

The impact of CO₂ emissions on economic growth: evidence from selected higher CO₂ emissions economies

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Abstract The main purpose of this work is to analyze the impact of environmental degradation proxied by CO₂ emissions per capita along with some other explanatory variables namely energy use, trade, and human capital on economic growth in selected higher CO₂ emissions economies namely China, the USA, India, and Japan. For empirical analysis, annual data over the period spanning between 1971 and 2013 are used. After using relevant and suitable tests for checking data properties, the panel fully modified ordinary least squares (FMOLS) method is employed as an analytical technique for parameter estimation. The panel group FMOLS results reveal that almost all variables are statistically significant, whereby test rejects the null hypotheses of non cointegration, demonstrating that all variables play an important role in affecting the economic growth role across countries. Where two regressors namely CO₂ emissions and energy use show significantly negative impacts on economic growth, for trade and human capital, they tend to show the significantly positive impact on economic growth. However, for the individual analysis across countries, the panel estimate suggests that CO₂ emissions have a significant positive relationship

with economic growth for China, Japan, and the USA, while it is found significantly negative in case of India. The empirical findings of the study suggest that appropriate and prudent policies are required in order to control pollution emerging from areas other than liquefied fuel consumption. The ultimate impact of shrinking pollution will help in supporting sustainable economic growth and maturation as well as largely improve society welfare.

Keywords CO₂ emissions · Economic growth · Higher CO₂ emitting economies

Introduction

Sustainable economic growth and development is desirably dire to improve social welfare. It implies that economic development should not be at the cost of environmental degradation, but rather environmental sustainability should be maintained. It has been observed that environmental degradation or pollution is a hot issue in the economic growth and development process. Because worsening of environment arises to have a direct effect on the quality of human life and economic performance as well. It is evident, that pollution has some ruthless effect on health, resource reduction, and natural disasters linked to climate change and necessitated the slowdown of the economic growth and development. Atmospheric pollution, land degradation, soil pollution, water pollution, and noise pollution are the major forms of pollution. Whereas, atmospheric pollution sources consist of (i) burning of fuels to generate energy for heating and power production in both the household and industrial sectors; (ii) deplete emissions from the vehicles that consume petrol, diesel oil, etc.; and (iii) waste gases, dirt, and heat from several industrial sites comprising chemical manufacturers and stations of electric power generating. Similarly, sulfur dioxide (SO₂), nitrogen dioxide (NO₂), and particulate matter (PM) are

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major pollutants of ambient air quality. Generally, carbon dioxide (CO₂) and methane (CH₄) are the main contributor in the greenhouse gas emission inventory (Srivastava et al. 2010). Indeed, global warming has become a notable universal concern, where pollution is mainly as an outcome of excessive uncontrolled CO₂ emission which is commonly considered one of the key atmospheric gases which basically lead to planetary heating. Consequently, environmental degradation badly affects available scarce resources and makes inefficient human capital to contribute much to enhance the aggregate output.

Apparently, environmental pollution grows due to industrialization, modernization, and urbanization that have severely become severe major environmental problems not merely for advanced world but equally in the developing world too. The changeover from the state of stagnation to growth and development commenced by the industrial revolution caused, via an enormous adverse effect on the environment, unfavorable influence on individuals' health condition in terms of disease and life expectancy (Galor and Weil 2000; Schaefer 2013). Pollutants have largely squeezed economic growth in Asia (Borhan et al. 2012). Every state makes effort to accomplish higher stages of economic growth at the cost of consuming the present, mainly, nonrenewable natural resources right from the industrial revolution. Due to which greenhouse gas emission upsurges, where mostly CO₂ emissions do play a critical part in the expansion of global warming as well as ozone exhaustion, the principal contributors to the human-induced heating are CO₂ emissions (Canadell et al. 2007; Friedlingstein et al. 2010; Le Quere et al. 2012).

Indeed, the available resources are largely inadequate and scanty; therefore, humans need to employ practices that allow effective and durable use of the available scarce resources in the environment. Sustainable development then becomes a device that supports assurance of the persistent and long enduring utilization of resources. The environmental degradation problem is rising largely in developing economic systems. For example, the extreme use of natural resources is related to negative environmental effects, including damage of forest and forested undergrowth, damage of habitat, loss of biodiversity, the reduction of fish stock, soil erosion, and pollution (Aikins 2012; 2014). The critical aim of every economy is to accomplish the desired level of economic growth and development for a long term. Most probably, achieving this target may damage environmental quality (Bozkurt and Akan 2014). Along with increase in level of growth rate, where it is expected that, environmental deterioration and climate change will have harmful impacts on the natural order, humanity, economies, and infrastructure as well. The inverse association between economic growth and environmental deterioration requires environmental policy reactions and plans on a local, regional, national, and worldwide scale.¹

¹ Auci and Trovato (2011).

It is evident that global CO₂ emissions from fossil fuel combustion and from industrial activities (i.e., cement and metal production) enlarged in 2013 to the maximum figure of 35.3 billion tonnes (Gt) CO₂, and it was 0.7 Gt greater as compared to the last year's figure. This increase is driven largely by emerging economies with the gradually growing energy consumption over the past decade. The six largest CO₂ emitting countries in 2013 were namely China, the USA, the European Union (EU28), the Russian Federation, India, and Japan with their share of 29, 15, 11, 6, 5 and 4 %, respectively. Where notable trends were perceived at the top three CO₂ emitting nations, which only account for 55 % of aggregate worldwide CO₂ emissions (see Fig. 1). The spread in China's CO₂ emission was equal to almost 60 % of the net global CO₂ emission expansion in 2013, whereas in the USA and India, this was about 15 %, while the EU shows a reduction of 10 % in the same year.² Figure 1 portrays a comparison of the global CO₂ emissions per region from fossil fuel consumption and cement production.

The relationship between environmental degradation and economic growth has been a crucial topic, therefore, to examine whether the growing level of CO₂ emissions has any impact on the economic growth or none at all. As we need sustainable economic growth and development, which would not be at the cost of future generation and would be without environmental degradation, environmental suitability needs to be maintained however. Thus, the prime aim of this work is to look into the impact of environmental degradation proxied by CO₂ emission per capita on economic growth in selected higher CO₂ emissions economies' namely China, the USA, India, and Japan. For empirical analysis, annual data over the period between 1971 and 2013 were used. This is an inclusive empirical study, which will certainly adds to the literature on the CO₂ emissions and economic growth relationship in the sample countries under the study and may be extended to other countries.

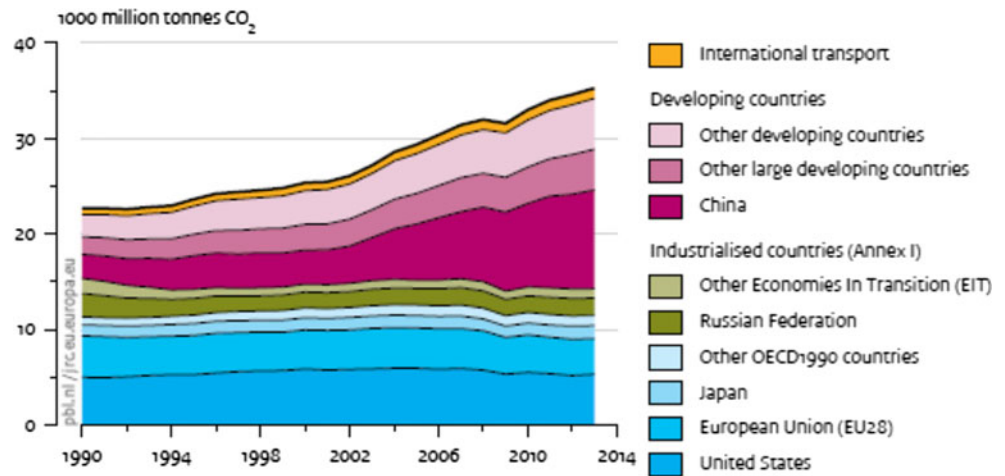
The design of this study is devised as follows: “Literature review” section handles with a literature review on the relationship between CO₂ emissions and economic growth. “Data description and methodology” section discusses the data description and empirical methodology used. “Estimation procedure” section interprets the empirical results. Finally, “Results and discussion” section concludes the study.

Literature review

The available literature reveals that empirical studies on the impact of environmental degradation on economic growth in the context of higher CO₂ emission countries are yet scanty.

² Trends in global CO₂ emissions—2014 report by Olivier et al. (2014)

Fig. 1 A comparison of the global CO₂ emissions per region from fossil fuel consumption and cement production. Source: JRC/PBL (2012); BP 2014, NBS China 2014; USGS 2014; WSA 2014; Olivier et al. (2014: 11)



For instance, the study of Menyah and Wolde-Rufael (2010) obtains a one-way causality running from CO₂ emissions to economic development in South Africa during 1965–2006. The findings suggest to mitigate CO₂ emissions by evolving energy replacements for coal, the core source of carbon emissions. Ghosh's (2010) study did not reach to determine long-term equilibrium connection and causality in CO₂ emissions and economic growth; though, the study further shows that there exists two-way short-term causality between CO₂ emissions and economic growth in India during 1971–2006. The findings imply that in the short run, any effort to decrease CO₂ emissions could lead to diminish in the economic growth of India. Pao and Tsai (2010) investigate causal linkages between pollutant emissions, energy use, and economic growth for BRIC (Brazil, Russia, India, and China) countries during 1971–2005, while in case of Russia time period (1990–2005). In general, the results suggest that to mitigate emissions and not to badly affect output, rising both energy supply investment and energy efficiency and marching up energy conservation policies to decrease needless wastage of energy can be launched for energy-dependent BRIC economies.

In a study by Chang (2010), it was mentioned that in all of the developed and developing economies, China is the main producer of CO₂ emissions and the highest consumer of energy, and a trend of stable exponential growth has become evident in recent years. The empirical findings of the study reveal that economic growth persuades a higher level of energy use and CO₂ emissions in China during 1981–2006; therefore, the implementation of an energy conservation policy would have opposing impacts on China's economic prosperity. The Granger causality tests of Lean and Smyth (2010) study indicate that in the long term, there is a one-way Granger causality running from carbon emissions to economic growth in five ASEAN countries during 1980–2006. Farhani and Rejeb's (2012) study fails to find causal linkage between gross domestic product (GDP) and energy use and between CO₂ emissions

and energy use in the short run, while in the long run, there exists one-way causality flowing from GDP and CO₂ emissions for 15 MENA countries during 1973–2008. Borhan et al. (2012) find that results in CO₂ emissions indicate a significant negative relationship with GDP per capita income for ASEAN-8 covering the period from 1965 to 2010. The study adds that the long-run destructive effect of the environmental pollution can contribute to damaging effects on human welfare and economic prosperity.

A study by Azlina et al. (2014) observes the existence of long-term association between energy usage, economic growth, and pollutant emission for Malaysia during 1970–2010. The empirical findings further show a one-way causality running from pollutant emissions to economic growth. Saboori and Sulaiman's (2013) study reveals that there exists bidirectional causality between economic growth and carbon dioxide emissions, with coal, gas, electricity, and oil usage in Malaysia during 1980–2009. The panel short-run Granger causality test results of Papiez's (2013) study show two-way causality between CO₂ emissions and economic growth for Visegrad group countries during 1992–2010. Zhao and Ren (2013) examine the causal linkage among CO₂ emissions intensity, energy consumption structure, energy intensity, and industrial structure in China over the period spanning between 1980 and 2009. The Granger causality test results show that there exist unidirectional causality relationships from CO₂ emissions intensity to industrial structure. In the same way, the study of Bozkurt and Akan (2014) explores the causal association among economic growth, energy structure, research and development (R&D) investment, and CO₂ emissions in China during 1990–2011. The results reveal that both the long- and short-run relationships, CO₂ emissions have a positive impact on the economic growth in China during the period under the study.

The study of Alam (2013) finds that in cases of the developed countries, short-term causality is flowing from CO₂ emissions to economic growth, while in case of developing

countries, both the short-run and strong-form causality estimates showed that economic growth causes CO₂ emissions for a panel of total 25 countries during 1993–2010. Lim et al. (2014) observe a unidirectional causality flowing from CO₂ emissions to economic growth in the Philippines over the period ranging from 1965–2012; the results indicates that economic growth can continue without growing CO₂ emissions in the country. Ghosh et al. (2014) find that CO₂ emissions have an inverse but insignificant impact during 1972–2011, confirming that economic growth in Bangladesh can be accomplished without degrading environment quality. In a similar vein, the study of Rahman and Porna (2014) detects that CO₂ emission and GDP are cointegrated, and to be more particular, pollution precedes GDP, which goes with the level of growth of six countries from SAARC namely Bangladesh, Bhutan, India, Nepal, Pakistan, and Sri Lanka during 1970–2008. The empirical findings of Hwang and Yoo’s (2014) study in the context of Indonesia suggest that energy conservation and/or CO₂ emissions cutback policies should be set up without the resulting damaging economic side effects. Yang and Zhao (2014) find that there is two-way causality between CO₂ emissions and economic growth in India during 1970–2008. Bhattacharya et al. (2014) find a unidirectional causality between economic growth and CO₂ emissions in India 1980–2010.

The study of Ejubbekpokpo (2014) examines the effect of carbon emission along with some other control variables on economic growth of Nigeria during 1980–2010. The empirical findings indicate that CO₂ emissions have significantly negative impact on economic growth in Nigeria. Alam et al. (2014) summarize that environmental quality indicators are indispensable for worthwhile policies. The study tests the association between environmental quality indicators and financial development in the context of Malaysia during 1975–2013. Using for environmental quality indicators is air pollution measured by CO₂ emissions, population density, cereal production, livestock production, and energy resources measured by energy consumption and fossil fuel energy use, which affect the financial development of Malaysia. A study on BRICS (Brazil, Russia, India, China, and South Africa) countries during 1971–2010, Sebri and Salha (2014) suggest an upsurge in CO₂ emissions, which is the major source of global warming. In a study on the relationship among energy use, economic growth, and CO₂ emission for Pakistan over the period 1975–2013, the study of Haseeb and Azam (2015) finds that energy consumption creates CO₂ which damage environmental quality in Pakistan. Similarly, the study of Saidi and Hammami (2015) finds that CO₂ emissions have statistically significant impact on energy use for three regional panels: Europe and North Asia, Latin America and Caribbean, and Sub-Saharan, North African, and Middle Eastern over the period ranging from 1990–2012.

The abovementioned studies reveal that mostly the prior studies focused either on the relationship among economic growths; CO₂ emissions and energy consumption as modest effort have been made to verify the effect of CO₂ emissions on economic growth in the context of a set of countries namely China, India, Japan, and the USA. The present study mainly focuses on analyzing environmental degradation retarding pace effect on economic growth by taking two developing and two developed countries; the result of this study will enable us to conclude that in which region, i.e., developed or developing countries environmental degradation retarding pace, is higher. Therefore, investigating the impact of CO₂ emissions on economic growth will certainly fill the gap and contribute to the literature on the topic under the study. The empirical findings will guide the policy makers to chalk out an appropriate policy in order to control pollution, and consequently, it will help to boost sustainable economic growth and development.

Data description and methodology

Data sources

Annual time series data ranging from 1971 to 2013 are used for empirical analysis. Data on variables namely CO₂ emissions (kg per 2005 US\$ of GDP) are used as a proxy for pollution, energy consumption is energy use (kg of oil equivalent per capita), exports of goods and services (% of GDP), GDP per capita data is taken as constant 2005 US\$, human capital (HC) data is taken school enrollment, and secondary (% gross) is used for analysis. The data are obtained from the World Development Indicators (2015), the World Bank database. Descriptive statistics and correlation matrix of the data are given in Table 1.

Table 1 Descriptive statistics and correlation matrix

Variable	Mean	Std. Dev.	Min	Max		
Y	8.30017	2.111355	5.013492	10.72899		
HC	4.182098	.4368115	3.172132	4.631575		
CO ₂	1.786404	1.915406	.2478769	7.853456		
T	12.19101	6.476002	2.823112	35.65157		
EU	7.445197	1.201091	5.620921	9.040548		
	Y	HC	CO ₂	T	EU	
Y	1.0000					
HC	0.9159	1.0000				
CO ₂	-0.7596	-0.5896	1.0000			
T	0.0336	0.2285	-0.0915	1.0000		
EU	0.9538	0.8904	-0.5837	0.0042	1.0000	

Model specification

The purpose of this study is to analyze the relationship among pollution, energy consumption, and economic growth in the case of the USA, Japan, China, and India using annual data over the period of 1971–2013. In this study, we employed Cobb–Douglas production function to analyze the relationship between pollution and economic growth, including energy usage, trade, and human capital as an additional factors of production. Generally, the equation of the production function is written as follows:

$$Y = ACO_2^{\alpha_1} EU^{\alpha_2} T^{\alpha_3} HC^{\alpha_4} \quad (1)$$

In Eq. (1), Y is domestic output per capita in real terms; CO_2 , EU , T , and HC indicate pollution, energy use, trade, and human capital, respectively, while A shows the level of technology (assumed to be constant) utilized in the country. The returns to scale are associated with pollution, energy consumption, trade, and human capital which are shown by α_1 , α_2 , α_3 , and α_4 , respectively. All the series are converted into logarithms in order to linearize the nonlinear form of Cobb–Douglas production. The non-linear specification does not seem to provide reliable results and not accommodating for policy making purposes (Shahbaz and Feridun 2012). The Cobb–Douglas production function is modeled in linear functional form as follows:

$$Y_t = A + \alpha_1 CO_{2t} + \alpha_2 EU_t + \alpha_3 T_t + \alpha_4 HC_t + \mu_t \quad (2)$$

The above empirical Eq. (2) will investigate the relationship between pollution and economic growth keeping technology constant. The linear model showing the relationship of pollution and economic growth after keeping technology constant can be written as follows:

$$Y_t = \alpha_0 + \alpha_1 CO_{2t} + \alpha_2 EU_t + \alpha_3 T_t + \alpha_4 HC_t + \mu_t \quad (3)$$

where Y , CO_2 , EU , T , and HC represent per capita GDP, pollution, energy use, trade, human capital, μ error term, and t time index.

Estimation procedure

Panel unit root test

The unit root test is used to determine whether the trend data in a research should be regressed on the focused to render it to data stationary. Most of economic theory suggests the long-run connection between the variables, and the cointegration techniques can be used to detect the long-run relation between those variables. Economic theory requires all variables to be stationary if the regressions are to be realistic. Therefore, all

the variables in the growth function should be tested to determine whether they are influenced by economic factors of relatively permanent nature or by self-correcting forces that indicate temporary elements in their dynamics.

In order to investigate the possibility of panel cointegration, it is first necessary to determine whether per capita GDP and the independent variables evolve as unit root processes. There are several unit root tests specifically for panel data which have been introduced in past decades. Among them are Quah (1992, 1994), Levin and Lin (1992, 1993), Maddala and Wu (1999), Hadri (2000), Levin et al. (2002), and Im et al. (2003, 1997). This panel unit root test is a continuation of the univariate unit root test identified earlier but which has low power like the augmented Dickey–Fuller test (Said and Dickey 1984).

The panel unit root test as above has the specification for a null hypothesis and an alternative and methodology to identify problems such as heterokedasticity and different correlations. Each panel unit root test data has its own benefits and limitations, and for this study, we have chosen the Levin, Lin, and Chu version (LLC) and Im et al. (1997; IPS hereafter), which are based on the well-known Dickey–Fuller procedure. This LLC test is not only considered simple when estimation is carried out but has also been widely used in empirical studies, and the strength of this test has been tested in various Monte Carlo tests.

Levin, Lin, and Chu (LLC; 2002)

In LLC, it is found that the main hypothesis of panel unit root is as follows:

$$\Delta y_{it} = \Phi_i y_{i,t-1} + \sum_{L=1}^{p_i} \rho_{i,L} \Delta y_{i,t-L} + \varepsilon_{i,t} \quad m = 1, 2, \dots \quad (4)$$

where y_{it} refers to variable $\ln FDI_{it}$, $\ln VA_{it}$, $\ln PI_{it}$, $\ln INS_{it}$, and $\ln GDP_{it}$. Δ refers to the first difference. The hypothesis test is $H_0: \Phi_i = 0$ for existence of unit root whereas $H_a: \Phi_i < 0$ for all i for non-existence of a unit root. As p_i is unknown, Levin, Lin, and Chu (LLC) suggest a three-step procedure in the test. In the first step, obtain the Augmented Dickey–Fuller (ADF) regression which has been separated for each individual in the panel, generate two orthogonal residuals.

The second step requires an estimation of the ratio of long runs to short-run innovation standard deviation for each individual. The last step requires us to compute the pooled t -statistics.

In the first step, we generate ADF regression for each individual i :

$$\Delta y_{it} = \Phi_i y_{i,t-1} + \sum_{L=1}^{p_i} \rho_{i,L} \Delta y_{i,t-L} + \varepsilon_{i,t} \quad (5)$$

The lag order for p_i is allowed to be distinguished for each individual. Campbell and Perron (1991) suggest a methodology used by Hall (1990; 1994) in choosing the appropriate lag order, that is, providing a sample span of T , choose a lag order which maximizes P_{MAX} , and then use t -statistics for $\hat{\rho}_L$ to determine if the order of a smaller lag order is preferred. [T -statistics have a standard normal distribution in a null hypothesis ($\hat{\rho}_{iL} = 0$), when $\Phi_i=0$ or $\Phi_i<0$.]

The order of autogression was determined for p_i which generates two auxiliary regressions to obtain orthogonal residuals. Carry out a regression $\Delta y_{i,t}$ and $y_{i,t}$ on $\Delta y_{i,t-L}$ ($L=1, \dots, p_i$), then get residuals $\hat{e}_{i,t}$ and $\hat{v}_{i,t-1}$ from these regression. Specifically, this model is shown as below:

$$\hat{e}_{i,t} = \Delta y_{i,t} - \sum_{L=1}^{p_i} \hat{\pi}_{i,L} - \Delta y_{i,t-L} \tag{6}$$

$$\hat{v}_{i,t} = \Delta y_{i,t} - \sum_{L=1}^{p_i} \hat{\pi}_{i,L} - \Delta y_{i,t-L} \tag{7}$$

To control heterogeneity among individuals, LLC has normalized $\hat{e}_{i,t}$ and $\hat{v}_{i,t-1}$ through standard error regression which is:

$$\tilde{e}_{i,t} = \frac{\hat{e}_{i,t}}{\hat{\sigma}_{\varepsilon,i}}, \quad \tilde{v}_{i,t-1} = \frac{\hat{v}_{i,t-1}}{\hat{\sigma}_{\varepsilon,i}} \tag{8}$$

where $\hat{\sigma}_{\varepsilon,i}$ is standardized error also be calculated from regression $\hat{e}_{i,t}$ on $\hat{v}_{i,t-1}$.

$$\hat{\sigma}_{\varepsilon,i}^2 = \frac{1}{T-p_i-1} \sum_{t=p_i+2}^T \left(\hat{e}_{i,t} - \hat{\Phi}_i \hat{v}_{i,t-1} \right)^2 \tag{9}$$

The second step is to estimate the ratio of long-run to short-run standard deviation. In this null hypothesis for unit root, long-term variance for the model can be estimated as below:

$$\hat{\sigma}_{y,t} = \frac{1}{T-1} \sum_{t=2}^T \Delta y_{i,t}^2 + 2 \sum_{L=1}^{\bar{K}} W_{K,L} \left[\frac{1}{T-1} \sum_{t=2+L}^T \Delta y_{i,t} \Delta_{i,t-L} \right] \tag{10}$$

where w refers to weights. The truncation lag parameter, \bar{K} , depends on data. For each individual i , LLC defines the ratio of the long-run standard deviation to innovation standard deviation as

$$s_i = \frac{\sigma_{y,i}}{\sigma_{\varepsilon,i}} \tag{11}$$

and mark this estimation with $\hat{s}_i = \hat{\sigma}_{y_i} / \hat{\sigma}_{\varepsilon,i}$. The average standard deviation ratio is $S_N = (1/N) \sum_{i=1}^N s_i$, and the estimation is $\hat{S}_N = (1/N) \sum_{i=1}^N \hat{S}_i$.

Before we proceed to the third stage, LLC reminds us that there are two items that should be noted. Firstly, the estimation for $\hat{\sigma}_{y,i}$ under a null hypothesis is $\hat{\sigma}_{\varepsilon,i}^2 / (1 - \sum_{i=1}^{p_i} \hat{\rho}_{i,L})^2$, and as a result of $\hat{\sigma}_{\varepsilon,i}^2$ being a constant estimation for $\hat{\sigma}_{\varepsilon,i}^2$ under the null hypothesis, thus, \hat{s}_i can be estimated with $|1 - \sum_{i=1}^{p_i} \hat{\rho}_{i,L}|$. Secondly, the feature of size and power for the panel unit root test is increased via first difference to estimate the long-term variance. In the null hypothesis for unit root, Schwert (1989) found long-term estimation based on first difference has a smaller bias in a limited sample compared to the long-term variance based on residuals in level.

The third step in the LLC version of the panel unit root test is to estimate coefficient Φ and to calculate the value of t -statistic for the panel. For this, combine all cross-sectional and time series observations to estimate

$$\tilde{e}_{i,t} = \Phi \tilde{v}_{i,t-1} + \tilde{\varepsilon}_{i,t} \tag{12}$$

based on the total of observations $N\bar{T}$, where $\bar{T} = T - \bar{g} - 1$ is the average of the number of observations per individual in the panel and $\bar{p} = \frac{1}{N} \sum_{i=1}^N p_i$ is the average interval for individual ADF regression. The conventional t -statistic regression to test $\Phi=0$ is

$$t_{\Phi} = \frac{\hat{\Phi}}{STD(\hat{\Phi})} \tag{13}$$

where

$$\hat{\Phi} = \frac{\sum_{i=1}^N \sum_{t=2+pi}^T \tilde{v}_{i,t-1} \tilde{e}_{i,t}}{\sum_{i=1}^N \sum_{t=2+pi}^T \tilde{v}_{i,t-1}^2} \tag{14}$$

$$STD(\hat{\Phi}) = \Phi^2 \left[\sum_{i=1}^N \sum_{t=2+pi}^T \tilde{v}_{i,t-1} \right] \tag{15}$$

$$\Phi^2 = \left[\frac{1}{N\bar{T}} \sum_{i=1}^N \sum_{t=2+pi}^T \left(\tilde{e}_{i,t} - \hat{\Phi} \tilde{v}_{i,t-1} \right)^2 \right] \tag{16}$$

In the hypothesis $H_0: \Phi=0$, LLC states that t -statistic regression (t_{Φ}) has a normal distribution for the ADF model without intercept and trend but diverges to a negative for the ADF model with intercept and trend.

Subsequently, the calculation of coordinated t -statistic is as below:

$$t_{\Phi}^* = \frac{t_{\Phi} N \bar{T} \hat{S}_N \hat{\sigma}_{\varepsilon}^{-2} STD(\hat{\Phi}) \mu^*}{\sigma^* m \bar{T}} \tag{17}$$

where tabulated mean value is adjustment for $\mu_{m\bar{T}}^*$ and the standard deviation is adjustment $\mu_{M\bar{T}}^*$ has been given by LLC with a deterministic specification ($m=1,2,\dots$) and time series dimension \bar{T} .

Levin et al. (2002) state that limited tabulation for corrected statistics if normal where $N \rightarrow \infty$ and $T \rightarrow \infty$ with $\sqrt{N/T} \rightarrow 0$ or $N/T \rightarrow 0$, depends on the model specification. Furthermore, the Monte Carlo simulation shows that this test is still suitable for a moderate-sized panel (value of N is between 10 and 250 individuals and T between a span of 20 and 250) whereby they are almost similar with panel data for this study.

Generally, the LLC test has been accepted as one of the panel unit root test. However, it should be mentioned that this LLC test has a homogeneity limitation, where a null hypothesis is $\Phi_i = \Phi = 0$ versus the alternative hypothesis $\Phi_i < 0$ for all individual units I .

Im, Pesaran, and Shin (IPS; 1997)

Im et al. (1997) denoted IPS proposed a test for the presence of unit roots in panels that combines information from the time series dimension with that from the cross-sectional dimension, such that little time observations are required for the test to have power. Since the IPS test has been found to have superior test power by researchers in economics to analyze long-run relationships in panel data, we will also employ this procedure in this study. The advantage of the IPS method over previous panel unit root tests is that it allows the data generating processes to vary across countries with respect to ADF coefficients and error structures. This can be particularly important with respect to the number of lagged difference terms in the ADF equation.

As with univariate tests, where setting the lag length can be a critical step in appropriate implementation, our experimentation suggests that it is important for the IPS test to allow the lag length to vary across countries rather than imposing a uniform lag length (McCoskey and Selden 1998). Another advantage of the IPS test is to allow for heterogeneity in the value of ρ_i under the alternative hypothesis. The IPS tests allow for individual unit root processes so that ρ_i may vary across cross sections. All the tests are characterized by combining individual unit root tests to derive a panel-specific result.

IPS begins by specifying a separate ADF regression for each cross section with individual effects and no time trend:

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \quad (18)$$

The null hypothesis may be written as, $H_0: \rho_i = 0$, for all $i = 1, \dots, N$, While the alternative hypothesis is given by

$$H_1: \begin{cases} \rho_i = 0 & \text{for } i = 1, 2, \dots, N_1 \\ \rho_i < 0 & \text{for } i = N+1, N+2, \dots, N, \text{ with } 0 < N_1 \leq N. \end{cases} \quad (19)$$

IPS use separates unit root tests for the N cross-sectional units. Their test is based on the ADF statistics averaged across groups. After estimating the separate ADF regressions, the average of the t-statistics for p_1 from the individual ADF regressions, $t_{iT}(p_i)$:

$$\bar{t}_{NT} = \frac{1}{N} \sum_{i=1}^N t_{iT}(p_i \beta_i) \quad (20)$$

is then adjusted to arrive at the desired test statistics. Under the crucial assumption of cross-sectional independence, this statistic is shown to sequentially converge to a normal distribution when T tends to infinity, followed by N . A similar result is conjectured when N and T tend to infinity while the ration N/T tends to a finite non-negative constant (Hurlin 2004).

In order to propose a standardization of the \bar{t} statistic, IPS has to compute the value of $E(\bar{t}_{iT}(p_i, \beta_i))$ and $Var(\bar{t}_{iT}(p_i, \beta_i))$. The standardization of the \bar{t}_{NT} statistic using the means and variances of $t_{iT}(p_i, 0)$ evaluated by simulation under the null $\rho_i = 0$. IPS shows that a properly standardized \bar{t}_{NT} statistic, denoted $W_{\bar{t}_{NT}}$, has an asymptotic standard normal distribution under the null of non stationary along the diagonal $N/T \rightarrow k$, with $k > 0$:

$$W_{\bar{t}_{NT}} = \frac{\sqrt{N} \left(\bar{t}_{NT} - N^{-1} \sum_{i=1}^N E(\bar{t}_{iT}(p_i, 0) | \rho_i = 0) \right)}{\sqrt{N^{-1} \sum_{i=1}^N Var(\bar{t}_{iT}(p_i, 0) | \rho_i = 0)}} \xrightarrow[T, N \rightarrow \infty]{d} N(0, 1) \quad (21)$$

The expressions for the expected mean and variance of the ADF regression t-statistics, $E(\bar{t}_{iT}(p_i, \beta_i))$ and $Var(\bar{t}_{iT}(p_i, \beta_i))$, are provided by IPS for various values of T and p and differing test equation assumptions. The IPS test statistic requires specification of the number of lags and the specification of the deterministic component for each cross-sectional ADF equation.

Maddala and Wu (1999)

This is known as Fisher's test. The advantage of this test is that it does not require a balanced panel as in the case of the IPS test. Also, one can use different lag lengths in the individual

ADF regressions. Another advantage of the Fisher test is that it can also be carried out for any unit root test derived.

A Fisher’s (p̄) test should be noted that the IPS test is for testing the significance of the results from *N* independent tests of a hypothesis. The Fisher test based on the sum of the log *p* values has been widely recommended. The advantage of this test is that it does not require a balanced panel as in the case of the IPS test. Also, one can use different lag lengths in the individual ADF regression. Another advantage of the Fisher test is that it can also be carried out for any unit root test derived. The disadvantage is that the *p* values have to be derived by Monte Carlo simulation.

The Fisher test and the IPS test are directly comparable. The aim of both tests is a combination of the significance of different independent tests. The Fisher test is non-parametric; the IPS test, on the other hand, is parametric.

Panel cointegration test

Pedroni (1999, 2004) extends the Engle and Granger (1987) two-step strategies to panels and relies on ADF and PP principles. First, the cointegration equation is estimated separately for each panel member. Second, the residuals are examined with respect to the unit root feature. If the null hypothesis is rejected, the long-run equilibrium exists, but the cointegration vector may be different for each cross section. In addition, deterministic components are allowed to be individual specific. The residuals are pooled either along the within or the between dimension of the panel, giving rise to the panel and group mean statistics (Pedroni 1999).

In the case of the panel statistics, the first order autoregressive parameter is restricted to be the same for all cross sections. If the null is rejected, the parameter is smaller than 1 in absolute value, and the variables in question are cointegrated for all panel members. In the group statistics, the autoregressive parameter is allowed to vary over the cross section, as the statistics amount to the average of individual statistics. If the null is rejected, cointegration holds at least for one individual. Hence, group tests offer an additional source of heterogeneity among the panel members (Dreger and Reimers 2005). To a certain limit, the statistics are distributed as standard normal with a left hand side rejection area, except for the variance ratio test, which is right, sided. Standardization factors arise from the moments of Brownian motion functional. The factors depend on the number of regressors and whether or not constants or trends are included in the cointegration relationships.

The procedures proposed by Pedroni make use of estimated residual from the hypothesized long-run regression of the following form (Pedroni 1999):

$$y_{i,t} = \alpha_i + \delta_i t + \beta_{1i} x_{1i,t} + \beta_{2i} x_{2i,t} + \dots + \beta_{Mi} x_{Mi,t} + e_{i,t} \quad (22)$$

for $t=1, \dots, T; i=1, \dots, N; m=1, \dots, M$, where *T* is the number of observations over time, *N* number of cross-sectional units in the panel, and *M* number of regressors. In this setup, α_i is the member specific intercept or fixed effects parameter which varies across individual cross-sectional units. The same is true of the slope coefficients and member specific time effects, $\delta_i t$.

The tests for the null of non cointegration are based on testing whether the error process e_{it} is stationary. This is achieved by testing whether $\rho_i=1$ in

$$\hat{e}_{it} = \rho_i \hat{e}_{it-1} + v_{it} \quad (23)$$

Pedroni (1999) has proposed seven tests which can be divided into two groups of panel cointegration statistics designed to test the null hypothesis of cointegration between the variables in Eq. (22) against the alternative hypothesis of cointegration. Similarly, the first category of four statistics we consider is what Pedroni labels as within-dimension statistic or Panel t-statistic which includes a variance ratio statistic, a non-parametric Philips- and perron-type ρ -statistic, a non-parametric Phillips- and Perron-type t-statistic, and a Dickey-Fuller-type t-statistic.

The second category of three panel cointegration statistics is defined as a between-dimension statistic or group t-statistic including a Phillips- and Perron-type ρ -statistic, a non-parametric Phillips- and Perron-type t-statistic, and finally an Augmented Dickey-Fuller-type t-statistic.

Pedroni (1999) proposes the heterogeneous panel and heterogeneous group mean panel test statistics to test for panel cointegration as follows:

1. Panel v -statistic:

$$T^2 N^{3/2} Z_{\hat{v}, N, T} = T^2 N^{3/2} \left(\sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1} \quad (24)$$

2. Panel ρ -Statistic:

$$T \sqrt{N} Z_{\hat{\rho}, N, T-1} = T \sqrt{N} \left(\sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1} \sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} (\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i) \quad (25)$$

3. Panel *t*-statistic (non-parametric):

$$Z_{iN, T} = \left(\hat{\sigma}_{N, T}^2 \sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1/2} \sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} \hat{e}_{i,t-1} (\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i) \quad (26)$$

4. Panel *t*-statistic (parametric):

$$Z_{iN, T}^* = \left(\hat{s}_{N, T}^2 \sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1/2} \sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} \hat{e}_{i,t-1} \Delta \hat{e}_{i,t}^* \quad (27)$$

5. Group ρ -statistic:

$$TN^{-1/2} \tilde{Z}_{\hat{\rho}_{N,T}^{-1}} = TN^{-1/2} \sum_{i=1}^N \left(\sum_{t=1}^T \hat{e}_{i,t-1}^2 \right)^{-1} \sum_{t=1}^T \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i \right) \tag{28}$$

6. Group t -statistic (non-parametric):

$$N^{-1/2} \tilde{Z}_{tN,T^{-1}} = N^{-1/2} \sum_{i=1}^N \left(\sum_{t=1}^T \hat{e}_{i,t-1}^2 \right)^{-1/2} \sum_{t=1}^T \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i \right) \tag{29}$$

7. Group t -statistic (parametric):

$$N^{-1/2} \tilde{Z}_{tN,T}^* = N^{-1/2} \sum_{i=1}^N \left(\sum_{t=1}^T \hat{s}_i^{*2} \hat{e}_{i,t-1}^{*2} \right)^{-1/2} \sum_{t=1}^T \hat{e}_{i,t-1}^* \Delta \hat{e}_{i,t}^* \tag{30}$$

where

$$\hat{\lambda}_i = \frac{1}{T} \sum_{s=1}^{k_i} \left(1 - \frac{s}{k_i + 1} \right) \sum_{t=s+1}^T \hat{\mu}_{i,t} \hat{\mu}_{i,t-s}, \tag{31}$$

$$\hat{s}_i^2 = \frac{1}{T} \sum_{t=1}^T \hat{\mu}_{i,t}^2, \quad \hat{\sigma}_i^2 = \hat{s}_i^2 + 2\hat{\lambda}_i, \tag{32}$$

$$\tilde{\sigma}_{NT}^2 = \frac{1}{T} \sum_{t=1}^T \hat{L}_{11,t}^2 \hat{\sigma}_i^2, \quad \hat{s}_i^{*2} = \frac{1}{T} \sum_{t=1}^T \hat{\mu}_{i,t}^{*2} \tag{33}$$

$$\tilde{s}_{N,T}^{*2} = \frac{1}{N} \sum_{i=1}^N \hat{s}_i^{*2} \tag{34}$$

and

$$\hat{L}_{11i}^2 = \frac{1}{T} \sum_{t=1}^{k_i} \hat{\eta}_{i,t}^2 + \frac{2}{T} \sum_{T=1}^T \left(1 - \frac{s}{k_i + 1} \right) \sum_{t=s+1}^T \hat{\eta}_{i,t} \hat{\eta}_{i,t-s} \tag{35}$$

and where the residuals $\hat{\mu}_{i,t}$, $\hat{\mu}_{i,t}^*$ and $\hat{\eta}_{i,t}$ are obtained from the following regressions:

$$\hat{e}_{i,t} = \hat{\gamma}_i \hat{e}_{i,t-1} + \hat{\mu}_{i,t} \tag{36}$$

$$\hat{e}_{i,t} = \hat{\gamma}_i \hat{e}_{i,t-1} + \sum_{k=1}^{K_i} \hat{\gamma}_{i,k} \Delta \hat{e}_{i,t-k} + \hat{\mu}_{i,t}^* \tag{37}$$

and

$$\Delta y_{i,t} = \sum_{m=1}^M \hat{b}_{mi} \Delta x_{mi,t} + \hat{\eta}_{i,t} \tag{38}$$

Δy_{it} is the first difference operator. Pedroni suggests some adjustments for each of all test statistics (both for panel unit root tests and panel cointegration tests) described above that produces standard normal distributions (Hatemi and Irandoust 2005).

According to Pedroni, those seven test statistics can be rescaled so that they are distributed as standard normal. The standardization of the cointegration statistics can be expressed as

$$\frac{K_{NT} - \mu \sqrt{N}}{\sqrt{\nu}} \Rightarrow N(0, 1) \tag{39}$$

where K_{NT} refer to the standardized form of the test statistic with respect to the N and T . The value of the mean (μ) and the variance (ν) are tabulated in Pedroni (1999).

The values of the normalized statistics are to be compared to the critical values implied by a one-tailed standard normal distribution. Consequently, for the panel variance test, the right tail of the standard normal distribution (large positive value) is used to reject the null of non cointegration and for the other six tests, the left tail is used (large negative value implies rejection of the null).

In a study, Harris and Sollis (2003) argue that in practice, it is possible for different tests to give contradicting conclusions. Choosing which test is more appropriate is not easy. The group mean tests particularly strength is that they are less restrictive. Regarding the best way to correct for autocorrelation, non-parametric tests are likely to be more robust to outliers but have poor size properties and tend to over-reject the null when it is true.

The ADF-type tests have better power if the errors follow an autoregressive process. Therefore, we followed from the other researcher that we report the adjusted values so that in all cases, the reported test values can be compared to the standard normal distribution. This is the case for both the cointegration and unit root tests.

FMOLS estimation

In order to obtain asymptotically efficient, consistent estimates in panel series, non-exogeneity, and serial correlation problems are tackled by employing fully modified ordinary least squares (FMOLS) introduced by Pedroni (1996). Since the explanatory variables are cointegrated with a time trend, and thus a long-run equilibrium relationship exists among these variables through the panel unit root test and panel cointegration test, we proceed to the method FMOLS for heterogeneous cointegrated panels (Pedroni 1996, 2000).

This methodology allows consistent and efficient estimation of cointegration vector and also addresses the problem of non-stationary regressors, as well as the problem of simultaneity biases. It is well known that OLS estimation yields biased results because the regressors are endogenously

determined in the $I(1)$ case. The starting point OLS as in the following cointegrated system for panel data:

$$y_{it} = \alpha_i + x'_{it}\beta + e_{it} \tag{40}$$

$$x_{it} = x_{i,t-1} + \varepsilon_{it} \tag{41}$$

Where $\xi_{it}=[e_{it}, \varepsilon'_{it}]$ is the stationary with covariance matrix. The estimator β will be consistent when the error process $\omega_{it}+[e_{it}, \varepsilon'_{it}]'$ satisfies the assumption of cointegration between y_{it} and x_{it} . The limiting distribution of the OLS estimator depends upon nuisance parameters. Following Phillips and Hansen (1990), a semi-parametric correction can be made to the OLS estimator that eliminates the second order bias caused by the fact that the regressors are endogenous. Pedroni (1996, 2000) follows the same principle in the panel data context and allows for the heterogeneity in the short-run dynamics and the fixed effects. FMOLS Pedroni’s estimator is constructed as follows:

$$\hat{\beta}_{FM}^{-\beta} = \left(\sum_{i=1}^N \hat{\Omega}_{22i}^{-2} \sum_{t=1}^T (x_{it} - \bar{x}_i)^2 \right)^{-1} \sum_{i=1}^N \hat{\Omega}_{11i}^{-1} \hat{\Omega}_{22i}^{-1} \left(\sum_{t=1}^T (x_{it} - \bar{x}_i) e_{it}^* - T \hat{\gamma}_i \right) \tag{42}$$

$$\hat{e}_{it}^* = e_{it} - \hat{\Omega}_{22i}^{-1} \hat{\Omega}_{21i}, \quad \hat{\gamma}_i = \hat{\Gamma}_{21i} + \hat{\Omega}_{21i}^0 - \hat{\Omega}_{22i}^{-1} \hat{\Omega}_{21i} \left(\hat{\Gamma}_{22i} + \hat{\Omega}_{22i}^0 \right)$$

where the covariance matrix can be decomposed as $\Omega_i = \Omega_i^0 + 1\Gamma_i + \Gamma_i$ where Ω_i^0 is the contemporaneous covariance matrix and Γ_i is a weighted sum of autocovariances. Also, $\hat{\Omega}_i^0$ denotes an appropriate estimator of Ω_i^0 .

In this study, we employed both the within-dimension and between-dimension panel FMOLS test from Pedroni (1996, 2000). An important advantage of the between-dimension estimators is that the form in which the data is pooled allows for greater flexibility in the presence of heterogeneity of the cointegrating vectors. Specifically, whereas test statistics constructed from the within-dimension estimators are designed to test the null hypothesis $H_0: \beta_i = \beta_0$ for all i against the alternative hypothesis, where the value β_A is the same for all i , test statistics constructed from the between-dimension estimators are designed to test the null hypothesis $H_0: \beta_i = \beta_0$ for all i against the alternative hypothesis $H_A: \beta_i \neq \beta_0$, so that the values for β_i are not constrained to be the same under the alternative hypothesis.

Clearly, this is an important advantage for applications such as the present one, because there is no reason to believe that, if the cointegrating slopes are not equal to one, which they necessarily take on some other arbitrary common value. Another advantage of the between-dimension estimators is that the point estimates have a more useful interpretation in the event that the true cointegrating vectors are heterogeneous. Specifically, point estimates for the between-dimension estimator can be interpreted as the mean value for the cointegrating vectors.

This is not true for the within-dimension estimators (Pedroni 2001).

Results and discussion

In order to decide the occurrence of a unit root in a panel data set and to check the results from the individual unit root of the ADF tests, panel unit test based on the Levin, Lin, and Chu and Im, Pesaran, and Shin procedure (LLC and IPS, respectively) will be employed. Furthermore, Akaike’s Information Criterion (AIC) will be used to find the appropriate number of lagged differences term and overall calculate the results. Table below reports the results of the LLC and IPS panel unit root tests for the data on technical efficiency for both the scenarios of constant and constant plus time trend term. Table 2 presents the results of the tests at level and first difference for LLC and IPS tests in constant and constant plus time trend. From the result, there is evidence that all the series are in fact integrated of order one $[I(1)]$. We can conclude that the results of panel unit root tests (IPS and LLC) represented in Table 2 support the hypothesis of a unit root in all variables as well as the hypothesis of zero order integration in first differences.

Table 3 shows that in constant level, all the dependent variables indicate that 5 out of 7 statistics reject null by hypothesis of non cointegration at the 1 % level of significance

Table 2 Panel unit root

Item	Level				First difference			
	Constant		Constant+trend		Constant		Constant+trend	
	LLC	IPS	LLC	IPS	LLC	IPS	LLC	IPS
Y	1.4453 (0.9258)	3.2495 (0.9994)	-1.2086 (0.1134)	0.8697 (0.8078)	-7.4160 (0.0000)	-7.1032 (0.0000)	-8.473 (0.0000)	-8.4550 (0.0000)
CO ₂	-3.7920 (0.9478)	-1.4677 (0.7711)	0.1657 (0.5658)	2.2780 (0.9886)	-6.3404 (0.0000)	-5.2011 (0.0000)	-8.1803 (0.0000)	-7.3754 (0.0000)
EU	3.9456 (0.9975)	3.5448 (0.9998)	1.4736 (0.9297)	2.3294 (0.9901)	-7.4410 (0.0000)	-8.0708 (0.0000)	-6.9657 (0.0000)	-8.1634 (0.0000)
T	1.9586 (0.9749)	2.2478 (0.9877)	1.5368 (0.9378)	1.4242 (0.9228)	-12.521 (0.0000)	-11.1229 (0.0000)	-12.332 (0.0000)	-10.8744 (0.0000)
HC	-0.5751 (0.2826)	0.2117 (0.5839)	-0.8553 (0.1962)	-0.5050 (0.3068)	-5.7551 (0.0000)	-7.2431 (0.0000)	-2.4477 (0.0072)	-4.9869 (0.0000)

except for the Panel-rho and Group-rho which are not significant. Overall, the results of the panel cointegration tests in the model with constant level show independent variable cointegration in the long run across countries.

Following Pedroni (1996, 2004), cointegrating independent variables for the data are estimated using the FMOLS technique. FMOLS method makes inferences in cointegrated panels with heterogeneous dynamics, whereby cross-sectional dimension becomes large even during short-time series. The results given in Table 4 reveal that panel group (FMOLS) shows that almost all variables are statistically significant and 1 % level, whereby test rejects the null hypotheses of non cointegration, indicating all variables play an important role in affecting the dependent role across countries. Two variables namely CO₂ emissions and EU show the negative sign which indicates that 1 % increase in both variables will decrease the dependent variable at 1.97 and 1.02. For T and HC, they tend to show the positive sign which reflects that 1 % increase in both variables will increase the dependent variable (economic growth measured by GDP per capita) at 0.01 and 0.94.

Table 3 Results from Pedroni's panel cointegration test

Test statistics	Constant+trend
Panel v-statistics	4.26412***
Panel rho-statistics	-0.96029
Panel pp-statistics	-2.91795***
Panel adf-statistics	-4.00891***
Group rho-statistics	-0.59380
Group pp-statistics	-2.81294***
Group adf-statistics	-4.55047***

Note: Probability values in parenthesis

***Denotes statistical significance at the 1 % level

For the individual analysis across countries, the USA shows the estimate of CO₂, EU, T, and HC, which are positive and statistically significant at the 1 % level except for EU with a negative sign. These results show that all independent variables have long-run cointegration effects of the dependent variable. Thus, this indicates that 1 % increase in CO₂ emission, T, and HC will increase the dependent variable at 1.77, 0.87, and 1.17. However, a 1 % increase in the EU will decrease the dependent variable at 2.25. Besides that, all independent variables also have a long-run effect in China, whereby CO₂, T, and HC are positive and statistically significant at 1 % level, while EU is negative and significant at 5 % level. This shows that 1 % increase in CO₂, T and HC will increase the dependent variable 1.07, 0.82, and 1.33. However, negative sign of EU shows that 1 % increase in EU will decrease

Table 4 Results from the between dimension FMOLS estimation

Time dummies	CO ₂	EU	T	HC
Group				
β	-1.97*** (4.44)	-1.02*** (-27.81)	0.01*** (3.12)	0.94*** (22.40)
Individual				
β_{USA}	1.77*** (3.17)	-2.25*** (-31.36)	0.87*** (3.15)	1.17*** (29.57)
β_{China}	1.07** (2.52)	-1.05** (-2.41)	0.82*** (2.96)	1.33*** (7.25)
β_{Japan}	0.21** (2.36)	-2.21*** (-10.50)	0.91*** (2.78)	0.76*** (5.60)
β_{India}	-1.09*** (-3.17)	-1.56*** (-12.96)	0.73** (2.25)	0.50** (2.37)

Note: ** and *** denote significance at the 5 and 1 % level t-statistics, from testing H0: $\beta=1$, in parentheses

the dependent variable at (1.05). Japan also shows that all independent variables are significant at 1 % level except CO₂, which is positive and significant at 5 % level, thus, indicates that 1 % increase in CO₂, T and HC will increase the dependent variable at 0.21, 0.91, and 0.76. EU shows negative and statistically significant at 1 % level. This indicates that 1 % increase in EU will decrease the dependent variable at 2.21. Finally, all independent variables show significant effects for India at 1 % level for CO₂ and EU. Furthermore, T is positive and statistically significant at 5 % level and HC at 10 % level, thus, indicates that 1 % increase in T and HC will increase the dependent variable at 0.73 and 0.50 while, 1 % increase in CO₂ and EU will decrease the dependent variable at 1.09 and 1.56. The empirical results of the study on the positive relationship between CO₂ emissions and economic growth are in line with the findings of Bozkurt and Akan (2014), while on the negative correlation between CO₂ emissions and economic growth are consistent with the findings of Borhan et al. (2012) and Ejuvbekpokpo (2014). Similarly, the empirical results on energy consumption and economic growth relationship are in line with the finds of Saatci and Dumrul (2013).

Though, it has been observed in the literature that usually CO₂ emissions affect destructively economic growth in the absence of not using green technology or not following the environmental protection agency rules. However, the empirical results for the individual analysis across countries reveal that the impact of CO₂ emissions in case of the USA, China, and Japan is positive and it implies that these countries are either using green technology or implementing the environmental protection agency rules. While in the case of India, the estimated coefficient found is significantly negative and it indicates that only country's top CO₂ emitter India is yet not using green technology or violating the environmental protection agency rules which need more concentration. Therefore, the empirical results of the study found are robust and statistically accepted and plausible for further policy implication.

Concluding remarks

This study is conducted in order to analyze the hypothesis that whether CO₂ emission has a positive/negative impact on economic growth in four countries from different region covering developing countries namely India and China and developed countries namely Japan and the USA. Annual data over the period of 1971 to 2013 were employed. The association between pollution measured by CO₂ emissions and economic growth is checked along with some other variables namely energy usage, trade, and human capital. The panel FMOLS method is employed as an analytical technique for parameter estimation. The panel group FMOLS results reveal that almost all variables are statistically significant at percent level,

whereby test rejects the null hypotheses of non cointegration, demonstrating that all variables play an important role in affecting the economic growth role across countries. CO₂ emissions and energy use show significantly negative impacts on economic growth, for trade and human capital, they tend to show the significantly positive impact on economic growth. However, for the individual analysis across countries, the panel estimate suggests that CO₂ emissions have a significant positive relationship with economic growth for China, Japan, and the USA, while it is found significantly negative in case of India during the period under the study.

The empirical findings of the study suggest that appropriate policies are required in order to reduce pollution emerging from other than liquefied fuel consumption. Energy generating from fuel consumption and trade boosting from faster communication are found to have a desirable impact on the environment, and these two factors are also becoming the key factors playing an important role in the process of economic development. Therefore, both developed and developing countries required to make the environment less pollutant by controlling pollution forming from undesirable factors. Among many other economic benefits of condensing pollution have increased crop yield, timber yields, livestock productivity, decreased risk of illness, and death and, thereby, enhance human capital and help in sustaining sustainable economic growth and development.

A suggestion for future research is that it may be remarkable to conduct a cross country as well using panel data covering the top ten CO₂ emissions countries including EU28. Empirical findings from such, further research are expected to produce the findings more expressive for policy consideration.

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