An analysis of the impact of clean and non-clean energy consumption on economic growth and carbon emission: evidence from PIMC countries

Arshad Ali1,2 · Magdalena Radulescu3,4 · Daniel Balsalobre Lorente5,6 · Viet-Ngu Vincent Hoang2

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Abstract
This study empirically estimates the impact of clean and non-clean energy consumption on economic growth and carbon dioxide emissions within the framework of the environmental Kuznets curve and pollution haven hypothesis in the case of PIMC countries from 1980 to 2019. The results of the panel co-integration test proposed by Westerlund (2007) show a long-term equilibrium relationship among the variables of each designated model. The long-term elasticities of economic growth and carbon emission estimated by AMG, CCEMG, and MG estimators indicate that both clean and non-clean energy consumption has a significant impact on economic growth, while carbon emission hinders growth. The results also reveal that economic growth, non-clean energy consumption, and interaction between trade openness and non-clean energy consumption have a driving effect on carbon dioxide emission; however, clean energy consumption is found to reduce carbon emission. In addition, the analysis confirms the existence of the inverted U-shaped environmental Kuznets curve and pollution haven hypothesis in the panel of PIMC economies. Finally, there is a one-way causality from non-clean energy consumption to economic growth, but no such causation exists between clean energy consumption and economic growth. The objective of sustained economic growth with a safe environment may be achieved by encouraging clean energy consumption in the PIMC economies.

Keywords Clean energy consumption · Carbon dioxide emission · Economic growth · PHH · EKC hypothesis · PIMC countries

Responsible Editor: Roula Inglesi-Lotz

Arshad Ali
arshadswata@yahoo.com
Magdalena Radulescu
mag.radulescu@yahoo.com
Daniel Balsalobre Lorente
daniel.balsalobre@uclm.es
Viet-Ngu Vincent Hoang
vincent.hoang@qut.edu.au

1 Department of Economics and Finance (HOD), Greenwich University, DK-10 38th St, D.H.A Phase 6 Darakhshan Villas Phase 6 Darakhshan, Karachi, Karachi City 75500, Sindh, Pakistan
2 School of Economics and Finance, QUT Business School, CRICOS No. 00213J, Brisbane, Australia
3 Department of Finance, Accounting and Economics, University of Pitesti, 110040 Pitesti, Romania
4 Institute for Doctoral and Post-Doctoral Studies, University “Lucian Blaga” Sibiu, Bd. Victoriei, No. 10, 550024 Sibiu, Romania
5 Department of Political Economy and Public Finance, Economics and Business Statistics and Economic Policy, University of Castilla-La Mancha, 16002 Cuenca, Spain
6 Department of Applied Economics, International Economy Institute University of Alicante, San Vicente del Raspeig, 03690 Alicante, Spain

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Introduction

Energy is an important spark of the world economy, a key functional factor for any country’s economic growth, and a basic input for almost all goods and services in the new world (Ramezani et al. 2020; Stern 2019; Ayres et al. 2013). In today’s era, every country mainly relies on energy at all stages of economic activities (from production to consumption). Thus, energy has become an important ingredient of industrialization and growth (Gong and Razmjooy 2020; World Economic Forum, 2012). However, in advanced, emerging, and developing economies, the widespread use of various energy sources increases carbon dioxide (CO₂) emissions and results in more residues and waste, thereby deteriorating the environment (Osobajo et al. 2020; Zou and Zhang 2020). China, Pakistan, India, and Malaysia (PIMC) are the panel of Asian developing economies mainly focused on this study. This is because the high dependence of these countries on nonrenewable energy is the main driving force for higher growth, but it also leads to CO₂ emissions and environmental degradation (Khan et al. 2020). In 2019, the PIMC economies accounted for 17.81% of global GDP, 32.7% of world non-clean energy consumption (NCEC), and 38.2% of world CO₂ (World Bank, 2020). The global gross domestic product (GDP) has grown significantly at an average annual growth rate of 2.9% and has been doubled between 1992 and 2019. Meanwhile, world NCEC has grown at an average annual rate of 2.0%, from 8223.6 million tons of oil equivalent (Mtoe) in 1992 to 13,939.7 (Mtoe) in 2019 (World Bank, 2020). The large-scale combustion of energy (mainly traditional non-clean energy) has led to an excessive increase in global CO₂ emissions, from 21.354 billion tons (Bt) in 1992 to 34.169 (Bt) in 2019 (Statistical Review of World Energy 2020).

The protagonist of international trade believes that open trade can bring the latest technology, innovation, and environmental improvement to developing countries, but the pollution haven hypothesis (PHH) runs counter to the international trade picture of developing economies. PHH describes international trade as making developing economies a pollution haven for developed countries (López et al. 2013a, b; Gani 2013).

Consequently, clean energy is an emerging alternative to carbon-intensive fossil fuels and the most efficient energy source in the world. Considering the potential environmental threats identified by the environmental scientists and the resulting economic losses by economists, policymakers, and international organizations, the energy model needs to be transformed from non-clean energy to clean energy (Zhang et al. 2020). The identification of such potential threats has led to the growing global demand for clean energy to reduce CO₂ emissions and control the problem of global warming. The widespread use of clean energy ranges from the household sector (solar energy) to the industrial fields, filling in the availability, reliability, and affordability of energy between urban and rural areas. The generated non-carbohydrate energy will reduce the dependence on imported non-clean energy sources (such as oil, natural gas, coal, etc.) and will not emit carbon dioxide. Therefore, formulating a clean energy plan will improve the macroeconomic performance of the world economy.

Being a major contributor to carbon emission, the PIMC countries need to shift their economies from non-clean energy to clean energy to secure the whole world from havoc. The PIMC countries, therefore, need to invest sufficient funds in clean energy projects to overcome this problem. The study by Arroyo and Miguel (2020) and more recently Xia et al. (2022) also consider clean energy as a viable solution to the problems of energy security and climate change through the development of clean energy. In 2015, Malaysia’s clean energy consumption (CEC) accounted for 3.1%, China’s 5.3%, India’s 2.8%, and Pakistan’s 4.1% (World Bank, 2020). In response to the growing concern, The United Nations Climate Summit was held in New York on September 23, 2019. This summit was based on four needs: the goal was to make polluters pay and achieve zero net income by 2050, no new coal, and no fossil fuel subsidies. The growing concern at the international forums has attracted people’s attention to the use of clean energy and is leading to the development of literature on the issue at hand. Therefore, the current study intends to four hypotheses to investigate the link between CEC and economic growth in the panel of PIMC countries. There is a one-way causal relationship between CEC and economic growth in the first growth hypothesis. Energy under this growth assumption plays an important positive role in economic growth. In this case, any energy-saving strategy will have an adverse effect on economic growth, and expansionary energy strategies will play a progressive role in economic growth. The second conservation hypothesis proposes a one-way causal relationship from economic growth to CEC. In this case, any drop in CEC will not adversely affect economic growth. In the third feedback hypothesis, a two-way causal relationship between CEC and economic growth is proposed. This connection speculates that the decline in CEC will hinder economic growth and vice versa. Finally, the neutrality hypothesis proposes no causality between CEC and economic growth. Therefore, the decline of one factor will not affect another factor.

The studies confirm that increasing CEC can reduce global CO₂ emissions. This may help create an environmental Kuznets curve (EKC) hypothesis between carbon dioxide and economic growth in PIMC countries.
The hypothesis of the EKC postulates that economic growth will initially accumulate CO₂ and then decline when economic growth reaches a certain level (there is an unfavorable correlation between these two factors). More precisely, the economy of any country begins with industrial development to achieve higher growth goals. Therefore, a large number of natural resources (NR), especially energy, and the demand for large-scale combustion of energy in industrial development would lead to higher CO₂ emissions. With the country’s economic growth experience in industrialization, policymakers, governments, and people have begun to realize the use of clean energy, energy efficiency, and environmental quality, thereby reducing CO₂ emissions. Hence, an inverted U-shaped link between CO₂ emission and economic growth is established. Thus, the main purpose of this study is to investigate the link between clean energy and NCEC and economic growth in the context of PIMC countries. Besides this, the study also intends to assess the impact of clean energy on environmental degradation proxy by CO₂ emissions in the PIMC economies. Moreover, the study tests the validity of the EKC hypothesis by analyzing the impact of PIMC countries’ GDP and GDPˢ on carbon emissions. Also, the legitimacy of the PHH can be tested by examining the interaction of trade openness (TOP) and unclean energy consumption on carbon emissions in PIMC countries. Hence, the current study claims to be the first to examine the links between clean and NCEC, economic growth, and CO₂ emission in the case of PIMC economies under the EKC and PHH hypothetical framework. Besides, in terms of the methods employed, this study is the first to explore the validity of the EKC hypothesis and the legitimacy of the PHH hypothesis, particularly by examining the interaction of TOP and unclean energy consumption on carbon emissions in PIMC countries.

**Literature review**

Kuznets (1955) proposed the inverted U-shaped relationship between income inequality and economic growth and predicted that in the early stages of development, as social income (per capita income) increases, assuming that income inequality will increase. Still, beyond a certain income level, income inequality will begin to decrease. This concept became popular in the name of the Kuznets curve. The official name is an inverted U-shaped curve. Kuznets received the Nobel Prize in 1971 in recognition of his work.

After Grossman and Kruger’s pioneering work in 1991, recent environmental economists came up with this notion by hypothesizing the same inverted U-shaped relationship between environmental degradation and income and named it the environmental Kuznets curve (EKC).

The inverted U-shaped EKC hypothesis shows that the initial economic activities will cause environmental degradation, but the continued economic growth to a certain level can reverse the trend of environmental degradation and begin to improve environmental quality. Regarding the relationship between CEC, NCEC, economic growth, and carbon emissions, there are a large number of findings in the literature. Such findings can be divided into two categories. The first category is related to single-country research literature, mainly using econometric techniques of time series data. Joo et al. (2015) chose the Chile case study, using vector error correction (VEC) to examine the relationship between clean energy, economic growth, globalization, and CO₂ emissions, covering the data range from 1965 to 2010. According to the research results, it is found that clean energy and carbon emissions are positively correlated with growth. Similarly, Işik (2010) used ARDL techniques to examine the role of natural gas consumption in Turkey’s economic growth during 1977–2008. The findings show that in the short term, the relationship between natural gas consumption and economic growth is significantly positive, but in the long run, the relationship between these variables is significantly negative in the Turkish economy. Saliminezhad and Bahramian (2020) found that using the Standard symatric framework covering the data range from 1965 to 2017, China’s economic growth, CEC, and CO₂ emissions have a long-term interdependence. This study further explored the adverse effects of clean energy on CO₂ emissions and the stimulus effect of clean energy on economic growth. Another empirical study using ARDL techniques by Işik et al. (2017) highlight that growth, international trade, financial development, and tourism spending contribute to Greece’s CO₂ emissions. It is worth noting that in the long term, tourism can have serious adverse environmental impacts on Greece. Khan et al. (2020) also pointed out that CEC, using autoregressive distributive lag (ARDL), promote Pakistan’s economic growth and reduces CO₂ emission from 1965 to 2015. However, Wu (2020) adopted the linear and nonlinear ARDL bound test methods, covering the data range from 1960 to 2015, established the adverse effect of CEC on economic growth and the stimulus effect of NCEC on economic growth. Sbia et al. (2014) designated the UAE as a case study to discover the link between CEC and economic growth. The study used the ARDL method over the data range from 1975 to 2011. The study indicates that CEC can stimulate economic growth. Liu et al. (2020) used simultaneous equation modeling to determine the links between China’s clean energy, haze pollution, and economic growth from 2006 to 2016. The results show that clean energy and haze pollution have significant adverse effects on economic growth. Haze pollution has a significant positive impact on clean energy and is negatively correlated.
with economic growth. In addition, the study recorded the stimulus effect of economic growth on clean energy and the adverse effect of economic growth on haze pollution. Sohag et al. (2019) applied both the symmetric and asymmetric ARDL methods over the data range from 1980 to 2017 to determine the impact of clean energy, carbon emissions, and technological innovation on the growth of Turkey’s green economy. The analysis reveals that carbon emissions have been found to be detrimental to economic growth, while clean energy and technological innovation are both the driving factors that promote the long-term growth of the green economy. Pata (2018) used three cointegration strategies: the ARDL bound test, Gregory-Hansen, and Hatemi-J cointegration to discover the long-term relationship between economic growth, carbon dioxide, and renewable energy consumption in Turkey from 1974 to 2014. The cointegration test confirmed the long-term relationship, and the parameters’ elasticities were tested with the fully modified least squares (FMOLS) test. The analysis indicates that economic growth gradually impacts CO$_2$ emissions, while renewable energy has no impact on CO$_2$ emissions. In addition, the analysis supports the existence of EKC in the context of Turkey. Bouznit and Pablo-Romero (2016) used the ARDL method to examine the correlation between energy use, CO$_2$ emissions, and economic growth and tested the effectiveness of Algeria’s EKC from 1970 to 2010. The results showed that the use of non-clean energy stimulated CO$_2$ emissions, while economic growth significantly hindered Algeria’s CO$_2$ emissions. This has confirmed the validity of the EKC hypothesis in the case of the Algerian economy.

The second type of research literature involves the use of cross-sectional and panel data estimation procedures to examine the correlation between clean and NCEC, economic growth, and CO$_2$ emissions. The Bootstrap ARDL boundary check method used by Cai et al. (2018) did not find a cointegration relationship between CEC, the real per capita GDP, and CO$_2$ emissions in the UK, the USA, Italy, France, and Canada. However, a cointegration relationship was found in the context of Germany and Japan, in which per capita real GDP and CO$_2$ emissions were included as dependent variables in the model. This study revealed that clean energy is positively correlated with per capita real GDP but negatively connected with CO$_2$ emissions. Isik et al. (2018) explored the causal relationship between renewable energy and economic growth, giving credibility to the notion that renewable energy contributes to growth in Spain and economic growth induces renewable energy in Turkey, Germany, and China. Of these, only Italy and the US demonstrated a two-way link. Likewise, Paramati et al. (2022) selected a sample of 28 OECD countries to investigate the impact of environment-related technologies on energy demand and energy efficiency using annual data for the period 1990–2014. The result of the study recommends that environmental technology supports the OECD countries to decrease their total energy consumption and expands overall energy efficiency. Yao et al. (2019) used the panel cointegration method to determine the long-term relationship between energy consumption, renewable energy consumption, carbon dioxide and economic growth, and the effectiveness of EKC in a panel of 17 developed and developing economies over the data range from 1990 to 2014. After determining the long-term cointegration relationship of the selected variables, the long-term elasticity of the coefficients estimated by the FMOLS method indicates that the impact of renewable energy and nonrenewable energy consumption on economic growth is gradually significant. The consumption of renewable energy is found to have a significant negative impact on CO$_2$ emissions. Moreover, the analysis also confirmed the EKC hypothesis in the selected countries. Sharif et al. (2019) also explored the reduction in CO$_2$ emissions caused by the use of clean energy and the excessive CO$_2$ emissions generated by the consumption of non-clean energy in 74 countries covering the data span from 1990 to 2015. Fotourehchi (2017) study conducted the two-way causality test between clean energy and economic growth in 42 developing economies from 1990 to 2012. This study used the long-term causality test of Canning and Pedroni (2008) found a long-term causality from clean energy to GDP growth in the panel countries. Bhattacharya et al. (2016) adopted the panel estimation techniques to investigate the relationship between CEC, NCEC, CO$_2$ emissions, and economic growth in some 38 countries having renewable energy sources. The long-term elasticity of the parameters indicates that CEC is harmful to greenhouse gases and significantly promotes economic growth. Likewise, Işık et al. (2019) found the validity of the inverted U-shaped EKC hypothesis in Ohio, New York, Florida, Michigan, and Illinois. Although Texas has demonstrated an interesting result despite the state’s leading oil-producing economy, the detrimental effect of fossil energy consumption on CO$_2$ emissions. Besides, Isik et al. (2021) also established the validity of the EKC hypothesis, with 4 out of 8 OECD countries with undecomposed models and undecomposed GDP series, whereas countries without the legitimacy of the EKC hypothesis have transition models and decomposed GDP series. Another latest panel study of Xia et al. (2022) on 67 developing and developed countries (spanning 1971–2018) supports the validity of the PHH, as globalization significantly improves carbon emissions, and the EKC hypothesis, like GDP, is gradual, while GDP$^2$ has an adverse effect on carbon emissions. However, Bölük and Mert (2014) tested the validity of the EKC hypothesis in the panel data analysis of 16 euro countries, involving the correlation between carbon emissions, economic growth,
and energy consumption during the period 1990–2008. The results show no inverted U-shaped EKC hypothesis in euro countries. In addition, the results reveal that both non-clean energy and clean energy are harmful to carbon emissions in the case of euro countries.

In a nutshell, the literature reviewed so far clearly shows the mixed results of exploring the EKC and the link between energy consumption, economic growth, and CO$_2$ emissions. Thus, it is necessary to reveal further the connection between clean and NCEC, economic growth, and CO$_2$ emissions in a dynamic setting within the hypothetical framework of EKC and PHH, especially in the PIMC economies. Therefore, the current study claims to be the first to examine the links between clean and NCEC, economic growth, and CO$_2$ emission in the case of PIMC economies under the EKC and PHH hypothetical framework.

**Data and methodology**

This study takes a panel of PIMC countries (i.e., Pakistan, India, China, and Malaysia) to cover the data from 1980 to 2019. The variable description and their measurement are shown in the following Table 1, such as clean energy consumption (CEC) data expressed as a percentage of total energy use, non-clean energy consumption (NCEC) in million tons of oil equivalent (Mtoe), carbon dioxide (CO$_2$) emissions in million metric tons (Mmt), trade openness (TOP) in the percentage of GDP, gross domestic product (GDP and capital (K)) are both in 2010 constant prices in US dollars and the total labor force (L) in millions. The data were taken from the World Development Indicators (WDI) published by the World Bank on CEC, carbon emissions, NCEC, K formation, GDP, L, and TOP. GDP reflects the country’s total output for a given year used in this study as a proxy for economic growth. Labor and capital are important factors in the production process used by several standard growth models, so this study also includes these two variables as controls that contribute to growth.

The main purpose of the study is to investigate the impact of clean and NCEC on economic growth and CO$_2$ emissions, and to verify the current status of EKC and PHH in the case of PIMC economies. Thus, in order to ascertain the goal, the following equations are proposed:

$$\ln GDP_i = \beta_0 + \beta_1 \ln CEC_i + \beta_2 \ln CO_2_i + \beta_3 \ln NCEC_i + \beta_4 \ln GDP_i + \beta_5 \ln L_i + \beta_6 \ln K_i + \mu_i$$

(1)

$$\ln CO_2_i = \alpha_0 + \alpha_1 \ln CEC_i + \alpha_2 \ln NCEC_i + \alpha_3 \ln GDP_i$$

(2)

$$\ln CO_2_i = \alpha_0 + \alpha_1 \ln CEC_i + \alpha_2 \ln NCEC_i + \alpha_3 \ln GDP_i + \alpha_4 \ln GDP^2_i + \alpha_5 \ln TOP_i + \ln NCEC_i + \epsilon_i$$

(2)

where GDP stands for gross domestic product, CEC indicates clean energy consumption, CO$_2$ shows carbon emission, and NCEC indicates NCEC. Furthermore, L expresses labor force, GDP$^{2}$ is the square of gross domestic product, TOP displays trade openness, and TOP*NCEC demonstrates the interaction between TOP and NCEC. $B_0$ and $\alpha_0$ are intercepts, $\beta$ and $\alpha$ are factor coefficients, $I$ is used for the country, $t$ is the time period. Similarly, $\mu$, $\alpha_i$ are the error terms. In order to verify the EKC hypothesis in the PIMC economies, GDP should be positively correlated with carbon dioxide ($\alpha_3 < 0$), and the square of GDP must be negatively connected with carbon dioxide ($\alpha_4 > 0$). And to validate the PHH, TOP*NCEC must have a positive influence on carbon emission ($\alpha_5 > 0$).

**Cross-section dependence test**

Due to the economic and social networks of exports, investment, economic and social integration, and imports, the interaction within the country dominates. This may lead to cross-sectional dependence within the economies. In addition, model specifications and common shocks are other factors that cause cross-section dependence (Chudik and Pesaran 2013). If the cross-section dependence is not handled properly, the estimation results may be biased and inconsistent (Breusch and Pagan 1980; Pesaran 2004; Phillips and Sul 2003). Hence, in panel data analysis, the detection of cross-sectional dependence becomes necessary.

| Variables | Definition | Measurement | Sources |
|-----------|------------|-------------|---------|
| GDP       | Gross domestic product | Constant 2010 US$ | World Development Indicators |
| NCEC      | Non-clean energy consumption | Million tons of oil equivalent (Mtoe) | World Development Indicators |
| CEC       | Clean energy consumption | Percentage of total energy use | World Development Indicators |
| CO$_2$    | Carbon dioxide emission | Million metric tons (Mmt) | World Development Indicators |
| TOP       | Trade openness | Percentage of GDP | World Development Indicators |
| K         | Capital | 2010 constant US dollars | World Development Indicators |
| L         | Labor force | Millions | World Development Indicators |
For this purpose, the general diagnostic test proposed by Pesaran (2004), which is the modified version of the LM test to adjust its biasness as follows:

$$\overline{\Delta}_{Adj} = \sqrt{N} \left[ \frac{N^{-1} \overline{S} - E(\overline{\zeta}_i)}{\sqrt{\text{Var}(\overline{\zeta}_i)}} \right]$$  \hspace{1cm} (6)

### Checking of panel unit roots

After solving the main cross-sectional dependence or independence problem and detecting the slope heterogeneity in the panel variables, we continue to use the panel unit root test to check the stationarity level of each panel variable. Nonstationary time series data in econometric modeling may lead to spurious regression estimates (Dickey and Fuller 1981). Thus, understanding the level of stationarity in the sequence is the first step in any econometric exercise. Hence, this study first employed Pesaran (2007), the CIPS unit root test based on the hypothesis of cross-section dependence and slope heterogeneity in the panel variables. This test is also called the popular second-generation panel unit root test, which is specifically used for heterogeneity and cross-sectional dependence within panel variables. Later, we also used the panel unit root test of Levin et al. (2002) and Im et al. (2003) for this purpose. The following panel ADF process can be followed for the Levin et al. (2002) panel unit root test.

$$\Delta Y_{it} = \kappa_i Y_{i, t-1} + \sum_{j=1}^{\kappa_i} \Delta Y_{i, t-j} + \mu_{i, no}$$  \hspace{1cm} (7)

According to Levine et al. (2002), it is assumed that the parameters $\kappa_i$ are always mutual in the cross-sections, that is, for all $i$, $\kappa_i = \kappa$. Here $\Delta$ indicates the first-order differential, $\Delta Y_i$ and $\Delta Y_{i, t-j}$ have independent regression relationships with $\Delta y_{i, t-j}$ and residuals, and $j$ represents the best time lag selected by SBC and AIC. The null hypothesis can be represented by $H_0$: $\rho_i = 0$, which means that there is a unit root, where $H_i$: $\rho_i < 0$ is an alternative hypothesis, indicating that for all $i$ there is no unit root. The Im et al. (2003) unit root test has the same Eq. (7) as Levine et al. (2002), but it makes the cross-section of $\rho_i$ uneven. The null hypothesis can be expressed as $H_0$: $\rho_i = 0$, which means that all $i$ have unit roots, and the alternative hypothesis can be stated as $H_1$: $\rho_i < 0$, indicating that there are at least one or more unit roots of $i$. Suppose it is found that the selected variables in the sequence are stationary at the first-order integration. In that case, it means that these variables are nonstationary at level I(0) and become stationary when the first-order derivative I(1) is adopted.

### Test of panel cointegration

Westerlund panel cointegration test will be the best choice for exploring long-term cointegration among panel variables with cross-sectional dependence and slope heterogeneity.
(Westerlund 2007). This test can be used to detect the error correction (\( \mu_i \)) of the entire panel and individual countries. The error correction (\( \mu_i \)) represents the adjustment speed towards balance.

\[
\Delta Y_{it} = \hat{\delta} + \mu_i \left( Y_{it-1} - \hat{\beta}_i X_{it-1} \right) + \sum_{j=1}^{p} \alpha_{ij} Y_{it-j} + \sum_{j=1}^{p} \alpha_{ij} X_{it-j} + \epsilon_{it}
\]  

(8)

The null hypothesis of no cointegration can be analyzed by using the group mean test, \( G_a \) and \( G_t \) statistics and the panel test, \( P_a \) and \( P_t \) statistics (Westerlund 2007).

\[
G_t = \frac{1}{N} \sum_{i=1}^{N} \frac{\mu_i}{SE(\hat{\mu}_i)}
\]  

(9)

\[
G_a = \frac{1}{N} \sum_{i=1}^{N} T \frac{\mu_i}{SE(\hat{\mu}_i)}
\]  

(10)

\[
P_t = \frac{\hat{\mu}_i}{SE(\hat{\mu}_i)}
\]  

(11)

\[
P_a = T \hat{\mu}_i
\]  

(12)

The cointegration of at least one cross-sectional country can be detected by using the statistics \( G_t \) and \( G_a \), and the statistics \( P_t \) and \( P_a \) can detect cointegration in the entire panel.

### Panel long-run estimates

Cross-section dependence phenomena produce combined ordinary least squares (OLS) and feasible generalized least squares (GLS), leading to biased estimates (Phillips and Sul 2003).

In addition, it avoids other common panel models, such as fixed effects (FE) and random effects (RE), from obtaining stable and consistent estimates (Sarafidis and Robertson 2009). The MG estimator first uses the OLS method to perform regression analysis on the time series of \( N \) countries, then averages the slope coefficients, and considers the heterogeneity of panel variables data when the coefficients and error variances vary from country to country (Pesaran and Smith 1995). However, it prevents panel data for common factors.

The CCEMG estimator proposed by Pesaran (2006) is very robust in the presence of cross-sectional dependence and slope heterogeneity in panel data and captures undiscovered common effects (ft) (Kapetanios et al. 2011; Atasoy 2017).

\[
Y_{it} = \alpha_i + \beta_i X_{it} + \lambda_i \bar{Y}_{it} + \kappa_i \bar{X}_{it} + C_j f_j + \mu_{it}
\]  

(13)

\( Y_{it} \) represents the dependent factor in Eq. (13), \( X_{it} \) indicates explanatory factors, \( \alpha_i \) shows intercept, \( \beta_i \) represents the slope of the country, \( f_j \) denotes unobserved and heterogeneous factors, and \( \mu_{it} \) indicates the error term.

Similarly, Eberhardt and Bond (2009) and Eberhardt and Teal (2010) proposed another AMG estimator to counter cross-section dependence and slope heterogeneity. AMG estimator controls the undiscovered common factor \( f_j \) by using common dynamic effect parameters, which can be explained well. The AMG estimation formula is established in Eq. (15) and calculated by \( \hat{\beta}_i \), where \( \hat{\beta}_i \) is the estimated parameter of \( \beta_i \) in Eq. (15), which interpret the analysis of the first derivative data of OLS regression. \( \kappa_i \) indicates the coefficient of time dummy \( D \) and \( \Delta \) denotes the difference operator in the Eq. (14).

\[
\Delta Y_{it} = \alpha_i + \beta_i \Delta X_{it} + \sum_{t=1}^{T} \kappa_i D_i + \lambda_i f_i + \mu_{it}
\]  

(14)

\[
AMG = \frac{1}{N} \sum_{i=1}^{N} \hat{\beta}_i
\]  

(15)

Moreover, in the Monte Carlo simulation, the AMG estimator with \( N \) countries and \( T \) settings is unbiased and more effective (Bond and Eberhardt 2013). Hence, for the estimation of long-run parameters, this study uses Eberhardt and Teal (2010) AMG estimator. Robustness can also be checked by running the EMG and CCEMG estimators at the same time.

### Granger’s panel causality test

Lastly, the Granger panel causality test is used in the study to find the short-term bi-variate Granger causality among the selected variables. Thus for this purpose, the techniques recommended by Dumitrescu and Hurlin (2012) require stationary data; hence the available data for all the factors in the study are stationary at first difference. Accounting for heterogeneity across countries is the unique nature of this test. The test is based on Granger non-causality using the average standard of Wald statistics derived from time-series data. The following linear model illustrates the causal relationship between \( Z \) and \( Y \).

\[
\Delta Z_{i,t} = \beta_i + \sum_{n=1}^{T} \kappa_i \Delta Z_{i,t-n} + \Delta Y_{i,t-n} + \mu_{i,t}
\]  

(16)

\[
\Delta Y_{i,t} = \beta_i + \sum_{n=1}^{T} \kappa_i \Delta Y_{i,t-n} + \Delta Z_{i,t-n} + \mu_{i,t}
\]  

(17)

where \( \Delta \) represents the first-order differential, \( \beta_i \) indicates lag parameter, and \( \kappa_i, \kappa_i \) show lag coefficients. If any individual from the sample has an economic behavior different
Empirical analysis

Multicollinearity test

When estimating the model concept of the EKC hypothesis, there is the possibility of multicollinearity, which is inadvertently ignored (Itkonen 2012; p.277). Hence in order to solve this problem, we used centered values of each independent factor. The data for each variable must be recalculated by subtracting the mean to obtain the centered data. Such, as we get the explanatory factors GDP-mean (GDP), L-mean (L), CO2-mean (CO2), CEC-mean (CEC)… We used GDP2 as the square of GDP after centering in the model. Both VIF (variance inflation factor) and coefficient of determination have been used to check for multicollinearity in the centered and original data-independent factors. As shown in Table 2, serious multicollinearity problems have been encountered in the absence of data-centricity. The VIF value of each factor is very high, and \( R^2 > 0.8 \), so the correlation matrix has a high correlation. However, after centring, the values of VIF are reduced to a certain extent, and the coefficient of determination, \( R^2 \) of the entire model becomes higher than the other factors of \( R^2_1, R^2_2, R^2_3,... \). As a result, we used the centred data of the independent variables in the model by applying these diagnoses.

Table 2  Testing of multicollinearity in the explanatory factors

| Correlation matrix | VIF | Coefficients of determination |
|--------------------|-----|--------------------------------|
| Without centering  | \( R^2 = 0.98 \) |                               |
| InGDP              | 1   | 152.43 \( R^2 = 0.98 \)       |
| InGDP2             | 0.132 1 | 64.23 \( R^2_2 = 0.99 \)    |
| InL                | 0.972 0.964 1 | 75.34 \( R^2_3 = 0.98 \) |
| InCO2              | 0.721 0.218 0.243 1 | 39.64 \( R^2_4 = 0.97 \) |
| InCEC              | 0.965 0.213 0.982 0.121 1 | 45.86 \( R^2_5 = 0.99 \) |
| InNCEC             | 0.324 0.167 0.131 0.134 0.132 1 | 89.47 \( R^2_6 = 0.97 \) |
| InK                | 0.235 0.201 0.141 0.133 0.132 0.103 1 | 93.73 \( R^2_7 = 0.97 \) |
| InTOP \times NCEC  | 0.943 0.315 0.651 0.452 0.143 0.134 0.412 1 | 32.70 \( R^2_8 = 0.98 \) |

With centering

| Correlation matrix | VIF | Coefficients of determination |
|--------------------|-----|--------------------------------|
| InGDP              | \ 1  | \ 1.47 \ R^2_1 = 0.42 |
| InGDP^2            | 0.120 1 | 2.25 \ R^2_2 = 0.44 |
| InL                | 0.922 0.921 1 | 1.14 \ R^2_3 = 0.63 |
| InCO2              | 0.501 0.102 0.120 1 | 1.94 \ R^2_4 = 0.35 |
| InCEC              | 0.142 0.123 0.342 0.031 1 | 1.69 \ R^2_5 = 0.29 |
| InNCEC             | 0.012 0.539 0.021 0.374 0.042 1 | 1.82 \ R^2_6 = 0.52 |
| InK                | 0.105 0.304 0.031 0.153 0.012 0.153 1 | 1.79 \ R^2_7 = 0.39 |
| InTOP \times NCEC  | 0.473 0.016 0.301 0.032 0.101 0.104 0.232 1 | 1.38 \ R^2_8 = 0.68 |
Results of slope heterogeneity test

The results of the slope heterogeneity test proposed by Pesaran and Yamagata (2008) are shown in Table 3. This test indicates that both the bias-adjusted statistics ($\Delta_{\text{Adj}}$) and the statistics ($\Delta$) are significant at the 1% significance level. Thus, it is concluded that the null hypothesis related to slope homogeneity (no heterogeneity) is rejected, and the alternative hypothesis that the panel data has slope heterogeneity is accepted.

### Panel estimation of cross-sectional dependence (CD) test and unit root tests

For the estimation of panel cross-section dependence, this study used the Pesaran (2004) cross-sectional dependence (CD) test to investigate dependency across countries. Table 4 lists the CD test of panel variables such as GDP, GDP square, CO$_2$ emissions, CEC, NCEC, K formation, total L, and interaction of trade openness and NCEC. The CD test strongly rejected the cross-sectional independence of the null hypothesis at the significance level of 1% in all the panel variables. Hence it is concluded that there is cross-sectional dependence for all the variables. After confirming that the panel data have cross-sectional dependence and slope heterogeneity, therefore we use second-generation CIPS unit root tests (Pesaran 2007) to investigate the stationarity of the variables. The result of the CIPS unit root test is also established in Table 3. Later, for the same purpose, Levin et al. (2002), Im et al. (2003) panel unit root tests were also used to reveal the order of

| Table 3 | Test of slope heterogeneity |
|---------|-----------------------------|
| Variables | $\Delta$ | $\Delta_{\text{Adj}}$ |
| InGDP | 73.43*** | 152.75*** |
| InGDP$^2$ | 132.31*** | 327.43*** |
| InL | 88.49*** | 284.37*** |
| InCO$_2$ | 135.32*** | 316.38*** |
| InCEC | 257.93*** | 289.23*** |
| InNCEC | 211.17*** | 142.23*** |
| InTOP$\times$NCEC | 274.28*** | 357.32*** |

*** indicates that the statistics is significant at the level of 1%

| Table 4 | Result of cross-sectional dependence (CD) test and CIPS unit roots test |
|---------|-----------------------------|
| Regressors | Pesaran CD test | Pesaran CIPS unit root test |
| | Statistic s | Probability | Level | First difference | Decision |
| InGDP | 11.311 | 0.000 | $-0.930$ (0.72) | $-3.280$*** (0.000) | I(1) |
| InGDP$^2$ | 41.101 | 0.000 | $2.200$ (0.92) | $-6.370$*** (0.000) | I(1) |
| InL | 211.426 | 0.000 | $-1.260$ (0.53) | $-3.480$*** (0.000) | I(1) |
| InCO$_2$ | 39.267 | 0.000 | $1.150$ (0.79) | $-2.910$*** (0.000) | I(1) |
| InCEC | 89.313 | 0.000 | $1.450$ (0.25) | $-3.070$*** (0.000) | I(1) |
| InNCEC | 41.342 | 0.000 | $0.919$ (0.39) | $-2.160$*** (0.000) | I(1) |
| InK | 57.123 | 0.000 | $-1.740$ (0.37) | $-4.020$*** (0.000) | I(1) |
| InTOP$\times$NCEC | 82.297 | 0.000 | $-1.261$ (0.61) | $-0.980$*** (0.000) | I(1) |

*** and ** indicate significance levels of 1 and 5%, respectively. The numbers in parentheses are the probability values

| Table 5 | Result of panel LLC and IPS unit roots test |
|---------|-----------------------------|
| Regressors | LLC test | IPS test |
| | Level | First difference | Level | First difference | Decision |
| InGDP | 1.090 (0.80) | 4.120*** (0.000) | 1.170 (0.80) | 4.090*** (0.000) | I(1) |
| InGDP$^2$ | 2.090 (0.61) | 6.500*** (0.000) | 2.160 (0.62) | 7.200*** (0.000) | I(1) |
| InL | 3.100*** (0.03) | 8.460*** (0.000) | 3.290 (0.13) | 8.680*** (0.000) | I(1) |
| InCO$_2$ | 0.530 (0.87) | 4.590*** (0.000) | 0.130 (0.89) | 4.710*** (0.000) | I(1) |
| InCEC | 0.860 (0.84) | 5.250*** (0.000) | 0.550 (0.85) | 5.020*** (0.000) | I(1) |
| InNCEC | 0.006 (0.91) | 5.194*** (0.000) | 0.019 (0.89) | 5.186*** (0.000) | I(1) |
| InK | $-2.670$ (0.31) | $-6.560$*** (0.000) | $-2.760$ (0.17) | $-6.540$*** (0.000) | I(1) |
| InTOP$\times$NCEC | $-0.630$ (0.83) | $-0.571$*** (0.000) | $-0.711$ (0.91) | $-0.720$*** (0.000) | I(1) |

*** and ** indicate significance levels of 1 and 5%, respectively. The numbers in parentheses are the probability values
integration of each panel variable. These tests assist in opting for appropriate empirical techniques for long-term cointegration. The CIPS unit root test shows that these variables are nonstationary in the level but become stationary with the first-order derivative, so this means that all panel variables are integrated with the same order of I(1). Also, in Table 5 below, the results of the LLC and IPS panel unit roots tests show the same findings as to the CIPS test. These two tests show that all panel variables have unit roots at the level, but they are converted to stationary after taking the first derivative.

**Result of panel cointegration test**

Next, when slope heterogeneity and cross-sectional dependence appear in the panel data, and all variables are stable on the first-order integral, we use Westerlund (2007) cointegration test to examine the long-term cointegration relationship among the selected variables. All the robust $P$-values in Table 6 are significant at the 1% significance level. Thus, reject the null hypothesis of no-cointegration, and accept the alternative hypothesis that there is a cointegration relationship among GDP, total L, CEC, NCEC, carbon emissions, and interaction of TOP and NCEC.

**Estimation of heterogeneous long run parameters through estimators of AMG, CCEMG, and MG**

The cointegration test did not prove the flexibility of the selected related factors, so this study chose AMG (Eberhardt and Teal 2010; Bond and Eberhardt 2013), MG (Pesaran and Smith 1995), and CCEMG (Pesaran 2006) estimators to examine the influence of the selected variables on the growth and carbon emission in the PIMC economies. These estimators can only be used when the panel data has slope heterogeneity and cross-sectional dependence. Moreover, AMG is the main estimator for finding long-term parameters, while other CCEMG and MG are used for robustness checks. Table 7 shows the long-term estimated heterogeneous parameters of the AMG, CCEMG, and MG estimators. Long-term estimation parameters based on economic growth ensure a 1% increase in NCEC, clean energy consumption, and K accumulation, which have significant stimulating effects on economic growth by 1.532%, 1.481%, and 0.341%, respectively. However, the total L is not significant, and carbon emissions have a significant adverse effect on growth. This empirical result is consistent with the results of the study conducted on Chile by Joo et al. (2015) and Piłatowska and Geise (2021) in three selected countries (France, Spain, and Sweden). Similarly, Obradović and Lojanica (2017) also found similar discoveries in Northeast European countries; Fotourehchi (2017) explored for developing countries in the world; Yao et al. (2019) used 17 major developing and developed countries in the world countries, the results come from two-panel data sets of 6 geo-economic regions; Awodumi and Adewuyi (2020) obtained the results by selecting the largest oil-producing economies in Africa.

**Table 6** Result of Westerlund (2007) panel cointegration test, $\ln GDP = f(\ln CO_2, \ln NCEC, \ln CEC, \ln L, \ln K)$

| Statistics | Values | Z-Value | Robust P-value |
|------------|--------|---------|----------------|
| $G_t$      | 2.630*** | −6.122  | 0.000          |
| $G_a$      | 15.520*** | 3.980   | 0.009          |
| $P_t$      | 5.310*** | −5.981  | 0.000          |
| $P_a$      | 8.873*** | −4.213  | 0.003          |

**Table 7** Long-term heterogeneous parameter estimation based on AMG, CCEMG, and MG estimators. $\ln GDP = f(\ln NCEC, \ln CEC, \ln K, \ln L)$

| Regressors | AMG | CCEMG | MG |
|------------|-----|-------|----|
| $\ln NCEC$ | 1.532*** (4.261) | 1.337*** (4.574) | 1.326*** (4.912) |
| $\ln CEC$  | 1.481*** (5.319) | 1.782*** (5.394) | 1.759*** (5.413) |
| $\ln CO_2$ | −1.132*** (−8.323) | −1.328*** (−8.401) | −1.319*** (−8.41) |
| $\ln K$    | 0.341*** (4.921) | 0.801*** (4.801) | 0.872*** (4.812) |
| $\ln L$    | −0.202 (−0.921) | −0.354 (−0.391) | −0.372 (−0.382) |
| $\ln CO_2 = f(\ln GDP, \ln GDP^2, \ln NCEC, \ln CEC, \ln TOP \times NCEC)$ | | | |
| $\ln GDP$  | 0.203*** (4.310) | 0.391*** (4.309) | 0.421*** (4.382) |
| $\ln GDP^2$| −0.215*** (−4.010) | −0.516*** (−4.094) | −0.514*** (−4.193) |
| $\ln NCEC$ | 1.515*** (6.235) | 1.332*** (6.763) | 1.384*** (6.213) |
| $\ln CEC$  | −0.214*** (−5.630) | −0.551*** (−5.596) | −0.583*** (−5.629) |
| $\ln TOP \times NCEC$ | 0.125*** (2.765) | 0.465*** (2.842) | 0.495*** (2.738) |

** and *** show significance levels of 10 and 1%, respectively
Long-term estimation parameters based on CO₂ emissions show that for every 1% increase in NCEC, carbon dioxide will surge by 1.515%. This finding is more similar to study results conducted by Bhattacharya et al. (2016) using panel estimation techniques, which found that NCEC contributes significantly to carbon emissions in selected 38 countries. Another study by Yao et al. (2019) used a panel cointegration approach and found that nonrenewable energy sources have significantly a positive impact on the panel carbon emissions of 17 developed and developing economies over the data range from 1990 to 2014. Likewise, another study by Bouznit and Pablo-Romero (2016) used the ARDL method and found that the consumption of non-clean energy significantly increased Algeria’s CO₂ emissions.

A 1% change in the interaction between TOP and unclean energy consumption significantly stimulates a 0.125% increase in carbon emissions. Hence, the interactive term parameter clearly confirms that PIMC countries have become a PHH for developed countries. And for every 1% increase in CEC, CO₂ will shrink significantly by 0.214%.

These results are in line with our expectations and reflect that clean energy can be regarded as the most effective alternative to other non-clean energy. In other words, the surge in CEC is battling carbon dioxide in the PIMC economies. This result is very consistent with Kahia et al. (2019) on the cross-border study of the Middle East and North African countries; Piłatowska and Geise (2021) explored the same results in three selected countries (France, Spain, and Sweden); Awodumi and Adewuyi (2020) found this result in Africa’s largest oil-producing economies. Analysis shows that higher consumption of clean energy promotes economic growth and significantly reduces CO₂ emissions. Thus, governments and policymakers concerned about emerging market economies should prioritize higher CEC. The other variables GDP helps accelerate CO₂, and the square of GDP reduces CO₂ emission. This shows that there is an environmental Kuznets curve (EKC) hypothesis in the panels of these emerging countries. This means that CO₂ emissions initially showed an upward trend, but they eventually deteriorated as GDP expanded during that period. This result is closely consistent with the study of Rauf et al. (2018) on the economies of the “Belt and Road” initiative, and the study on the Turkish economy by Kılavuz and Doğan (2021). Arouisi et al. (2012) also found the same result in the study of the countries of the Middle East and North Africa.

### Findings of panel causality

The empirical short-term two-way causality between the selected variables will be tested using the Dumitrescu and Hurlin (2012) panel causality test. The results are shown in Table 8, indicating that there is only a two-way causal relationship between CO₂ and economic growth, while a one-way causal relationship exists from non-clean energy and clean energy to economic growth. Similarly, in the other variables of Eq. 2, apart from NCEC and CO₂ emissions, we did not find any two-way causality, and there is one-way causality from CO₂ to economic growth, from NCEC to economic growth, from clean energy to economic growth, and from CO₂ to the square of GDP. However, there is no evidence that there is a causal relationship between CEC and economic growth. It is now clear that with the opening of trade in dirty products with developed economies,

### Table 8

| Dependent variable | Independent variables |
|--------------------|-----------------------|
| InGDP              | InNCEC, InCEC, InCO₂, InK, InL |
| InGDP              | InGDP (0.753)         | InK (0.891)         | InL (0.042)         | InCEC (1.841)         | InNCEC (2.123)         | InCO₂ (0.012)         |
| InNCEC             | 0.987 (0.786)         | 0.874 (0.451)       | 0.964 (0.132)       | 0.567 (0.423)       | -                    | 0.524 (0.038)         |
| LnCEC              | 0.986 (0.965)         | 0.325 (0.712)       | 1.512 (0.213)       | -                    | 0.231 (0.314)         | 0.021 (0.121)         |
| LnCO2              | 2.132 (0.864)         | 0.913 (0.124)       | 1.652 (0.312)       | 0.822 (0.432)       | 3.215 (0.032)         | -                    |
| LnK                | 1.534 (0.913)         | -                   | 0.341 (0.315)       | 1.301 (0.614)       | 1.013 (0.152)         | 0.142 (0.314)         |
| LnL                | 0.241 (0.714)         | 0.864 (0.241)       | -                   | 0.251 (0.213)       | 0.142 (0.213)         | 0.213 (0.213)         |

** and *** show significance levels of 5 and 1%, respectively.
NCEC has played an important role in promoting economic growth, leading to a sharp increase in CO₂ emissions from PIMC economies. However, in view of concerns about climate change and greenhouse gas emissions, these emerging market economies should give priority to the use of clean energy and provide tax incentives for clean energy projects without affecting economic growth. The finding that there is a one-way causal relationship from CEC to economic growth is consistent with the study of Fotourehchi (2017), Cai et al. (2018).

**Conclusion and policy recommendations**

This study examines the impact of clean and unclean energy consumption, trade liberalization, K and L on economic growth and CO₂ emissions and tests the validity of the EKC and PHH hypothesis in PIMC countries from 1980 to 2019. Two independent specification models were developed in this research. The first model selects economic growth as the dependent variable, and the second model uses carbon dioxide emissions as the dependent factor. This study first tested for multicollinearity issues and then for slope heterogeneity and cross-sectional dependence of the variables for each specified model. After confirming the slope heterogeneity and cross-sectional dependence of the panel data, this study continues to use unit root tests to reveal the smoothness of each selected panel factor data. Afterward, panel cointegration tests were used to explore long-term cointegration relationships within each of the specified model variables and to examine the long-term elasticity of economic growth and CO₂ emissions using the AMG, CCEMG, and MG estimators. Finally, for the short-term causality between selected variables, the panel causality test is applied.

The results of the analysis confirmed the heterogeneity slope and cross-sectional dependence of the panel variable data. Later, the results of the unit root test show that all variables are nonstationary in levels but become stationary under the first derivative, so this means that all panel variables are integrated with the same I(1) order. The findings of the panel cointegration test indicate a long-term equilibrium relationship among the variables specified in Eq. 1 and Eq. 2. The long-term elasticities of economic growth and CO₂ emission assessed by AMG, CCEMG, and MG estimators concluded that in the PIMC economies, NCEC, CEC, and K have a significant gradual influence on economic growth. In contrast, CO₂ emission has an adverse effect on economic growth. The research results also show that both economic growth, NCEC, and interaction of TOP and NCEC have a driving effect on CO₂, but CEC has a negative impact on CO₂ emission. In addition, the analysis confirmed the existence of the inverted U-shaped EKC and PHH hypothesis in the panel of PIMC economies. Finally, there is a one-way causal relationship between NCEC to economic growth. On the contrary, there is no causal relationship between economic growth to NCEC. However, we did not find any causal relationship between CEC and the economic growth of PIMC economies. Based on the above analysis, we can predict that higher economic growth brought about by trade liberalization and the use of NCEC stimulate CO₂, which indicates that these three parameters are the main triggers for CO₂ in PIMC economies. NCEC makes CO₂ soar, while CEC makes CO₂ shrink, clearly indicating that CEC is a predictable element to slow down CO₂ emissions. Here, it needs to be pointed out seriously that accelerating economic growth and the NCEC is of great significance to the merger of any emerging economy with an advanced economy. But CEC is a key driving force for reducing CO₂ emissions and the road to sustainable growth and a potential determinant of building a healthy environment. Thus, based on the results of this study, it is recommended that policymakers in PIMC countries prioritize the reduction of CO₂ by stimulating the consumption of clean energy rather than non-clean energy to attain sustainable growth at the macro level.

The important policy implications are based on the empirical analysis of this research. First, the impact of NCEC and CEC on economic growth is gradually significant, but NCEC stimulates CO₂, and CEC significantly decreases CO₂ emissions. Thus, policymakers in PIMC countries should give priority to the maturity of clean energy, which can not only meet energy needs but also reduce CO₂ emissions. Secondly, in order to promote and expand the development of clean energy in these emerging market countries, it is necessary to combine their respective professional knowledge and expertise, strengthen the guiding principles, and cooperate in research activities, development, and demonstration. Third, the PIMC economies should attract domestic and foreign investment in clean energy projects, especially hydropower energy projects will be the best way to solve environmental problems. More importantly, in the production process of the PIMC economies, the high proportion of primary and secondary products exported to rich countries is based on the use of unclean energy. This higher productivity leads to higher carbon emissions and causes serious pollution to society and the environment. Thus, if decision-makers in exporting countries (in the PIMC economies) want to continue exporting products to rich countries, they must explore ways to invest and promote carbon emission reduction technologies in the production process to seek economic growth.

The model used in this study can be extended on a wider scale for future research in developing and emerging
economies. Moreover, the validity of the N-shaped EKC hypothesis can also be tested in future studies on the proposed PIMC countries and other emerging economies. PHH could also be tested as a future study of foreign developed countries investing in emerging economies, as developing countries have become pollution havens for developed countries.

Author contribution A.A. (Ali) has contributed to the idea and conceptualization of the study, design, analysis, and conclusion, reviewed and edited the manuscript, and approved submission. D.B.L. (Balsalobre-Lorente) conceptualized the study, software data curation, and literature search. V.V.H. (Hoang): review and editing.

Data Availability The data that support the findings of this study are openly available on the World Development Indicator page published by (World Bank, 2020), at https://databank.worldbank.org/source/world-development-indicators.

Declarations

Ethical approval The study obtained ethical approval from The University of Queensland, Brisbane, Australia.

Consent to participate Not applicable.

Consent for publication The authors have provided consent to publish this work.

Competing interests The authors declare no competing interests.

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