Environmental Science and Pollution Research (2021) 28:48112–48122
https://doi.org/10.1007/s11356-021-14056-5

RESEARCH ARTICLE

Exploring a new perspective of sustainable development drive through environmental Phillips curve in the case of the BRICST countries

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Received: 17 January 2021 / Accepted: 19 April 2021 / Published online: 26 April 2021

Abstract

Considering that the rigor of economic activities has widely been linked with the turbulent nature of the increasing global atmospheric and environmental hazards thus hampering environmental sustainability, it then presented a suggestive dilemma realizing that increasing unemployment, i.e., de-economizing human activities posit a desirable environmental quality effect. Given this backdrop, and employing the more recent estimation techniques, the current study probes the validity of the novel environmental Phillips curve (i.e., negative relationship between unemployment and environmental degradation) opined by Kashem and Rahman (Environ Sci Pollut Res 1–18, 2020). In this case, the panel of BRICST (Brazil, Russia, India, China, South Africa, and Turkey) economies for the selected data set over the experimental period 1992-2016 is analyzed. After using related approaches that are designed to account for probable country-specific factors, i.e., the cross-sectional dependence concern, the findings from the PMG-ARDL model affirmed the validity of the environmental Phillips curve for the BRICST countries. Thus, there is a significant trade-off between unemployment and environmental degradation. Moreover, this study concludes that renewable energy consumption improves the environmental quality, while conventional energy sources remained detrimental factors to environmental quality in the panel of the examined countries. Therefore, the study identified that the share of renewable energy in the energy mix should be escalated to improve environmental quality and maintain or improve the employment level, thus advancing the sustainable development goals (SDGs) of the BRICST countries.

Keywords Environmental Phillips curve · Renewable energy · Energy consumption · Panel data methods · BRICST countries

JEL classification C23 · Q40 · Q45

Responsible Editor: Philippe Garrigues

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Introduction

Environmental degradation is repeatedly cited as one of the most critical issues nowadays (Adedoyin et al. 2020a). Therefore, environmental economists have long been concerned with the relationship between economic prosperity and environmental quality (Dong et al. 2017; 2018; Li et al. 2021; Wang and Dong 2019; Khan et al. 2021). Also, energy consumption leads to economic growth (Ali et al. 2020a), which in turn alters environmental quality (Adedoyin et al. 2020b; 2021; Gyamfi et al. 2021a, b). More specifically, there is a long line of research on the environmental Kuznets curve, which postulates an inverse-U-shaped relationship between economic growth and environmental quality (Baloch et al. 2021). However, the main criticism of this hypothesis has to do with the fact that it has not effectively explained the specific factors that may translate increased income into environmental quality (Carson 2010). However, it is highly important for policymakers to investigate how certain macroeconomic variables, such as the unemployment rate, affect environmental quality.

According to Kashem and Rahman (2020), environmental pollution shares the basic characteristic that in case pollution increases in one part of the world, potential negative impacts are expected to affect not only that part alone, but also other parts of the world as well. In such a case, it is a great concern for many stakeholders, such as policymakers, researchers, and the global population that the arising pollution crisis needs someone or something to curb pollution without decreasing income (and in this case increasing unemployment). Previous practical, as well as academic research, shows that when income increases, pollution also increases. The literature has also documented that pollution and income are strongly correlated (Buzkurt and Akan 2014; Mohapatra and Giri 2015; Shahbaz et al. 2016; Gardiner and Hajek 2019; Wang et al. 2020). Given that pollution is strongly associated with production, any reduction in new output production contributes to more pollution. By contrast, unemployment is also closely associated with production and income. Hence, in case that income increases, unemployment goes down.

Based on Okun's law (1962), the association between unemployment and income reduction is positive. As a result, GDP has a positive association with both pollution and employment, i.e., which also confirms that pollution and employment are positively associated. There exists one strand of the literature that explores the link between unemployment and environmental preferences. Torgler and García-Valiñas (2007) examine the role of certain variables as the drivers of Spanish individuals' environmental attitudes. They make use of the role of the employment status, but they are unable to track any relationship between the labor status and environmental attitudes. Witzke and Urfei (2001) also investigate the determinants of the willingness to pay for environmental protection, including the occupation status. Relative to an individual being employed, only individuals who are engaged in household work have a different willingness to pay. Veisten et al. (2004) provide robust evidence that unemployment is correlated with a lower willingness to pay for environmental quality. Finally, two more research outlets investigate the link between income and environmental preferences, without, however, offering any evidence on a valid and statistically significant relationship between these two variables (De Silva and Pownall 2014; Ferreira and Moro 2013). Overall, the relevant literature findings provide mixed evidence on how income (and potentially unemployment) is associated with environmental preferences. The aforementioned literature expounds that researches have been conducted on environmental preferences and unemployment; however, there exists scant literature that examines the relationship between unemployment and environmental degradation. To fill this gap, recently, Kashem and Rahman (2020) characterize the association between unemployment and environmental degradation as the environmental Phillips curve (EPC). They reported that unemployment has a negative impact on CO_2 emissions in the case of developed countries. Our paper extends the work of Kashem and Rahman (2020).

The present study contributes to the existing literature in two dimensions. Firstly, the present study explores the validation of this hypothesis for the case of developing countries (i.e., BRICST countries) using a set of panel methods. Secondly, Kashem and Rahman (2020) use CO_2 emissions as an indicator for pollution (environmental degradation). On the contrary, this study employs ecological footprint (EF) as an indicator for environmental degradation, which is a better proxy for environmental degradation and has been widely used in recent literature (Bagliani et al. 2008; Ozturk et al. 2016; Dogan et al. 2019; Baloch et al. 2019).

The remainder of the study is organized as follows. Section 2 discusses the "literature review." Section 3 reports the "data." Section 4 presents the "model," whereas section 5 presents the "methodology." Additionally, section 6 reports the "Empirical results and discussion." Next, section 7 concludes the study.

Literature on determinants of ecological footprint

This section reports the prior studies on the driving factors of ecological footprint (EF). Since economic growth has extensively been cited as the prime determinant of EF, several research studies explore the relationship between economic growth and EF through the environmental Kuznets curve (EKC) hypothesis. The studies have contrasting conclusions based on different methodologies, time period, and cross-sections. One line of research supports EKC hypothesis using EF as proxy of environmental degradation (Al-Mulali et al. 2015; Destek and Sarkodie 2019). On the contrary, there are many studies which expound that EKC does not exist (Bagliani et al. 2008; Wang et al. 2013).

Apart from economic growth, there exist several other factors that affect EF. For instance, non-renewable energy consumption is responsible for greenhouse gasses' emission and exploits natural resources, which in turn lead to higher EF (Nathaniel, 2020; Sharif et al. 2020). On the contrary, renewable energy consumption, which is a substitute of non-renewable energy, plunges the EF (Danish Ulucak and Khan, 2020; Dogan et al. 2019). In addition to energy consumption, natural resources are also considered as a key determinant of EF, since their exploration and exploitation adversely affect biodiversity (Ahmed et al. 2020; Hassan et al. 2019). Further, financial development and

FDI are also regarded as the prime drivers of EF in many developed and developing countries (Ali et al. 2020b; Baloch et al. 2019; Saud et al., 2020). Also, population growth, population density, and urbanization are the influencing factors of EF because they surge the demand for goods and services, and they turn natural resources (e.g., woods or forest) into cities and/or residential colonies (Ahmed et al., 2020; Baloch et al. 2019; Nathaniel et al. 2020). Next, the trade of goods and services also influences EF. The net effect of trade on EF depends on the nature of goods and services (either energy intensive or labor intensive); hence, trade can either escalate or plunge EF (Al-Mulali and Ozturk 2015; Ali et al. 2020b).

Moreover, several studies declare that political institutions and/or political (in) stability also effect EF (Charfeddine and Mrabet 2017; Al-Mulali and Ozturk 2015). Also, globalization leads to financial, political, and social integration among countries, which contributes to higher EF (Sabir and Gorus 2019; Sharif et al. 2019). Besides, there exist a few studies that claim that life expectancy and fertility rate are the key influencing factors of EF (Alola et al. 2019a; Charfeddine and Mrabet 2017). Human capital also ameliorates environmental degradation, since it plunges the EF (Zafar et al. 2019). Parallel to this, a few researchers expound various other driving factors of EF such as oil prices (Mrabet et al. 2017), imports and exports (Dogan et al. 2019), and technology and/or innovations (Sabir and Gorus 2019).

Table 2 Descriptive statistics

		EF	*GDP*	*ENE*	*POP*	*UNE*	*REN*
Brazil	Mean	1.08	9.17	7.07	19.01	2.09	1.65
	Standard Dev.	0.04	0.13	0.15	0.08	0.18	0.10
	Min.	0.98	8.96	6.84	18.85	1.79	0.56
	Max	1.14	9.36	7.31	19.14	2.45	1.89
Russia	Mean	1.64	9.02	8.43	18.79	2.01	0.55
	Standard Dev.	0.09	0.27	0.08	0.01	0.28	0.01
	Min.	1.47	8.61	8.28	18.77	1.65	0.21
	Max	1.93	9.36	8.58	18.81	2.58	0.65
India	Mean	-0.06	6.91	6.14	20.83	1.72	1.67
	Standard Dev.	0.13	0.34	0.19	0.16	0.01	0.21
	Min.	-0.22	6.38	5.89	20.62	1.66	1.10
	Max	0.15	7.53	6.45	21.00	1.74	2.01
China	Mean	2.90	9.85	7.16	20.97	1.35	1.33
	Standard Dev.	0.29	0.63	0.40	0.04	0.21	0.14
	Min.	0.47	6.78	6.62	20.87	0.86	1.11
	Max	1.31	8.63	7.71	21.04	1.55	1.45
South Africa	Mean	1.16	8.78	7.85	17.66	3.33	1.23
	Standard Dev.	0.06	0.12	0.06	0.10	0.11	0.01
	Min.	1.05	8.61	7.63	17.47	3.11	1.20
	Max	1.29	8.93	7.98	17.84	3.51	1.27
	Mean	1.26	8.38	7.85	13.26	3.21	1.20
Turkey	Standard Dev.	0.05	0.14	0.16	0.19	0.11	0.01
	Min.	1.03	8.63	7.69	17.07	3.01	1.10
	Max.	1.39	8.41	8.98	17.81	3.90	1.29

Data

In this study, a comprehensive study is conducted to explore the determinants of ecological footprint for the BRICST countries (i.e., Brazil, Russia, India, China, South Africa, and Turkey), spanning the period 1992-2016. The variables employed for the study are implied in Table 1, while Table 2 offers some descriptive statistics. In particular, the mean value of *EF* (environmental degradation) and *GDP* is the highest for China, which is 2.90 and 9.85 respectively. The implication is that a country with relatively high income has also experienced the most severe environmental degradation. Next, the mean value of energy consumption is the highest for Russia, while, on average, unemployment is relatively high in South Africa.

Model

This study is primarily based on the underlying intuition of the STIRPAT approach presented by Dietz and Rosa (1994). In fact, the STIRPAT approach is extracted from the IPAT approach, presented by Ehrlich and Holdren (1971). The IPAT

Table 1 Summary of data

Abbreviation	Indicator name	Measurement scale	Source
EF	Ecological footprint	Gha per person	GFN
GDP	GDP per capita	GDP per capita (constant 2010 \$ US)	WDI
ENE	Non-renewable energy consumption	Oil equivalent per capita	WDI
REN	Renewable energy consumption	Percentage of total final energy	WDI
UNE	Unemployment rate	Percentage of labor force	WDI
POP	Population	Total population	WDI

Note: GFN is global footprint network whereas WDI is world development indicators.

model examines the impact of socioeconomic indicators on environmental quality. In this model, I, P, A, and T indicate influence, population, affluence, and technology, respectively. In spite of the fact that the IPAT model has many merits, there are also a few shortcomings. York et al. (2003) note that the hypothesis testing cannot be applied on the IPAT model because of its mathematical form. Next, this model assumes fixed proportionality across the independent variables, which is not valid in reality. Further, the IPAT approach cannot distinguish the relative eminence of each factor. To overcome these shortcomings, the STIRPAT model has been developed. This model examines the stochastic impact of population, affluence, and technology on environmental quality through a regression approach. The standard form of the STIRPAT model is expressed as follows:

$$\log(EF_{it}) = \varphi P_{it}^{\alpha} A_{it}^{\beta} T_{it}^{\gamma} \varepsilon_{it} \quad (1)$$

Furthermore, we transform all variables into their logarithmic form in order to plunge heterogeneity (Farhani et al. 2013a, b). The STIRPAT model, after its logarithmic transformation, yields:

$$\log(EF_{it}) = \varphi + \alpha(logP_{it}) + \beta(logA_{it}) + \gamma(logT_{it}) + \varepsilon_{it} \quad (2)$$

In equation (2), φ is the intercept whereas ε_{it} is the error term. Moreover, α, β, and γ are coefficients, with i and t denoting cross-section and time, respectively. The empirical STIRPAT model we employ in this study is posted in equation 3:

$$\begin{aligned} logEP_{it} = \beta_0 + \beta_1 logGDP_{it} + \beta_2 logENE_{it} + \beta_3 logPOP_{it} + \beta_4 logUNE_{it} \\ + \beta_5 logREN_{it} + \alpha i + \varepsilon_{it} \end{aligned} \quad (3)$$

The *EP* is the ecological footprint, whereas *GDP* is the gross domestic product per capita. In addition, *ENE* denotes non-renewable energy consumption, whereas *POP* is the total population. Moreover, *UNE* is the unemployment rate and *REN* is the renewable energy consumption. Finally, ε_{it} shows the error term and α_i denotes fixed effects.

The envisaged coefficient of *GDP* is positive, because a rise in GDP is responsible for environmental degradation (Apergis and Payne 2010; Alola et al. 2019a, b). Next, the analysis expects the sign of the coefficient of *ENE* to be positive. This implies that energy surges environmental degradation (Anser et al. 2021a, b; Dogan and Ozturk 2017; Baloch et al. 2019). Although population and environmental degradation are expected to be positively correlated, the evidence from different studies has posited diverse perspectives (Alola et al. 2020), a negative nexus (Dogan et al. 2020), or a positive nexus (Charfeddine and Mrabet 2017; Weber and Sciubba 2019). Furthermore, the analysis anticipates a negative sign for *UNE*. In addition, the expected sign of *REN* is negative, as renewable energy consumption decelerates environmental degradation (Dogan and Seker 2016a, b; Dong et al. 2020; Syed and Bouri, 2021).

Empirical methodology

To investigate the validity of the environmental Phillips curve for the BRICST countries using panel data, the analysis follows a five-step procedure for robust and reliable results.

The cross-sectional dependence

In step 1, the cross-sectional dependence (CD) is examined. This is essential because the CD is a serious and common problem of most panel studies that may yield unreliable results (Pesaran 2015). The CD exists if shocks in one country have spillover effects to other countries; therefore, the proper handling of CD is necessary to avoid pseudo results. In the literature, there are many CD tests; however, the most widely used tests are the Breusch-Pagan LM test, the Pesaran LM test, and the Pesaran CD test. This study also employs all these three tests to investigate the presence of CD.

Panel unit roots

In step 2, we probe the presence of unit roots to avoid spurious regression. There are a handful of panel unit root tests available in the literature; however, every test has its own merits and demerits. The present study applied the CIPS unit root test developed by Pesaran (2007) as it allows for CD in the data. In this test, the cross-sectional ADF (CADF) regression equation is posted as:

$$\begin{aligned} \Delta X_{it} = \propto_i + \delta_{it} + \gamma_i Y_{i,t-1} + \varphi_i \overline{Y}_{t-1} + \textstyle\sum_{j=0}^{p} d_{ij} \Delta \overline{Y}_{t-j} \\ + \textstyle\sum_{j=1}^{p} \pi_{ij} \Delta Y_{i,t-j} + \varepsilon_{it} \end{aligned} \quad (4)$$

In equation (4), X_{it} is any variable in logarithmic form. Subscripts i and t, respectively, indicate cross-section and time. Equation (4) is the Dickey-Fuller regression's general (standard) equation. As can be seen, it includes the lagged levels and first differences of cross-sectional means (arithmetic mean) of individual time series. The null hypothesis of CIPS postulates that there is unit root across all-time series in the given panel; however, the alternative hypothesis concludes that there is at least one individual stationary time series in the data. Additionally, CADF statistics are calculated for every individual time series. Next, the CIPS statistic is calculated by taking the mean of CADF statistics:

$$CIPS = \frac{1}{N} \textstyle\sum_{i=1}^{N} t_i(N, T) \quad (5)$$

In equation (5), $t_i(N, T)$ is the CADF statistic for each time series in the panel.

Panel co-integration

In step 3, the co-integration among the variables is examined. There are many panel data co-integration tests, e.g., the Kao (1999), the Pedroni (2004), and the Westerlund (2007). However, in this study, we employ the Westerlund co-integration test (2007) to account for the potential presence of CD. This test is superior to other aforementioned panel data co-integration tests due to the following reasons. First, the Westerlund (2007) test gives reliable results even in the case of CD. Second, the test is relatively efficient in heterogeneous panels. Third, the test resolves the issue of common factor restrictions.

The Westerlund (2007) test consists of four test statistics: G_α, G_τ, P_α, and P_τ. The null hypothesis of P_α and P_τ postulates that no co-integration exists in the whole panel. On the contrary, the null hypothesis of G_α and G_τ concludes that co-integration does not exist across all cross-sections. Based on the error correction model (ECM), the standard (general) equation of the Westerlund (2007) test is as follows:

$$\Delta DV_{it} = \varnothing d_t + \partial_i (DV_{it-1} - \gamma_i INDV_{it-1}) + \sum_{j=1}^{p_i} \partial_{ij} \Delta DV_{it-j} + \sum_{j=-qi}^{p_i} \pi_{ij} \Delta INDV_{it-j} + \varepsilon_{it} \quad (6)$$

In equation (6), DV and $INDV$ show the dependent and independent variables, respectively. Subscripts i and t indicate cross-section and time respectively. Moreover, d_t represents the deterministic component.

PMG-ARDL approach

As the purpose of this study is to reveal the dynamic relationship between unemployment and ecological footprint (the environmental Phillips curve), other panel data models (e.g., fixed effects and random effects models) are inappropriate. The dynamic GMM model is discouraged, while estimating long panel time series data. Based on these shortcomings, we employ the PMG-ARDL model (pooled mean group-autoregressive distributed lags) in step 4. Pesaran et al. (1999) conclude that the PMG-ARDL approach is relatively efficient in long panel time series data. Additionally, this approach generates both short- and long-term coefficients simultaneously. Furthermore, it allows different lags for the dependent and independent variables. Next, this approach is also applicable if the variables are integrated at different orders (e.g., I(1) and/or I(0)). The PMG-ARDL approach also gives homogenous long-run coefficients across the cross-sections, whereas the model renders heterogeneous short-run coefficients across the cross-sections.

$$logEF_{it} = \sum_{j=1}^{p} \tau_{it} logEF_{i,t-j} + \sum_{j=0}^{q} X_{i,t-j} \theta_{ij} + \rho_i + \varepsilon_{it} \quad (7)$$

The equation (7) depicts the PMG-ARDL model. EF indicates ecological footprint, whereas X shows the vector of independent variables (e.g., population, energy, and GDP). Moreover, τ and θ are coefficients to be estimated. Next, ρ_i denotes cross-sectional effects, whereas ε_{it} represents the error term. Subscripts i and t, respectively, show the cross-section and time. In addition, the error correction (ECM) model can be posted as follows:

$$log\Delta EF_{it} = \eta_i ECT_{it} + \sum_{j=1}^{p-1} \tau_{ij} \Delta logEF_{i,t-j} + \sum_{j=0}^{q-1} \Delta X_{i,t-j} \alpha_{ij} + \varepsilon_{it} \quad (8)$$

$ECT_{i,\,t} = logEF_{i,\,t-1} - X_{it}\theta$ (9)

In equations (8) and (9), Δ shows the first difference whereas ECT is the error correction term. Moreover, η_i denotes the short-run coefficient whereas θ is the long-run coefficient.

Panel Granger causality

In order to discern the direction of the causality between variables, we apply the Dumitrescu and Hurlin (2012) heterogeneous panel causality test (hereafter D-H). Destek and Sarkodie (2019) note that this test is a modified form of the panel Granger causality test and it is superior to a selected number of causality tests since it takes into account the heterogeneity and CD in panel data. The D-H process is posted as follows:

$$W_{N,T}^{HNC} = \frac{1}{N} \sum_{i=1}^{N} W_{i,t} \quad (10)$$

$$Z_{N,T}^{HNC} = \sqrt{\frac{N}{2K}} \left(W_{N,T}^{HNC} - K \right) \ \mathrm{N}(0,1) \quad (11)$$

Where, $W_{i,\,t}$ is the Wald statistic and we can calculate $W_{N,T}^{HNC}$ by averaging each Wald static for cross-sections.

Empirical results and discussion

Preliminary results

A series of preliminary estimations were conducted to investigate the environmental Phillips curve for the case of BRICST countries. In essence, the CD is explored through the Breusch-Pagan LM test, the Pesaran LM test, and the Pesaran CD test, with the results presented in Table 3. As can be seen, the findings posit a rejection of the null hypothesis of no CD. Thus, the CD is present, implying that shocks in one country have spillover effects to other BRICST countries.

Considering the aforementioned CD results, and to avoid spurious regression, we next examine the presence of unit roots with the help of the CIPS panel unit root test. The results are reported in Table 4. The findings highlight that we cannot reject the null hypothesis of a unit root at I (0). However, the null hypothesis of a unit root can be rejected at I (1). Thus, we can conclude that all variables are stationary at I (1). Furthermore, the test examines whether the linear combination of non-stationary series is stationary (i.e., whether there is co-integration across the variables).

With this in mind, the Westerlund (2007) test is employed to examine the co-integration between the variables. The findings from this test are reported in Table 5.

Consequently, Table 5 highlights that we can reject the null hypothesis of no co-integration. Thus, co-integration holds among EF, GDP, ENE, RNE, POP, and UNE. The presence of co-integration implies that there exists a long-run relationship across the variables under study. Thus, the results provide a suitable ground to investigate the presence of potential long- and short-run relationships between ecological footprint and the explanatory variables.

The empirical analysis employs the PMG-ARDL model to determine the long-run relationship between the variables. The findings are reported in Table 6.

Short- and long-run results

Given that the logarithm of all variables has been used, the long-run coefficients imply the elasticity of EF with respect to the independent variables. The findings from the PMG-ARDL methodology document the following conclusions: in the long-run, the coefficient of the unemployment rate is negative and statistically significant. This implies that an increase in the unemployment rate is responsible for a decline in environmental degradation. Moreover, the coefficient of the population is positive and significant, implying that population escalates the ecological footprint in the BRICST countries. In addition, the coefficient of GDP is negative and significant, which indicates that GDP escalates environmental quality. Finally, the coefficient of renewable energy consumption is negative and significant. Thus, we can deduce that renewable energy consumption improves environmental quality. In contrast, in the short-run, all coefficients are statistically insignificant, except that of ENE, which is positive and statistically significant.

Table 4 CIPS unit root tests

	I (0)	I (1)
EF	-1.17	-2.60***
GDP	-0.86	-2.74***
ENE	-0.19	-3.12***
REN	-0.98	-3.74***
POP	-0.76	-2.81***
UNE	-1.63	-2.61***

Note: *** indicates the level of significance at 1%. Moreover, the critical value at 1% is -2.57. EF, GDP, ENE, REN, POP, and UNE are respectively the Ecological Footprint, GDP, non-renewable energy, renewable energy, population, and unemployment.

Table 7 reports country-based short-run results. In the short-run, we conclude the presence of the environmental Phillips curve for Russia, India, and Turkey. By contrast, we are unable to report the validity of the environmental Phillips curve for Brazil, China, and South Africa.

Results from causality tests

Next, the Dumitrescu and Hurlin (2012) panel causality test (D-H test) is employed to determine any two-way causality between the variables. This test is superior to other panel causality tests as it takes into account the issue of heterogeneity and CD in the data (Danish Baloch et al., 2019). The results from the D-H test are posted in Table 8.

As illustrated in Table 8, there is bidirectional causality between *EF* and *GDP*. Next, we also detect bidirectional causality between *EF* and *REN*. Furthermore, bidirectional causality is noticed between *EF* and *ENE* as well. Similarly, we identify two-way causality between *EF* and *POP*. In contrast, there is one-way causality (uni-directional causality) running from *UNE* to *EF*.

Discussion

This section explains the results in more details. The findings from the PMG-ARDL model report the following

Table 3 Cross-sectional dependence test

	Breusch-Pagan LM	Pesaran scaled LM	Pesaran CD
EF=f (GDP, ENE, REN, POP,UNE)	(28.01) [0.00]***	(4.65) [0.00]***	(3.88) [0.00]***

Note: (.) indicates t-statistics, whereas [.] shows p-values. *, **, and *** represent levels of significance at 10%, 5%, and 1%, respectively. The LM, CD, EF, GDP, ENE, REN, POP, UNE are respectively Lagrange Multiplier, Cross-sectional Dependence, Ecological Footprint, GDP, Non-renewable energy, renewable energy, population, and unemployment

Table 5 Co-integration test

Statistic	P_t	P_a	G_t	G_a
Value	-3.71***	-2.99***	-3.65***	-3.01***

Note: *** indicates level of significance at 1%.

conclusions. First, in the long-run, the coefficient of the unemployment rate shows that a 1% increase in the unemployment rate plunges the ecological footprint by 0.16%. This implies that an increase in the unemployment rate is responsible for a rise in environmental quality, which validates the presence of the environmental Phillips curve for the panel of BRICST economies. The economic intuition from the results is the fact that an increase in unemployment plunges production and income, i.e., reduction of economic-related activities, which in turn decelerate environmental degradation. Considering that full employment of labor is expected to spur economic productivity vis-à-vis increase economic growth, the trade-off of environmental quality is potentially unavoidable especially in a developing economy such as the BRICS. Thus, in this case, an increase in unemployment (possibly across economic sectors) is tantamount to a declining economic productivity of the panel of BRICS countries, thus causing ecological footprint to wane (improved environmental quality). In essence, it translates that the environmental Phillips curve does exist in the case of the BRICST countries. Also, there are several other reasons behind the results: (1) high unemployment leads to poverty and income inequality, which escalate environmental degradation; (2) Considering energy consumption as a substitute of labor, a rise in unemployment implies that energy consumption is also being increased. Thus, environmental degradation will be surged. This finding is in line with Kashem and Rahman (2020), but has a mixed comparison with Lasisi et al. (2020). Lasisi et al. (2020) infer that male unemployment in a panel of OECD countries escalates environmental degradation, while female unemployment is a recipe for environmental quality. Moreover, this study further posits that a 1% increase in population escalates the ecological footprint by 0.08%, indicating that population increases are detrimental to the quality of the environment, especially in the panel of the examined countries. The rise in population leads to higher production and consumption of both goods and services, which in turn increases environmental degradation. Next, population growth depletes the natural resources; as a result, environmental degradation will be escalated. This evidence is in line with the recent study by Tarazkar et al. (2020).

Table 6 Results from the PMG-ARDL model

Variable	Coefficient	*p*-values
Long-run estimates		
UNE	-0.16	0.00***
GDP	-0.55	0.00***
POP	0.08	0.00***
ENE	0.75	0.00***
REN	-0.33	0.00***
Short-run estimates		
ECT	-0.60	0.03**
UNE	-0.13	0.28
POP	0.80	0.35
GDP	-0.02	0.84
ENE	0.80	0.03**
REN	0.13	0.43

Note: ** and *** show the level of significance at 5% and 1% respectively. EF, GDP, ENE, REN, POP, and UNE are respectively the Ecological Footprint, GDP, non-renewable energy, renewable energy, population, and unemployment.

In addition, the coefficient of GDP indicates that a 0.55% rise in ecological footprint is fostered by a 1% decrease in GDP. This point describes that increases in GDP are responsible for the reduction of environmental degradation. Since GDP is expected to trigger an increase of renewable energy consumption, thus, it could prompt households to demand for a clean environment, leading to a decline in environmental degradation due to an improved economic wellbeing of the people. Also, an increase in income (higher GDP) leads to R&D investment, innovations, and technological advancements. As a result, environmental degradation plunges. Further, higher income level also upsurges the willingness to pay for improved environmental quality, which ameliorates the environment. This finding is in line with the study of Dogan et al. (2020). However, the current findings are in contrast to the conclusions by Alola et al. (2019a, b) and Dogan et al. (2019). The difference between the results of the present study as compared with the prior studies could be due to the choice of proxy for environmental degradation.

Next, the coefficient of non-renewable energy consumption explains that a 0.75% increase in ecological footprint is fostered by a 1% increase in non-renewable energy consumption. In regard to the role of conventional energy, the study implies that non-renewable energy consumption escalates environmental degradation. This is because the coefficient of non-renewable energy is positive and statistically significant, indicating that the utilization of conventional (such as fossil fuel) energy escalates environmental degradation. Interestingly, this positive result of the nexus between non-renewable energy utilization and environmental quality is not different from those of the extant studies (Dogan and Ozturk 2017; Baloch et al. 2019; Destek and Sarkodie 2019; Alola and Joshua 2020; Asongu et al. 2020).

In addition, the findings describe that a 1% increase in renewable energy consumption decreases the ecological

Table 7 Country short-run results

Variable	Brazil	Russia	India	China	South Africa	Turkey
UNE	-0.00	-0.23	-1.33	0.02	0.80	-0.05
	(0.72)	(0.00)***	(0.00)***	(0.00)***	(0.80)***	(0.00)***
GDP	0.80	0.04	0.34	-0.03	0.76	0.43
	(0.75)	(0.00)***	(0.00)***	(0.00)***	(0.86)	(0.23)
REN	-0.21	0.21	-0.12	-0.24	0.34	-0.45
	(0.00)***	(0.54)	(0.00)***	(0.00)***	(0.10)	(0.65)
ENE	0.08	-0.32	0.65	0.01	0.41	0.05
	(0.00)***	(0.87)	(0.51)	(0.00)***	(0.12)	(0.00)***
POP	121.01	32.98	431.89	110.09	0.98	23.45
	(0.84)	(0.40)	(0.64)	(0.77)	(0.12)	(0.19)

Note: ***, **, and * indicate level of significance at 10%, 5%, and 1% respectively. (.) shows probability value.

footprint by 0.33%, indicating that renewable energy consumption improves the environmental quality in the case of the BRICST countries. This conclusion is consistent with extant studies such as (Apergis et al. 2010, 2018), Dogan et al. (2019), Bekun et al. (2019), and Destek and Sinha (2020).

Parallel to the long-run estimates, in the short-run, the results from the PMG-ARDL model are reported as follows. The coefficient of the error correction term (ECT) is negative and statistically significant. The value of ECT is -0.60, which indicates that any deviation from long-run equilibrium is corrected by 60% each year. Indicatively, the coefficient of ENE is 0.80, implying that a 1% increase in non-renewable energy consumption escalates the ecological footprint by 0.80%, apparently illustrating a more severe environmental hazard compared to the long-term situation. This experience is consistent with the findings by Al-Mulali and Ozturk (2015), Adedoyin et al. (2020b), and Ibrahim and Alola (2020). In addition, the population also exerts a higher damaging impact on the environment in the short-run, while GDP and UNE exert a lesser, albeit significant and desirable impact, in the short-run. Moreover, the impact of unemployment increases in the short-run is significant and environmentally desirable across all the countries, except in the cases of China and South Africa (Table 7).

Table 8 D-H causality test results

Null Hypothesis:	W-Stat.	Z-bar-Stat.	Prob.
EF <≠>GDP	7.36	11.01	0.00***
GDP <≠>EF	5.37	7.57	0.00***
EF <≠> POP	15.02	25.54	0.00***
POP <≠>EF	5.70	8.15	0.00***
EF <≠>ENE	2.59	2.75	0.00***
ENE <≠> EF	4.67	5.47	0.00***
EF <≠> REN	4.34	5.32	0.00***
REN <≠> EF	8.52	13.07	0.00***
EF <≠> UNE	1.33	1.47	0.18
UNE <≠> EF	4.43	6.96	0.00***

Note: *** indicates the level of significance at 1%. Moreover, X <≠> Y represents that X does not Granger-cause Y. EF, GDP, ENE, REN, POP, and UNE are respectively the Ecological Footprint, GDP, non-renewable energy, renewable energy, population, and unemployment.

Moreover, the results from the D-H causality test provide a robustness check that shows that there is bidirectional causality between ecological footprint and GDP. This result supports the validity of the feedback hypothesis, implying that the previous value of information of GDP is an effective tool to predict the future environmental situation, especially regarding the quality of the environment, and vice versa. Furthermore, there is bidirectional causality between ecological footprint and non-renewable energy consumption. It also translates that the consumption of conventional energy in the panel countries is capable of predicting the environmental quality in the panel economies, while the reverse is also true. Similarly, there is bidirectional causality between ecological footprint and renewable energy consumption and GDP, indicating that the informational content from renewable energy consumption is a significant predictor of the environmental quality and GDP growth. Finally, there is one-way causality running from the unemployment rate to ecological footprint, indicating that we can control the environmental deterioration by efficiently managing the a priori information or statistics of the unemployment rate.

Conclusion

Environmental degradation and unemployment are two undesirable challenges across the global economies. In most cases, these two pertinent challenges have been studied independently. However, recent studies have further shown the curiosity of policymakers and researchers in exploring these environmental and macroeconomic variables simultaneously, especially in the context of climate change. This adventure is in line with the desirous attempt at mitigating the rise in unemployment and environmental degradation. On this basis, this study probed the impact of unemployment on environmental degradation using the ecological footprint as an indicator for environmental degradation. In other words, this study scrutinized the validity of the environmental Phillips curve that has been recently put forward by Kashem and Rahman (2020) who highlighted the negative relationship between environmental degradation and unemployment.

In this context, the more recent panel data approaches were employed to investigate the environmental Phillips curve for the case of the BRICST countries (i.e., Brazil, Russia, India, China, South Africa, and Turkey). By taking a clue from the results of the co-integration estimates, the findings from the PMG-ARDL model reported that a rise in the unemployment rate was responsible for an increase in environmental quality. This suggests a trade-off between unemployment and environmental degradation. Considering the socioeconomic adverse effects of unemployment, it is certainly unsustainable to implement the unemployment policy instrument as a way of achieving the carbon emissions mitigation targets across economies. Thus, governments and policymakers should apply a more sustainable policy pathway (such that targets the economic activities, i.e., the production process, technological developments, and energy sources developments) to mitigate environmental degradation, especially not at the detriment of job creation and availability. More specifically, the BRICST countries could improve environmental quality without causing job losses or aiding unemployment if they continue to invest in alternative and renewable energy sources, technologies, innovations, production, and manufacturing processes.

Furthermore, this study concludes that renewable energy consumption improves the environmental quality without affecting unemployment. Therefore, the findings recommend that the BRICST countries should further increase the share of renewable energy consumption in total energy consumption in order to increase environmental quality without causing job losses. Policymakers and energy stakeholders should encourage investments in the renewable energy consumption sector. Moreover, incentives and subsidies through public-private partnerships should be also provided to advance the development of renewable energy sources. Next, recycling, innovations, and clean production methods should be also adopted to decelerate environmental degradation and unemployment. In addition, the BRICST countries could further invest in R&D activities in order to unmask clean production methods that necessitate a clean environment without necessarily causing unemployment. Considering that this investigation found that non-renewable energy consumption deteriorated environmental quality, the aforementioned policies that drive the energy transition mechanism should be consciously implemented by the BRICST and similar economies.

For future research directions, a prospective study could be centered on examining whether financial development, urbanization, technology, and innovation can curb environmental degradation without affecting employment. Moreover, researchers may investigate the validity of the environmental Phillips curve across countries, regions, and geographical locations with relatively high unemployment rates. In addition, the investigation of the environmental Phillips curve can be done by employing non-linear methods.

Abbreviations EKC, environmental Kuznets curve; PMG-ARDL, pooled mean group-autoregressive distributed lags; GDP, gross domestic product; ENE, non-renewable energy consumption; REN, renewable energy consumption; POP, population; UNE, unemployment; CD, cross-sectional dependence; BRICST, Brazil, Russia, India, China, South Africa, Turkey; EPC, environmental Phillips curve

Authors' contributions 1- M.K. Anser: conceptualization and data analysis

2- Q.R.Syed: drafting

3- N. Apergis: supervision

4- A. A. Alola: drafting and evaluation

Data availability Data will be available upon request.

Declarations

Consent to participate Not applicable.

Ethical Approval Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests for this manuscript.

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