Exploring the determinants of ecological efficiency in selected emerging economies using pooled mean group estimator

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The current study suggests ways for emerging economies, which are currently experiencing major transitions, to make efficient use of their ecological footprint for survival. The authors utilise panel data from 1980 to 2016 and the pooled mean group estimation technique for the analysis. The determinants of ecological efficiency (EE) include gross domestic product (GDP) per capita, GDP per capita square, industrialisation, population density, and life expectancy. The relationship between GDP per capita and EE exhibits a curvilinear trend among these countries. An increase in life expectancy and industrialisation has a positive impact on EE, while an increase in population density reduces EE. The study suggests that efforts should be made to attain a higher level of GDP, more industrialisation, and higher life expectancy so that EE may be increased with population stabilising measures needed to achieve such efficiency.

Introduction

Information is critical for human survival. For example, if someone is flying an aircraft with no fuel gauge, it will be dangerous to do so as the pilot has no information about whether the aircraft has sufficient fuel to reach the destination. Similarly, it will be reckless to make life-changing decisions without knowledge of the ecological resources we possess. Economies with several indicators do not possess any "fuel gauge." A framework is therefore required for governments to comprehend the significance of resource overuse control. They require a fuel gauge to determine how much nature (or ecosystem capacity) they have, how rapidly they are using it, and how soon nature's reserves can be replenished.

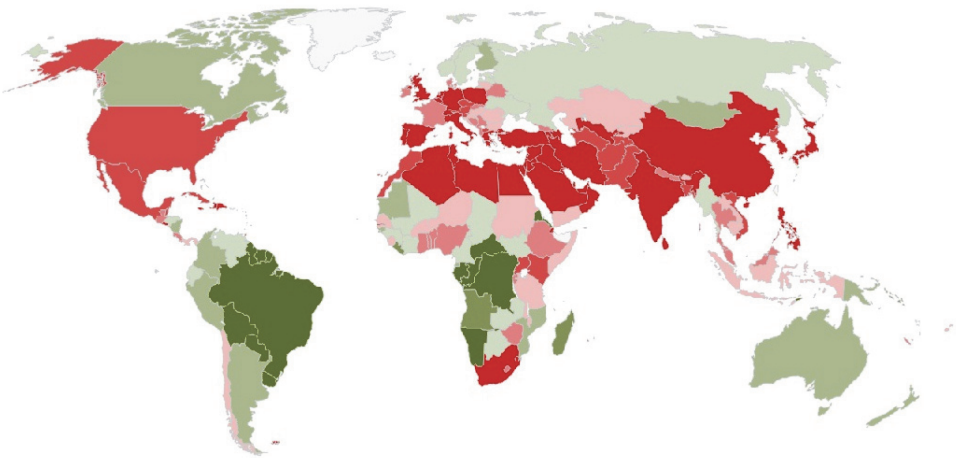
Ecological footprint[1] (EF) analysis provides such a gauge. The EF is a technique for resource accounting using EF and biocapacity (Wackernagel–Galli 2012). EF is a metric that indicates how much biologically beneficial land has been set aside for human use (Wackernagel et al. 2002, Ewing et al. 2012). Cropland, forest, grazing, fishing ground, urbanisation, and land required for carbon uptake are the six mainland categories of EF indicators. A total of two scaling factors, nation-specific yield and land-specific equivalency factors, are utilised to transform nation-specific and area-type specific real hectares into global hectares, respectively (Galli et al. 2007).

The process of economic growth is normally resource dependent and is accompanied by an increasing environmental burden. The environmental Kuznets curve (EKC) is commonly employed to relate economic development with environmental degradation. Bo (2010) states that the relationship between environmental quality and economic progress is controversial. The author conducted a literature survey on the EKC consisting of genesis, explanations, and empirical evidence. This study concluded that on theoretical grounds, various factors are responsible for EKC on the empirical side and different data type leads to different empirical results. Hence, there is a need to choose suitable indicators and data. Ben et al. (2017) empirically investigated the long-run relationship between carbon dioxide (CO_2) emissions, energy use, and real gross domestic product (GDP) per capita in the Middle East and North Africa (MENA) and validated the EKC hypothesis. Demissew Beyene–Kotosz (2020) tested the EKC hypothesis for East African countries using the CO_2 emissions and per capita income data and identified a bell-shaped relationship. Mitsis (2021) tested the EKC hypothesis using the Bayesian model averaging technique and found an N-shaped relationship. However, empirical research utilising the EF as an indicator of environmental deterioration to test the EKC hypothesis is rare. Most emerging countries depend on natural resources for economic growth and are vulnerable to water and food scarcity and the consequences of climate change. Therefore, it is critical to understand the amount of natural resources a country or region possesses and consumes. Ecological resources are essential for humans and economies, with a country's ability to compete for natural resources determining its success. We already consume too much of the world's non-renewable resources, leading to scarcity and driving up prices.

[1] The term *ecological footprint* refers to an assessment of human demand for land and water regions that compares human resource consumption and waste absorption to the Earth's ecological ability to recover (Butnariu–Avasilcai 2014).

Figure 1

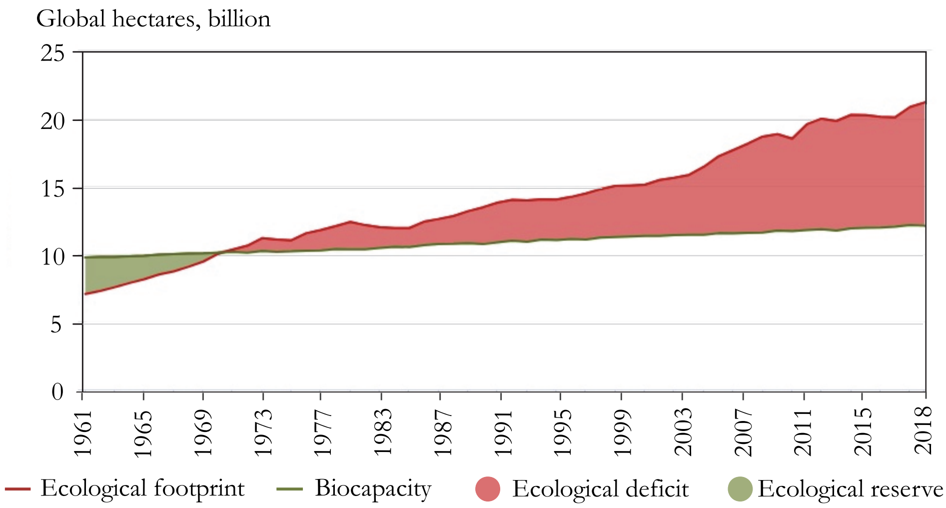
Ecological deficit/reserves around the world, 2022



Source: Global Footprint Network, 2022

Figure 2

Global trend of ecological deficit/reserves



Source: Global Footprint Network, 2022.

The situation is unsustainable; it is becoming clear that the 21st century will be dominated by ecological constraints. Global successes in economic growth, poverty reduction, and increased welfare have been counterbalanced by the rising pressure on the biosphere over the past 50 years. Forests are cut down faster than they can regenerate, particularly in tropical areas. Fish are caught faster than they can be replenished. The recent situation of ecological deficit[2] and reserves around the world is illustrated in Figure 1. It is clear that the majority of countries are in ecological deficit and such deficit is more than one-hundred percent (biocapacity is less than half of ecological footprint) in the majority of these. Very few countries have significant ecological reserves. The global trend of ecological reserve/deficit over time is represented in Figure 2. It is clear that the world has faced ecological deficit since 1970 and this deficit is increasing day by day, which is of concern. Therefore, the efficient use of natural resources is important for the survival of future generations.

The concept of resource/ecological efficiency (EE) has gained traction; it expresses the efficiency of economic activities in terms of natural resource use, with the ultimate goal of providing governments with a tool for measuring their performance in terms of EE as a precondition of environmental sustainability (Economic and Social Commission on Asia and Pacific 2009). Concerns regarding the long-term sustainability of economic activity have sparked interest in the idea of eco-efficiency, which has resulted in a surge in the literature on the subject in recent years (Lansink–Wall 2014). Schaltegger–Sturm (1990) suggested the concept of eco-efficiency. First posited in 2003, the "Marrakesh Process" offered new prospects for developing countries to "do more and better, with less," by enhancing resource efficiency, redesign economic growth saving environmental degradation (UNEP 2014).

Various methods for measuring economic efficiency have been developed, including the ratio approach (Callens–Tyteca 1999, Huppes–Ishikawa 2005b, Yu et al. 2013), material flow analysis (Pelletier et al. 2008, Wang et al. 2016, Besné et al. 2018), the frontier approach (Callens–Tyteca 1999, Huppes–Ishikawa 2005a, Yu et al. 2013, Kuosmanen–Kortelainen 2005, Picazo-Tadeo et al. 2012, Rebolledo-Leiva et al. 2017, Xing et al. 2018), input-output analysis (Wiedmann et al. 2006, Zurano-Cervelló et al. 2018), ecosystem services value accounting (Shi et al. 2017), life cycle assessment (Teng–Wu 2014, Valente et al. 2019), environmental management accounting based on case studies and surveys (Van Caneghem et al. 2010), and emergency analysis (Geng et al. 2010, Li et al. 2020).

Irshad–Hussain (2017) used cross-sectional data from various economies and analysed EE in terms of intensity, that is, EF consumption per unit of GDP production, EF/GDP. They confirm the validity of the cross-national EKC between eco-efficiency and GDP per capita. Furthermore, the study revealed that population density has a positive effect while there is no significant effect of industrialisation on

[2] An ecological deficit occurs when the EF of a population exceeds the biocapacity of the area available to that population. An ecological reserve exists when such biocapacity exceeds its population's EF. (EF is a measure of how much area of biologically productive land and water a population requires to produce all the resources it consumes and to absorb the waste it generates. Biocapacity is the ecosystems' capacity to produce biological materials used by people and to absorb waste material generated by humans.)

eco-efficiency. According to Li, Cai, and Zhang (2020), in the short term, technical development and environmental regulation have a beneficial influence on eco-efficiency but an inhibitory effect in the long term. The authors suggest that technical innovation and industrial adaptation are excellent ways to increase eco-efficiency. Hickel (2020) highlighted the shortcomings of the human development index (HDI) as a measure of development and recommended the Sustainable Development Index (SDI) as a replacement. The SDI is a powerful sustainability indicator that assesses a country's ecological efficiency in achieving human development.

Following the conventional approach of previous studies, the current study uses EE in terms of eco-intensity as used by Irshad–Hussain (2017). Eco-intensity is the ratio of EF consumption per unit of GDP) production, that is, EF/GDP. Eco-intensity is the mathematical inverse[3] of eco-efficiency (eco-efficiency is the ratio of output per unit of natural resource, i.e., GDP/EF). In the last few decades, human beings use of natural resources to support increasing population and economic prosperity has produced an alarming global impact. Particularly, emerging countries are experiencing major demographic and economic transitions. To ensure the future survival of human beings, it is imperative for these economies to make efficient use of their ecological footprint. There is therefore a need to identify important factors that may have an impact on the eco-efficiency of these countries. The current study is an effort to meet this objective.

Model specification and variable description

The EF intensity (efficiency) may be affected by many economic, demographic, and climatic factors. We focus on the assessment of EE performance via EF per unit of GDP and identify the potential of major influencing factors affecting EE for emerging economies. The six types of areas (Cropland, Grazing Land, Fishing Grounds, Forest, Carbon Uptake, and Built-up-Land Footprint) are added to obtain total ecological footprints (McLellan 2014). The measurement unit for EF is global hectares. The theoretical background of the current study is based upon the IPAT model used by Ehrlich–Holdren (1971) to analyse the proportionate impact of the growing population on the environment, given by

$$\mathrm{I} = \mathrm{P.A.T} \quad (1)$$

where I represent environmental impact, P is population, A is affluence, and T is technology. Here, the modified form of the model is used. Its general form may be written as

$$\mathrm{EE_{it}} = \beta_0 + \beta_1 \mathrm{PD_{it}} + \beta_2 \mathrm{LGDP_{it}} + \beta_3 \mathrm{LGDPSQ_{it}} + \beta_4 \mathrm{IS_{it}} + \beta_5 \mathrm{LE_{it}} + \varepsilon_{it} \ . \quad (2)$$

where *i* denotes the cross-sectional dimension, and *t* denotes the time dimension of the variable.

[3] It indicates that higher the value of ecological intensity, the lower the ecological efficiency.

- β_0 = Constant term
- EE = ecological efficiency (Proxy for I)
- PD = population density (Proxy for P)
- LGDP = log of GDP (Proxy for A)
- LGDPSQ = log of the square of GDP
- IS = industrial value-added growth (Proxy for T)
- LE = life expectancy
- ε_{it} = error term

This study utilised data for the period 1980 to 2016 for emerging economies including Brazil, China, India, Indonesia, Malaysia, Mexico, South Africa, Thailand, and Turkey. The data were collected from the Global Footprint Network and World Bank's database of world development indicators (WDI). Data on ecological footprints were taken from the Global Footprint Network database. Affluence level of the economy (level of GDP), industrial growth (a proxy for technology), population density (P), and life expectancy were taken from the World Bank's database of WDI.

Ecological efficiency (EE)

EE is simply the wise use of natural resources, and it can be represented by ecological-intensity which is the ratio of EF consumption per unit of GDP, that is, EF/GDP. In this situation, ecological intensity (EE) is the mathematical inverse[4] of ecological efficiency. According to the conceptual definition, ecological efficiency may be referred to as the ratio of output or activity per unit of natural resources; thus, ecological intensity is the inverse of ecological efficiency. We use ecological intensity, which is the ecological footprint consumption of the economy per unit of GDP. The lower the value of this ratio, the better it will be. The lower the resource intensity, the higher the ecological efficiency per unit of GDP. York et al. (2004) and Irshad–Hussain (2017) also used the same indicator.

Gross domestic product (GDP)

The level of GDP is included as an indicator of the nation's level of affluence level, and the quadratic term of GDP is taken as the indicator of economic development. These variables have been frequently used in the literature. York et al. (2003) and Irshad–Hussain (2017) investigated the curvilinear link between economic development and environmental impacts, measured in ecological footprints. The EKC hypothesis suggests that the environmental impacts increase at the initial level of development and tend to decrease with further increases in the level of economic development (Grossman–Krueger 1995). At higher levels of development, structural

[4] It indicates that higher the value of ecological intensity, the lower the ecological efficiency.

shifts toward industries and services, along with stringent environmental laws and improved technology, result in a steady reduction in environmental deterioration (Stern 2004).

Industrialisation

Industrial value-added growth has been taken as a general indicator of the economic structure or modernisation of the economy. Increased modernisation can tackle ecological problems through more modernised methods such as the use of an energy mix that is more environmentally friendly; however, if industrialisation is not environmentally friendly, its impact can also be negative.

Population density

Population density refers to the number of people per square kilometre of the geographical area. Increased population density as a result of population growth may worsen a country's resource scarcity. A large percentage of the population already lives in marginal regions and less productive natural ecosystems, relying on natural resource-based industries, including agriculture, grazing, forest products, and fishing, to survive. A total of two key areas, changes in land-use patterns and climate change, may be utilised to understand the complicated influence of population increase on the environment.

Life expectancy

Life expectancy is the projected average number of years of life left at a certain age. The worrying status of the environment creates even greater concerns for the futures of future generations. For example, people in countries with longer life expectancies are often more concerned about their own and/or descendants' prospects. As a result, when people expect to live longer, they are more inclined to invest more in environmental quality.

Econometric methodology

In recent research studies, due to the fact that data for larger periods is easily availability, panel data analysis comprises models with large time periods (T) and large cross-sections (N). The characteristics of large N and T dynamic panels differ from those of large N and small T dynamic panels. Fixed and random effect estimators, as well as the generalised method of moments, are used in the small T-panel estimation. Assuming slope coefficient homogeneity, these estimators pool individual cross-sections and only allow the constant term to change across cross-sections. However, as highlighted by Pesaran–Smith (1995), Pesaran et al. (1997), Moon–Phillips (2000), and Im et al. (2003), the assumption of slope coefficient homogeneity is usually inappropriate. In the mean group (MG) estimator, the model of each cross section is built separately, and the arithmetic mean of coefficients is calculated. Pesaran–Smith (1995) derived this method. In the MG technique, the intercepts, slope coefficients, and error variances are all allowed to change between cross-sections. Pesaran et al. (1997, 1999) developed the pooled mean group (PMG) method for estimating non-stationary dynamic panels, which grow increasingly significant as the study period lengthens.

The PMG estimator is based on combining and averaging coefficient approaches (Pesaran et al. 1997, 1999). Similar to the MG estimate, this estimator allows for differences in short-run parameters, intercept terms, and error variance between groups, but it requires equivalent long-run coefficients $\widehat{\theta}$. Starting with a basic estimate of the long-run coefficient, we can compute the short-run coefficients and correction period pace.

This information is then utilised to estimate θ, and the procedure is repeated until convergence is obtained. The equations of the PMG model have lags of dependent and independent variables. Adding lags overcomes the issues of endogeneity and autocorrelation so the estimated parameters are unbiased and efficient. The empirical specification of the PMG model may be stated in the following general manner.

$$\boldsymbol{Y_{it}} = \sum_{j=1}^{P} \boldsymbol{\lambda_{ij} y_{i,t-j}} + \sum_{j=0}^{q} \boldsymbol{\delta_{ij} X_{i,t-j}} + \boldsymbol{\mu_t} + \boldsymbol{\varepsilon_{it}} \tag{3}$$

where *i*=1, 2,......... N is the number of cross-sections, and *t*=1,2,3......... is the time. X_{it} is a vector of $K * 1$ regressors, λ_{ij} is a scalar, and μ_i is a group-specific effect. The disturbance term is an I(0) process if the variables are I(1) and co-integrated. The reaction of the co-integrated variables to any deviation from the long-run equilibrium is one of its most notable characteristics. This property implies that the error-correction dynamics of the system variables are affected by the departure from equilibrium. Consequently, it is customary to rewrite the above equation as an error-correction equation as follows:

$$\Delta Y_{it} = \Phi_i \, y_{i,t-j} - \theta_i \, X_{i,t-j} \sum_{j=1}^{P-1} \lambda_{ij} \, \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij} \, \Delta X_{i,t-j} + \mu_t + \varepsilon_{it} \tag{4}$$

The speed of adjustment is indicated by the error-correction parameter Φ_i. If Φ_i=0, there is no indication that variables have a long-term relationship. Under the previous hypothesis that variables reflect a convergence to long-run equilibrium in the event of any disturbance, Φ_i is predicted to be negative and statistically significant.

This problem was addressed using the Levin, Lin, and Chu (LLC) unit root test.

Levin et al. (2002) present various panel unit root tests with different specifications depending on the assumption regarding entity-specific intercept terms and temporal trends. The LLC test applies homogeneity to the autoregressive coefficient (the intercept and trend may differ across different series), revealing the presence or absence of a unit root. To evaluate unit root problems, this test is based on augmented Dickey–Fuller (ADF) regression. The most common version of the LLC test with a single intercept term is as follows:

$$\triangle y_{i,t} = \gamma_{0i+}\rho y_{it-1} + \sum_{j=0}^{P_i} \gamma_{1i} \triangle y_{i,t-j} + \mu_{i,t} \tag{5}$$

The constant term γ_{0i} is expected to vary across cross-sectional entities, whereas p is the identical autoregressive coefficient, P_i is the lag order, and $\mu_{i,t}$ is the disturbance term that is supposed to be sovereign across panel entities and follows the auto-regressive moving average (ARMA) stationary process in the above equation.

$$\mu_{i,t} = \sum_{j=0}^{\infty} \gamma_{1i} \triangle y_{i,t-j} + \varepsilon_{i,t} \tag{6}$$

The null and alternative hypotheses can be written as follows:

- $H_0: \rho_i = \rho = 0$ (7)
- $H_A: \rho_i = \rho < 0 \; for \; all \; i$ ………… (8)

The LLC model is based on t-statistics, in which ϱ is expected to be constant across entities under both the null and alternative hypotheses.

$$t_\rho = \frac{\hat{\rho}}{SE(\hat{\rho})} \tag{9}$$

When N and T → ∞ and $\sqrt{N/T} \rightarrow 0$, statistics for the panel regression test under the premise of an independently and normally distributed error term and cross-sectional independence, t_ρ converge to a standard normal distribution. Test statistics do not converge to zero if the cross-sectional units are dependent, the error term is serially correlated, and there is a temporal trend. In such instances, LLC suggests using a modified version of the test statistics such as

$$t_{\dot{\rho}} = \frac{t_\rho - N\tilde{T}\hat{S}_N \hat{\sigma}_0^{-2}(\hat{\rho})\mu_m^*}{\sigma_m^*} \tag{10}$$

μ_m^* and σ_m^* are the modified mean and standard deviation, respectively, with values derived from LLC's Monte Carlo simulation.

Following Asghar et al. (2015), we adopt the econometric methodology.

Empirical results

The descriptive statistics of the variables included in the study are presented in Table 1. It includes the number of observations, mean value, standard deviation, and minimum and maximum values of the variable.

Table 1

Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Ecological Footprint intensity	333	0.051	0.039	0.006	0.221
Real GDP per capita	333	5 331.851	3 343.72	347.887	14 117.43
Industrial value-added growth	333	4.928	5.61	–13.951	21.016
Life expectancy at birth	333	67.751	5.992	52.567	77.118
Population density	333	106.228	93.817	14.496	445.371

The findings of the LLC panel unit root test are reported in Table 2. The null hypothesis of the test is that the panel has a unit root, or in other words, that it is non-stationary. If the null hypothesis of the LLC unit root test of a variable is rejected at the level I(0), the variable is said to be stationary at level or I(0); if the null hypothesis is rejected at the first difference, the variable is said to be stationary at the first difference or I(1) (1). To reject the null hypothesis, the probability value must be less than 0.05. The results indicate that at the first difference, the log of GDP per capita and its square term is constant; that is, they are integrated of order I(1), while the remainder are I(1) (0). The suitable regression technique is PMG, often known as the panel autoregressive distributed lag (ARDL) model since the variables are a mix of I(1) and I(0).

Table 2

Panel unit root test (LLC)

Variable	Level		First difference		Result
	Statistic	Prob.	Statistic	Prob.	
Log of GDP per capita	0.314	0.623	–5.951	0.000***	I(1)
Square of log of GDP per capita	1.778	0.962	–5.50	0.000***	I(1)
Life expectancy	–6.665	0.000***	–	–	I(0)
Industry value-added growth	–7.760	0.000***	–	–	I(0)
Ecological efficiency	–8.367	0.000***	–	–	I(0)
Population density	–9.654	0.000***			I(0)

*** = significant at the 1 percent level.

The long- and short-run results of the panel ARDL model are presented in Table 3. The long-run results are displayed using the log of GDP per capita as the first independent variable. The coefficient of this variable is positive, indicating that an increase in GDP per capita will increase ecological intensity. The increase in ecological intensity means that ecological footprint per capita is greater, which means that EE is reduced. However, this variable is statistically insignificant. The square of GDP per capita is the next quantity of relevance. The coefficient of this variable is negative; thus, it is statistically significant. This indicates that if there is a significant increase in

GDP per capita, the intensity of footprint consumption will decrease. Such a decrease means an increase in EE. An important finding is that the coefficients of GDP per capita are positive and its squared term is negative.

Table 3

Results of panel ARDL model

Variable	Coefficient	Std. error	t-statistics	Prob
Long Run Results				
Log of GDP per capita	0.067623	0.063568	1.063798	0.2885
Square of log of GDP per capita	–0.007696	0.003761	2.046303	0.0419**
Life expectancy	–0.000371	0.000358	1.03626	0.3012
Industry value-added growth	–0.000496	0.000221	–2.23966	0.0261**
Population density	0.000311	0.000179	1.734230	0.0842*
Short Run Results				
ECM	–0.25514	06949	–3.671754	0.000***
D(Ecological efficiency (–1))	0.165863	0.126052	1.315822	0.1895
D(log of per capita income)	–0.650129	0.116025	–5.603365	0.0000***
D(log of per capita income (–1))	0.107454	0.083779	1.282582	0.2009
D(log of per capita income square)	0.036455	0.006415	5.682886	0.0000***
D(log of per capita income square (–1))	–0.006561	0.005072	–1.293508	0.1971
D(life expectancy)	–0.000509	0.000621	–0.820545	0.4128
D(industry value-added growth)	6.03E–06	1.89E–05	0.319358	0.7497
D(industry value-added growth(–1))	–2.66E–06	3.63E–06	–0.732337	0.4647
D(Population density)	0.000835	0.000500	1.671322	0.0960*
C	–0.000169	0.001506	–0.112114	0.9108
Number of observations 333				

*, **, and *** = significant at the 10, 5, and 1 percent levels, respectively.

Theoretically, when the coefficient of GDP per capita is positive and GDP per capita ^2 is negative, the validity of the EKC holds. The EKC hypothesis suggests that the environmental impacts increase at the initial level of development and tend to decrease with further increase in the level of economic development (Grossman–Krueger 1995). This is because structural changes towards industries and services, along with stronger environmental laws and better technology, result in a steady reduction in environmental degradation at higher levels of development (Stern 2004). In the present study, the relationship between GDP per capita (indicating the level of economic development) and EE (indicating environmental degradation) displays a curvilinear trend among the group of emerging countries. These results satisfy the findings in York et al. (2004), who also found that the EF intensity per unit of GDP is lower for more affluent nations globally. According to York et al. (2004), "more affluent nations are more eco-efficient and use less resources per unit of economic activity." This phenomenon may be due to the shift in the economic structure of emerging economies from highly natural resource-intensive segments of the economy (e.g. agriculture) to less resource-intensive sectors (United Nations Department of Economic and Social Affairs 2013). However, as the coefficient of GDP per capita is statistically insignificant, we can say that the EKC has partial validity.

The next variable in the long-run analysis is life expectancy; the coefficient of this variable is negative, which indicates that there will be an increase in EE with an increase in expected years of life. It may be due to the fact that with such an increase, people become more vigilant about their future and consume natural resources more wisely. However, this variable is statistically insignificant. The next variable is industrial value-added growth, which has been employed as a proxy for technical development. As the coefficient of this variable is negative, it is statistically significant. This demonstrates that as technology becomes more advanced, the intensity of natural resource usage decreases, which is considered environmentally efficient. Thus, our analysis indicates that EE increases with technological advancements. The next variable is population density, the coefficient of which is positive and statistically significant. The positive sign indicates that, with an increase in population, the intensity of resource consumption increases, which indicates that EE decreases. This may be because a substantial percentage of the population makes a living from natural resource-based occupations such as agriculture, grazing, forest products, and fishing, and lives in remote natural areas. The intensity of resource use increases as the world's population rises, lowering EE.

We now examined the short-run results. The most important variable in the short-run analysis is the coefficient of the error-correction term (ECM). It represents the model's convergence towards equilibrium in the case of a shock, as well as an indication that the variables have a long-term connection if it is negative and statistically significant. The magnitude of this coefficient indicates how rapidly things are coming together. In our analysis, the coefficient of error-correction is negative and statistically significant. This indicates that there is convergence in the model and there is a long-run relationship among the variables. The value of this coefficient is -.255, which indicates that in the case of any shock, the model will converge at approximately 25 percent per annum. The results of GDP per capita are quite interesting in the short run as they are significantly different to the long run. In the short run, an increase in per capita GDP enhances EE, while a large increase in GDP per capita reduces EE. Therefore, in the short run, this finding is opposite to the EKC. However, the coefficients of the difference lag of GDP per capita and GDP per capita square have similar signs in the long run. Similarly, this is the case for the industrial value-added growth variable. However, this phenomenon requires further investigation. Life expectancy and population density have similar signs in the long run.

Conclusion

The process of economic growth is normally resource dependent and is accompanied by an increasing environmental burden. In the last few decades, human beings' use of natural resources to support increasing population and economic prosperity has produced an alarming impact. In particular, emerging countries are experiencing major demographic and economic transitions. It is imperative for these economies to efficiently utilise their ecological footprint because it is the only way to ensure our survival in the future. As a result, there is a pressing need to identify the key elements that may influence the eco-efficiency of emerging nations. Keeping this in mind, the current study attempted to achieve this goal. Panel data from 1980 to 2016 were used for the following emerging economies: Brazil, China, India, Indonesia, Malaysia, Mexico, South Africa, Thailand, and Turkey. EE was adopted as a dependent variable and PMG estimation used for analysis. The independent variables were GDP per capita, GDP per capita square, industrialisation, population density, and life expectancy. Results signal that the relationship between GDP per capita and EE displays a curvilinear trend among these countries. More affluent nations are more eco-efficient and use fewer resources per unit of economic activity. However, the coefficient of GDP per capita is statistically insignificant, hence, there is partial validity of the EKC in these economies. An increase in the expected years of life leads to an increase in EE. The progress of industrialisation progress also contributes to an increase in EE. Finally, high population density lowers EE. In light of the findings, efforts should be made to enhance EE by achieving greater levels of GDP, more industrialisation, and longer life expectancy. To attain EE, population stabilisation methods are needed.

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