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RESEARCH ARTICLE

Sustainability assessment using STIRPAT approach to environmental quality: an extended panel data analysis

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Abstract
The consequence of increasing economic activities is observable in the incidence of environmental deterioration. Many studies have explored the precedents of environment quality. In this regard, the proposed stochastic impacts by regression on population, affluence, and technology (STIRPAT) and environmental Kuznets curve (EKC) analysis are valuable not only for academic analysts, but also for policymakers. This study has focused on 80 selected countries between 1990 and 2017, which confirms the existence of EKC within the STIRPAT framework. The results are estimated with the help of dynamic ordinary least square (DOLS), which controls for the autocorrelation in long periods. According to the estimated results, this study confirms U-shaped EKC based on industrial-, agricultural-, and services-based economic activities. This means that over-reliance on one specific economic activity may harm the environment and create footprint. In this regard, urbanization is responsible for affecting carbon dioxide emissions. Moreover, governance and technology are protecting the environment. This quadratic function had classified the sample countries in terms of the degree of sustainability of their economic activity sectors. This study proposes that countries should work on a balanced composition of economic activity so that the lowest possible environmental deterioration is caused.

Keywords Environmental quality · Environment Kuznets curve · Agriculture · Services · STIRPAT · Technology · Governance

Introduction

The efforts of human explorations have led to the development of issues that had never existed earlier; the most prominent of them is the alarming rate of environmental deterioration. The survival of humans barely depends on the quality of the air humans breathe in. This drastic change in the environment started from the industrial revolution and discovery of bio-degradability resilient materials. The literature has blamed non-regulated economic activities that are responsible for damaging the environment (Bai et al. 2017; Franchini et al. 2015). It is also observed that carbon dioxide emissions grew by 1.4% in 2017, reaching a historic high of 32.5 gigatons (GT) universally. Even though this damage of the environment is not universal, this increase was observed in many economies (according to International Energy Agency, Global Energy & CO2 Status Report 2017). There are several researched consequences of depleting environment quality across the world, and especially in populated regions. It is reported that climate change has its effects on physical and economic health. This includes delays in early development, vulnerability of older people, post-traumatic stress disorder, anxiety, depression, aggression, and homelessness (Eckart 2017; European Academies' Science Advisory Council 2019; Loira 2018).

Extreme weather conditions such as a heatwave, urban and rural flooding, smog/fog, and irregular rains are leading to poverty because of damages to property and possessions. An increase in sea levels and flooding is forcing people to flee to higher lands as it is increasingly becoming difficult to grow crops. China, Pakistan, and India are included in the most vulnerable region to climate change. This region is facing an increasing risk of flash floods and drought, as in this century, about one third of the ice in the Hindukush Karakorum Himalaya (HKH) region has been melted away. Further, one third is expected to be melted by 2100 (Khan 2019). This devastating event will affect access to the freshwater of about 250 million people directly and further 1.65 billion indirectly

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who are fed by the great rivers flowing from HKH. According to a moderate assessment of 1.5 degrees increase in temperature, with the present level of carbon emissions, two thirds of ice will disappear from the HKH region. This cataclysmic event will firstly increase the flow of rivers causing lake bursts and floods till 2060, after which rivers will dry up causing acute water scarcity (Wester et al. 2018). Because of these consequences, several efforts can be observed to control the environmental deterioration, among them United Nations 8th Millennium Development Goal, and 13th to 15th Sustainable Development Goals are noticeable (Darbo 2010).

The relationship between economic activities and carbon emissions can be better understood by the environmental Kuznets curve (EKC) and the stochastic impacts by regression on population, affluence, and technology (STIRPAT). These are two subjects which are readily used not only to describe how economic activities affect the environment but also to investigate the implications of human action in other disciplines. Basically, the EKC represents the non-linear impact of economic activity on the environment, just like an inverted-U–shaped relation. This means that, in the initial phase, economic activities firstly damage the environment. However, after a specific threshold, these activities become environment-friendly. On the other hand, the STIRPAT is used to analyze how population size, gross domestic product (GDP), and technology influence the environment. Several studies combined both the EKC and the STIRPAT (Awad and Qarsame 2017; Ge et al. 2018; Li et al. 2015; Marin and Mazzanti 2013; Rafiq et al. 2016; Uddin et al. 2016; Wang et al. 2017; Yuan et al. 2015; Zhao 2010; Zineb 2016).

While discussing the viability of the EKC model, most of the studies are in favor of inverted-U–shaped EKC, but some studies suggest the U-shaped relationship EKC (Ahmed and Qazi 2013; Destek et al. 2018; Och 2017; Twerefou et al. 2016). Starting from this debate, in this study, the authors integrated the EKC in the STIRPAT framework using a sample of 68 countries and classified the countries based on human development. In this regard, the authors used disaggregated GDP as an indicator of economic activity in the EKC, along with urbanization and patent application (both resident and non-resident) as indicator of technology as controlling variables.

By using disaggregated GDP, in this study, the authors could estimate three EKCs: (1) the industry EKC (Arshed and Iqbal 2018), (2) the agricultural EKC (Och 2017; Vlontzos et al. 2017; Wang and Shen 2016), and (3) the services sector EKC (Alcantara and Padilla 2009; Buntar and Llop 2011; Och 2017). The authors used the control variables in the perspective of the STIRPAT, in this study. Stating from urbanization, the existing literature indicates that it has both negative and positive impacts (Wang et al. 2015). Some studies argue the positive effect of urbanization on the environment (Fan et al. 2006; Xiong et al. 2019). Instead, others proved the detrimental role in environmental quality (Cui et al. 2018; Hong 2017; Li et al. 2015; Wen and Liu 2016). Furthermore, the STIRPAT proposes technology. Most of the studies show that technology increases energy consumption, which leads to environmental deterioration (He and Hu 2018; Hong 2017; Wen and Liu 2016; Xiong et al. 2019). However, in China, technological progress has mixed results; it has both negative and positive impacts (Wang et al. 2015). Similarly, the role of governance is quite clear in the protection of the environment (Dadgara and Nazari 2017; Martin and Andres 2012).

Thus, the objective of this study is to explore the existence of the EKC in the perception of industry, agriculture, and services sectors. Moreover, this study also follows the STIRPAT approach regarding control variables and estimating how a rapid increase in urban population and technological progress is affecting the environment. The authors categorized the countries in terms of sustainability or non-sustainability of the real sector with respect to the environment. This study is instrumental in categorizing the countries in terms of the sustainability of agriculture, services, and industry sectors of the selected countries within the STIRPAT–EKC framework. It will consequently help the policymakers to find the optimal composition of the real sector strategy.

After discussing the importance of protecting the quality of the environment in the introduction section, the second section provides a review of empirical studies that determined precedents of environmental quality. “Theoretical model” provides the theoretical model, and “Research methodology” provides the methods which the authors used to achieve the objectives of this study. Lastly, “Results and interpretation” provides the estimation results and answers to the research questions.

Literature review

Time series STIRPAT

Several literary efforts have been made in investigating the environment using the STIRPAT. Exploring the cases of time series data, evidence from Henan Province of China between 1983 and 2006 confirmed that the GDP per capita excluding services and its square increase ecological footprint (Jia et al. 2009). A similar outcome was evident for the case of the Gennan pasturing area of China between 1980 and 2007, where the GDP per capita followed an inverted-U shape (Zhao 2010). While studying West Jillin province of China, the GDP per capita had a detrimental effect on the ecological footprint within the STIRPAT framework (Wang et al. 2010). For the data between 1998 and 2009, there was significant evidence for the STIRPAT model in Minhang district, China (Wang et al. 2011). For the case of China during 1990–2012, one study assessed the role of economic growth within the

STIRPAT framework. The results based on ridge regression confirmed that the GDP per capita increases carbon emissions (Zhao and Yan 2013). Another study from China showed that, between 2000 and 2015, the positive effect of tertiary industrialization index was an increase in energy consumption leading to environment degradation (Ma et al. 2017).

Based on the evidence from the Chinese agriculture sector from 1990 to 2009, estimations using ridge regression confirmed that agricultural activity could increase water footprint (Zhao et al. 2014). Similar results were confirmed for the case of industrialization and urbanization. The STIRPAT was confirmed using the data of Tianjin China between 1996 and 2012 (Li et al. 2015). Evidence from the Hebei province of China confirmed a similar outcome using GDP, urbanization, and industrialization (Wen and Liu 2016).

Another study used the auto-regressive distributed lag (ARDL) approach on quarterly data of Malaysia, between 1970 and 2011. There is empirical evidence of detrimental environmental effects of the GDP per capita and urbanization (Shahbaz et al. 2016). Evidence of the STIRPAT was confirmed in Iran from 2003 to 2013, where population and the GDP per capita led to carbon emissions (Noorpoor and Kudahi 2015). Ridge regression for Australia from 1960 to 2014 showed a positive effect of the GDP per capita on the ecological footprint (Uddin et al. 2016). Using the ARDL model, Azerbaijan also confirmed the decisive role of GDP on carbon emissions (Mikayilov et al. 2017).

Three studies assessed China in the periods 1996–2016, 2000–2015, and 1995–2016 using the STIRPAT model. The results showed that urbanization, secondary industry, and GDP per capita were increasing carbon emissions, while technology was reducing it (Cui et al. 2018; He and Hu 2018; Hong 2017). At the same time, a study in Kazakhstan estimated three models for three time periods. The authors concluded that population, GDP per capita, technological progress, secondary industry, tertiary industry, foreign direct investment, trade openness, and energy consumption structure were causing an increase in carbon emissions, while urbanization was decreasing carbon emissions (Xiong et al. 2019). Ongan et al. (2020) confirmed the existence of the EKC both in actual form and in decomposition from using data from 1990M1 to 2019M7 for USA using the ARDL model. Moreover, Ongan et al. (2020) found fossil fuel and renewable energy to be damaging and protecting the environment, respectively.

Cross-sectional STIRPAT

Li et al. (2017) conducted a cross-sectional study and explored different cities of China. The results showed that industrialization, per capita disposable income of urban residents, and per capita city building and maintenance capital were damaging the environment. Instead, at the macro-level, the assessment of 173 countries confirmed that GDP per capita is responsible for increasing carbon emissions (McGee et al. 2015).

Panel data STIRPAT

While exploring the panel data, the authors considered studies which had assessed the STIRPAT approach to environmental quality. A large number of studies on the STIRPAT are available for the case of China; in this subsection, the authors explore the studies from China, first.

Cole and Neumayer (2004)'s study on 86 countries between 1975 and 1999 showed that GDP per capita, manufacturing, and urbanization lead to sulfur dioxide emissions. Similar outcomes were evident for carbon emissions (Fan et al. 2006). A study on 22 OECD countries and referring to data between 1960 and 2007 confirmed that GDP per capita, energy use, and total population damage the environment (Liddle 2011). A similar result was proposed by Bargaoui et al.'s (2014) study on 214 countries between 1980 and 2010, by Yuan et al.'s (2015) state-level study in China between 1997 and 2010, and by Wang et al.'s (2015) provincial-level study of China between 1995 and 2011. Another study on significant regions of China between 2000 and 2012 confirmed that industry, urbanization, population, and GDP per capita have a positive effect on carbon emissions (Wen and Liu 2016). An analysis of 29 different major cities, between 1998 and 2010, showed that urbanization, population density, GDP per capita, and industry were causing consumption that was leading to deterioration of the environment (Ji and Chen 2017). Using 30 provinces of China from 2006 to 2014, the STIRPAT model showed GDP per capita, internationalization, and urbanization were damaging the environment (Lin et al. 2017). Similar results are evidenced when integrating the EKC (Wang et al. 2017).

Similarly, a study on 29 Chinese provinces between 2002 and 2013 showed that population, GDP per capita, energy intensity, and urbanization (urban primary index) were increasing carbon emissions (Niu and Lekse 2018). Also, for the 30 provinces and 3 regions of China between 2010 and 2014, it showed an N-shaped EKC with respect to nitrogen dioxide (Ge et al. 2018; Lv and Wu 2019).

One study merged the EKC and the STIRPAT in a panel data of high-, medium-, and low-income countries between 1980 and 2010 which showed that GDP per capita has a quadratic effect on the environment. Also, agriculture has a less detrimental effect on the environment as compared with industry (Rafiq et al. 2016). Following this, another study using 176 countries showed that the EKC exists (Zineb 2016). Using data of 54 African countries from 1990 to 2014, Awad and Qarsame (2017) rejected the presence of the EKC when carbon emissions are taken as an indicator of environmental quality. According to an estimation of the STIRPAT approach based on the tailpipe emission standard policy of the

California Air Resources Board, using the panel data of 49 states of the USA from 1987 to 2015, population, GDP per capita, energy intensity, and vehicle miles traveled are the main factors that damage the environment (Lim and Won 2019).

Anser et al. (2020) tested the theory of the EKC for Latin American and Caribbean economies from 1990 to 2015. According to the estimated results by a two-step system generalized method of moments robust estimator, an inverted-U–shaped EKC exists in the sampled countries. Altıntaş and Kassouri (2020) confirmed the existence of an inverted-U–shaped EKC for the selected European countries from 1990 to 2014 by applying the interactive fixed-effect model. Moreover, they found renewable energy consumption, such as fossil fuel energy consumption, harms the environment. Mania (2020) tested the EKC theory for the case of 98 developed and developing countries during the period from 1995 to 2013. Using the generalized method of moments and the long-run pooled mean group, Mania confirmed the existence of the EKC. Erdogan et al. (2020) used 21 OECD countries from 2000 to 2015 for testing the EKC theory. According to the estimated results using fully modified OLS, Erdogan confirmed the existence of the EKC. Ansari et al. (2020) used countries of the Gulf Cooperation Council to test the EKC theory by collecting data from 1991 to 2017. According to the estimated results from fully modified OLS and dynamic fully modified OLS, these authors did not confirm the existence of the EKC. Ng et al. (2020) used paned data of 76 countries from 1971 to 2014 to test the EKC theory. According to the estimated results using common correlated effect mean group and augmented mean group, Ng et al. (2020) confirmed the existence of EKC only in 16 countries. Similarly, Hassan et al. (2020) compared 32 developing and 32 developed economies and confirmed inverted-U–shaped EKC.

Most of the previous studies used the STIRPAT model for regions within the country, and there is a dearth of countries which have incorporated the effect of institutes as behavior/culture (Schulze 2002). In this study, the authors used diverse data for generalization and governance to incorporate institutional quality. Most of the previous studies estimated population and urbanization in the same model, which makes the model susceptive to multicollinearity (Cui et al. 2018; Ge et al. 2018; Lin et al. 2017; Niu and Lekse 2018; Uddin et al. 2016; Wen and Liu 2016). Similarly, few others used GDP per capita and industrialization, which are interrelated (Cui et al. 2018; Lin et al. 2017).

In this study, the authors proposed industry value added, agriculture value added, service value added, and their squares in separate models as indicators of economic activity, rather than GDP per capita, in order to estimate the EKC within the STIRPAT framework. Hence, these indicators will trace the EKCs for three different types of economic activity which can be sorted with an appropriate policy framework (Erdogan 2020). Other indicators such as population and technology have been used differently in the literature. The role of population is clear enough; in this study, it is captured using urban migration (Cui et al. 2018; Hong 2017; Rehman and Zeb 2020; Xiong et al. 2019). If technology has an innovative aspect, it can protect the environment (Dinda 2018; Mensah et al. 2019). Thus, in this study, the authors used patent applications as a proxy of technology, governance as a proxy of behavior (Abduqayumov et al. 2020; Dadgara and Nazari 2017; Baloch and Wang 2019), and urbanization as a proxy of population.

Theoretical model

Before setting up a model for environmental quality, one must not ignore the popular model of STIRPAT and EKC. Generally, it could be said that the STIRPAT is the updated form of Impact of Population, Affluence, and Technology (IPAT) and Impact of Population, Affluence, Consumption, and Technology (ImPACT). Theoretically, there is a deep relation between STIRPAT, IPAT, and ImPACT (Wen and Liu 2016; York et al. 2003). IPAT means detrimental environmental impacts (I) are the multiplicative product of three economics viewpoint variables, such as population (P), affluence (A), and technology (T) (Awad and Qarsame 2017; Niu and Lekse 2018; Zineb 2016). Instead, ImPACT means detrimental environmental impacts (I) are the multiplicative product of population (P), affluence (A), energy consumption per unit of GDP (C), and technology (T) (Zhao and Yan 2013).

As far as the STIRPAT, it means stochastic (ST) detrimental impacts (I) by regression (R) by population (P), GDP per capita or affluence (A), and technology (T). Several studies related to the STIRPAT approach exist (Bargaoui et al. 2014; Niu and Lekse 2018; Wang et al. 2011; Wen and Liu 2015; Xiong et al. 2019; York et al. 2003; Zhao and Yan 2013). In this study, the authors added urbanization instead of the population for (P) and governance to incorporate behaviors (B), as Lin et al. (2008) and Schulze (2002) discussed. On the contrary, in order to incorporate the EKC effect, the literature uses the square form of GDP per capita.

Figure 1 shows the theoretical outlook of the EKC regarding the STIRPAT analysis with Figure 1a and 1b representing the positive and negative effect of disaggregated GDP on CO2 emissions. Commonly, it is an inverted-U curve, which represents the relationship between disaggregated GDP and carbon emission. By utilizing STIRPAT strategies such as

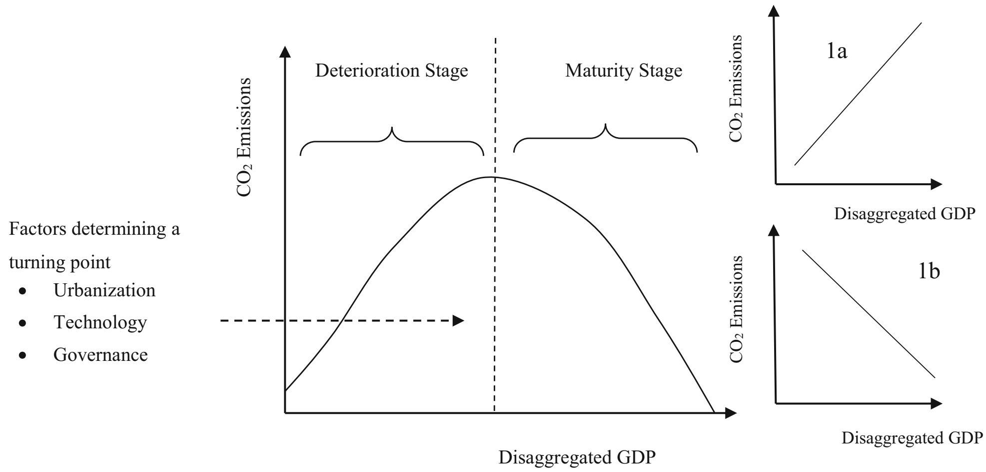

Fig. 1 Theoretical model of inverted-U-EKC

urbanization and technology, along with a control variable such as governance, we can say that these mutable objects are also related to the environment (Arshed and Iqbal 2018).

As per the methodology to explain quadratic relationships (Haans et al. 2016; Rehman et al. 2020), the inverted-U shape of the relationship of CO2 emissions and economic activity is due to the multiplicative aggregation of two phenomena. Figure 1a explains this with the increase in economic activity: an increase in the engagement of natural resources increases CO2 emissions. On the other hand, Fig. 1b explains that increase in economic activity also initiates the process of innovation and efficiency, which reduces the reliance on or utilization of energy, thus reducing CO_2 emissions.

Figure 2 shows the opposite case, where economic activity may affect the environment in a U-shaped pattern, which is a resultant of two linear effects in Fig. 2a and b. Several studies which used ecological footprint confirmed that over-reliance on a particular economic activity may increase the pressure on the natural resources, leading to the deterioration of environment quality (Ahmed and Qazi 2013; Destek et al. 2018; Twerefou et al. 2016). Figure 2a denotes that increase in the economic activity increases economies of scale in terms of utilization of resources, ensuring optimal utilization; this process reduces CO_2 emissions. Beyond a specific absorptive capacity, economic activity creates diseconomies of scale, leading to an increase in CO_2 emissions.

Research methodology

Variables and sample

This study is based upon panel data from 1990 to 2017, and the authors selected the countries (presented in Table 4). This study is based on 80 selected countries. Table 1 provides details of the variables the authors used in this study.

In this study, there are three functional forms, and each functional form represents the separate type of EKC (i.e., industrial, agricultural, and services EKC) along with the STIRPAT exploration. In order to capture the impact of affluence, the authors used disaggregated GDP (i.e., industrial,

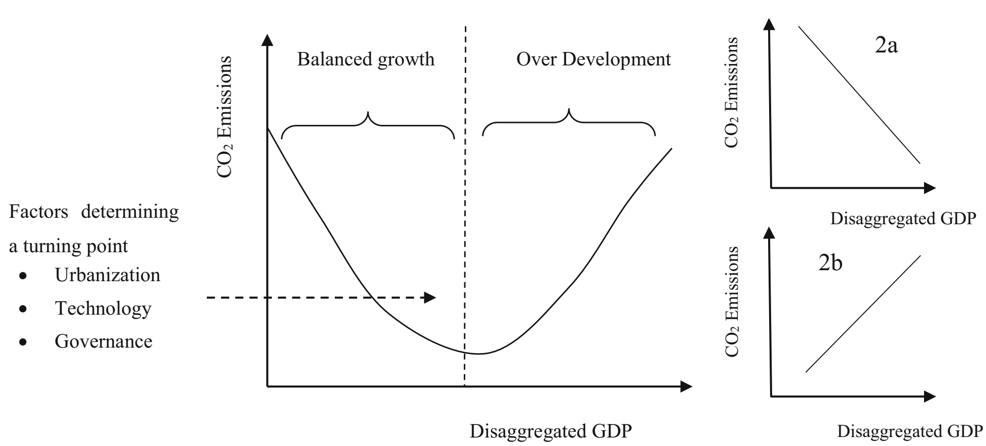

Fig. 2 Theoretical model of U-shaped EKC

Table 1 Description of variables

Variable name (symbols)	Full form	Source
CO_2	Log of CO_2 emission per capita	World Development Indicators (WDI)
ECO	Ecological footprint (Earths)	Footprint Network
IND	Log of industrial value added as % of GDP	WDI
IND^2	Square of log of industrial value added	WDI
AGR	Log of agricultural value added as % of GDP	WDI
AGR^2	Square of a log of agricultural value added	WDI
SVC	Log of services value added as % of GDP	WDI
SVC^2	Square of log of services value added	WDI
URB	Log of urban to rural population ratio	WDI
Tech	Log of summation of patent application resident and non-resident	WDI
GOV	Index of 6 constructs of governance[a]	Worldwide Governance Indicators (WGI)

[a] These 6 constructs include control for corruption, government effectiveness, political stability/absence of violence, regulatory quality, rule of law, and voice and accountability

agricultural, and services value addition) instead of GDP per capita.

For the non-linear impact of disaggregated GDP, the authors used the square form of industrial, agriculture, and services value added (Chiang and Wainwrigth 2009). Furthermore, many studies have applied a square form for non-linearity (Awad and Qarsame 2017; Ge et al. 2018; Rafiq et al. 2016; Uddin et al. 2016; Wang et al. 2017; Zineb 2016):

$$CO_2 = f\ (\text{IND}, \text{IND2}, \text{URB}, \text{TECH}, \text{GOV})$$

$$CO_2 = f\ (\text{AGRI}, \text{AGRI2}, \text{URB}, \text{TECH}, \text{GOV})$$

$$CO_2 = f\ (\text{SVC}, \text{SVC2}, \text{URB}, \text{TECH}, \text{GOV})$$

Estimation approach

Based upon the above function forms, below are three regression equations. Here, the square from which is presenting the non-linear effect of industry, agriculture, and services sector on the environment respectively. These regression lines are estimated with the help of the DOLS method (Gujarati 2009). Previous studies estimating the EKC used the DOLS model (Dong et al. 2017; Erdogan et al. 2020; Ponce and Alvarado 2019). Anwar et al. (2019) assessed 59 countries using the DOLS model and showed that increase in agriculture value added has a positive effect on CO_2 for high-income countries, while it has a negative effect for low-income countries. This method provides long-run OLS coefficients, which are constant for all cross-sections, but the intercept varies, and it uses the independent variables, which vary across cross-sections to incorporate non-stationarity of the model. Three equations for each type of EKC are provided below, estimated by the DOLS, where βs are the coefficients of each variable. Moreover, in the equations ε_t is the error term or disturbance of the model (Galeotti et al. 2009). The square forms will be handled by taking the first derivative and equating it to zero (Arshed et al. 2018, 2019):

$$CO_2 = \beta_0 + \beta_1 \text{IND}_{\text{it}} + \beta_2 \text{IND}^2_{\text{it}} + \beta_3 \text{URB}_{\text{it}} + \beta_4 \text{TECH}_{\text{it}} + \beta_5 \text{GOV}_{\text{it}} + \varepsilon_t$$

$$CO_2 = \beta_0 + \beta_1 \text{AGRI}_{\text{it}} + \beta_2 \text{AGRI}^2_{\text{it}} + \beta_3 \text{URB}_{\text{it}} + \beta_4 \text{TECH}_{\text{it}} + \beta_5 \text{GOVit} + \varepsilon_t$$

$$CO_2 = \beta_0 + \beta_1 \text{SVC}_{\text{it}} + \beta_2 \text{SVC}^2_{\text{it}} + \beta_3 \text{URB}_{\text{it}} + \beta_4 \text{TECH}_{\text{it}} + \beta_5 \text{GOV}_{\text{it}} + \varepsilon_t$$

Results and interpretation

In Table 2, the mean is greater than the standard deviation in the case of all the variables except governance and urbanization; this means these variables are underdispersed. Kurtosis of every variable, except governance and urbanization, is equal to 3. These variables show that there are either too many (kurtosis > 3) or too few (kurtosis < 3) outliers in the data as compared with a normal distribution leading to cross-sectional heteroskedasticity. This shows pooled OLS should not estimate the model, because it assumes that cross-sections are similar in every aspect. Except for services, urbanization, and technology, all the variables are positively skewed. Based on panel unit root tests of Levin Lin Chu (LLC) and Im, Pesaran, Shin (IPS), all the variables are found to be non-stationary in nature.

Table 3 shows the estimated results by the DOLS. According to these results, there is a U-shaped EKC

Table 2 Descriptive statistics

	CO_2	IND	AGRI	SVC	URB	TECH	GOV
Mean	10.9991	27.18729	25.39674	25.27143	0.446164	7.543713	0.349542
Median	10.87651	26.69043	25.41204	25.64018	0.6612	7.676937	0.04465
Maximum	16.14687	35.88053	34.73002	30.13765	2.758988	14.10706	1.9587
Minimum	6.233848	20.05507	18.5041	20.29455	− 1.94747	0.00000	− 1.6523
Std. Dev.	1.991658	3.297956	2.969726	2.117451	1.178022	2.680455	0.957065
Skewness	0.019427	0.622467	0.459306	− 0.2285	− 0.20448	− 0.21251	0.300437
Kurtosis	2.889184	3.37697	3.541354	2.575901	1.949839	3.008089	1.647414

(Ahmed and Qazi 2013; Destek et al. 2018; Och 2017; Twerefou et al. 2016), which is also confirming the cointegrated relationship. It means that, at the initial level, disaggregated GDP protects the environment by decreasing the carbon emissions, but, over time, when production increases, it starts to damage the environment by releasing more and more carbon dioxide. This is because, at the initial level of production, every producer follows a decent way of production, but, when the demand increases, they only focus on production, rather than also on rules and regulations. These results are robust as a similar outcome is observable for the case of ecological footprint in the appendix.

The most exciting aspect regarding urbanization is it is damaging the environment in every estimated result. However, in the services sector, it becomes environment-friendly. Thus, a sound services sector has the potential to absorb this migration in urban areas, and, in this way, the overpopulated areas, due to urbanization, become environment-friendly. Negative signs of the coefficient of technology and governance show that improvement in these segments is caused to control environmental problems. The results provided in Table 3 passed the diagnostics tests (i.e., normality, autocorrelation, and heteroskedasticity), while to avoid multicollinearity, disaggregated GDP are estimated in seperate equations.

The estimated results are in favor of the U-shaped EKC, and the control variables which are related to the STIRPAT theory are also significantly affecting the environment. Here, it can be seen that overall economic activities from industry, agriculture, and services must remain below 20.38%, 30.69%, and 25.89%, respectively, so that they are environmentally sustainable. In Fig. 3, a post-regression quadratic effect plot (Dawson and Richter 2006) confirms that based on the incidence of the real sector, the sample countries are already over-industrialized, hinted by a positive slope, while an increase in agriculture is decreasing CO_2 emissions. Lastly, for the case of the services sector, the sample includes few countries which are under- and over-reliant on the services sector, which is making the curve U-shaped.

Using the estimates of the EKC, Table 4 provides the countrywide assessment of the sustainability of the real sector. It is calculated by comparing the average value of real sector activity and the cutoff value calculated in Table 3, adapted from Arshed et al.'s (2018, 2019) research. These data highlight

Table 3 Estimated results

Dependent variable: CO_2			
Variables	Industrial EKC Coeff. (*P* value)	Agricultural EKC Coeff. (*P* value)	Services EKC Coeff. (*P* value)
IND	− 1.3532 (0.0476)		
IND^2	0.0332 (0.0045)		
AGRI		− 5.3951 (0.0000)	
$AGRI^2$		0.0879 (0.0000)	
SVC			− 14.7504 (0.0008)
SVC^2			0.2848 (0.0010)
URB	0.2316 (0.0000)	2.0721 (0.0000)	− 1.4120 (0.0233)
TECH	− 0.2131 (0.0000)	− 0.0290 (0.0014)	− 0.0420 (0.3624)
GOV	− 0.1978 (0.0015)	− 0.0512 (0.0109)	− 0.6879 (0.0000)
R-Square	0.9999	0.9999	0.9999
Cut-off value	20.38%	30.69%	25.89%
Kao cointegration test	− 2.68 (0.00)	1.72 (0.04)	− 3.56 (0.00)

that, other than Indonesia, almost all of the countries have sustainable agriculture sector activity, while no country has a sustainable level of industry-level activity.

While comparing for the case of sustainability of the services sector activity, the data evidence there is a healthy share of sustainable and not sustainable countries. The analysis of the study does not advocate that, if some specific sector grows out of bounds and leads to an increase in CO_2 emission, we should restrict it. This study promotes that we should regulate the sector, which is growing beyond the threshold level. Figure 4 confirms that all of the real sector economic activity has a two-way causal relationship with CO_2 emissions.

Conclusion and policy implication

Conclusion

Following the ever-increasing need for research on the sustainability of the environment, several studies have tried to estimate the determinants of CO_2 emissions. Most of the studies were available for the case of China. While exploring the determinants of CO_2 emissions, the authors of this study integrated the EKC and the STIRPAT phenomenon and added governance as an indicator of behavior (Schulze 2002). They selected the unbalanced panel data of 80 countries between 1990 and 2017. Since the time periods are long, to counter the expected presence of autocorrelation in the model, they estimated the results using the dynamic OLS model. When the EKC is studied while controlling for the STIRPAT, the U-shaped impact of disaggregated GDP is noticeably witnessed. Only a few studies in the literature advocated this outcome. Hence, the evidence proposes the over-reliance on anyone of the real sector components. Here, an increase in industry, agriculture, and services leads to abnormal growth of that sector, which leads to an increase in harmful environmental consequences. The most prominent consequences are in industry and services (Fig. 4).

Future studies must explore the role of different indicators of technology and governance in terms of their ability to achieve sustainability. This will play a role as a moderator to a high level of economic activity such that nations do not have to slow down for the posterity.

Policy implications

Based on the estimations, nations must keep industry, agriculture, and services sectors within 20.38%, 30.69%, and 25.89% of their GDP, respectively, so that they are environmentally sustainable. The remaining 23.04% can be achieved by moderating, using the STIRPAT controls of urbanization, technology, and governance.

The U-shaped EKC model has provided the authors with the grouping of countries in terms of sustainable and not

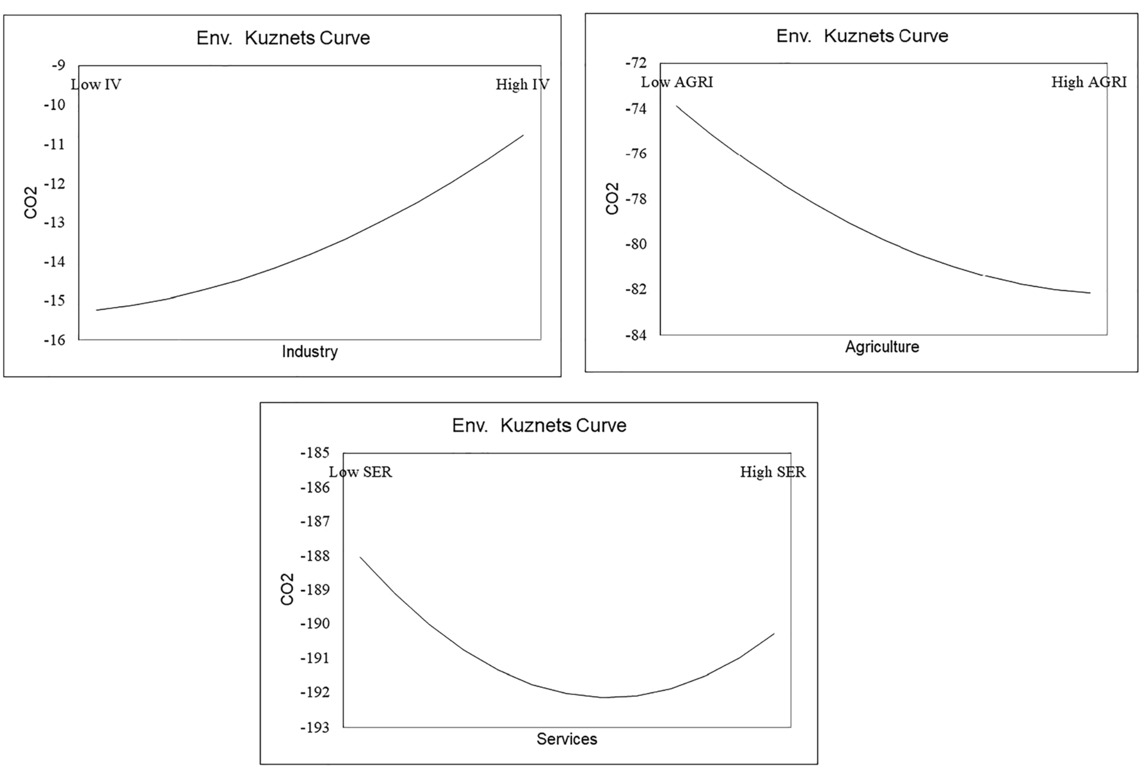

Fig. 3 Effects of real sector on CO_2

Table 4 Countrywide EKC

Countries	Agriculture Share	Agriculture Sustainability	Industry Share	Industry Sustainability	Services Share	Services Sustainability
Afghanistan	23.88695	Sustainable	25.1406	Not Sustainable	22.5727	Sustainable
Australia	25.67551	Sustainable	26.338	Not Sustainable	27.1189	Not Sustainable
Azerbaijan	21.68661	Sustainable	22.2368	Not Sustainable	22.6638	Sustainable
Bangladesh	25.97061	Sustainable	27.5874	Not Sustainable	24.5152	Sustainable
Bhutan	21.03822	Sustainable	23.0136	Not Sustainable	19.5791	Sustainable
Bolivia	22.323	Sustainable	22.8368	Not Sustainable	22.6509	Sustainable
Botswana	21.54526	Sustainable	23.7325	Not Sustainable	22.1468	Sustainable
Brazil	26.26545	Sustainable	26.4301	Not Sustainable	27.6368	Not Sustainable
Bulgaria	22.94256	Sustainable	23.672	Not Sustainable	23.8147	Sustainable
Cameroon	25.45119	Sustainable	28.5392	Not Sustainable	23.0583	Sustainable
Canada	25.99746	Sustainable	26.8784	Not Sustainable	27.7375	Not Sustainable
Central African Rep.	23.25129	Sustainable	25.2849	Not Sustainable	20.0377	Sustainable
China	28.46861	Sustainable	29.7858	Not Sustainable	27.9237	Not Sustainable
Colombia	28.20886	Sustainable	32.2875	Not Sustainable	25.4815	Sustainable
Congo	25.30381	Sustainable	28.3559	Not Sustainable	22.6517	Sustainable
Denmark	24.83275	Sustainable	26.6372	Not Sustainable	25.9533	Not Sustainable
Egypt	25.67521	Sustainable	26.8175	Not Sustainable	22.5918	Sustainable
Finland	23.84969	Sustainable	24.4083	Not Sustainable	25.5627	Sustainable
Germany	26.02272	Sustainable	27.2313	Not Sustainable	28.2976	Not Sustainable
Haiti	21.43723	Sustainable	21.5414	Not Sustainable	20.9449	Sustainable
Hong Kong	23.64934	Sustainable	25.6817	Not Sustainable	25.9483	Not Sustainable
Iceland	24.10791	Sustainable	26.5962	Not Sustainable	22.7495	Sustainable
India	28.41338	Sustainable	30.3072	Not Sustainable	26.7098	Not Sustainable
Indonesia	31.19073	Not Sustainable	35.3525	Not Sustainable	26.3299	Not Sustainable
Iran	29.61864	Sustainable	35.3416	Not Sustainable	25.9181	Not Sustainable
Ireland	23.55842	Sustainable	24.3579	Not Sustainable	25.5527	Sustainable
Israel	24.39741	Sustainable	25.7036	Not Sustainable	25.6372	Sustainable
Japan	29.21898	Sustainable	32.5827	Not Sustainable	28.9869	Not Sustainable
Jordan	21.24384	Sustainable	21.206	Not Sustainable	23.1015	Sustainable
Kazakhstan	25.81071	Sustainable	28.591	Not Sustainable	24.6478	Sustainable
Kenya	25.30964	Sustainable	26.8668	Not Sustainable	23.4409	Sustainable
Korea (Rep.)	28.83396	Sustainable	33.3023	Not Sustainable	26.7896	Not Sustainable
Kyrgyzstan	22.1733	Sustainable	22.2209	Not Sustainable	21.2954	Sustainable
Lebanon	26.06074	Sustainable	29.4107	Not Sustainable	23.7339	Sustainable
Madagascar	23.96657	Sustainable	24.8194	Not Sustainable	22.0225	Sustainable
Malawi	23.91823	Sustainable	25.3692	Not Sustainable	21.6188	Sustainable
Malaysia	25.05004	Sustainable	26.3203	Not Sustainable	25.0793	Sustainable
Mali	24.59913	Sustainable	26.9724	Not Sustainable	21.7156	Sustainable
Mexico	26.92437	Sustainable	28.9671	Not Sustainable	27.0265	Not Sustainable
Morocco	24.69372	Sustainable	31.6083	Not Sustainable	24.2936	Sustainable
Namibia	22.45699	Sustainable	23.5759	Not Sustainable	22.3218	Sustainable
Nepal	24.13076	Sustainable	24.9888	Not Sustainable	22.3978	Sustainable
Netherlands	24.95752	Sustainable	25.4834	Not Sustainable	26.9098	Not Sustainable
New Zealand	24.30144	Sustainable	24.2691	Not Sustainable	25.0403	Sustainable
Nigeria	27.48953	Sustainable	30.0359	Not Sustainable	25.3082	Sustainable
Norway	25.06868	Sustainable	27.5054	Not Sustainable	25.9502	Not Sustainable
Oman	21.66092	Sustainable	23.4688	Not Sustainable	23.6729	Sustainable
Pakistan	26.53298	Sustainable	27.898	Not Sustainable	24.97	Sustainable
Panama	21.96671	Sustainable	22.0139	Not Sustainable	23.4137	Sustainable

Table 4 (continued)

Countries	Agriculture Share	Agriculture Sustainability	Industry Share	Industry Sustainability	Services Share	Services Sustainability
Peru	24.16159	Sustainable	25.2856	Not Sustainable	24.7059	Sustainable
Philippines	26.08279	Sustainable	27.9883	Not Sustainable	25.1093	Sustainable
Rwanda	24.39056	Sustainable	26.5979	Not Sustainable	21.2504	Sustainable
Singapore	22.12372	Sustainable	24.6852	Not Sustainable	25.4092	Sustainable
South Africa	25.33497	Sustainable	27.2213	Not Sustainable	25.9006	Not Sustainable
Sri Lanka	25.32394	Sustainable	27.784	Not Sustainable	23.7984	Sustainable
Sweden	25.44035	Sustainable	27.2848	Not Sustainable	26.2902	Not Sustainable
Switzerland	24.40386	Sustainable	25.668	Not Sustainable	26.607	Not Sustainable
Tajikistan	20.70145	Sustainable	20.5714	Not Sustainable	21.0751	Sustainable
Tanzania	26.23641	Sustainable	29.018	Not Sustainable	23.0002	Sustainable
Thailand	26.35101	Sustainable	28.4695	Not Sustainable	25.6821	Sustainable
Turkey	25.81033	Sustainable	26.0364	Not Sustainable	26.5461	Not Sustainable
Turkmenistan	21.44477	Sustainable	26.0364	Not Sustainable	22.5726	Sustainable
Uganda	26.22381	Sustainable	28.9765	Not Sustainable	22.5967	Sustainable
UK	25.56433	Sustainable	26.3872	Not Sustainable	28.032	Not Sustainable
USA	27.87029	Sustainable	28.7075	Not Sustainable	30.0043	Not Sustainable
Viet Nam	28.90834	Sustainable	33.7354	Not Sustainable	24.1075	Sustainable
Yemen	23.45306	Sustainable	24.986	Not Sustainable	21.2673	Sustainable
Zimbabwe	21.7038	Sustainable	21.8276	Not Sustainable	22.19	Sustainable

sustainable incidence of real sector as percentage of GDP. This classification is handy in finding countries that are not sustainable in terms of their real sector activity. Hence, a suitable policy can be devised for them.

While assessing the effect of incidence of the agriculture sector, only Indonesia falls in the case where it is not sustainable for the environment. The assessment of the effect of incidence of the services sector highlighted several countries are not sustainable for the environment. These countries are mentioned in Table 4. The assessment of the effect of the incidence of the industry sector showed all the countries are experiencing not-sustainability. The not-sustainability categorization denotes that the growth of this region is reducing its environmental quality. Thus, here, policymakers need to design appropriate regulations which can trim the abnormal growth of agriculture, industry, and services sectors, where ever applicable. Some examples are promoting pesticide-less agricultural practices, promoting paper-less services sector, and promoting recycle materials in the industry sector.

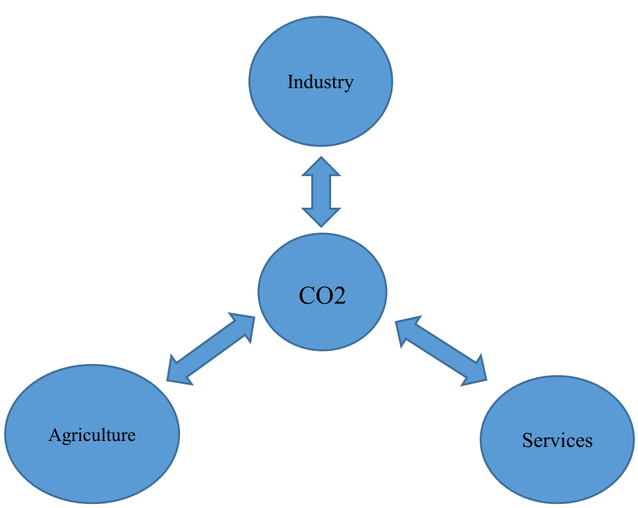

Fig. 4 Causality test between real sector and CO2 emissions

At present, migration from rural to urban areas is an emerging problem; in this regard, there should be proper planning to control it. The government should provide balanced facilities in both areas so that migration could be under control. Moreover, the services sector should be more efficient, in order to make the migration towards this sector environment-friendly.

Good governance delivers good results, and this emerged also in the estimated results. According to the estimated results of sampled data, governance protects the environment. Thus, economies should assure better governance to overcome the environmental challenges and to achieve economic development, not at the cost of the environment. Every new day brings in some innovations, and this means new technology replaces the old one. It means that technological progress also has the potential to protect the environment, because every new technology has some new benefits. In this regard, every economy should upgrade its production techniques and install new and eco-friendly machinery and production techniques to overcome environmental challenges.

Author contributions Noman Arshed, Mubbasher Munir and Mubasher Iqbal have contributed equally to the preparation of this research manuscript.

Data availability The data are publically available, and their sources are mentioned in Table 1.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval Not required as the data is publically available.

Consent to publish The authors give their consent to publish the manuscript.

Appendix

Table 5 Estimated results with ecological footprint

Dependent variable: ECO			
Variables	Industrial EKC Coeff. (*P* value)	Agricultural EKC Coeff. (*P* value)	Services EKC Coeff. (*P* value)
IND	− 3.4679 (0.0000)		
IND^2	0.0634 (0.0000)		
AGRI		− 0.7084 (0.0022)	
$AGRI^2$		0.0204 (0.0001)	
SVC			− 16.0215 (0.0000)
SVC^2			0.3711 (0.0000)
URB	0.0645 (0.3332)	− 0.2667 (0.0162)	− 10.0656 (0.0002)
TECH	− 0.0416 (0.1660)	0.0206 (0.0601)	− 0.0650 (0.2410)
GOV	− 0.0629 (0.4273)	0.0378 (0.3863)	0.1561 (0.4452)
R-square	0.9988	0.9646	0.9960
Cut-off value	27.35%	17.36%	21.59%

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