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The asymmetric effect of oil price on ecological footprint: evidence from oil-producing African countries

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Abstract
This study investigates the asymmetric impact of oil price (OP) on the ecological footprint (EF) in the major oil-producing African countries over the period 1988–2018. Results from the dynamic seemingly unrelated regression (DSUR) and the countrywise FMOLS regressions establish the asymmetric impact of OP on EF in the countries. Both GDP per capita and non-renewable energy (NRE) consumption are also affirmed as drivers of environmental degradation, while renewable energy consumption is found to be a promoter of environmental sustainability. Furthermore, a unidirectional causal relationship is found from OP to EF, GDP and NRE, while feedback is reported between EF and GDP. Therefore, the study proposes the need for diversification of the energy mix in these countries through the formulation of policies that would drive renewable energy usage without slowing down growth.

Keywords Oil price, Environmental sustainability, Ecological footprint, Asymmetric, DSUR, FMOLS, African countries, GDP, Anthropogenic, Energy

Introduction

The impact of various human actions on the environment has engendered dangerous repercussions which have posed serious threats not only to the attainment of global sustainable development but also to human survival (Cramer et al., 2018). In a bid to enhance economic output and to achieve long-run sustainable growth, the ever-increasing economic activities continue to place rising demand on nature for biologically productive land and ocean areas, thereby creating a huge challenge for nature in its bid to recover its ecosystems (Destek & Sarkodie, 2019). This has resulted in various deleterious occurrences such as warmer atmospheres, heat waves, rising sea levels, melting ice caps, floods, and forest fires. The situation is so bad that the Global Footprint Network (GFN) claims at least 80% of the globe is presently in deficit ecologically because the natural resources being consumed far outweigh their biocapacity [1]. Apart from humans, agricultural species, wildlife, and aquatic habitats are other constituents of the global ecosystem that are highly vulnerable to the perils of environmental degradation. Therefore, the evolution of ecological footprint (EF) boils down to the question surrounding the recovery of the ecosystem in response to the huge pressure it continually faces from human activities[1].

The EF is an all-inclusive framework for tracking human anthropogenic activities which include the consumption of nature's renewable resources in the productive land and ocean areas. It exhaustively captures the different compositions of the ecosystem which comprise built-up land, carbon footprint, cropland, fishing grounds, forest products and grazing land[1]. As human economic activities are mostly anthropogenic with damning consequences on EF, the GFN classifies EF

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[1] http://www.footprintnetwork.org/our-work/ecological-footprint/.

into four groups: consumption EF (EF_C), production EF (EF_P), imports EF (EF_I) and exports EF (EF_E)[1]. While the EF_C captures the acceleration of EF within a geographical location via consumption by inhabitants, the EF_P covers the weakening of the ecosystem through production activities. Both EF_I and EF_E constitute the net EF of trade, as they refer to the degradation of biocapacity because of international trade. The global ecological deficit has been increasing over the years,[2] with the concomitant continuous enlargement of imbalance between humans and the ecosystem.

Starting from the seminal work of Hamilton (1983) which establishes a strong oil price (OP)-GNP nexus for the US, the importance of the OP in determining the level and scale of economic activities has been investigated severally in the literature. As a follow-up to Hamilton (1983) article, other studies have emphasized the essential role that changes to OP play in stimulating or dampening various macroeconomic indicators through impact on economic activities (Cologni & Manera, 2008; Lardic & Mignon, 2006; Lee & Ni, 2002). More recent studies also affirm the relevance of OP in shaping the overall economic activities in the country (Abdel-Latif et al., 2018; Agbanike et al., 2019; Hassan, 2021). A notable channel through which the OP impacts economic activities is energy consumption. Most growth-enhancing economic activities have over the years relied heavily on energy-intensive inputs, thereby making energy the lifeblood of the global economy (Alam, 2006). Following a decline in the global demand for energy by 1% in 2020 due to the COVID-19 pandemic, the International Energy Agency (IEA) affirms that global energy demand would outstrip the pre-COVID-19 levels by increasing in 2021 by 4.6%[3]. However, increasing global energy demands have continued to apply huge pressure on the environment and the ecosystem, with perilous repercussions (Baz et al., 2020; Majeed et al., 2021).

More often, the impact of changes in OP on oil-exporting countries differs from that of oil-exporting countries. As revealed by the literature, earnings from oil export is a crucial revenue source for oil-producing countries (Alley, 2006; Hassan, 2021; Mensah et al., 2019), while spending on oil products constitutes a major expenditure for oil-importing economies (Nasir et al., 2018). As found by Acar (2017), dependence on oil is a major inducer of sustainability problems in oil-resource-abundant countries. Moreover, results from a study by Fuinhas and Marques (2013) on Algeria and Egypt show that apart from influencing the demand for energy in the two oil-producing African countries, OP also exerts a key impact on the connection of energy consumption to the determinants of economic activities. This finding is supported by Hasanov et al. (2016) who investigated a panel of oil-exporting countries and found that OP, alongside income and attributes of population, is an important driver of energy consumption. It is also argued by Attala et al. (2018) that in Saudi Arabia, keeping local OP below what is obtained in the global market increases energy demand.

Meanwhile, some studies have also assessed the OP-carbon emissions link in oil-producing economies. In studying Saudi Arabia, Alshehry and Belloumi (2015) conducted a causality test and found that a spike in energy consumption could cause carbon emissions to increase because of the underlying influence of oil revenue on economic activities. This supports Hasanov et al. (2018) and Raggad (2018). While the former asserts that oil and its consumption lead to more carbon emissions in oil-exporting economies, the latter, in an assessment of the drivers of pollutants in Saudi Arabia, established the positive impact of income and energy consumption on carbon emissions. In another study on Venezuela, a major oil-producing country, Agbanike et al. (2019) investigated the interaction between OP and carbon emissions. They found that the former exerts a positive impact on the latter. Furthermore, for Ecuador, Nwani (2017) employed the ARDL technique and annual data from 1971 to 2013. Both the short- and long-run estimates showed that an increase in crude oil export earnings engendered higher carbon emissions through its underlying positive influence on economic activities. What's more, the causality analysis reveals that OP Granger causes energy consumption and GDP.

The contribution of Africa to the global supply of crude oil cannot be brushed aside. Apart from being home to 5 of the top 30 global oil producers,[4] both North and West African sub-regions contributed about 9% to the global oil supply in 2020, while the crude oil reserves in the continent amount to 125.3 billion barrels, which make up of about 8.09% of the global oil reserves[5] Notable in this regard is the high dependence of oil-producing African countries on revenue from oil (Alley, 2016; Koh, 2017; Mensah et al., 2019). For example, oil revenue constitutes at least 20% of GDP for countries like Algeria, Angola, Chad, Congo, Gabon, and Libya,[6] while it accounts for

[2] http://data.footprintnetwork.org/.

[3] https://iea.blob.core.windows.net/assets/d0031107-401d-4a2f-a48b-9eed19457335/GlobalEnergyReview2021.pdf.

[4] https://www.eia.gov/international/data/world/petroleum-and-other-liquids/annual-petroleum-and-other-liquids-production

[5] https://www.statista.com/statistics/1207906/share-of-oil-exports-from-africa-by-region/.

[6] https://www.statista.com/statistics/1235000/oil-revenue-as-share-of-gdp-in-africa-by-country/.

about 86%, 89%, 85% and 69% of export revenue for Nigeria, Angola, Algeria and Libya respectively [7] Consequently, fiscal spending that is required to drive aggregate demand towards increased economic activities in these African oil-producing countries largely depends on earnings from oil exports (Abdel-Latif et al., 2018; Hassan, 2021).

Considering the central role that energy consumption plays in stimulating economic activities, OP spike may result in the acquisition of more sophisticated and energy-intensive technologies, as well as increased energy-intensive consumption in oil-rich countries, thereby contributing to increased degradation of the environment. Because of the high incidence of poverty in Africa, some of the gains from positive OP shocks are channelled to consumption-oriented schemes which could increase the use of energy, with attendant environmental consequences (Mhlanga, 2020, 2022; Mhlanga & Dunga, 2020; Rogat, 2007). Evidence from non-African oil-rich countries supports the increase in carbon emissions following positive OP shock. In the case of Venezuela, Saboori et al. (2016) established that an increase in OP harms EF. They also reported that OP causes oil consumption in the case of Algeria and UAE. For Saudi Arabia, Mahmood et al. (2020) investigated the asymmetric impact of the oil sector on CO2 emissions and found that both rising oil income and falling oil income have positive impacts, with a higher impact from rising oil income. This is despite the intuitive expectation that a negative OP shock should slow down economic activities in such countries through reduced export earnings, as fewer financial resources become available (Hassan, 2021).

Meanwhile, the literature has also found that OP impacts energy consumption negatively (Li et al., 2019). For example, Mensah et al. (2019) argued that an upsurge in OP could trigger reduced oil consumption, thereby lowering carbon emissions. Besides, it has been argued by Wong et al. (2013) that an increase in OP promotes innovation, as well as research and development, which enhances the increased use of renewable energy, which results in greater environmental quality. Furthermore, the Environmental Kuznets Curve (EKC) hypothesis suggests that as incomes of oil-producing countries increase (because of rising OP), there is a tendency for investment in research and development which would engender a technological shift that induces departure from traditional energy consumption, thereby resulting in better environmental outcomes.

Li et al. (2020) have argued that as a reaction to the OP upsurge, oil-importing countries could move to cheaper and environment-friendly energy substitutes, with a resulting decline in environmental degradation. What's more, OPEC's activities in influencing OP through supply control could prompt them to the need to diversify into renewable energy sources, which would reduce the detrimental effects of energy consumption (Nasir et al., 2018). This argument has been reinforced by Malik et al. (2020) who conducted an asymmetric analysis of the effect of OP on carbon emissions in Pakistan and established that an upsurge in OP leads to reduced detrimental effects in the long run, while negative oil-price shocks aggravate carbon emissions.

It is clear from the foregoing that empirical findings on the exact impact of positive and negative shocks to oil prices on environmental outcomes are inconclusive. Therefore, considering the volatile nature of OP, this study aims to shed light on the issue of environmental sustainability for African oil-producing economies in the face of constant OP changes by investigating the asymmetric impact of oil price on the ecological footprint in major oil-producing African countries.

This study will fill a research gap on the subject in the following ways: First, there is a dearth of studies on the oil price–environmental sustainability nexus, especially for African countries. The only known studies on the subject consist of Abumunshar et al. (2020), Agbanike et al. (2019) and Malik et al. (2020) and none of them have been conducted for African countries.

Second, in all these studies, environmental quality is measured by carbon emissions. Much as carbon emissions tend to provide some validation concerning the condition of the environment, they are unable to convey the full picture of the environmental situation. This is because carbon emissions only measure the 'air pollution' fragment of environmental degeneration (Ulucak & Lin, 2017). This study overcomes this limitation by utilising the ecological footprint, which is an all-encompassing environmental quality indicator that monitors the biologically productive areas necessary for the generation of human resource needs (GFN, 2023).

Third, all the extant studies for Africa, except for Malik et al. (2020) presumed linearity in the OP-environment nexus, and as such, could not provide insight into how environmental outcomes are influenced by both positive and negative OP changes. By conducting an asymmetric analysis, this study would assess the distinct impacts of the increase and decline in OP on the quality of the environment. As far as we know, this is the first study to explore the asymmetric impact of OP on EF, as Malik et al. (2020) focussed on carbon emissions. This study is therefore very important, considering the constantly changing nature of the OP in the international market,

[7] https://www.opec.org/opec_web/en/about_us/166.htm.

Table 1 Definition of variables and data sources

Variable	Code	Measurement	Source
Ecological footprints	EF	Global hectares per head	GFN
Crude OP	OP	USD	US EIA
Real GDP per capita	GDP	Constant 2015 USD	WDI
Non-renewable energy consumption	NRE	% of total consumption	WDI
Renewable energy consumption	RE	% of total consumption	WDI

Table 2 Descriptive statistics and pairwise correlation

	EF	BRENT	WTI	GDP	NRE	RE
Mean	1.555	49.931	48.915	3890.33	54.328	46.979
Median	1.343	28.85	31.08	2899.679	34.949	63.018
Maximum	4.294	111.63	99.67	9267.869	99.978	88.749
Minimum	0.627	12.76	14.42	1414.101	15.825	0.069
Std. dev	0.797	34.823	30.823	2315.15	35.006	35.316
Observations	217	217	217	217	217	217
EF	1					
BRENT	0.364	1				
WTI	0.371	0.592	1			
GDP	0.614	0.148	0.156	1		
NRE	0.574	0.132	0.133	0.116	1	
RE	−0.535	− 0.138	−0.141	−0.076	−0.593	1

coupled with the contribution of oil-producing African countries to the global oil market.

The remainder of the study is organized as follows. Section "Data and methodology" captures the methodology and data. In Sect. "Results and discussion", the results from the various tests and regressions are presented and discussed. Section "Conclusion" concludes the study.

Data and methodology

Data and descriptive statistics

This study explores the asymmetric impact of OP on EF in the major oil-producing African countries: Algeria, Angola, Congo Republic, Egypt, Gabon, Libya and Nigeria, over the period 1988–2018. The study period is limited by data availability. The dependent variable, EF, is sourced from GFN. The crude OP (both Brent and West Texas Instrument [WTI] variants), is our main explanatory variable and it is drawn from the US Energy Information Administration (EIA). Real GDP per capita, non-renewable energy (NRE) and renewable energy (RE) are included in the model as control variables, and they are sourced from World Development Indicators (WDI). NRE is measured by fossil fuel energy consumption as a percentage of total energy consumption, while RE represents renewable energy consumption as a percentage of total energy consumption. A synopsis of the variables and their sources is depicted in Table 1.

Table 2 presents a summary of the statistical properties and correlation coefficients of the variables. On average, the population in the seven countries generates EF of 1.56 hectares per person over the study period. The highest EF of 4.29 hectares per head is recorded in 2010 by Libya, while the lowest of 0.627 is recorded in 1995 by Angola. The mean Brent and WTI crude OP are $49.93 and $48.92, respectively. They recorded the highest levels of $111.63 (in 2012) and $99.67 (in 2008) respectively, as well as the lowest levels of $12.76 and $14.42, both in 1998. The mean of each EF, BRENT, WTI, GDP and NRE exceeds the median. This indicates that the data distribution of each of the variables is skewed to the right. Contrariwise, the mean of RE is less than the median, which implies that the data distribution is skewed to the left. Besides, the correlation matrix of the variables is displayed underneath the descriptive statistics in Table 2. The coefficients suggest the inexistence of multicollinearity among the variables, as the highest coefficient in the matrix is 0.614, which is moderate. Moreover, the coefficient relates to the linkage between the dependent variable (EF) and an explanatory variable (GDP). Hence, the model is devoid of multicollinearity variations in EF in the countries under study.

Model specification and methodology

The empirical model is specified to include both OP rise and decline. Transmuting series into their negative and positive components emanated from Granger and Yoon (2002) and has been used in various studies (for example, Hassan, 2021; Hatemi-J et al., 2016; Malik et al., 2020). Hence, as suggested by Granger and Yoon (2002), we decompose our main explanatory variable, the OP, into its positive and negative partial sums as follows:

$$OP_{it}^{+} = \sum_{j=1}^{k} \Delta OP_{j}^{+} = \sum_{j=1}^{k} \max(\Delta OP_{ij}, 0), \tag{1}$$

and

$$OP_{it}^{-} = \sum_{j=1}^{k} \Delta OP_{j}^{-} = \sum_{j=1}^{k} \min\left(\Delta OP_{ij}, 0\right) \tag{2}$$

Therefore, by accounting for asymmetries, the empirical model for the relationship between EF and OP is expressed as follows in line with a similar study by Malik et al. (2020):

$$EF_{it} = \beta_{0i} + \beta_{1i}OP_{it}^{+} + \beta_{2i}OP_{it}^{-} + \beta_{3i}GDP_{it} + \beta_{4i}NRE_{it} + \beta_{5i}RE_{it} + \epsilon_{it} \tag{3}$$

where the variables are as earlier described, OP^{+} and OP^{-} are positive and negative shocks to OP respectively and ϵ is the error term.

The hypothesis of asymmetry in Eq. (3) revolves around the estimates of β_{1i} and β_{2i}, as OP's influence on EF are deemed asymmetric, if and only if both parameters are statistically significant and bear different magnitudes. If this is the case, then the nature and/or level of impact of both on the environment are adjudged to be unequal. However, should either or both conditions be violated, then the impact of OP on EF is deemed linear, and not asymmetric.

To achieve the objective of this study, several cutting-edge econometric techniques are employed. First off, we verify the presence or otherwise of cross-sectional dependence (CD) in our data. This is followed by the conduct of panel unit root tests. Subsequently, a test of cointegration, based on Westerlund (2007) is conducted to verify long-run association. Long-run estimates of the regressors are determined through dynamic seemingly unrelated regression (DSUR). Furthermore, countrywise long-run analysis is also conducted utilizing fully modified ordinary least squares (FMOLS). The econometric analysis is concluded with the investigation of causal relationships among the variables in the model.

The presence of CD in panel data can lead to unreliable and biased estimates if left unaddressed (Eberhardt & Teal, 2010; Pesaran, 2006). Therefore, for starters, we conduct CD tests to ensure the use of appropriate estimation techniques. For this purpose, in line with Yang et al. (2021), we employ three CD tests, namely Breusch and Pagan (1980) LM test, Pesaran (2004) CD test the bias-correlated scaled LM test of Baltagi et al. (2012). The null in each test is that the variables are cross-sectionally dependent. Moreover, to verify the order of integration of variables, 2nd generation stationarity tests, namely cross-sectionally augmented IPS (CIPS) and cross-sectionally augmented ADF (CADF), developed by Pesaran (2007) are conducted. These tests are reputed for their ability to account for the problem of CD. The test statistics for CADF is expressed as follows:

$$\Delta Z_{it} = \beta_i + a_i z_{i,t-1} + \alpha_i \bar{z}_{t-1} + \sum\nolimits_{j=0}^{k} b_{ij} \Delta \bar{z}_{t-j} + \sum\nolimits_{j=1}^{k} \delta_{ij} \Delta z_{i,t-j} + \varepsilon_{it} \tag{4}$$

where $\bar{z}_{t-1}$ is the lagged level of cross-sectional averages, while $\Delta\bar{z}_{t-j}$ is first-order integration of every cross section.

On the other hand, the test statistics for CIPS are obtained from CADF as follows:

$$\text{CIPS} = N^{(-1)} \sum\nolimits_{(i=1)}^{N} CADFi \tag{5}$$

To investigate cointegration, we employ the ECM-based Westerlund (2007) test for cointegration which is suited for heterogeneous panels, addresses CD and produces unbiased results. This cointegration test involves the computation of four test statistics: G_t and G_a—group statistics; P_t and P_a—panel statistics. Westerlund (2007) test is estimated based on the following least-squares model:

$$\Delta Z_{it} = \rho_i \prime d_t + \delta_i (Z_{it-1} - \alpha_i \prime x_{it-1}) + \sum\nolimits_{j=1}^{pi} \delta_{ij} \Delta z_{it-j} + \sum\nolimits_{j=-p_i}^{pi} \theta_{ij} \Delta x_{i,t-j} + \varepsilon_{it} \tag{6}$$

For the group statistics (G_t and G_a), t-statistics are derived as follows:

$$G_t = \frac{1}{N} \sum\nolimits_{(i=1)}^{N} \frac{\Psi_i}{SE\left(\widehat{\Psi_i}\right)} \tag{7}$$

$$G_a = \frac{1}{N} \sum\nolimits_{i=1}^{N} \frac{TY}{\Psi_i\prime(1)} \tag{8}$$

Table 3 Cross-sectional dependence tests

	Breusch-Pagan	*p* value	Pesaran	*p* value	Baltagi et al. (2012)	
	Statistic		Statistic		Statistic	*p* value
EF	8.321***	0.000	3.207**	0.012	15.312***	0.000
BRENT	5.672***	0.000	6.509***	0.000	9.217***	0.000
WTI	3.517***	0.000	4.113*	0.072	7.807**	0.034
GDP	12.229***	0.000	8.271***	0.000	13.466***	0.000
NRE	7.514***	0.000	6.119**	0.026	21.612***	0.000
RE	4.658***	0.000	5.573*	0.068	10.594***	0.000

***, ** and * represent 1%, 5% and 10% levels of significance respectively

Moreover, for the panel statistics (P_t and P_a), t-statistics are derived as thus:

$$P_t = \frac{\Psi_i}{SE(\Psi_i)} \tag{9}$$

$$P_a = T \cdot \Psi \tag{10}$$

where Ψ_i is the speed of adjustment.

Meanwhile, to obtain the long-run estimates of parameters, this study employs the second-generation DSUR estimation procedure, proposed by Mark et al. (2005), which is suited for panel data in which the time dimension is higher than the cross sections. In our case, the cross sections are less than the time dimension, as we employed data from seven oil-producing African countries from 1988 to 2018. In developing the DSUR technique, Mark et al. (2005) extended the single-equation DOLS and accounted for the problems of endogeneity, heterogeneity, and CD. Therefore, in line with extant studies (Saud et al., 2019; Yang et al., 2021), this study employs the DSUR approach to estimate long-run parameters in our model. In addition to the panel cointegration estimation, this study also proceeds to estimate long-run cointegration for each country through FMOLS approach. The FMOLS can deliver unbiased estimates despite simultaneity, endogeneity, and serial correlation (Ozcan, 2013). Therefore, following Yang et al. (2021), the FMOLS is employed by this study to estimate country-wise long-run analysis. According to Pedroni (2001), the FMOLS regression is captured by the following model:

$$Z_{it} = \alpha_i + \beta X_{it} + \varepsilon_{it} \tag{11}$$

where X and Z are cointegrating vectors for individual cross section i.

The final stage of our estimation involves the investigation of causal relationships among the variables. The need for testing for causality among the variables is motivated by Engle and Granger (1987), who argues that evidence of cointegration between variables implies the existence of at least one-way causality between them. Besides, information regarding causality between EF and the explanatory variables in this study can aid policymakers in their efforts to formulate effective policies to better the environment. To this end, we apply the Dumitrescu and Hurlin (D–H) (2012) causality test, which overcomes the issues of heterogeneity and CD in panel data.

Results and discussion

Cross-sectional dependence tests

The outcomes of the CD tests are presented in Table 3, the null hypothesis of no CD in the panel data is rejected for each series by all the CD tests conducted, thereby indicating the strong existence of CD in all the series. This result indicates the need to employ estimation techniques that accommodate the problem of CD, as a disturbance in one country could be transmitted into another.

Panel unit root tests

To examine the variables' unit root attributes, second-generation panel unit root tests (CADF and CIPS) are employed, with results presented in Table 4. The null hypothesis that each of the variables contains a unit root cannot be rejected at the level by both tests. However, both tests confirm that they are stationary after the first difference. This implies that all the variables in our model are integrated of order 1, thereby necessitating the need to investigate long-run cointegration among the variables.

Panel test for cointegration

With all the variables confirmed to be I(1) processes, the next stage in the econometric analysis involves the investigation of cointegration through Westerlund (2007) cointegration approach, and the results are presented in Table 5. While G_t, G_a and P_t reject the null hypothesis of no cointegration, P_a accepts the null. Since three out of four statistics indicate rejection of the null, then

Table 4 Panel unit root tests

	CADF		CIPS	
	Level	1st difference	Level	1st difference
EF	− 1.507	− 3.582***	− 1.261	− 4.381***
$BRENT^{+}$	− 2.072	− 3.209***	− 0.337	− 3.622***
$BRENT^{-}$	− 1.966	− 2.081***	− 1.629	− 4.081***
WTI^{+}	− 1.204	− 3.719***	− 2.038	− 3.83***
WTI^{-}	− 1.938	− 2.553***	− 1.670	− 2.981***
GDP	− 3.107	− 5.618***	− 2.511	− 5.071***
NRE	− 2.481	− 4.637***	− 1.113	− 5.443***
RE	− 2.286	− 3.119***	− 1.006	− 3.192***

*** represents 1% level of significance

Table 5 Westerlund cointegration test

Test	Value	*Z* value	*p* value
G_t	− 6.207***	− 7.413	0.000
G_a	− 8.521**	4.011	0.016
P_t	− 6.311***	− 8.677	0.000
P_a	− 9.690	3.551	0.349

*** and ** represent 1% and 5% levels of significance respectively

we submit that a long-run association exists among the variables.

Panel regressions

The regression coefficients of OP^{+}, OP^{-}, GDP, RE and NRE were obtained using the DSUR econometric method and the estimates are presented in Table 6. To confirm the robustness of the results, two different models were estimated. Model 1 involves the use of Brent crude OP as OP^{+}/OP^{-}, while Model 2 has WTI crude OP as OP^{+}/OP^{-}. As exhibited by the table, all the variables are adjudged as exerting a significant impact on EF at 1%, 5% and 10% levels of significance. In Model 1, the coefficient of positive shocks to Brent crude OP is positive and statistically significant at 1%. The same result holds for the coefficient of positive shocks to WTI crude OP in Model 2. This research outcome implies that an increase in OP exacerbates the problem of environmental degradation in the oil-producing African countries under study. Specifically, the estimates imply that a 1-unit increase in the price of Brent crude oil and WTI crude oil is associated with a 0.019-unit and a 0.027-unit respective increase in EF.

As abovementioned, for a typical oil-dependent economy, an increase in OP could boost the acquisition of more sophisticated and energy-intensive technologies, as well as increased energy-intensive consumptions,

Table 6 DSUR regression

Variables	Model 1: OP = Brent		Model 2: OP = WTI	
	Coefficient	*p* value	Coefficient	*p* value
OP^{+}	0.019***	0.0095	0.027***	0.004
OP^{-}	− 0.0018**	0.016	− 0.009**	0.025
GDP	0.186***	0.000	0.155***	0.001
NRE	0.592***	0.000	0.609***	0.000
RE	− 0.036*	0.068	− 0.054*	0.081

*** and ** represent 1% and 5% levels of significance, respectively

thereby contributing to increased deterioration of the environment and owing to the high incidence of poverty in Africa, some of the gains from positive OP shocks are channelled to consumption-oriented schemes which could increase the use of energy, with attendant environmental consequences (Rogat, 2007). This result confirms findings by Agbanike (2019) that positive changes to crude OP are associated with higher CO_2 emissions for Venezuela through increased consumption of energy. It also corroborates Nwani (2017), who confirms a positive causal impact of crude OP on CO_2 emissions in Ecuador. Meanwhile, the result is contradictory to that of Abumunshar et al. (2020) who report a negative effect of OP on CO_2 emissions in Turkey. Just like the countries in our panel data, Venezuela and Ecuador are major oil-producing countries, while Turkey is an oil-importing country. An important implication of this result is that changes in the price of crude oil affect oil-producing countries differently relative to non-oil-producing ones, as alluded to in the introduction.

Furthermore, the coefficients of negative shocks to crude OP in Model 1 (Brent oil) and Model 2 (WTI oil) respectively, are negative and statistically significant at 5%. These results show that negative shocks to OP in the international market exert negative impacts on EF (that is, it reduces environmental deterioration) in the countries under study. Specifically, the results suggest that a 1-unit decrease in Brent crude OP and WTI crude OP is associated with a 0.0018-unit and a 0.009-unit respective decline in environmental degradation. Again, as the countries in the study are oil-dependent, it is expected that negative OP shocks would dampen economic activities in these economies through reduced export earnings (Hassan, 2021), which would, in turn, reduce the EF.

The statistical significance and varying magnitudes of OP^{+} and OP^{-} confirm that the OP's influence on environmental quality is indeed asymmetric, as positive and negative shocks to OP exert varying impacts on the environment. Furthermore, a comparison of the respective magnitudes (0.019/0.027 and 0.0018/0.009

for positive and negative OP shocks respectively) shows that the influence of the increase in OP on the environment is stronger than that of the decrease in OP. This research outcome bespeaks the need for these countries to direct their consumption/economic activities to renewable energy-powered ones. This asymmetric result is in line with Mahmood et al. (2020) who confirm the asymmetric impact of oil income on CO_2 emissions in Saudi Arabia, with positive shocks to oil income bearing a more significant positive impact than its negative counterpart. However, the research outcome negates Malik et al. (2020) who also report asymmetry in the OP-carbon emissions link for Pakistan. Again, this result is reflective of the varying impacts of changes in OP on the environment in oil-producing vis-à-vis oil-importing countries. Saudi Arabia is a major oil-producing country, whereas Pakistan is a net importer of oil.

Now turning to the control variables, GDP per capita has positive and statistically significant coefficients in both Model 1 and Model 2. Specifically, a 1-unit increase in GDP per capita is expected to cause EF to increase by 0.186/0.155 units. The implication of this is that higher GDP per capita leads to more environmental deterioration. This is expected as GDP is often enhanced by increased economic activities which usually put a strain on the ecosystem. This research outcome is in line Abumunshar et al. (2020), Mahmood et al. (2020), Malik et al. (2020), Nathaniel et al. (2020) and Yang et al. (2021) who establish that GDP per capita contributes to environmental degradation in Turkey, Saudi Arabia, Pakistan, MENA countries and BICS countries, respectively. NRE also has positive and significant coefficients in both models. This implies that increased consumption of NRE increases EF in the countries under study. Precisely, a 1-unit increase in the consumption of NRE leads to a 0.592-unit or 0.609-unit increase in EF.

This research outcome and the relatively high coefficient of NRE are expected as increased non-renewable energy consumption is globally considered inimical to the sustainability of the environment. This result corroborates Abumunshar et al. (2020), Khan et al. (2021), Nathaniel et al. (2020) and Xue et al. (2021) who find non-renewable energy as a key contributor to environmental deterioration in Turkey, the US, MENA countries and South Asian countries, respectively. Lastly, the coefficient of RE is negative and weakly significant at 10% in both Model 1 and Model 2. This indicates that an increase in the consumption of renewable energy weakly somewhat improves environmental quality. Precisely, a 1-unit increase in renewable energy consumption is expected to moderately reduce EF by 0.036/0.054 units. This finding somehow reinforces results from previous studies (Abumunshar et al., 2020; Danish et al., 2020; Khan et al., 2021; Nathaniel et al., 2020; Xue et al., 2021) for different countries and regions.

Countrywise regressions

The long-run DSUR regression estimates of the panel data have just been discussed. However, to strengthen the formulation of healthier policies, an analysis of the long-run asymmetric OP-EF nexus for each of the selected oil-producing African economies is additionally discussed in this section. Hence, we apply the FMOLS, and the results are presented in Table 7, which is divided into two compartments. The first compartment contains Model 1 for all 7 countries, where OP is the Brent crude OP, while in the second compartment, we display Model 2 for all the countries with WTI crude OP as OP. OP^{+} is positive and statistically significant at 1%, 5% and 10% significance levels for all the countries in both models. This implies that increased OP contributes to environmental deterioration in each of the countries. Holding other factors constant, a 1-unit increase in Brent/WTI crude OP increases environment deterioration by about 0.141/0.406 units, 0.101/0.470 units, 0.113/0.106 units, 0.159/0.176 units, and 0.059/0.580 units, 1.509/1.572 units and 0.566/1.022 units in Algeria, Angola, Congo Republic, Egypt, Gabon, Libya and Nigeria.

These coefficients reveal Libya as suffering the worst environmental degradation due to increased OP. A look at the descriptive statistics of the variables also shows Libya as the country with the highest EF. OP^{-} is statistically significant at 1%, 5% and 10% in 5 out of the 7 countries in the two models and it is negative/positive for 2/3 of the countries. Precisely, holding other factors constant, a 1-unit decrease in Brent/WTI crude OP decreases environmental degradation by 0.004/0.004 units and 0.085/0.068 units in Algeria and Congo, respectively while it increases it in Egypt, Libya, and Nigeria by 0.038/0.035 units, 0.094/0.009 units and 0.017/0.003 units, respectively. The results imply that the asymmetric impact of OP on EF is confirmed for Algeria, Congo, Egypt, Libya, and Nigeria, while the impact is linear and not asymmetric for Angola and Gabon.

Regarding the coefficients of GDP, for both models, it is found that improvement in GDP per capita contributes significantly to environmental degradation in all the countries. This is because its coefficient is positive and statistically significant at 1%, 5% and 10%, throughout. NRE is equally positive and significant at the 1% and 5% levels in all the models, indicating that consumption of non-renewable energy exerts a strongly deteriorating impact on the environment in all the countries. Meanwhile, it is noteworthy that Libya and Nigeria (with 0.351/1.501 and 1.024/1.189 coefficients respectively) are

Table 7 Countrywise FMOLS regressions

Variables	Countries						
	Algeria	**Angola**	**Congo**	**Egypt**	**Gabon**	**Libya**	**Nigeria**
Model 1 (OP = Brent crude OP):							
OP^{+}	0.141***	0.101*	0.113*	0.159*	0.056***	1.509**	0.566***
	(0.005)	(0.061)	(0.065)	(0.091)	(0.000)	(0.028)	(0.000)
OP^{-}	− 0.004***	− 0.005	− 0.085**	0.038**	− 0.008	0.094**	0.017**
	(0.001)	(0.637)	(0.032)	(0.032)	(0.079)	(0.016)	(0.015)
GDP	0.585***	0.047**	0.192***	0.402***	0.303*	0.446***	0.194***
	(0.000)	(0.025)	(0.000)	(0.005)	(0.066)	(0.003)	(0.000)
NRE	0.607**	0.058**	0.030***	0.432***	0.073**	0.351***	1.024**
	(0.034)	(0.046)	(0.000)	(0.000)	(0.019)	(0.000)	(0.049)
RE	− 0.048	0.033	− 0.018**	− 0.011*	0.027	− 0.145**	− 0.024**
	(0.340)	(0.108)	(0.021)	(0.074)	(0.109)	(0.032)	(0.042)
Model 2 (OP = WTI crude OP):							
OP^{+}	0.406*	0.470*	0.106*	0.176*	0.580**	1.572**	1.022**
	(0.065)	(0.073)	(0.087)	(0.052)	(0.038)	(0.016)	(0.019)
OP^{-}	− 0.005***	− 0.023	− 0.068**	0.035**	0.011	0.009*	0.003**
	(0.000)	(0.681)	(0.046)	(0.031)	(0.061)	(0.082)	(0.019)
GDP	0.674***	0.037***	0.151**	0.038***	0.271**	0.606**	1.102**
	(0.000)	(0.007)	(0.036)	(0.010)	(0.012)	(0.014)	(0.041)
NRE	0.628***	0.078**	0.029***	0.094*	0.007***	1.501***	1.189**
	(0.000)	(0.011)	(0.003)	(0.069)	(0.000)	(0.000)	(0.037)
RE	− 0.249	− 0.043*	− 0.016**	− 0.003*	− 0.018	− 0.161	− 0.086
	(0.648)	(0.058)	(0.028)	(0.059)	(0.137)	(0.250)	(0.340)

***, ** and * represent 1%, 5% and 10% levels of significance respectively

the countries with the highest impacts. Finally, regarding the estimates for RE, results in Model 1 show that it is negative and significant at the 5% and 1% levels for Congo, Egypt, Libya, and Nigeria, while in Model 2, it is negative and significant at 5% and 1% levels for Angola, Congo and Egypt. These estimates suggest that the impact of renewable energy on EF is rather weak in these countries, and this is in line with the panel results earlier discussed.

Panel causality test

The last stage of the econometric process is the discussion of the results from the D–H panel causality test. Information regarding causality directions can aid policymakers in making policies towards promoting environmental sustainability. It could also provide insight into the role of OP, economic growth and energy mix in reducing EF in the countries under study. As displayed in Table 8, a bidirectional causality is found between GDP and EF, which suggests feedback. This result suggests that economic growth in these oil-producing countries leads to increased oil exploration, which in turn exerts a negative impact on biocapacity, thereby increasing the EF (Destek & Sarkodie, 2019). This result corroborates Danish et al. (2020) for the BRICS countries.

Table 8 Dumitrescu–Hurlin panel causality test

Variable	EF	OP	GDP	NRE	RE
EF		0.116	0.016**	1.216	0.117
		(1.276)	(2.124)	(1.513)	(1.520)
OP	0.039***		1.038***	0.649***	0.514
	(6.341)		(8.319)	(1.641)	0.126
GDP	1.073***	0.042		0.319	(1.118)
	(3.074)	(1.719)		(0.927)	0.283
NRE	0.602**	0.137	0.281		0.014
	(2.13)	(1.278)	(1.637)		(1.307)
RE	0.413	1.337	1.007	0.571	
	(1.217)	(1.009)	(1.211)	(0.995)	

Values in parentheses are z-statistics; OP = Brent crude OP; *** and ** represent 1% and 5% levels of significance

Moreover, a unidirectional causality is found from OP to EF, GDP and NRE. This serves to further confirm the important role that changes in OP play in driving economic activities in these oil-producing economies, which in turn influence NRE consumption, GDP per capita and EF. These research outcomes are in line with Malik et al. (2020) and Nwani (2017) who report a one-way causality from OP to CO2 emissions, GDP per capita and non-renewable energy. Lastly, a unidirectional causality exists from NRE to EF. This result supports extant studies which establish that non-renewable energy consumption Granger causes environmental degradation (Nathaniel et al., 2020; Xue et al., 2021).

Conclusion

The deleterious impact of human activities on the environment has elicited unremitting debates in the literature in modern times. One of the key determinants of aggregate demand and economic activities in a typical oil-dependent economy is changes in the price of crude oil (Abdel-Latif et al., 2018; Agbanike et al., 2019; Hassan et al., 2021). However, despite the central role that OP plays in stimulating economic activities in these economies, empirical studies on the oil-price-EF nexus have been sparse. Therefore, the focus of this study is to investigate the asymmetric effect of OP on EF in the seven major oil-producing countries in Africa for the period 1988–2018. To achieve the study objectives, the DSUR is employed to estimate the long-run impact of decreasing and increasing OP on EF, while the D-H test for causality is used to obtain information about the causality directions among the variables in the study. Furthermore, countrywise FMOLS regressions are also conducted to determine the effect of the explanatory variables on EF in each country.

The outcomes of DSUR establish asymmetry in the OP-EF link in the countries under study, as the increase in OP is found to contribute to heightened EF, while the decrease in OP is reported to contribute to reduced EF. A closer look at the estimates of the two variables also reveals that the impact of positive OP shock is much higher than that of negative OP shock. Findings from the panel regression also establish that an increase in GDP per capita and consumption of renewable energy are significant drivers of environmental deterioration, while consumption of renewable energy somewhat reduces environmental deterioration. Moreover, results from the countrywise FMOLS regressions fairly corroborate the panel regression. While the symmetric effect of OP on EF is confirmed for Algeria, Congo, Egypt, Libya and Nigeria, symmetric OP impact on EF is affirmed for Angola and Gabon, where only positive OP shock affects the EF. Lastly, results from the D-H panel causality test reveal a case of the bidirectional causal relationship between EF and GDP per capita, which suggests a feedback effect between the two variables. Furthermore, a unidirectional causality is discovered from OP to EF, GDP and NRE, and from NRE to EF. This further reinforces the long-run estimation results which establish OP as an important driver of economic activities in the countries.

Following these findings, some policy recommendations become important. First, under the aegis of the African Union (AU), the major oil-producing African countries should champion the diversification of the energy mix in the continent, with a much greater concentration in renewable energy. This way, increased energy consumption accompanying positive OP shocks would not exacerbate environmental degradation. Moreover, in their countries, diversification can be promoted by investing in the oil boom windfall in developing and providing renewable energy-oriented technologies for production and consumption. Policies should also be formulated to encourage both industrial and household consumption of clean energy. For example, emission trading systems and carbon pricing can be introduced both at the country level and the continental level through the African Continental Free Trade Agreement (AfCFTA). In addition, as a way of maintaining a healthy balance between diversifying into renewable energy and sustainable growth, the governments could provide tax holidays, subsidies and rebates to companies that are investing in production and research-related activities regarding renewable energy.

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AH-conceptualisation, Writing an original draft, Methodology, Performed Analysis. DM- writing Original draft, editing, Performed Analysis.

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Declarations

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Authors declare no competing interests.

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References
Abdel-Latif, H., Osman, R. A., & Ahmed, H. (2018). Asymmetric impacts of oil price shocks on government expenditures: evidence from Saudi Arabia. *Cogent Economics & Finance, 6*(1), 1–22.

Abumunshar, M., Aga, M., & Samour, A. (2020). Oil price, energy consumption, and CO2 emissions in Turkey: new evidence from a Bootstrap ARDL Test. *Energies, 13*(5588), 1–15. https://doi.org/10.3390/en13215588

Acar, S. (2017). *The curse of natural resources: A developmental analysis in a comparative context*. New York: Springer.

Agbanike, T. F., Nwani, C., Uwazie, U. I., Anochiwa, L. I., Onoja, T. C., & Ogbonnaya, I. O. (2019). Oil price, energy consumption and carbon dioxide (CO2) emissions: insight into sustainability challenges in Venezuela.

Latin America Economic Review, 28(8), 1–26. https://doi.org/10.1186/s40503-019-0070-8
Alam, M. S. (2006). *Economic growth with energy*. Germany: University of Munich.
Alley, I. (2016). Oil price volatility and fiscal policies in oil-exporting countries. *OPEC Energy Review, 40*(2), 192–211. https://doi.org/10.1111/opec.12074
Alshehryy, A. S., & Belloumi, M. (2015). Energy consumption, carbon dioxide emissions and economic growth: the case of Saudi Arabia. *Renewable and Sustainable Energy Reviews, 41*, 237–247.
Attala, T. N., Gasim, A. A., & Hunt, L. C. (2018). Gasoline demand, pricing policy, and social welfare in Saudi Arabia: a quantitative analysis. *Energy Policy, 114*, 123–133.
Baltagi, B. H., Feng, Q., & Kao, C. (2012). A Lagrange multiplier test for cross-sectional dependence in a fixed effects panel data model. *Journal of Econometrics, 170*(1), 164–177. https://doi.org/10.1016/j.jeconom.2012.04.004
Baz, K., Xu, D., Ali, H., Ali, I., Khan, I., Khan, M. M., & Cheng, J. (2020). Asymmetric impact of energy consumption and economic growth on ecological footprint: using asymmetric and nonlinear approach. *Science of the Total Environment, 718*, 137364. https://doi.org/10.1016/j.scitotenv.2020.137364
Breusch, T. S., & Pagan, A. R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. *Review Economic Studies, 47*(1), 239–253. https://doi.org/10.2307/2297111
Cologni, A., & Manera, M. (2008). Asymmetric effects of oil shocks on output growth, a Markov-switching analysis for G-7 countries. *Economic Modeling, 26*, 1–29.
Cramer, W., Guiot, J., Fader, M., Garrabou, J., Gattuso, J. P., Iglesias, A., & Xoplaki, E. (2018). Climate change and interconnected risks to sustainable development in the Mediterranean. *Nature Climate Change*. https://doi.org/10.1038/s41558-018-0299-2
Danish, U., & R. and Khan, S. U. (2020). Determinants of the ecological footprint: role of renewable energy, natural resources, and urbanization. *Sustainable Cities and Society, 54*, 101996. https://doi.org/10.1016/j.scs.2019.101996
Destek, M. A., & Sarkodie, S. A. (2019). Investigation of environmental Kuznets curve for ecological footprint: the role of energy and financial development. *The Science of the Total Environment, 650*, 2483–2489. https://doi.org/10.1016/j.scitotenv.2018.10.017
Dumitrescu, E. I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic Modelling, 29*(4), 1450–1460. https://doi.org/10.1016/j.econmod.2012.02.014
Eberhardt, M., and F. Teal., 2010. Productivity analysis in global manufacturing production. Discussion Paper 515, Department of Economics, University of Oxford. http://www.economics.ox.ac.uk/research/WP/pdf/paper515.pdf.
Fuinhas, J. A., & Marques, A. C. (2013). Rentierism, energy and economic growth: the case of Algeria and Egypt (1965–2010). *Energy Policy, 62*, 1165–1171.
GFN. 2023. Global footprint network. http:// data. footp rintn etwork.org
Granger, C. W., & Yoon, G. (2002). Hidden cointegration. *SSRN Journal*. https://doi.org/10.2139/ssrn.313831
Hamilton, J. (1983). Oil and the macroeconomy since World War II. *Journal of Political Economy, 91*(2), 228–248.
Hasanov, F. J., Bulut, C., & Suleymanov, E. (2016). Do population age groups matter in the energy use of the oil-exporting countries? *Economic Modelling, 54*, 82–99.
Hasanov, F., Liddle, B., & Mikayilov, J. (2018). The impact of international trade on CO2 emissions in oil-exporting countries: Territory vs. consumption emissions accounting. *Energy Economics, 74*, 343–350.
Hassan, A. S. (2021). Asymmetric effects of oil revenue on government expenditure: insights from oil-exporting developing countries. *OPEC Energy Review, 45*(2), 257–274.
Hatemi-J, A., Ajmi, A. N., El Montasser, G., Inglesi-Lotz, R., & Gupta, R. (2016). Research output and economic growth in G7 countries: new evidence from asymmetric panel causality testing. *Applied Economics, 48*(24), 2301–2308.
Khan, D., & Ulucak, R. (2020). How do environmental technologies affect green growth? Evidence from BRICS economies. *Science of the Total Environment*. https://doi.org/10.1016/j.scitotenv.2020.136504
Khan, I., Hou, F., & Le, H. P. (2021). The impact of natural resources, energy consumption, and population growth on environmental quality: fresh evidence from the United States of America. *Science of the Total Environment, 754*, 142222. https://doi.org/10.1016/j.sc.itotenv.2020.142222
Koh, W. C. (2017). Fiscal policy in oil-exporting countries: the roles of oil funds and institutional quality. *Review of Development Economics, 21*(3), 567–590. https://doi.org/10.1111/rode.12293
Lardic, S., & Mignon, V. (2006). The impact of oil price on GDP in European countries: an empirical investigation based on asymmetric cointegration. *Energy Policy, 34*, 3910–3915.
Lee, K., & Ni, S. (2002). On the dynamics of oil price shocks: a study using industry level data. *Journal of Monetary Economics, 49*(4), 823–852.
Li, K., Fang, L., & He, L. (2020). The impact of energy price on CO2 emissions in China: a spatial econometric analysis. *Science of the Total Environment, 706*, 135942. https://doi.org/10.1016/j.scitotenv.2019.135942
Mahmood, H., Alkhateeb, T. T. Y., & Furan, M. (2020). Oil sector and CO2 emissions in Saudi Arabia: asymmetry analysis. *Palgrave Communications, 6*(88), 1–10. https://doi.org/10.1057/s41599-020-0470-z
Majeed, M. T., Tauqir, A., Mazhar, M., & Samreen, I. (2021). Asymmetric effects of energy consumption and economic growth on ecological footprint: new evidence from Pakistan. *Environmental Science and Pollution Research, 28*, 32945–32961. https://doi.org/10.1007/s11356-021-13130-2
Malik, M. Y., Latif, K., Khan, Z., Butt, H. D., Hussain, M., & Nadeem, M. A. (2020). Symmetric and asymmetric impact of oil price, FDI and economic growth on carbon emission in Pakistan: evidence from ARDL and non-linear ARDL approach. *Science of the Total Environment, 726*, 138421. https://doi.org/10.1016/j.scitotenv.2020.138421
Mark, N. C., Ogaki, M., & Sul, D. (2005). Dynamic seemingly unrelated cointegrating regressions. *Review of Economic Studies, 72*, 797–820.
Mensah, I. A., Sun, M., Gao, C., Omari-Sasu, A. Y., Zhu, D., Ampimah, B. C., & Quarcoo, A. (2019). Analysis on the nexus of economic growth, fossil fuel energy consumption, CO2 emissions and oil price in Africa based on a PMG panel ARDL approach. *Journal of Cleaner Production, 228*, 161. https://doi.org/10.1016/j.jclepro.2019.04.281
Mhlanga, D. (2020). Artificial Intelligence (AI) and poverty reduction in the Fourth Industrial Revolution (4IR). *Preprints*. https://doi.org/10.20944/preprints202009.0362.v1
Mhlanga, D. (2022). Stakeholder capitalism, the fourth industrial revolution (4IR), and sustainable development: issues to be resolved. *Sustainability, 14*(7), 3902.
Mhlanga, D., & Dunga, S. H. (2020). Measuring financial inclusion and its determinants among the smallholder farmers in Zimbabwe: an empirical study. *Eurasian Journal of Business and Management, 8*(3), 266–281.
Nasir, M. A., Naidoo, L., Shahbaz, M., & Amoo, N. (2018). Implications of oil price shocks for the major emerging economies: a comparative analysis of BRICS. *Energy Economics, 76*, 76–88. https://doi.org/10.1016/j.eneco.2018.09.023
Nathaniel, S., Anyanwu, O., & Shah, M. (2020). Renewable energy, urbanization, and ecological footprint in the Middle East and North Africa region. *Environmental Science and Pollution Research, 27*, 14601–14613. https://doi.org/10.1007/s11356-020-08017-7
Nwani, C. (2017). Causal relationship between crude oil price, energy consumption and carbon dioxide (CO2) emissions in Ecuador. *OPEC Energy Review, 41*(3), 201–225.
Ozcan, B. (2013). The nexus between carbon emissions, energy consumption and economic growth in Middle East countries: a panel data analysis. *Energy Policy, 62*, 1138–1147.
Pedroni, P. (2001). Purchasing power parity tests in cointegrated panels. *Review Economics and Statistics, 83*(4), 727–731. https://doi.org/10.1162/003465301753237803
Pesaran, M. H. (2004). General diagnostic tests for cross-section dependence in panels. *SSRN Journal*. https://doi.org/10.2139/ssrn.572504
Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica, 74*, 967–1012.
Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Economics, 22*(2), 265–312.
Raggad, B. (2018). Carbon dioxide emissions, economic growth, energy use, and urbanisation in Saudi Arabia: evidence from the ARDL approach and impulse saturation break tests. *Environmental Science and Pollution Research, 25*(15), 14882–14898.
Rogat, J. (2007). The politics of fuel pricing in Latin America and their implications for the environment. *Energy and Environment, 18*(1), 1–12.

Saboori, B., Al-mulali, U., Bin Baba, M., & Mohammed, A. H. (2016). Oil-induced environmental Kuznets curve in organization of petroleum exporting countries (OPEC). *International Journal of Green Energy, 13*(4), 408–416.
Saud, S., Chen, S., & Danish and Haseeb, A.,. (2018). Impact of financial development and economic growth on environmental quality: an empirical analysis from belt and road initiative (BRI) countries. *Environmental Science and Pollution Research, 26*, 2253–2269.
Ulucak, R., & Lin, D. (2017). Persistence of policy shocks to ecological footprint of the USA. *Ecological Indicators, 80*, 337–343.
Westerlund, J. (2007). Testing for error correction in panel data. *Oxford Bulletin of Economics and Statistics, 69*(6), 709–748.
Xue, L., Haseeb, M., Mahmood, H., Alkhateeb, T. T. Y., & Murshed, M. (2021). Renewable energy use and ecological footprint mitigation: evidence from selected South Asian economies. *Sustainability, 13*, 1613. https://doi.org/10.3390/su13041613
Yang, B., Jahanger, A., & Ali, M. (2021). Remittance inflows affect the ecological footprint in BICS countries: do technological innovation and financial development matter? *Environmental Science and Pollution Research, 28*, 23482–23500. https://doi.org/10.1007/s11356-021-124003

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