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Research article

Beyond the barrels: The impact of resource wealth on the energy-economy-climate targets in oil-rich economies

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ABSTRACT

This study models the Kaya identity equation for carbon dioxide (CO_2) emissions in a panel of 20 oil-rich countries from 1994 to 2019. The estimators used are robust to cross-sectional dependence and allow for heterogeneous slope coefficients. The results indicate that natural resource extraction hinders environmental sustainability in oil-rich countries by altering the structural composition of their consumption mix towards energy- and carbon-intensive technologies. However, this relationship is only significant after reaching a turning point level of resource extraction. This suggests that the carbon curse is only triggered at higher levels of resource dependence, supporting a U-shaped relationship between natural resource extraction and CO_2 emissions. The threshold for the natural rents to GDP ratio, beyond which natural resource extraction triggers the carbon curse, is found to be 12.18 %. The vulnerability assessment reveals that 17 countries in the panel, including Algeria, Kazakhstan, the United Arab Emirates, Iran, Iraq, Kuwait, Qatar, Oman, Saudi Arabia, the Congo Republic, and Libya, are already within the carbon curse zone. From a policy perspective, promoting sustainable development in oil-rich economies requires a shift towards renewable energy sources, reducing reliance on fossil fuels, and widespread adoption of energy efficiency and conservation mechanisms.

1. Introduction

As global temperatures continue to rise, the discernible impact of climate change on ecosystems is becoming increasingly apparent. Recent global events have underscored the observable outcomes of rising sea levels, extreme weather events, flooding, droughts, and storms, providing compelling evidence of the real-world impacts brought about by these environmental phenomena [1,2]. These shifts in climate patterns are predominantly ascribed to the substantial emission of greenhouse gases (GHGs), especially carbon dioxide (CO_2), by economic entities. The emission of CO_2 is largely attributed to the combustion of fossil fuels such as coal, oil, and gas [3]. According to the IEA [4], global energy-related CO_2 emissions will increase by 0.9 %, or 321 Mt, in 2022, setting a new record of almost 36.8 Gt. In light of this pressing concern, countries worldwide have reached a unanimous consensus to implement crucial measures

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aimed at limiting the increase in the average global temperature to a level below 2 °C above the preindustrial era [5]. Until now, policy discussions have primarily focused on economic trends within developed economies and China. However, growing attention is being directed towards the environmental consequences stemming from the excessive consumption and overexploitation of natural resources, particularly in developing countries that possess substantial reserves of fossil fuels [6,7]. The reliance on an undiversified energy structure within these developing economies could exacerbate the challenges associated with climate mitigation [6,7].

Therefore, to mitigate the most severe consequences of climate change, a radical shift in global energy production and consumption is needed, involving reduced use of coal, oil, and natural gas. Reducing primary energy intensity is a significant way to reduce emissions and achieve climate targets, and it can be done by increasing energy efficiency [8]. Electrification using renewable energy is another direct alternative that is gaining traction. For oil-producing economies, many of which are controlled by a public sector that depends on oil exports and the money they generate, this would mean a 75 % drop in net revenues [9]. This makes it very evident that the stability of the world's energy markets as well as regional and international security may be severely impacted by an energy transition that ignores the demands of oil-rich countries.

Furthermore, the dependence on natural resources has been linked to economic and social sustainability challenges [10–12], but it can also exacerbate environmental concerns, such as waste and carbon emissions [13]. In relation to countries that are rich in fossil fuels, the logic of resource abundance deepens energy-environmental concerns [14]. Unlike other countries, the technological structure of their energy mix relies heavily on fossil fuels, and in some countries, such as Algeria, Iran, Qatar and Saudi Arabia, more than a quarter of production is used for subsistence needs. To theorize how the logic of abundance deepens energy-related environmental concerns, Friedrichs and Inderwildi [14] proposed the carbon curse theory. The theory embodies the causal mechanisms underlying carbon mitigation challenges in fossil fuel-rich countries and specifically highlights the impact of extractive industries, incentives for energy efficiency investment, structural weaknesses that stifle the development of green energy sources, and large and institutionalized subsidies for fuel consumption. Considering these factors collectively, it becomes evident that there is a pressing need for a more comprehensive examination of the role of economic dependence on natural resources, particularly in the context of fossil fuel-rich countries, within ongoing climate policy discussions.

This study utilizes the carbon curse theory as a foundation to investigate the influence of economic reliance on natural resources on concerns related to mitigating CO_2 emissions in oil-rich economies. The empirical process is guided by the following research questions:

(i) What are the underlying transmission mechanisms that explain the occurrence of the carbon curse anomaly in oil-rich economies?
(ii) At what threshold level of resource dependence does further extraction intensify the environmental impact?

To empirically verify these questions, we relate CO_2 emissions to the energy and carbon intensities of the consumption mix and use nonlinear equations to explain the role of natural resource abundance. The existing empirical literature on the carbon curse has made limited efforts to deepen our understanding of its underlying mechanisms. Many empirical tests have aggregated countries with varying degrees of resource dependence and different resource endowments [15,16]. Moreover, previous empirical literature has frequently focused on the broader objective of assessing the significance of natural resources in the context of carbon mitigation. As a result, the empirical findings have been inconsistent and distorted, leading to inconclusive policy recommendations. For instance, Xiaoman et al. [17] show that natural extraction reduces CO_2 emissions in the Middle East and North Africa (MENA) economies, while Zafar et al. [18] show that it increases CO_2 emissions in the Asian region. In fact, taking the United States and China out of context, only a few empirical studies can be identified in the specific context of the mechanisms underlying the carbon curse in oil-rich economies. Among these recent analyses are Mousavi et al. [19] and Anser et al. [20]. A better awareness of oil-rich economies and the obstacles they must overcome to maintain a balance between economic benefits and environmental concerns associated with natural resource dependence is necessary to facilitate sustainable transformation. Therefore, it is worthwhile to re-evaluate the case of oil-rich economies in light of the current emphasis on supply-side policies.

This study contributes to the literature in the following ways. First, to the best of our knowledge, it is the first empirical study to employ the Kaya identity equation in modelling the carbon curse, specifically in economies rich in oil resources. By utilizing an extended Kaya equation, we gain valuable policy insights and are able to examine the underlying mechanisms through which resource dependence influences CO_2 emissions. This includes the integration of factors such as energy efficiency, carbon intensity, and resource dependence into the CO_2 emissions model for oil-rich economies. Second, we go a step further to investigate the existence of a U-shaped curve between resource dependence and CO_2 emissions. Moreover, we estimate the threshold level of resource abundance beyond which natural resources trigger the carbon curse. This analysis provides an additional layer of understanding and allows for a more precise assessment of the relationship between resource dependence and CO_2 emissions. Such a potential threshold suggests that the carbon curse hypothesis may indeed exhibit nonlinearities in the relationship. For example, Chiroleu-Assouline et al. [15] show evidence of a U-shaped relationship between carbon intensity and natural resource abundance for developed countries. For oil-rich countries, determining such a threshold point is pertinent and can be helpful for designing both environment and resource management policies that are consistent with current climate change targets. This is expedient, as oil-rich countries face the risk of becoming "stranded nations" with stranded assets (i.e., resource assets becoming commercially unattractive) in the near future with the gradual shift towards green development and low carbon technologies [21].

The remainder of this study is organized as follows: in Section 2, a review of the related literature and theoretical background is provided. Section 3 then delves into the details of the model, data, and modelling strategies employed in this study. Moving on to Section 4, the study's findings and their subsequent discussion are presented, shedding light on important insights. Finally, Section 5 concludes the research by offering final thoughts on the policy implications and synthesizing the key takeaways.

2. Review of related literature

The first systematic discussion of anthropogenic drivers of environmental impact derived the IPAT identity and defined environmental impact (I) from the mathematical combination of population (P), affluence (A), and technology (T) as described in the prima-facie study of [22,23]. These drivers (PATs) can have an impact on the environment directly and can be shaped by other factors. Subsequent discussions have expanded the model to a much more complex set of impact frameworks. The environmental Kuznets curve (EKC) hypothesis assumes an important role for the affluence (A) factor in the impact equation. As captured in the work of Grossman and Krueger [24], the EKC model posits that environmental impact (degradation) declines with an increase in A once a threshold level is achieved, resulting in an inverted U-shaped curve [25]. The IPAT framework has been further developed through the Kaya identity equation, which posits that T is influenced by the technological composition of the energy mix, specifically, the energy intensity and carbon intensity of energy consumption [26,27]. The energy intensity (EI) trajectory focuses on the technological makeup of the energy mix by recognizing that greater energy conservation and economic efficiency can lead to reduced environmental impact of energy consumption [28]. The carbon intensity (CI) path underscores the carbon content of fossil fuels in the energy structure and the environmental balance that green energy sources can provide in the carbon mitigation model [29].

The abundance of fossil fuels is a crucial factor that shapes the technological structure of the energy mix [30]. From this aspect, Friedrichs and Inderwildi [14] proposed the carbon curse theory as an environmental extension of the resource curse anomaly, which provides theoretical underpinnings regarding social and economic challenges associated with dependence on natural resources [31]. The carbon curse theory postulates that fossil fuel abundance drives carbon intensity, making it difficult for countries naturally endowed with fossil fuels to control CO_2 emissions. To derive plausible explanations, Friedrichs and Inderwildi [14] implemented an exploratory data analysis involving 41 countries. The analysis suggests four underlying mechanisms. One is that the extraction of fossil fuels is associated with wasteful practices that contribute to CO_2 emissions, such as gas flaring. Second, overreliance on abundant fossil fuels stifles the development of green energy sources, leading to a carbon-intensive energy structure. Another is that economic reliance on fossil fuel rent weakens incentives to invest in energy efficiency. The fourth mechanism is through consumption subsidies, which encourage wasteful demands for fossil fuels. The combined effects of these factors make it certainly difficult for countries naturally endowed with fossil fuels to limit CO_2 emissions.

The testing of how economic dependence on natural resources shapes the CO_2 emissions mitigation model is a subject of recent empirical attention in the literature [15,17,20,23,32–34]. Indeed, few of these empirical attempts focused on the particular case of oil-rich economies or, more specifically, on the underlying mechanisms of the carbon curse theory. In particular, Anser et al. [20], Chiroleu-Assouline et al. [15], Wu et al. [34], Khan et al. [16] and Luo et al. [35] used different datasets to examine the causal mechanisms of the carbon curse. Utilizing a slack-based technique, Wang et al. [36] derived a measure of the carbon emissions efficiency of the energy structure in China from 2003 to 2016 and used the panel Tobit model to examine the direct and indirect impacts of resource dependence based on the output value of resource extractive sectors. Regarding the direct effect, their results suggest that resource dependence reduces the carbon emissions efficiency of the energy structure, and they showed that the higher the intensity of economic dependence on natural resources is, the lower the carbon emissions efficiency of the energy structure. The test for indirect causal mechanisms showed that resource dependence limits industrial structure transformation away from carbon-intensive sectors.

In a study conducted by Chiroleu-Assouline et al. [15], scholars empirically tested the carbon curse hypothesis from the perspective of the causal relationship between economic dependence on natural resource rents and the carbon emission intensity of GDP using a panel dataset of 29 developed countries spanning from 1995 to 2009. The results show a U-shaped relationship between the variables, suggesting that environmental concerns are aggravated by resource dependence only when a country reaches a certain level of dependence. Wu et al. [34] tested the hypothesis from the perspective of environmental concerns associated with energy endowment, relying on the causal impact of primary energy production on CO_2 emissions in 30 Chinese provinces from 2003 to 2017. The spatial Durbin analysis shows that energy endowment positively and significantly exacerbates environmental sustainability concerns in China. Luo et al. [35] used data from 250 peripheral Chinese cities spanning from 2000 to 2018 to examine the carbon curse from the perspective of the manufacturing sector's employment dependence on natural resources. It was established that resource dependence accelerates CO_2 emissions. Khan et al. [16] approached resource dependence from the perspective of rents from oil, coal, natural gas and minerals and tested their impact on CO_2 emissions using a global dataset of 115 countries from 1995 to 2018 and the two-stage GMM dynamic system technique. The results support the presence of the carbon curse anomaly in the panel.

Regarding the gains from energy efficiency and clean energy transition to climate targets, Jinapor et al. [37] determine whether energy efficiency is a significant factor in mitigating environmental concerns using data for 20 sub-Saharan African nations from 2000 to 2020. The results of the study based on the dynamic GMM demonstrate that energy efficiency is useful for lowering environmental pollution both directly and indirectly. The findings also demonstrate that the clean energy transition via the use of renewable energy has a positive environmental impact. Notably, the study discovers that energy efficiency and energy consumption interact to provide notable reductions in greenhouse gas emissions. Bargaoui [38] examines the effects of adopting energy efficiency and renewable energy initiatives on the CO2 emissions of 36 OECD nations between 2000 and 2019. The findings of the GMM model reveal that energy efficiency and renewable energy use reduce carbon emissions. Applying the bootstrap panel cointegration test and the PMG/ARDL estimation techniques to panel data of Africa's OPEC member countries, Iorember et al. [39] confirm that cleaner energy transition via increased renewable energy use mitigates climate change through a reduction in CO2 emissions, while nonrenewable energy consumption exerts upwards pressure on the environment. In another recent study by Nwani et al. [40], an extended Kaya identity framework was used to analyse trade-adjusted CO_2 emissions in Europe using a dataset spanning from 1995 to 2019. The findings of the study highlight the importance of a technological shift in the energy consumption mix towards renewables as the path to improving energy and carbon efficiency and, in turn, reducing CO_2 emissions. Similar conclusions have been drawn by previous studies conducted by Xu et al. [41] and Usman et al. [42].

In general, previous studies have produced mixed findings regarding the impact of natural resources on CO_2 emissions. This disparity can be attributed to several modelling considerations. One noticeable issue is the inclusion of countries with minimal or no resource dependence in panel data models, which may have introduced distortions or biases in the parameter estimates. Additionally, most of the studies have examined more general equations aimed at assessing the overall relevance of natural resources in the impact model rather than specifically designed to test the underlying mechanisms of the carbon curse observed in oil-rich economies. Consequently, there has been a lack of empirical focus on the role of energy transition paths in monitoring and advancing progress in climate mitigation. As a result, the present study makes a valuable contribution to the literature by addressing these gaps and providing meaningful insights.

3. Methodology

3.1. Specification of model

The impact of human activities on the environment is defined by the IPAT model, taking into account population size (P), affluence (A) and technology (T) [22,23]. Kaya [43] expanded the impact identity by suggesting two energy policy variables to measure the impact of technology: energy intensity (i.e., the amount of energy consumed per unit of GDP) and carbon intensity (i.e., the amount of CO2 emitted per unit of energy). These variables, when combined, result in the Kaya identity equation:

$$\text{Total CO}_2\text{ emissions} = \text{Population} \times \frac{\text{GDP}}{\text{Population}} \times \frac{\text{Energy use}}{\text{GDP}} \times \frac{\text{CO}_2\ Emissions}{\text{Energy use}} \tag{1}$$

where

$$\text{Affluence (Income per capita)} = \frac{\text{GDP}}{\text{Population}} \tag{2}$$

$$\text{Energy Intensity} = \frac{\text{Energy use}}{\text{GDP}} \tag{3}$$

$$\text{Carbon Intensity} = \frac{\text{CO}_2\ Emissions}{\text{Energy use}} \tag{4}$$

From a policy perspective, Equation (1) introduces the role of affluence (see Equation (2)) and the technological makeup of the energy consumption mix into the carbon mitigation model. The energy intensity of the consumption mix, as defined in Equation (3), is determined by the technologies used to promote energy conservation and efficiency, while the carbon intensity path, as defined in Equation (4), corresponds to the effects of relying solely on fossil fuels for energy. The stochastic formulation of Equation (1) is derived through algebraic manipulation in the following form:

$$lnI_{i,t} = \varphi_0 + \varphi_1 lnP_{i,t} + \varphi_2 lnA_{i,t} + \varphi_3 lnEI_{i,t} + \varphi_4 lnCI_{i,t} + \varepsilon_{i,t} \tag{5}$$

The variables are introduced in their natural logarithmic form represented by the notation "*ln*". Other notations in Equation (5) include "i, t" for country *ith* in year *t* and ε as the stochastic error term. φ_0 is the constant of the functional relationship, whereas $\varphi_1, \ldots, \varphi_4$ represent the elasticity coefficients of (P), GDP per capita (A), energy intensity (EI) and carbon intensity (CI), respectively, quantifying their impacts on CO_2 emissions (I). The model is extended in Equation (6) to account for the EKC hypothesis and the intensity of natural resource dependence:

$$lnI_{i,t} = \varphi_0 + \varphi_1 lnP_{i,t} + \varphi_{2A} lnA_{i,t} + \varphi_{2ASQ} lnASQ_{i,t} + \varphi_3 lnEI_{i,t} + \varphi_4 lnCI_{i,t} + \varepsilon_{i,t} \tag{6}$$

A valid inverted U-shaped relationship between affluence and CO_2 emissions exists if $\varphi_{2A} > 0$ and $\varphi_{2ASQ} < 0$. Other possible options will predict a deviation from the EKC hypothesis. Building on the carbon curse theory, it is expected that economic dependence on natural resources will adjust the carbon mitigation model from the technological structure of the energy consumption mix (EI and CI), giving its role in defining production and consumption patterns in oil-rich economies. Taking this into consideration, the following empirical model is further formulated:

$$TM_{i,t} = \delta_0 + \delta_1 ln\ P_{i,t} + \delta_{2A} lnA_{i,t} + \delta_{2ASQ} lnASQ_{i,t} + \delta_3 lnNR_{i,t} + \varepsilon_{i,t} \tag{7}$$

where *TM* is for the transmission mechanisms underlying the carbon curse anomaly as defined from the technological structure of the energy consumption mix. Specifically, *TM* is defined using EI and CI so that energy intensity and carbon intensity functions are estimated. NR is a measure of natural resource dependence with the elasticity coefficient δ_3 indicating the presence of the carbon curse or otherwise. To determine the intensity level of resource dependence that triggers the carbon curse, the functional relationship in Equation (7) is augmented with the quadratic term of the NR variable as follows:

$$TM_{i,t} = \delta_0 + \delta_1 lnP_{i,t} + \delta_{2A} lnA_{i,t} + \delta_{2ASQ} lnASQ_{i,t} + \delta_{3nr} lnNR_{i,t} + \delta_{3nrsq} lnNRSQ_{i,t} + \varepsilon_{it} \tag{8}$$

where *NRSQ* is the quadratic term, indicating a higher level of NR. A valid U-shaped relationship between TM and NRR exists if $\delta_{3nr} < 0$ and $\delta_{3nrsq} > 0$ and will indicate that the incidence of the carbon curse becomes stronger as the intensity of economic dependence on natural resources increases [15]. The turning point of this representation is obtained by setting the derivative of Equation (8) equal to zero, which yields $ln\ NR_t = -\delta_{3nr}/2\delta_{3nrsq}$.

3.2. Data

Time series data from 1994 to 2019 are used in this study. On the basis of data availability, we construct a panel consisting of 20 oil-rich countries (see Table A.1 in Appendix A) principally on the basis of data availability over the study period. The data were obtained from two sources:

- **Kaya Identity Dataset** compiled by ourworldindata.org.

Series from the dataset and their notations in this study include carbon dioxide emissions (**CO2**), population size (**POP**), GDP per capita (**GDPC**), energy intensity (**EI**) and carbon intensity (**CI**).

- **World Development Indicators (WDI)** Dataset compiled by the World Bank

Series from the dataset include total natural resource rents (% of GDP) (**NR**), a measure of the intensity of economic dependence on natural resources, including rents from oil, coal, natural gas, minerals and forest resources.

Table 1 presents the computational definitions of the variables, summary statistics and sources of the data. The correlation matrix in Panel An of Table A1 (see Appendix A) describes the degree of linear relationship between the variables. The low (weak) correlation coefficients between explanatory variables are of particular importance since they imply that these variables may consistently model changes in CO_2 emissions in the selected countries without introducing multicollinearity bias.

3.3. Estimation techniques

Given longer time dimensions (T) and lower cross-section dimensions (N), that is, [T > N], a series of macro panel techniques are designed to aid in the estimation process.

3.3.1. Data screening

The first point of call is the data screening, which encapsulates preliminary test checks for cross-section dependence (CD) in the data series of the variables using the Pesaran [44,45] approach. This method is utilized to confirm the presence of CD in accordance with the hull hypothesis: $H_o : \widehat{p}_{ik} = corr(\epsilon_{it}\epsilon_{kt}) = 0 \forall i \neq k$ based on the specification in Equation (9):

$$CSD = \sqrt{\frac{2T}{n(n-1)}} \left(\sum_{i=1}^{n-1} \sum_{k=i+1}^{n} \widehat{p}_{ik} \right) \sim n(0,1)\ i,k \tag{9}$$

$T = (1994, \ldots\ldots\ldots\ldots 2019)$, n is the number of cross-sections, that is, 20 oil-rich countries. $\widehat{p}_{ik}$ is a component that introduces the ADF in the pairwise cross-sectional dependency.

The second preliminary test checks for the presence of slope heterogeneity in the panel equations using the Pesaran and Yamagata (2008) testing approach. The test is based on the specification in Equation (10):

Table 1
Summary, definition and data sources.

Notation	Definition	Mean	Median	Maximum	Minimum	Std. Dev.	Obs
I	Carbon dioxide emissions in tonnes	107000000	53533445	733000000	76944	142000000	520
P	Population, total	25171600	14918019	201000000	479099	36114092	520
A	GDP per capita in 2011 international-$ PPP	22552.190	11629.930	156299.000	1120.848	27079.470	520
EI	Energy Intensity: primary energy consumption per unit of GDP measured in kilowatt-hours per international-$	2.085	1.601	18.355	0.141	2.132	520
CI	Carbon Intensity: CO_2 in kilograms per kilowatt-hour of primary energy consumption	0.252	0.236	1.633	0.085	0.114	520
NR	Total natural resources rents (% of GDP)	27.810	26.640	67.890	0.786	15.358	520

Data Sources.
•**CO2, POP, GDPC, EI** and **CI** were obtained from the Kaya identity dataset compiled by ourworldindata.org from Global Carbon Project; UN; BP; World Bank; Maddison Project Database. Available online at: https://ourworldindata.org/grapher/kaya-identity-co2?country=~Africa.
•**NR** were obtained from the World Development Database, available online at https://data.worldbank.org.

$$\left(\widehat{\Delta}_{SH}\right) = (N)^{\frac{1}{2}}(2k)^{-\frac{1}{2}}\left(\frac{1}{N}\overline{S} - k\right); \ \left(\widehat{\Delta}_{ASH}\right) = (N)^{\frac{1}{2}}\left(\frac{2k(T-k-1}{T+1}\right)^{-\frac{1}{2}}\left(\frac{1}{N}\overline{S} - 2k\right) \tag{10}$$

The delta tilde and adjusted delta tilde statistics, denoted by $\widehat{\Delta}_{SH}$ and $\widehat{\Delta}_{ASH}$, are utilized to test the null hypothesis of homogeneity in the slope coefficients. Pesaran [46] cross-sectional augmented Im–Persaran–Shin (CIPS) test is used for a third preliminary test to confirm the unit root properties of the variables. Nonstationarity is assumed in the formulation of the equation.

$$\Delta Y_{it} = \omega_i + \rho_i^* Y_{i,t-1} + d_0 \overline{Y}_{t-1} + \sum_{j=0}^{p} d_{ij} \Delta \overline{Y}_{t-j} + \sum_{j=1}^{p} c_{ij} \Delta Y_{i,t-j} + \varepsilon_{it} \tag{11}$$

The case variable and the difference operator are represented by Y and Δ, respectively. Equation (11) is used to calculate the CIPS statistics as defined in Equation (12):

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i \tag{12}$$

To mitigate the impact of extreme outcomes caused by insufficiently large T, the adjusted or truncated version of the CIPS statistic (i.e., CIPS-TR) is computed. The formula for CIPS-TR is given in Equation (13):

$$CIPS - TR = \frac{1}{N}\sum_{i=1}^{N} CADF_i^* \tag{13}$$

3.3.2. *Test for cointegration*

Using the error-correction-based panel cointegration tests developed by Westerlund [47], we examine the following equation to see if the variables are linked over the long run:

$$\Delta Y_{i,t} = \gamma_i^{'} d_t + \alpha_i \left(Y_{i,t-1} - \beta_i^{'} X_{i,t-1}\right) + \sum_{m=1}^{k} \partial_{im} \Delta Y_{i,t-m} + \sum_{m=1}^{k} \varphi_{im} \Delta X_{i,t-m} + \varepsilon_{it} \tag{14}$$

where α_i is the speed of adjustment towards correction into a stable state. The dependent and independent variables are $Y_{i,t}$ and $X_{i,t}$, respectively. We expect to obtain four different test statistics from Equation (14) as follows:

$$G_t = \frac{1}{N}\sum_{i=1}^{N} \frac{\widehat{\alpha}_i}{se(\widehat{\alpha}_i)} \tag{15}$$

$$G_a = \frac{1}{N}\sum_{i=1}^{N} \frac{T\widehat{\alpha}_i}{1 - \sum_{m=1}^{K} \alpha_{im}^{'}} \tag{16}$$

$$P_t = \frac{\widehat{\alpha}}{se(\widehat{\alpha})} \tag{17}$$

$$P_a = P\widehat{\alpha} \tag{18}$$

Under the hull hypothesis of no cointegration, the group statistics defined as G_t in Equation (15) and G_a in Equation (16) test the existence of cointegration in at least one cross-sectional group, while the panel statistics, P_t and P_a, as defined in Equations (17) and (18) respectively, pool information over all the cross-sectional units to test for the existence of cointegration in the entire panel.

3.3.3. *Regression technique*

The parameters of the specified models are estimated using the mean group (MG) estimator developed by Pesaran and Smith [48] and the more robust augmented mean group (AMG) estimator by Eberhardt and Teal [49]. Both MG and AMG estimators allow for heterogeneous slope coefficients across panel groups. However, the MG cannot handle issues created by the unobserved correlation across panel groups (cross-section dependence). Thus, this study relies on the AMG estimator, which is augmented with additional capabilities to resolve issues created by cross-section dependence. The AMG estimator uses a first difference estimate of a pooled regression model with time dummies [49]. It starts with the implementation of Equation (19):

$$Y_{it} = \omega_i + \rho_i^* \Delta Y_{i,t} + \tau_I \delta_t + \sum_{t-1}^{T} \varnothing_t D_t + \varepsilon_{it} \tag{19}$$

The slope is represented by ρ_i^*, while δ_t and τ_I denote the unobserved common factor and the heterogeneous factor loadings, respectively. The year dummies (D_t) and their coefficients ($\varnothing_t$) are also included. In the last phase of the estimation process, the model parameters specific to each group are averaged across the panel based on the definition in Equation (20):

$$AMG = \frac{1}{N}\sum_{i=1}^{N}\widehat{\alpha}_i \tag{20}$$

4. Analysis and discussion of findings

4.1. Data and model screening

The outcomes of a cross-sectional dependence test are shown in Table 2. The test statistics reject the null hypothesis of cross-sectional independence for lnI, lnP, lnA, lnEI and lnNR, suggesting that the data series are cross-sectionally dependent. However, the null hypothesis is not rejected for the lnCI series. Table 3 reports the results of the slope homogeneity test based on the Pesaran and Yamagata [50] test. The test statistics indicate a rejection of the null hypothesis of homogeneity of the slope coefficients in all equations, implying that the slope coefficients of the model specifications are heterogeneous. Since the data series of the variables are cross-sectionally dependent, we test for the integrating properties of the variables in the presence of cross-sectional dependence using a second-generation panel unit root testing technique. Specifically, we employ the CIPS test by Pesaran [46], relying on the more robust truncated statistics. Table 4 presents findings indicating that when cross-sectional dependence is present, the variables are nonstationary in terms of their levels. Nevertheless, they attain stationarity when analysed in their first differences, meaning that the variables are characterized by an I(1) process.

The variance inflation factors (VIFs) test is used to screen the models for multicollinearity bias (see results in Panel B of Table A2 in Appendix A). The presence of multicollinearity is rejected by both VIF and mean VIF estimates, showing that the models are consistent and likely to produce unbiased explanations for climate mitigation challenges in oil-rich countries. Having established that the variables follow the I(1) process, we proceed to examine whether there is cointegration among the variables. We utilize the panel cointegration test proposed by Westerlund [47] to assess the presence of cointegration. The findings, presented in Table 5, indicate the existence of panel cointegration (as indicated by Pa and Pt statistics) in the Kaya identity equation, regardless of any modifications made to the combination of variables. There is also cointegration in the carbon intensity model specifications. For the EI model specifications, the test statistics show no significant panel cointegration. To ensure the robustness of the parameter estimates, we rely on the AMG estimator, which performs well in panels with nonstationary variables (cointegrated or not) and multifactor error terms (cross-section dependence) with the common dynamic process imposed with a unit coefficient.

4.2. Results of the extended kaya equations

The elasticity coefficients from the specifications are presented in Table 6. From the AMG estimates of the Kaya identity equation (see column 2), a percentage increase in the population size increases CO_2 emissions in the selected oil-rich countries by 0.91 %. This finding, in line with theoretical expectations [51], indicates that population growth makes a significant contribution to CO_2 emissions in countries. The results also show that a percentage increase in per capita GDP (A) increases CO_2 emissions in the countries by 0.96 % (based on AMG estimates of the Kaya equation, column 2). The extended specification in column 4 shows that the coefficient of the quadratic term, ASQ, is negatively associated with CO_2 emissions but not statistically significant. These parameter estimates show that the EKC hypothesis is not valid for this selection of oil-rich economies. Algebraically, the estimates indicate a monotonically increasing linear impact, suggesting that rising per capita GDP is related to rising levels of CO_2 emissions [25]. By implication, using economic policies to tackle growth in CO_2 emissions in oil-rich economies might be ineffective and might not yield the desired results.

The elasticity coefficient of EI is positive and statistically significant and indicates that a percentage increase in energy intensity increases CO_2 emissions by 0.97 % (see column 2). The finding resonates with the study of Murshed et al. [28] on the energy intensity (EI) path tracks from the perspective that allowing for greater energy conservation and economic efficiency reduces the environmental impact of energy consumption. This could also be interpreted to mean a 0.97 % decrease in CO_2 emissions for a percentage increase in energy efficiency. This finding underscores the role of the UN SDG 7.3 target of accelerating efforts toward energy efficiency in the mitigation of CO_2 emissions in oil-rich economies. This finding also aligns with the finding of De La Pe~na et al. [29], who accentuate the path of carbon content fuels in the energy structure and the environmental balance that green energy sources provide in the carbon mitigation model. Another transitional path to sustainable development is to improve the carbon efficiency of the energy consumption

Table 2
Cross-section dependence test.

Variable	CD-test	p-value	average joint T	mean ρ	mean abs(ρ)
lnI	41.914***	0.000	26	0.60	0.67
lnP	65.492***	0.000	26	0.93	0.93
lnA	44.199***	0.000	26	0.63	0.84
lnASQ	44.032***	0.000	26	0.63	0.84
lnEI	20.36***	0.000	26	0.29	0.70
lnCI	−0.027	0.979	26	0.00	0.27
lnNR	47.827***	0.000	26	0.68	0.68
lnNRSQ	46.906***	0.000	26	0.67	0.67

The notation *** signifies significance at the 1 % level.

Table 3
Slope heterogeneity test.

Model Specifications	Delta tilde ($\widetilde{\Delta}$)	*P*-value	Adjusted delta tilde ($\widetilde{\Delta}_{Adj}$)	*P*-value
1. Kaya Identity	7.833***	0.000	8.930***	0.000
2. Kaya Identity extended with EKC	7.135***	0.000	8.346***	0.000
3. EI model	23.914***	0.000	27.266***	0.000
4. EI model with quadratic term	18.729***	0.000	21.910***	0.000
5. Robustness: lnCO2 - NR for EI	19.522***	0.000	22.837***	0.000
6. Robustness: lnCO2 - NR for EI Quadratic	15.360***	0.000	18.460***	0.000
7. CI Model	23.914***	0.000	27.266***	0.000
8. CI model with quadratic term	18.729***	0.000	21.910***	0.000
9. Robustness: lnCO2 - NR for CI	11.166***	0.000	13.062***	0.000
10. Robustness: lnCO2 - NR for CI Quadratic	9.537***	0.000	11.462***	0.000

The notation *** signifies significance at the 1 % level.

Table 4
CD augmented Panel Unit Root Tests.

Variable	CIPS				CIPS-TR			
	Level I(0)		First Difference I(1)		Level I(0)		First Difference I(1)	
	Constant	Intercept and Trend	Constant	Intercept and Trend	Constant	Intercept and Trend	Constant	Intercept and Trend
lnI	−2.989	−2.906	−4.420***	−5.056***	−2.976	−2.893	−4.363***	−5.000***
lnP	−2.748	−4.301	−5.149***	−6.871***	−2.280	−3.663	−3.938***	−4.838***
lnA	−3.123	−2.653	−3.382***	−3.483***	−3.123	−2.653	−3.314***	−3.436***
lnASQ	−3.144	−2.629	−3.386***	−3.521***	−3.144	−2.629	−3.321***	−3.476***
lnEI	−2.128	−2.285	−4.354***	−4.847***	−2.128	−2.285	−4.256***	−4.775***
lnCI	−2.438	−3.08	−5.164***	−5.342***	−2.438	−3.08	−5.038***	−5.241***
lnNR	−1.668	−2.676	−5.145***	−5.168***	−1.668	−2.676	−4.660***	−4.685***
lnNRSQ	−1.777	−2.612	−5.139***	−5.059***	−1.777	−2.612	−4.671***	−4.617***

The notation *** signifies significance at the 1 % level.

Table 5
Cointegration tests.

Model considerations		Gt	Ga	Pt	Pa
1. Kaya Identity	Value	−1.034	−6.587	−9.168	−10.600**
	Robust p-value	(0.800)	(0.340)	(0.320)	(0.030)
2. Kaya Identity extended with EKC	Value	−1.732	−10.575***	−13.600***	−15.185***
	Robust p-value	(0.620)	(0.000)	(0.000)	(0.000)
3. EI model	Value	−3.495***	−6.195	−7.767	−2.016
	Robust p-value	(0.000)	(0.720)	(0.560)	(0.880)
4. EI model with quadratic term	Value	−3.325***	−4.400	−7.337	−1.495
	Robust p-value	(0.000)	(0.960)	(0.700)	(0.960)
5. Robustness: lnCO2 - NR for EI	Value	−2.492	−4.043	−10.946***	−2.599
	Robust p-value	(0.120)	(0.960)	(0.010)	(0.540)
6. Robustness: lnCO2 - NR for EI Quadratic	Value	−3.737***	−1.848	−10.058**	−0.992
	Robust p-value	(0.000)	(0.980)	(0.50)	(0.960)
7. CI Model	Value	−3.676***	−3.137	−13.023***	−3.899
	Robust p-value	(0.000)	(0.980)	(0.000)	(0.800)
8. CI model with quadratic term	Value	−3.962***	−4.846	−12.579***	−3.406
	Robust p-value	(0.000)	(0.920)	(0.000)	(0.860)
9. Robustness: lnCO2 - NR for CI	Value	−3.932***	−5.552	−10.636**	−3.379
	Robust p-value	(0.000)	(0.800)	(0.030)	(0.500)
10. Robustness: lnCO2 - NR for CI Quadratic	Value	−3.747***	−5.213	−12.992***	−3.999
	Robust p-value	(0.000)	(0.980)	(0.000)	(0.880)

Note: *P*-values reported here are robust and were obtained through the use of bootstrap replications of critical values notation *** denotes statistical significance at the 1 % level, ** indicates significance at the 5 % level, while * signifies significance at the 10 % level.

mix [36]. The results show that a percentage increase in the carbon intensity of the energy mix increases CO_2 emissions by 0.99 % (based on the Kaya equation in column 2). This could also be interpreted as a 0.99 % decrease in CO_2 emissions for a percentage increase in the carbon emission efficiency of the energy consumption mix. This finding is consistent with the objective of the UN SDG 7.2 target, which aims to increase the proportion of renewable energy in the overall energy mix. It also aligns with the conclusion drawn by Nwani et al. [40] regarding the carbon intensity path to addressing climate challenges. This emphasizes the significance of transitioning towards renewable energy sources as a crucial approach to mitigating climate challenges. Taking a comparative look at

Table 6
Results of the extended Kaya equations.

Variables	Mean Group (MG) Estimator		Augmented Mean Group (AMG) Estimator	
	(1)	(2)	(3)	(4)
	Kaya Identity	Kaya identity with EKC	Kaya Identity	Kaya identity with EKC
lnP	0.946***	0.907***	0.986***	0.934***
	(0.032)	(0.036)	(0.067)	(0.062)
	[29.303]	[24.892]	[14.629]	[15.054]
lnA	0.979***	0.959***	0.935***	1.187***
	(0.024)	(0.244)	(0.027)	(0.249)
	[41.033]	[3.938]	[34.245]	[4.775]
lnASQ		0.003		−0.017
		(0.011)		(0.011)
		[0.241]		[-1.492]
lnEI	0.974***	0.967***	0.964***	0.956***
	(0.018)	(0.033)	(0.031)	(0.038)
	[53.931]	[29.605]	[30.874]	[25.341]
lnCI	0.988***	0.988***	0.968***	0.973***
	(0.006)	(0.007)	(0.010)	(0.010)
	[157.066]	[143.630]	[99.729]	[94.575]
Constant	−5.864***	−4.995**	−6.231***	−6.752***
	(0.617)	(2.329)	(0.897)	(2.286)
	[-9.511]	[-2.145]	[-6.948]	[-2.954]
Observations	520	520	520	520
Number of ID	20	20	20	20

The standard errors are enclosed in parentheses (), while the t-statistics are enclosed in square brackets []. Please take note that the notation *** indicates statistical significance at the 1 % level, ** indicates significance at the 5 % level, and * signifies significance at the 10 % level.

the parameter estimates of the Kaya identity equation in column 2, it is evident that the technological structure of the energy mix remains a key contributor to the growth in CO_2 emissions in the selected oil-rich countries.

4.3. Results of the mechanisms underlying the carbon curse

Next, we test for the transmission mechanisms underlying the carbon curse anomaly based on the technological structure of the

Table 7
Energy intensity channel of the carbon curse hypothesis.

Variables	Transmission Mechanism = EI				Robustness check (I = lnCO2)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MG	MG	AMG	AMG	MG	MG	AMG	AMG
lnP	0.060	0.040	−0.108	−0.144	0.978***	0.969***	0.980***	0.986***
	(0.190)	(0.196)	(0.217)	(0.224)	(0.176)	(0.184)	(0.208)	(0.211)
	[0.315]	[0.203]	[-0.496]	[-0.644]	[5.551]	[5.255]	[4.713]	[4.665]
lnA	−2.794	−2.663	−1.871	−1.769	−1.231	−1.142	0.822	0.701
	(2.293)	(2.389)	(2.423)	(2.330)	(1.769)	(1.769)	(1.736)	(1.933)
	[-1.218]	[-1.115]	[-0.772]	[-0.759]	[-0.696]	[-0.645]	[0.474]	[0.362]
lnASQ	0.122	0.112	0.077	0.070	0.098	0.094	−0.016	−0.010
	(0.117)	(0.121)	(0.128)	(0.122)	(0.097)	(0.097)	(0.094)	(0.103)
	[1.042]	[0.924]	[0.600]	[0.573]	[1.014]	[0.965]	[-0.170]	[-0.095]
lnCI					0.711***	0.718***	0.737***	0.750***
					(0.072)	(0.073)	(0.077)	(0.080)
					[9.838]	[9.774]	[9.562]	[9.392]
lnNR	−0.004	0.171	−0.076***	0.088	−0.010	−0.056	−0.026	−0.015
	(0.023)	(0.165)	(0.021)	(0.204)	(0.016)	(0.106)	(0.017)	(0.168)
	[-0.165]	[1.034]	[-3.521]	[0.433]	[-0.594]	[-0.529]	[-1.567]	[-0.089]
lnNRSQ		−0.021		−0.023		0.010		0.006
		(0.024)		(0.031)		(0.018)		(0.026)
		[-0.866]		[-0.732]		[0.570]		[0.236]
Constant	14.973	15.822	8.163	6.856	3.997	3.740	−5.221	−4.449
	(12.033)	(12.612)	(10.034)	(9.400)	(10.268)	(10.404)	(8.686)	(9.200)
	[1.244]	[1.255]	[0.813]	[0.729]	[0.389]	[0.359]	[-0.601]	[-0.484]
Observations	520	520	520	520	520	520	520	520
Number of ID	20	20	20	20	20	20	20	20

The standard errors are enclosed in parentheses (), while the t-statistics are enclosed in square brackets []. Please take note that the notation *** indicates statistical significance at the 1 % level, ** indicates significance at the 5 % level, and * signifies significance at the 10 % level.

energy consumption mix of the countries in the panel. The results presented in Table 7 test the carbon curse hypothesis from the perspective that resource dependence inhibits energy efficiency and conservation. The elasticity coefficient of NR in column 3 is negative and statistically significant at the 1 % level but returns an insignificant coefficient when the square term, NRSQ, is included in the model (see column 4). To ensure robustness, we introduce NR for EI in the Kaya identity equation. The results of these extended specifications in columns 5–8 also indicate that NR has a statistically insignificant effect. Based on these results, we can conclude that economic dependence on resource extraction does not transmit the carbon curse through the energy intensity channel in the panel. Also important are the statistically insignificant coefficient estimates of A and ASQ in columns 1–4. By implication, growth in affluence has no effect on enhancing energy efficiency in the selected oil-rich economies. However, such evidence should be interpreted with caution, as higher income growth can influence energy efficiency and, in turn, reduce a country's carbon footprint with the shift towards low-carbon technologies. Moreover, economic development, as often proxied by income per capita, is a constellation of several other driving elements (e.g., institutional quality, physical infrastructure, financial markets, human capital). Which, in conjunction with higher income, can have diverging environmental effects [52]. These subtleties make it difficult to detect the true causal relationship between income growth and the environment; hence, there is limited consensus on the empirical validity of the EKC hypothesis [53].

The results presented in Table 8 test the carbon curse hypothesis from the perspective of the causal impact of resource dependence on the carbon intensity of the energy mix. The coefficient estimates of NR in columns 1 and 3 are positive and statistically significant. The quadratic term, NRSQ, is introduced into the model to check the shape of the curve between NR and CI. The results in columns 2 and 4 are statistically insignificant for NR and a statistically positive coefficient for NRSQ. These results are consistent with the study conducted by Wang et al. [36], which demonstrated that resource dependence is associated with higher carbon intensity in China. Similarly, Chiroleu-Assouline et al. [15] observed a similar trend in a panel of developed economies. However, the extended model specifications (see columns 2 and 4) show that resource dependence increases the carbon intensity of the energy mix only after a turning point level of resource extraction. This finding aligns with the finding of Wu et al. [34], who show that energy endowment has greatly increased carbon emissions and that the 'resource curse' phenomenon is present in the context of carbon emissions in China's 30 provinces. Clearly, lower degrees of dependence on resource extraction, as denoted by the coefficient of NR (see columns 2 and 4), have a statistically insignificant impact on the CI. Thus, the carbon curse anomaly only appears at higher levels of resource extraction.

Still on the parameter estimates in Table 8, the CO_2 emissions model is adjusted by introducing NR for CI in the Kaya identity equation. The results of these extended specifications in columns 5–8 indicate that NR has a statistically significant negative coefficient, while the quadratic term, NRSQ, has a statistically significant positive coefficient. Relying on the more robust AMG estimator, a percentage increase in the intensity of economic dependence on natural resource rents leads to a 0.34 % decrease in CO_2 emissions at lower levels of extraction. The curve reverses at a turning point level of NR, and further increases in resource extraction generate a

Table 8
Carbon intensity channel of the carbon curse hypothesis.

Variables	Transmission Mechanism = CI				Robustness check (I = lnCO2)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MG	MG	AMG	AMG	MG	MG	AMG	AMG
lnP	0.097	0.112	0.293	0.334	0.944***	0.995***	1.152***	1.178***
	(0.171)	(0.176)	(0.223)	(0.217)	(0.176)	(0.189)	(0.174)	(0.192)
	[0.566]	[0.637]	[1.314]	[1.540]	[5.356]	[5.261]	[6.638]	[6.144]
lnA	3.271	2.949	0.376	0.728	−0.734	−0.943	2.104	1.979
	(3.390)	(3.374)	(3.095)	(3.119)	(1.922)	(1.986)	(1.921)	(1.572)
	[0.965]	[0.874]	[0.122]	[0.233]	[-0.382]	[-0.475]	[1.095]	[1.259]
lnASQ	−0.167	−0.143	0.025	−0.000	0.074	0.078	−0.065	−0.087
	(0.173)	(0.172)	(0.143)	(0.149)	(0.094)	(0.097)	(0.094)	(0.070)
	[-0.966]	[-0.833]	[0.173]	[-0.003]	[0.788]	[0.803]	[-0.694]	[-1.255]
lnEI					0.305***	0.343***	0.202***	0.203***
					(0.070)	(0.063)	(0.068)	(0.070)
					[4.345]	[5.414]	[2.980]	[2.901]
lnNR	0.055*	−0.263	0.121***	−0.474	0.016	−0.365***	0.048**	−0.340**
	(0.031)	(0.220)	(0.035)	(0.336)	(0.018)	(0.117)	(0.024)	(0.156)
	[1.795]	[-1.196]	[3.448]	[-1.412]	[0.888]	[-3.121]	[2.042]	[-2.182]
lnNRSQ		0.059*		0.110**		0.072***		0.068***
		(0.035)		(0.053)		(0.022)		(0.025)
		[1.658]		[2.079]		[3.269]		[2.708]
Constant	−15.312	−13.481	−11.095	−11.500	2.066	3.850	−12.540	−10.959
	(16.816)	(15.935)	(17.022)	(16.321)	(11.183)	(11.696)	(9.435)	(8.853)
	[-0.911]	[-0.846]	[-0.652]	[-0.705]	[0.185]	[0.329]	[-1.329]	[-1.238]
Threshold ($-\delta_{3nr}/2\delta_{3nrsq}$)	–	2.229	–	2.155	–	2.535	–	2.500
Threshold (Total natural resources Rents as % of GDP	–	9.290	–	8.624	–	12.613	–	12.182
Observations	520	520	520	520	520	520	520	520
Number of ID	20	20	20	20	20	20	20	20

The standard errors are enclosed in parentheses (), while the t-statistics are enclosed in square brackets []. Please take note that the notation *** indicates statistical significance at the 1 % level, ** indicates significance at the 5 % level, and * signifies significance at the 10 %.

0.07 % increase in CO_2 emissions. These findings indicate a U-shaped relationship between NR and CO_2 emissions similar to the shape of the curve Chiroleu-Assouline et al. [15] identified from a panel of developed economies. By implication, the undiversified and fossil fuel-reliant energy structure (i.e., the carbon emission intensity of the energy mix) is confirmed as the mechanism underlying the carbon curse anomaly in this selection of oil-rich countries. The results in Table 8 are therefore consistent with the exploratory data evidence by Friedrichs and Inderwildi [14] on the carbon curse anomaly in oil-rich countries. A similar finding was also documented by Khan et al. [16] from a global sample.

One interesting component of the results in Table 8 is the U-shaped relationship between economic dependence on resource extraction and CO_2 emissions. This suggests that environmental concerns are aggravated by resource dependence only when a country reaches a certain level of dependence. The turning point of 12.18 % of GDP is estimated as the threshold level of rents at which further extraction of natural resources triggers the carbon curse. This additional empirical insight explains why empirical findings from previous studies using panel selection of countries with different degrees of resource dependence and from different resources have remained inconclusive in their policy recommendations. For countries below the threshold rent of 12.18 % of GDP, the economic contribution of natural resource extraction also supports environmental sustainability by reducing CO_2 emissions. As economic dependence on natural resource extraction increases, the possibility of the carbon curse intensifies until the turning point is reached.

Relying on the threshold natural resource rents of 12.18 % of GDP, we can assess the vulnerability of the countries in the panel to the carbon curse anomaly. As shown in Table 9, the ratio of natural resource rents to GDP in Nigeria, Yemen, Bahrain, Kazakhstan, the United Arab Emirates, Algeria, Iran, Qatar, Gabon, Angola, Equatorial Guinea, Oman, Saudi Arabia, Congo Republic, Iraq, Kuwait and Libya are on average higher than the threshold rent of 12.18 % of GDP, indicating that resource abundance has triggered the carbon curse anomaly in these oil-rich economies. There is also an indication that further extraction of natural resources may trigger the carbon curse in Ecuador. From a policy perspective, these countries can break the carbon curse anomaly by adjusting the technological structure of the consumption mix towards a less carbon-intensive energy structure, particularly by replacing fossil fuels with renewable energy sources.

5. Conclusion and policy remarks

This study examined the potential transmission mechanism underlying the carbon curse hypothesis by analysing a panel of 20 oil-rich countries from 1994 to 2019. Relying on the Kaya identity framework for empirical model formulation, the study examined how economic dependence on natural resources impacts CO_2 emissions. The empirical exploration relates the technological features of the energy structure using intensity metrics that specify the economic and carbon makeup of the consumption mix. To account for potential nonlinear relationships within the panel dataset, the study conducted further tests to identify the turning point level of resource dependence. This turning point indicates the threshold at which additional resource extraction intensifies environmental impact. The study employed the augmented mean group (AMG) estimator to ensure robust parameter estimates that account for cross-sectional

Table 9
Countries' vulnerability to the carbon curse.

Threshold Natural Resources Rents: 12.182 % of GDP:					
Countries	Total natural resources rents (% of GDP) Average NRR 1994–2019	Countries	Total natural resources rents (% of GDP) Average NRR 1994–2005	Countries	Total natural resources rents (% of GDP) Average NRR 2006–2019
Syria	5.871	Syria	5.012	Syria	6.607
Egypt	8.754	Egypt	8.312	Egypt	9.133
Ecuador	10.608	Ecuador	9.709	Ecuador	11.378
Nigeria	14.786	Kazakhstan	16.109	Nigeria	12.682
Bahrain	18.476	Nigeria	17.240	Yemen	16.848
Kazakhstan	18.869	Bahrain	18.221	Bahrain	18.695
United Arab Emirates	20.180	United Arab Emirates	18.342	Kazakhstan	21.236
Algeria	22.525	Algeria	20.324	United Arab Emirates	21.755
Iran	24.377	Iran	23.134	Algeria	24.411
Yemen	25.224	Gabon	29.321	Iran	25.443
Gabon	29.073	Qatar	33.936	Qatar	28.114
Qatar	30.801	Saudi Arabia	34.167	Gabon	28.860
Angola	34.992	Yemen	34.996	Angola	31.460
Oman	36.149	Libya	36.220	Equatorial Guinea	34.370
Saudi Arabia	36.753	Oman	36.350	Oman	35.978
Congo	41.709	Angola	39.112	Saudi Arabia	38.970
Equatorial Guinea	42.781	Congo	41.764	Congo	41.662
Libya	43.219	Kuwait	42.023	Iraq	45.358
Kuwait	44.800	Iraq	47.315	Kuwait	47.181
Iraq	46.261	Equatorial Guinea	52.594	Libya	49.217

dependence and allow for heterogeneous slope coefficients, thereby preventing skewed parameter values. The key findings of the study can be summarized as follows:

- Both energy intensity and carbon intensity have a positive effect on carbon emissions, which suggests that the adoption of energy efficiency technologies and improving carbon efficiency in the energy consumption mix can help mitigate further global warming caused by carbon emissions;
- Natural resource dependence is associated with an increase in the carbon intensity of the energy mix only beyond a turning point level of resource extraction. In other words, natural resource dependence is associated with the carbon curse hypothesis only at higher levels of resource extraction, which lends support to the feasibility of the carbon intensity channel of the carbon curse;
- There is a U-shaped relationship between natural resource dependence and CO_2 emissions with the threshold level natural rents to GDP ratio estimated at 12.18 %. This means that beyond the threshold, natural resource extraction will trigger the carbon curse;
- Excluding Syria, Egypt and Ecuador, all other countries in the sample have natural resource rents beyond the threshold of 12.18 % GDP share, which suggests the validity of the carbon curse hypothesis.

These findings have policy implications for shaping climate and sustainable development actions in the post-COP26 era. First, taking natural resource abundance as a key variable in climate policy considerations can help draw our attention to the specific challenges of decarbonizing energy structures in oil-rich economies. Instead of dividing the world into industrialized and developing nations based on climate, it would be more effective to organize and coordinate post-COP26 actions based on each country's relative reliance on its natural resource endowment. Second, the vulnerability assessment of the countries in the panel studied shows that Nigeria, Yemen, Bahrain, Kazakhstan, United Arab Emirates, Algeria, Iran, Qatar, Gabon, Angola, Equatorial Guinea, Oman, Saudi Arabia, Congo Republic, Iraq, Kuwait, and Libya are already within the carbon curse zone. Therefore, structural diversification should be a priority for scaling up climate action in these countries. Unfortunately, the mechanisms that underlie these countries' vulnerability to the carbon curse are defined by economic and institutional incentives that can combine to hinder structural diversification. As a result, scaling up climate action in these countries will require a radical change in the incentive structure of political leaders and economic stakeholders.

Third, targeted efforts should be made to deepen energy transitions in oil-rich economies. This typically requires two major technological changes: one, a technological shift away from fossil fuels to renewable energy sources; and two, extensive adoption of energy efficiency and conservation mechanisms. For this purpose, a well-structured transition strategy designed to progressively abandon the current development paradigm that prioritizes the exploitation of natural resources at the expense of the environment is urgently needed. The target should be to create green development paradigms that support low-carbon transition and environmental sustainability. There are a number of policy steps to be considered in this regard. The first step is to discourage the further inflow of new investment projects in the fossil fuel sectors. Rather, all new investment initiatives should be directed towards expanding investment in modern renewable technologies such as solar and wind power that promote green growth. The subsequent stage involves launching broad-based energy conservation initiatives and incentives aimed at heightening awareness of energy efficiency across industrial, residential, and commercial domains. The third step is to optimize and upgrade the industrial structure to the technologically driven sectors that require less energy and create more reliance on renewable energy sources. For these policy steps to yield the desired results, oil-rich economies must end fossil fuel consumption subsidies and make a more dramatic transition by imposing carbon taxes. In addition, countries should make efforts to reduce flaring and other sources of extractive emissions by tightening environmental regulations and enforcement and by requiring energy exploration companies to use flare recovery technologies that offer environmental and economic efficiencies.

One notable limitation of this study is the exclusion of developed oil-rich economies from the panel used for empirical exploration. This omission hampers the ability to conduct comparative analyses that could yield additional policy insights. Future studies should aim to expand the analysis by including developed economies and considering variations in resource endowments and economic structures. Moreover, future research could enhance policy considerations by incorporating alternative measures of climate vulnerability, such as ecological degradation. By delving deeper into these aspects, a more comprehensive understanding of the subject matter can be achieved, leading to more informed policy decisions.

Data availability statement

Data used for this study are freely available from online sources, including:

- Kaya identity indicators, Available online at: https://ourworldindata.org/grapher/kaya-identity-co2?
- Natural resources rents were obtained from The World Development Indicators (WDI) available online: https://databank.worldbank.org/source/world-development-indicators/preview/on

CRediT authorship contribution statement

Chinazaekpere Nwani: Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Ekpeno L. Effiong:** Writing – original draft, Methodology, Data curation. **Kingsley Ikechukwu Okere:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Paul Terhemba Iorember:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis.

Declaration of competing interest

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

Appendix A

Table A.1
List of countries in the study panel

Algeria	Qatar
Angola	Yemen
Bahrain	Syria
Congo Republic	Saudi Arabia
Ecuador	Kazakhstan
Egypt	Kuwait
Equatorial Guinea	Libya
Gabon	Iraq
Iran	Oman
United Arab Emirates	

Table A.2
Correlation matrix and multicolinearity test

Panel A: Pairwise Correlation matrix						
	lnCO2	lnP	lnA	lnEI	lnCI	lnNR
lnCO2	1.000					
lnP	0.585	1.000				
lnA	0.307	−0.478	1.000			
lnEI	0.404	−0.254	0.335	1.000		
lnCI	0.086	0.126	−0.154	−0.268	1.000	
lnNR	−0.178	−0.362	0.254	0.002	0.099	1.000
Panel B: Variance inflation factors (VIFs) test						
		VIF		1/VIF		Mean VIF
Kaya Identity Equation		≤1.390		≤0.922		1.250
Kaya Identity (extended)		≤1.450		≤0.903		1.280
Energy Intensity equation		≤1.410		≤0.860		1.290
Energy Intensity (Robustness)		≤1.430		≤0.945		1.250
Carbon Intensity Equation		≤1.410		≤0.860		1.290
Carbon Intensity extended		≤1.440		≤0.862		1.300

Note: Theoretically, VIF ≥10 and Mean VIF ≥6 suggest the presence of multicollinearity.

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