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The use of ecological footprint in estimating the Environmental Kuznets Curve hypothesis for BRICST by considering cross-section dependence and heterogeneity

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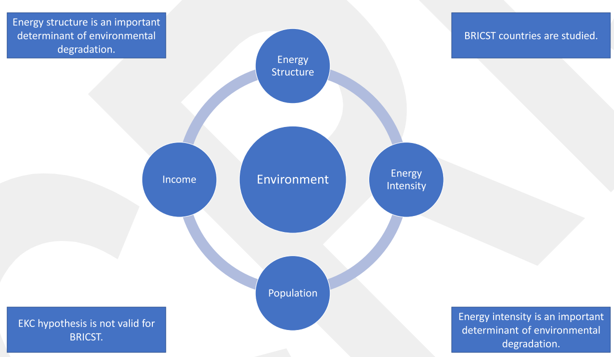
HIGHLIGHTS

- EKC hypothesis is investigated using EFP for BRICST countries.
- Heterogeneity and cross-section dependence are considered.
- The EKC is not valid for the panel of analyzed countries.
- Energy structure and energy intensity are vital determinants of EFP.

GRAPHICAL ABSTRACT



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ABSTRACT

A vast body of literature estimates the impact of economic growth on environmental degradation in the framework of EKC model. Typical empirical studies proxy environmental degradation with CO_2 emissions; however, this indicator does not consider the complex nature of environmental degradation. To fulfill this omission, ecological footprint that tracks the use of multiple categories of productive surface areas is used as proxy for the environment. Moreover, studies that do not consider issues of heterogeneity and cross-sectional dependence may not produce reliable outcomes. Hence, the present study re-investigates the validity of the EKC hypothesis for BRICST (Brazil, Russia, India, China, South Africa, Turkey) by using ecological footprint and considering the mentioned issues in the estimation process. Based on the annual data covering the period of 1980–2014, excluding Russia due to data unavailability, empirical results show that the EKC hypothesis is not valid, and energy intensity and energy structure are important determinants of environmental degradation. In line with the empirical outputs, possible policy suggestions are discussed in the present study.

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1. Introduction

Kuznets (1955) reported a non-linear relationship between income distribution and economic growth, which was later, called the Kuznets curve. According to this curve, at the beginning of the economic development process, income inequality rises in conjunction with the increase in income per capita. However, when the gross domestic product (GDP) per capita reaches a certain level, income inequality begins to decrease. This indicates that economic growth causes a decline in income inequality in the long run. In the 1990s, Kuznets' approach was reinterpreted by Grossman and Krueger (1991, 1995) due to increasing environmental problems and the availability of data on environmental pollution called Environmental Kuznets Curve (EKC hereafter). According to the EKC hypothesis, there is a threshold for environmental degradation in the process of per capita income level along its pathway. This threshold reveals an inverted U-shaped relationship between the environment and economic growth. Most environmental degradation factors indicate a tendency to get worse due to economic growth until the average income reaches a certain level (Stern, 2004).

The EKC hypothesis was initially supported by the findings of Beckerman (1992) and Panayotou (1993) concluding that economic growth causes environmental degradation. Later, Stern et al. (1996) studied the role of development in the increase of pollutants of economic activity. Then, the EKC concept has become one of the major research topics in energy and environmental economics literature (Apergis and Ozturk, 2015; Charfeddine and Mrabet, 2017; Dong et al., 2018; Ozcan et al., 2018; Shahbaz et al., 2016, 2017). According to the web of science statistics, the EKC studies have dramatically increased since the 2000s. One might see this growing body of research for the EKC through Fig. 1. In brief, there are 3014 (three thousand and fourteen) studies published in various journals indexed by SCI, SCI-E, SSCI, and 78,319 citations for them.

Despite a great number of the EKC studies, some arguments are questioning the hypothesis from various aspects. Accordingly, Arrow et al. (1995) raised doubts about the feedback effect of environmental degradation on production loss since irreversibility cannot be possible for the environmental values as is underlined by Stern (2004). This viewpoint was also supported by the invalidity of limitless growth (Acemoglu et al., 2012; Ulucak, 2018). Martínez-Alier (1995) highlighted that there was no evidence that people become more conscious about the environment as per capita income rises. McConnell (1997), while discussing this issue indicated that consumption activities have a much greater effect on pollution than production activities do. Stokey (1998) also underlined the role of the need for consumption in the EKC process. Kaika and Zervas (2011) emphasized the ignorance of the pollution created in the manufacturing process of imported goods in national emission calculations. Similarly, Zhang et al. (2017) pointed out that trans-boundary outcomes of pollution generated by international trade of goods and services which are specially manufactured in developing countries. Gill et al. (2018) underlined irreversible damages caused in the industrialization process of developing countries, heavily based on dirty production technologies, by considering not only CO_2 emissions but also other solid, liquid, gas and radioactive wastes generated by such industries.

One of the main difficulties is how environmental degradation can be considered in empirical investigations of the EKC to reach more reliable results (Ulucak and Apergis, 2018). For instance, an inverted U-shaped relationship between economic growth and environmental degradation may be verified by CO_2 that is extensively regarded as an environmental indicator. This relationship is, however, required to investigate by considering multi-dimensional aspects of degradation as much as possible to capture a whole impact of human activities on the environment in the process of per-capita income growth (Dasgupta et al., 2002; Gill et al., 2018; Kaika and Zervas, 2013; Stern, 2014). Accordingly, ecological footprint may be an alternative variable of the EKC concept to take overall environmental degradation into account.

Ecological footprint (EFP) settled by Wackernagel and Rees (1996) constitutes a favorable alternative when studying the effects on the environment. It includes six factors: forest land, carbon footprint, fishing grounds, cropland, grazing land and built-up land (Lin et al., 2018). The EFP is an indicator of the usage of the re-creative natural capacity of the World by creatures including production and consumption of resources (Kitzes and Wackernagel, 2009). The EFP is beneficial in drawing attention to production and consumption, either direct or indirect effect of EFP on environmental quality (McDonald and Patterson, 2004). In Bartelmus (2008), it is defined as a concept, which refers to the impact of human activities on nature. Costanza (2000), introduces this concept as a widely accepted, effective, heuristic and comprehensible means of dealing with the total consumption of resources. The EFP can also be used as a measure to predict resource consumption, distribution and sustainability in the Earth (Borucke et al., 2013). The EFP is employed to proxy for environmental degradation in the empirical framework of related studies since it is considered as an analysis of sign of human wants on the Earth (Aydin et al., 2019; Baležentis et al., 2019; Destek et al., 2018; Destek and Sarkodie, 2019; Rudolph and Figge, 2017; Solarin et al., 2019; Ulucak and Bilgili, 2018; Yilanci et al., 2019). The sample of BRICST (Brazil, Russia, India, China, South Africa, Turkey) countries makes up 43% (3.2 billion) of the population and occupies 30% (sq. km 129.7 billion) land area in 2017. These countries also produce 23% of the world's GDP, 24% of the economic aggregate, and 17% of international trade in 2017, while contributing 43% of the world's gas emissions in 2014 according to the 'World Development Indicators'. Additionally, the BRICST countries keep hold of 40% of the forest area and 9% of the fish species area in 2016. Last but not least, it is expected that the GDP of BRICST will be larger than G7 economies by 2050 (Pao and Tsai, 2010).

The possible contribution of the present study is three-fold. **Firstly,** this is the first attempt, to the best of our knowledge, in the EKC literature to use EFP for a study involving BRICST countries. The BRICST countries are important to the literature because they agreed that they coordinate their environmental policies by following Paris climate agreement and they declared to prioritize to addressing common challenges with collaboration in the tenth Summit convened in Johannesburg, South Africa, 2018 (http://sdg.iisd.org/news/brics-declaration-calls-for-full-implementation-of-paris-agreement-and-2030-agenda/). Turkey was also invited and participated in this summit focusing primarily environmental issues. **Second**, this study employs second-generation estimation methods; namely, heterogeneity test, cross-sectional dependence test, panel unit root test, Westerlund cointegration test and Augmented Mean Group estimator (AMG) because studies mostly do not consider the issues of cross-sectional dependence and heterogeneity among variables across countries, and thus may result in biased estimation. **Third,** this study controls the role of energy intensity, energy structure and population on the EFP upon the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model as different from the available studies that employ the EFP as an indicator of environmental degradation. Energy structures as well as energy intensities are important determinants of environmental degradation and have vital importance to direct energy-related pollution (He and Lin, 2019). Besides, the population is one of the essential elements for a pioneering approach modeling environmental impacts (Fan et al., 2006). The results of this study are expected to contribute to the EFP literature and suggestions for policymakers and practitioners regarding environmental sustainability.

2. Literature review

There is a growing body of research on the investigation of the EKC hypothesis by employing the EFP measurement to take environmental degradation into account in broader perspectives (Altıntaş and Kassouri, 2020). These studies using different research methods and different data collection tools have significantly contributed to the

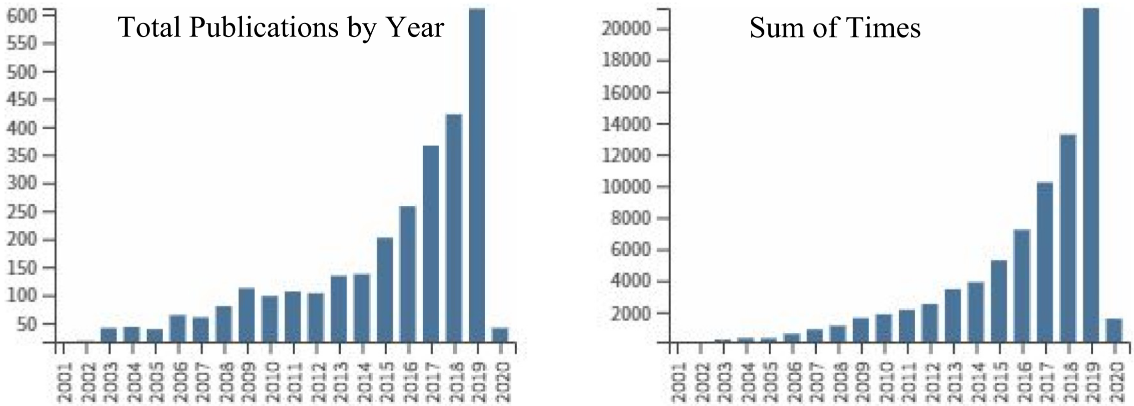

Fig. 1. EKC studies by year (www.webofknowledge.com, 2020-02-05).

discussion of the EKC relationship. Table 1 displays available studies using the EFP in the literature from several points.

As early studies, Bagliani et al. (2008), Caviglia-Harris et al. (2009), Wang et al. (2013) found that the environmental degradation does not decrease as per capita income rises for a large country dataset. Then, Hervieux and Darné (2015) verified the findings of initial studies for seven Latin American countries. Later, mixed results were obtained by many studies analyzing the relationship for various countries and country groups. Some studies conducting panel data analyses found similar results with previous ones (Almeida et al., 2017; Figge et al., 2017; Aşıcı and Acar, 2018; Masron and Subramaniam, 2018; Aydin et al., 2019) while some others confirmed inverted U-shaped relationship (Acar and Aşıcı, 2015; Aşıcı and Acar, 2018; Charfeddine and Mrabet, 2017; Ulucak and Bilgili, 2018; Destek et al., 2018; Katircioglu et al., 2018; Destek and Sarkodie, 2019). On the other hand, considering the income level of panel samples Al-Mulali et al. (2015) and Ozturk et al. (2016) found evidence in favor of the EKC relationship for upper-middle and high-income economies but not for low and lower middle income countries. Time-series analysis for single country investigations are a limited number in the literature. Among those, the hypothesis was affirmed for Qatar by Charfeddine (2017) and Mrabet and Alsamara (2017), for Turkey by Acar and Aşıcı (2017), for Malaysia by Bello et al. (2018), for Pakistan by Hassan et al., (2019), and for India by Ahmed and Wang (2019). Contrary to confirmative results for single country investigations, Ozcan et al. (2018), Mikayilov et al. (2019) found results against the EKC for Turkey and Azerbaijan, respectively.

Different from the current literature that employs ecological footprint, summarized in Table 1, this study focuses on the driving factors of ecological footprint which are main pillars indicators of the STIRPAT approach by following by Rosa and Dietz (1998), York et al. (2003) and Dietz et al. (2007). Researchers have focused on different underlying factors of ecological footprint, i.e., energy consumption (Charfeddine, 2017; Mikayilov et al., 2019; Dogan et al., 2019); financial

Table 1
A Summary literature review of the EKC using ecological footprint (EFP).

Author	Period	Country	Method	Result
Bagliani et al. (2008)	2001	144 Countries	Cross Section, OLS, Weighted LS	No
Caviglia-Harris et al. (2009)	1961–2000	146 Countries	Panel FE, 2SLS GMM	No
Wang et al. (2013)	2005	150 Countries	Spatial econometric approach	No
Hervieux and Darné (2015)	1961–2007	7 Latin American Countries	Time Series Cointegration	No
Acar and Aşıcı (2015)	2006	105 Countries	cross-section analysis	Yes
Al-Mulali et al. (2015)	1980–2008	93 Countries	Panel FE, GMM	Mixed results
Ozturk et al. (2016)	1988–2008	144 Countries	Time Series GMM, S-GMM	Mixed results
Aşıcı and Acar (2018)	2004–2008	116 Countries	Panel FE	Yes
Charfeddine (2017)	1970–2015	Qatar	MS-ECM	Yes
Acar and Aşıcı (2017)	1961–2008	Turkey	Time Series OLS	Yes
Charfeddine and Mrabet (2017)	1995–2007	MENA 15	Panel FMOLS Panel DOLS	Yes
Mrabet and Alsamara (2017)	1980–2011	Qatar	ARDL	Yes
Almeida et al. (2017)	6 Observations	152 Countries	Panel FE, Panel RE	No
Figge et al. (2017)	1971–2012	171 Countries	Panel OLS	No
Ulucak and Bilgili (2018)	1961–2013	45 Countries	CUP-FM, CUP-BC	Yes
Aşıcı and Acar (2018)	2004–2010	87 Countries	Panel FE, Panel RE	No
Masron and Subramaniam (2018)	2005–2013	64 Countries	Panel GMM	No
Destek et al. (2018)	1980–2013	15 EU countries	Panel FMOLS/DOLS	Yes
Bello et al. (2018)	1971–2014	Malaysia	ARDL, VECM	Yes
Ozcan et al. (2018)	1961–2013	Turkey	Bootstrap Causality	No
Katircioglu et al. (2018)	1995–2014	10 Countries	Panel RE	Yes
Aydin et al. (2019)	1990–2013	EU Countries	PSTR	No
Hassan et al., (2019)	1970–2014	Pakistan	ARDL	Yes
Ahmed and Wang (2019)	1971–2014	India	ARDL	Yes
Destek and Sarkodie (2019)	1977–2013	11 Countries	AMG	Yes
Mikayilov et al. (2019)	1996–2014	Azerbaijan	FMOLS, ARDL	No
Destek and Sinha (2020)	1980–2014	24 OECD countries	Panel FMOLS, DOLS and CCE	No
Dogan et al. (2019)	1971–2013	MINT countries	ARDL	Yes
Shujah-ur-Rahman et al. (2019)	1991–2014	CEE countries	DSUR	Yes
Sabir and Gorus (2019)	1975–2017	S. Asian countries	ARDL	Yes

development (Mrabet and Alsamara, 2017; Destek and Sarkodie, 2019; Shujah-ur-Rahman et al., 2019); globalization (Figge et al., 2017; Sabir and Gorus, 2019); urbanization (Ozturk et al., 2016; Bello et al., 2018; Katircioglu et al., 2018; Ahmed and Wang, 2019); natural resources; trade or openness (Al-Mulali et al., 2015; Acar and Aşıcı, 2016; Aşıcı and Acar, 2018; Destek et al., 2018); corruption (Masron and Subramaniam, 2018); human capital (Ulucak and Bilgili, 2018), and political institution (Charfeddine and Mrabet, 2017). A recent study Danish et al. (2020) uses renewable energy, non-renewable energy, and urbanization for BRICS countries as control variables. Overall, the available literature mostly has paid attention to energy consumption in terms of renewable and non-renewable sources but none of them considers energy structure (ratio of non-renewables to total energy consumption) and energy intensity (energy needed to produce a certain level of GDP).

The study focuses on how the ecological footprint of sample countries is directed by explanatory variables and therefore its movements in each country over time are of importance to see the sample countries' ecological situation against biocapacity that reflects their ecological budgets. Therefore, this study differs from the available ones by investigating the role of energy structure and energy intensity. The study also draws an EKC and a STIRPAT framework simultaneously in terms of analyzed variables.

3. Model, data, and methodology

To investigate the validity of the EKC hypothesis and the impact of the population energy intensity and energy structure on the environment in BRICST countries, we consider the literature (Álvarez-Herránz et al., 2017; Bilgili et al., 2016; Koçak and Ulucak, 2019; Li and Lin, 2015; Lin et al., 2016) and use a model as in Eq. (1). It also represents an IPAT approach (Influence = Population, Affluence, and Technology), originally introduced by Ehrlich and Holdren (1971) but later reformulated by Rosa and Dietz (1998) to analyze Stochastic Impacts and called the STIRPAT. Because model variables in Eq. (1) are widely used in the STIRPAT estimations (Fan et al., 2006; Lin et al., 2009). In this direction, one can follow York et al. (2003) and Dietz et al. (2007) to justify this approach with ecological footprint and related variables, that are complementary studies of the STIRPAT model reformulated by (Rosa and Dietz, 1998).

$$\ln(\mathrm{EFP})_{it} = \beta_0 + \beta_1 \ln\mathrm{GDP}_{it} + \beta_2 \ln\mathrm{GDP}^2{}_{it} + \beta_3 \ln\mathrm{ES}_{it} + \beta_4 \ln\mathrm{EI}_{it} + \beta_5 \ln\mathrm{POP}_{it} + e_{it} \quad (1)$$

In Eq. (1), β_0 and e indicate the constant and error term. *EFP*, *GDP*, GDP^2, *ES*, *EI*, and *POP* show the ecological footprint per capita, GDP per capita, the square of GDP per capita, energy structure, energy intensity, and population growth, respectively. β_i's $(i = 1, 2, \ldots, 5)$ imply predictive parameters for descriptive variables. The ecological footprint is composed of six components as given in the introduction section; the real gross domestic product is valued at the 2010 constant US dollar; the energy structure is measured as the ratio of non-renewables (petroleum, coal, and gas) to total energy consumption; population growth is the percentage change of the number of people; energy intensity is calculated as the energy needed to produce a certain level of GDP. Energy intensity represents energy efficiency, which is an outcome of technological development in a country (Bilgili et al., 2017). The data covers the period 1980–2014 that is the available longest data set. However, the study excludes Russia from the panel sample due to a lack of data for the period of 1980–1991 and come from "the World Development Indicators" (http://data.worldbank.org), "U.S. Energy Information Administration" (www.eia.gov), and "Global Footprint Network" (www.footprintnetwork.org). They are transformed into their logarithm to obtain the elasticities of the dependent variable (EFP) for the GDP, the square of GDP, energy structure, energy intensity, and population. It should be noted that we optimize the data such that the longest available data with the greatest number of countries as possible.

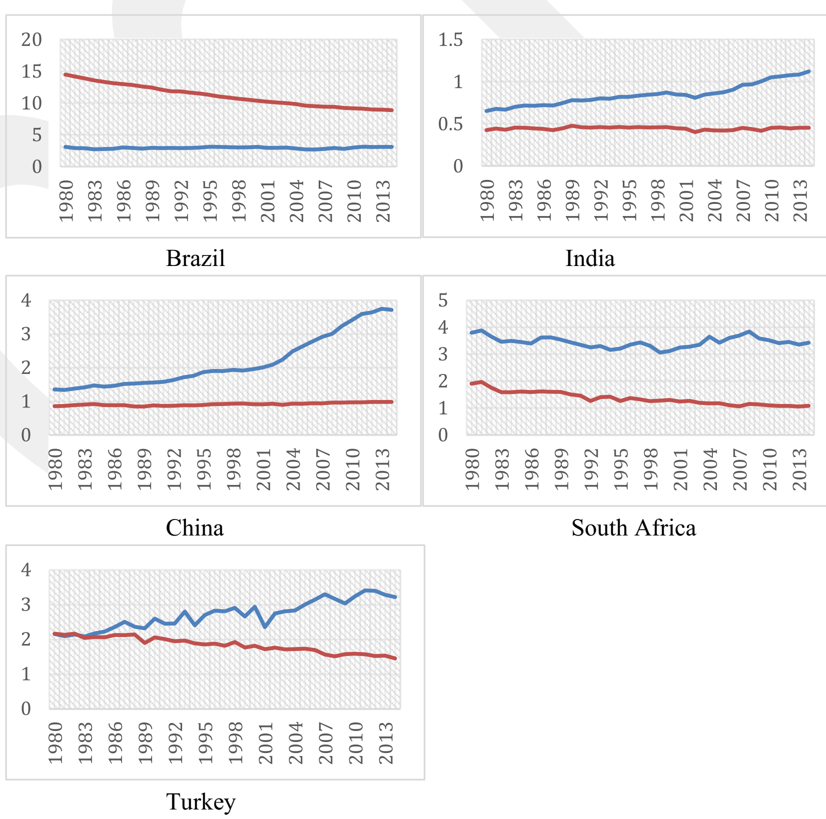

Fig. 2. Ecological footprint and biocapacity for Brazil, India, China, South Africa and Turkey.

The Fig. 2 indicates ecological deficits in India, China, South Africa, and Turkey by using per capita values of ecological footprint (blue line) and biocapacity (red line). Global Footprint Network describes that countries are in ecological deficit when they have a greater ecological footprint than biocapacity. Accordingly, BRICST have exceeded their biocapacities and they have been in highly critical situations in terms of pressure on the environment over the years. Brazil has lower ecological footprint values than biocapacity over the sample period but dramatical declines in its biocapacity draw the attention. This means that Brazil has still an ecological surplus due to its large area that is an important factor reshaping biocapacity measurement with lower population density.

Considering growing economic activities in BRICST countries, that are the main causes of environmental degradation, ecological degradation is alarming and the difference between ecological footprint and biocapacity is getting bigger for China, India, South Africa, and Turkey, implying that more ecological threats would be triggered if required actions are put into practice. As an indicator of economic activities, GDP is a major determinant of environmental assessment models such as the EKC and the STIRPAT approaches. Especially, the EKC approach includes GDP and its square to observe the long-run behavior of environmental degradation against per capita GDP. To this end following alternatives can be reached through the estimation of Eq. (1): (a) If $\beta_1 = \beta_2 = 0$, there is no significant relationship between environmental degradation and GDP per capita. (b) If $\beta_1 > 0$ and $\beta 2 = 0$, there is a monotonically increasing relationship between environmental degradation and GDP per capita. (c) If $\beta_1 < 0$ and $\beta_2 = 0$, there is a monotonically decreasing relationship between environmental degradation and GDP per capita. (d) If $\beta_1 < 0$ and $\beta_2 > 0$, there is a U-shaped relationship between environmental degradation and GDP per capita. (e) If $\beta_1 > 0$ and $\beta_2 < 0$, there is an inverse U-shaped relationship between environmental degradation and GDP per capita. That is, the EKC hypothesis is valid. Finally, following the relevant literature, the sign of coefficients β_3 and β_4 are expected to be positive, and the sing of coefficient β_5 to be negative.

We use a three-stage empirical method to estimate the parameters of Eq. (1). Firstly, to prevent the problem of spurious regression, panel unit root tests are applied to reveal whether or not the series are stationary. In the literature, panel unit root tests developed by Im et al. (hereafter IPS, 2003); Levin et al. (hereafter LLC, 2002); Maddala and Wu (hereafter PP-Fisher, 1999) are often used for stationarity investigation. Also, Pesaran (2007) modified IPS test by considering cross-sectional dependence (CIPS) to investigate unit root properties of the series. For the test, the null hypothesis is that the series has a unit root. The decision for the null hypothesis is given by t statistics. According to the test results, if the series is not stationary at level (X_i), the difference of the series ($X_t - X_{t-1}$) is taken, and the unit root test is applied again. If the first difference is stationary, the cointegration relationship should be investigated before the parameter estimation.

In the second stage of empirical analysis, we focus on the cointegration relationship. We perform panel cointegration tests developed by Pedroni (1999, 2004) and Kao (1999) to investigate the cointegration relationship. For cointegration tests, the null hypothesis is that there is no cointegration for the sections. Pedroni (1999, 2004) developed 7 different test statistics using the results obtained from panel cointegration regression to test the null hypothesis. Test statistics are calculated by following Eqs. (2) and (3).

$$y_{it} = \alpha_{it} + \delta_{it} t + \beta_i X_{it} + e_{it} \tag{2}$$

$$\Delta y_{it} = \beta_i \Delta X_{it} + \eta_{it} \tag{3}$$

First, Eq. (2) is estimated and the residuals are obtained. In Eq. (2), y is the dependent variable, X is the explanatory variable, α_i fixed effects, e is an error terms, and t represents the trend. Then, with Eq. (3), the difference regression is estimated, and the residues are obtained. Secondly, the long-term variance is calculated using the Newey and West (1987) estimator. Third, autocorrelation is estimated using residues. Finally, test statistics are generated to test the cointegration relationship.

To check the Pedroni (1999, 2004) cointegration tests, we also use a second-panel cointegration test proposed by Kao (1999). To produce this test statistic, ADF (Generalized Dickey-Fuller) test is recommended, considering Eq. (4), in which u_{it} represents residuals, and ρ and ϕ coefficients to test the presence of unit root. Finally, the ADF test statistic proposed by Kao (1999) is calculated according to Eq. (5).

$$u_{i,t} = \rho u_{i,t} + \Sigma_{(i=1)}^{n} f_j \Delta u_{i,t-1} + v_{it} \tag{4}$$

$$ADF = \left(t_{ADF+}\sqrt{6\,N\sigma_V}/2\sigma_{0v}\right)/\sqrt{\left(\sigma_{0v}^2/2\sigma_v^2\right) + \left(3\sigma_v^2/10\sigma_{0v}^2\right)} \tag{5}$$

The final stage of empirical analysis is the estimation of the cointegration coefficients. The fully modified ordinary least squares (FMOLS) and the dynamic ordinary least squares (DOLS) estimators developed by Pedroni, (2000, 2001) are commonly used in the literature. Panel DOLS and FMOLS estimator eliminate the endogeneity and autocorrelation problems between independent variables and error term and produce effective results. For this reason, we follow the panel FMOLS and DOLS methods whose basic procedures are given in Eqs. (6) and (7), where A/EFP stands for explanatory/dependent variable in Eq. (1), to estimate both the validity of the EKC hypothesis and effects of energy intensity, energy structure and population on ecological footprint.

$$\hat{\beta}_{FMOLS} = \left[\frac{1}{N}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\left(A_{it}-\bar{A}_i\right)^2\right)\right]^{-1} \times \left[\left(\sum_{t=1}^{T}\left(A_{it}-\bar{A}_i\right)\widehat{EFP}_{it}-T\hat{\Delta}_{\varepsilon u}\right)\right] \tag{6}$$

$$\hat{\beta}_{DOLS} = \left[\frac{1}{N}\sum_{i=1}^{N}\left(\sum_{t=1}^{T} A_{it}A\prime_{it}\right)^{-1}\left(\sum_{t=1}^{T} A_{it}\widetilde{EFP}_{it}\right)\right] \tag{7}$$

where EFP is the dependent variable and A represents explanatory variables in Eq. (1). Despite their statistical power and robustness, FMOLS and DOLS estimators may not produce efficient results in case panel sections are correlated. Eberhardt and Teal (2010) and Bond and Eberhardt (2013) propose a new estimator called augmented mean group (AMG) that accounts for cross-sectional dependence by including a common dynamic process in a two-stage regression approach as is in Eq. (8):

$$\begin{aligned}\Delta EFP_{it} &= b'\Delta A_{it} + \sum_{t=2}^{T} c_t \Delta D_t + u_{it} \rightarrow \hat{c}_t \equiv \hat{\mu}_t\ EFP_{it} \\ &= a_i + b\prime_i A_{it} + c_i t + d_i \hat{\mu}_t + u_{it}\ \hat{b}_{AMG} = N^{-1}\sum_i \hat{b}_i \end{aligned} \tag{8}$$

where Δ is difference operator, A represents explanatory variables, b is the parameter of explanatory variables, and D is the dummy variable that captures period effects in panel data and c_t is the parameter of period dummies. u is an error term, N and T stand for the number of cross-sections and observations. AMG approach considers heterogeneity and cross-sectional dependence issues that are the main problems of panel data estimations and produce more reliable results under heterogeneous panels with cross-sectional dependence (Baltagi, 2015; Coakley et al., 2006). Cross-sectional dependence may be due to policy shocks, interactions and socioeconomic linkages among countries. Those effects may also be at different degrees and heterogenous, which leads to inconsistent parameter estimation when they are correlated with explanatory variables (Coakley et al., 2006; Pesaran, 2015).

4. Results and discussions

This study firstly applies the cross-sectional dependence test (CD-test) developed by Pesaran (2004) to see whether or not each panel data is cross-sectional independent. Results from the CD-test are

Table 2
Results from the CD-test.

	EFP	GDP	ES	EI	POP
CD-test	3.66**	14.29**	5.02**	2.10*	18.26**
p-Value	0.00	0.00	0.00	0.04	0.00

** Denotes the statistical significance at 1%.
* Denotes the statistical significance at 5%.

Table 3
Results from heterogeneity tests.

test	EFP	GDP	ES	EI	POP
$\tilde{\Delta}$	33.23**	38.78**	17.63**	33.40**	56.33**
$\tilde{\Delta}_{adj}$	35.43**	40.42**	18.34**	34.81**	59.14**

** Denotes the statistical significance at 1%.

presented in Table 2. We can conclude that cross-sectional dependence is present for each panel data.

In addition to the cross-sectional dependence test, we employ the slope homogeneity test developed by Pesaran and Yamagata (2008). This approach is based on the estimation of delta $\tilde{\Delta}$ and the adjusted delta $\tilde{\Delta}$. Related results are posted in Table 3. Because we reject the null hypothesis of slope homogeneity for the analyzed variables, heterogeneity exists across BRICST countries for EFP, GDP, GDP^2, ES, EI, and POP.

Table 4 shows the panel unit root test results for LLC, IPS, PP-Fisher, and CIPS. It should be noted that the CIPS unit rot test is reliable when there exist heterogeneity and cross-sectional dependence across sample countries for the analyzed variables (Pesaran, 2007). We do not have enough evidence to reject the null hypothesis of non-stationarity of ecological footprint, real income, energy structure, energy intensity and population in their levels; however, we can reject the non-stationarity of ecological footprint, real income, energy structure, energy intensity and population in their first differences.

Pedroni (1999, 2004) cointegration test results are reported in Table 5. Four out of seven test statistics reject the null hypothesis that there is no cointegration. EFP, real income, energy structure, energy intensity, and population are cointegrated referring to most of the test statistics. To check the results of the Pedroni (1999, 2004) cointegration test, we also apply the Kao (1999) and Westerlund (2005) cointegration tests, the latter one can be applied in the presence of the issues of cross-sectional dependence and heterogeneity. Table 5 depicts the robustness control results. Kao (1999) cointegration test and Westerlund (2005) cointegration results also support the cointegration relationship between variables. After all, it is decided that there is a long-run equilibrium relationship between ecological footprint, GDP per capita (and square), energy structure, energy intensity and population.

The output of the FMOLS and the DOLS and the AMG estimators are given in Table 6. Because the logarithm values of the data are put into the model, the elasticities of EFP for GDP, GDP^2, ES, EI, and POP are the same as the long-run coefficient estimates of real income, the square of real income, energy structure, energy intensity, and population. All the estimators provide consistent results for the signs of coefficients of the estimated model in Eq. (1). However, DOLS and AMG estimators produce statistically insignificant results for GDP, GDP, and GDP^2 respectively. Apart from these results, all of the coefficient estimates are statistically significant at 1% level of significance due to reported probabilities. According to FMOLS, a rise in real income has a statistically significant impact on EFP for BRICST. More precisely, the marginal of real income on EFP is calculated by $\beta_1 + 2 * \beta_2 * GDP$ $(-0.17 + 2 * 0.09 * GDP)$, and thus the marginal effect of GDP on the environment is negative for BRICST economies; yet, it increases and finally turns to positive as the BRICST countries increase their real output. In other words, the EKC hypothesis is not valid for the mentioned countries since the coefficient estimate of real GDP and the square of real GDP is negative and positive, respectively. Considering FMOLS, DOLS and AMG results, it is clear that the EKC hypothesis cannot be verified for the sample countries. The invalidity of the EKC hypothesis is consistent with Al-Mulali et al. (2016), Baek (2015) and Pal and Mitra (2017). On the other hand, the outcome of invalidity of the EKC for the panel of BRICST countries in this study is in contrast to that of Dong et al. (2017) and Haseeb et al. (2018), which previously investigated the EKC using CO_2 emissions as an environmental indicator for the analyzed economies.

The coefficient estimate indicating the environmental impact of energy structure is marked as positive. The elasticity of EFP for energy structure implies that a 1% increase in the share of fossil-fuel energy in

Table 5
Results from the cointegration test.

Pedroni (1999, 2004)	Statistic	Prob.	Weighted statistic	Prob.
Panel v-statistic	1.08	0.13	0.87	0.19
Panel rho-statistic	0.9	0.81	0.81	0.79
Panel PP-statistic	−4.95**	0.00	−3.50**	0.00
Panel ADF-statistic	−4.73**	0.00	−3.52**	0.00
Kao (1999)	−2.51			0.00**
Westerlund (2005)	−1.70			0.04*

** Denotes statistical significance at 1%.
* Denotes statistical significance at 5%.

Table 6
Long-run coefficients (EFP is the dependent variable).

Regressors	FMOLS		DOLS		AMG	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
GDP	−0.17**	−26.58	−0.22	−1.42	−2.15	−0.55
GDP^2	0.09**	3.91	0.04**	5.18	0.13	0.72
ES	0.40**	19.75	0.35**	2.93	0.73**	3.64
EI	0.45**	11.96	0.37**	7.39	0.19**	4.65
POP	−0.37**	−12.5	−0.39**	−5.21	−0.69**	−2.50

** Denotes statistical significance at 1%.

Table 4
Results for LLC, IPS, PP and CIPS unit root tests.

Variables	Level				First-difference			
	LLC	IPS	PP-Fisher	CIPS	LLC	IPS	PP-Fisher	CIPS
GDP (GDP^2)	3.12	6.08	0.22	−2.23	−6.66**	−7.44**	67.9**	−4.21**
EFP	0.88	0.93	10.25	−1.96	−10.1**	−12.2**	113.8**	−4.89**
ES	−1.88	−0.81	6.89	−1.66	−7.66**	−7.54**	80.99**	−4.28**
POP	−6.75	−0.24	14.2	−0.60	−5.17**	−6.61**	25.86**	−2.60*
EI	−0.42	1.7	5.31	−2.01	−12.3**	−11.5**	112.6**	−5.35**

The optimal lag lengths are selected based on the Akaike Information Criterion (AIC).
** Denotes statistical significance at 1% level.
* Denotes statistical significance at 5% level.

total energy (energy structure) increases the levels of EFP emissions by 0.40%. There is a common consensus on the harmful effect of fossil fuel energy consumption on the environment (Inglesi-Lotz and Dogan, 2018; Shafiei and Salim, 2014). In this line, one possible option to fight for environmental degradation should be to financially support institutions to focus on cheaper production from renewables. The other option should be to offer policies to upgrade the consciousness of households about energy types and their impacts on the environment.

Last, as an environmental indicator variable, increases in population also push EFP down for the group of BRICST countries. In detail, a 1% increase in population growth causes a 0.37% decline in ecological footprint. As in line with expectations, this study reveals that increases in energy intensity increase environmental degradation for BRICST. More precisely, with a strong level of significance (99%), a 1% increase in energy intensity leads to a 0.45% increase in ecological footprint in the long run. This makes energy intensity one of the largest contributors of environmental degradation. These findings are in line with Lin et al. (2016) and Shahbaz et al. (2015).

5. Concluding remarks and policy suggestions

One of the vitally important gaps in the existing energy-growth-environment literature is the use of CO_2 emissions as a proxy for environmental degradation. Therefore, there is a growing body of literature that uses ecological footprint since it is widely accepted as a comprehensive environmental degradation indicator. However, available literature needs to be extended by using the ecological footprint with different control variables for different samples. So, there is still a lack of literature to investigate the validity of the EKC hypothesis by employing different control variables. To contribute to the literature, this study tests the EKC hypothesis by using ecological footprint for a panel of the BRICST countries for the period 1980–2014 by controlling energy structure, energy intensity and population.

The outcomes of panel unit root tests reveal that ecological footprint, the real income, the square of real income, energy structure, energy intensity, and population turn into stationary at their first-differences. Moreover, outputs from panel cointegration approaches indicate the existence of a long-run relationship among ecological footprint, real income, energy structure, energy intensity and population. Results from the long-run estimators (FMOLS DOLS, and AMG) show that population, energy intensity and energy structure are vital determinants of environmental degradation. Besides, long-run estimators show that the EKC hypothesis is not valid for the sample countries. So, environmental degradation increases as BRICST countries continue to increase their production after they pass a threshold level of income.

Results support the view that income increase cannot be a solution to improve environmental quality, contrary to the theoretical expectation of the EKC hypothesis. So, additional measures should be put into practice such as environmental management, environmental regulations, and incentives that promote green technological progress. Besides, environmental regulations and incentive mechanisms are accepted as the main policy tools of green technological progress on the way of emission mitigation (Hashmi and Alam, 2019). There is also an important solution offers strongly underlined by international agreements like Kyoto and Paris Climate conferences (COP21, 2015). In this direction, COP23 that is one of the annual assessment meetings of United Nations Framework Convention on Climate Change (UNFCCC), held in Bonn in 2017, draws a general framework and urges countries to establish their infrastructures for efficient environmental management, technical and organizational measures (COP23, 2017). There are also main targets of each country of our sample in the intended nationally determined contribution document submitted to UNFCCC (see https://www4.unfccc.int/sites/NDCStaging/Pages/All.aspx). On the other hand, such applications are consistent with suggestions of the BRICST collaboration meeting, known as Johannesburg declaration 2018 (http://sdg.iisd.org/news/brics-declaration-calls-for-full-implementation-of-paris-agreement-and-2030-agenda/), to improve common environmental policies and measures in the direction of full implementation of Paris agreement and 2030 agenda. The declaration gives special attention to energy cooperation to build more environmentally sustainable energy systems, underlines green financial supports to promote sustainable developments. Also, low energy efficiency is one of the main problems paid special attention to these meetings. Therefore, energy intensity may be a key indicator that explains the findings of the study for BRICST countries to follow appropriate policies for the environment. Empirical findings reveal that energy intensity and the current energy structure of the sample countries increase the pressure on the environment. Although a moderate decrease has been observed in energy intensity in recent years, BRICST countries have still high energy intensity in their production process. It should be noted that one of the main benefits of environmental technological progress is to decrease the ratio of energy per output. Therefore, policymakers should focus on decreasing energy intensity or increasing energy efficiency to improve environmental quality. In this respect, more renewable energy can be an alternative in parallel with the decreasing share of non-renewable energy in the energy structure of the BRICST countries. Renewable energy rules and regulations are designed to boost the use of renewable energy sources and promote energy innovations to control the adverse effects of using fossil fuels on environmental degradation. Besides, the policymakers in BRICST economies should be focused on supporting researchers and scientific institutions to obtain higher levels of energy efficiency. The use and the motivation of energy-efficient and clean technologies should be encouraged and supported in various sectors, especially energy-related industries. In line with the empirical findings of the study, the Johannesburg collaboration is a roadmap of BRICST countries to tackle heterogeneities stemming from the socioeconomic dynamics of sample countries in establishing a sustainable future.

CRediT authorship contribution statement

Eyup Dogan: Supervision, Methodology. **Recep Ulucak:** Writing - original draft, Writing - review & editing, Validation, Writing - original draft, Writing - review & editing. **Emrah Kocak:** Data curation, Validation, Investigation. **Cem Isik:** Writing - original draft, Writing - review & editing, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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