sub>2</sub>O emissions is, therefore, necessary to establish energy and agricultural policies that ensure a balance between economic growth and the environmental impact of agriculture.

The governments of OIC countries should limit such industrial and human activities which are hazardous for the biological and ecological capacity of the countries. Moreover, these countries should formulate policies to provide jobs in villages and small towns so that the burden of overpopulation in big cities should be minimized. The OIC platform should be used for enhancement and strengthening of the region’s obligations to the multilateral environmental agreements, the promotion of green technology, the management and prevention of transboundary pollution, proper utilization of natural resources, sustainable use and management of biocapacity and resources of freshwater, and sustainable forestry.

In the end, we give some limitations for this research which will provide guidance for future research in this field. First, we have ignored some GHG emissions like sulfur dioxide (SO<sub>2</sub>), sulfur hexafluoride (SF<sub>6</sub>), perfluorocarbons (PFCs), and hydrofluorocarbons (HFCs) due to incomplete data set. Moreover, we have used the total ecological footprint rather than its sub-components (biocapacity, carbon footprint, cropland, fishing grounds, grazing lands, and forest products). Future studies can use these proxies of environmental quality to see how the outcomes vary across these indicators. Second, we have taken 49 countries out of a total of 57 OIC countries by dropping ten countries due to non-availability of data. The future research will further clearly elaborate on the models when the data for missing countries are available. Third, in future research, the trade effect on EKC can be further decomposed into scale, technique, composition, and comparative advantage effect to check the impacts of trade-environment nexus at four different transition points.

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**Author’s contribution** All the authors contributed equally.

**Compliance with ethical standards**

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**Appendix**

**Table 10** Classification of selected OIC countries

Lower income OIC Countries		Higher income OIC Countries	
Low-income countries (per capita GDP of \$1025 or less)	Lower middle-income countries (per capita GDP of \$1026 to \$3995)	Upper middle-income countries (per capita GDP of \$3996 to \$12,375)	High-income countries (per capita GDP of \$12,376 or more)
Benin	Bangladesh	Gabon	Saudi Arabia
Sierra Leone	Indonesia	Algeria	Bahrain
Guinea-Bissau	Cameroon	Albania	Qatar
Burkina Faso	Sudan	Azerbaijan	Kuwait
Mali	Senegal	Iraq	Brunei Darussalam
Chad	Cote d’Ivoire	Iran	Oman
Syrian Arab Republic	Tunisia	Guyana	United Arab Emirates
Togo	Mauritania	Lebanon	
Yemen	Egypt	Kazakhstan	
Uganda	Morocco	Jordan	
Mozambique	Pakistan	Malaysia	
Gambia	Nigeria	Suriname	
Guinea		Libya	
Niger		Turkey	
Tajikistan		Turkmenistan	

The OIC countries are placed in different income groups according to the classification of World Bank (2018) on the basis of per capita GDP (constant 2010 prices)

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