Resources Policy 83 (2023) 103738

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

Technological pathways to decarbonisation and the role of renewable energy: A study of European countries using consumption-based metrics

Chinazaekpere Nwani[a,*], Ojonugwa Usman[b], Kingsley Ikechukwu Okere[c], Festus Victor Bekun[d,e]

[a] Department of Economics and Development Studies, Alex Ekwueme Federal University, Ndufu-Alike, Ebonyi State, Nigeria
[b] Department of Economics, Istanbul Ticaret University, Istanbul, Turkey
[c] Department of Economics, Banking and Finance, Gregory University, Uturu, Abia State, Nigeria
[d] Faculty of Economics Administrative and Social sciences, Department of International Logistics and Transportation Istanbul Gelisim University, Istanbul, Turkey
[e] Adnan Kassar School of Business, Department of Economics Lebanese American University, Beirut, Lebanon

A R T I C L E I N F O

Keywords:
CO_2 emissions
Energy intensity
Carbon intensity
Renewable energy
Consumption-based kaya identity metrics
COP26

A B S T R A C T

To decarbonise Europe in the post-COP26 era, current policies must be adjusted to account for the cross-border consequences of its consumption pattern. Using consumption-based Kaya identity metrics adjusted for emissions and energy embodied in traded goods and services, this study examines the nexus between technological factors defining energy transition progress, specifically energy and carbon intensities of the consumption mix, and carbon dioxide (CO_2) emissions, in a sample of 20 European countries from 1995 to 2019. The empirical steps rely on panel-data estimators that are robust to cross-sectional dependence and allow for heterogeneous slope coefficients. The results show that energy and carbon intensities of the consumption mix have a positive relationship with CO_2 emissions but a negative relationship with renewable energy consumption. The findings also verify an inverted U-shaped relationship between affluence and CO_2 emissions through the energy and carbon intensity metrics. Additional tests show a unidirectional causality from carbon intensity of the energy mix to CO_2 emissions and from renewable energy to the carbon intensity. Also, bidirectional causality exists between CO_2 emissions and per capita GDP and energy intensity, and between renewable energy and energy intensity. By implication, renewable energy provides the technological path to mitigating consumption-induced emissions in Europe.

1. Introduction

The demand for energy has grown steadily. From the 1960s, the consumption of primary energy has grown by 3.818 times, increasing from 155.88 EJ (EJ) to 595.15 EJ in 2021 (BP, 2022). The majority of energy is derived from fossil fuels (oil, coal, and natural gas). There is no doubt that fossil fuels provide economic gains, but their extraction, processing, and usage are major sources of carbon dioxide (CO_2) emissions (Soeder, 2021). The global policy debate on the climate emergency places great importance on the mitigation of CO_2 emissions (Soeder, 2021). CO_2 absorbs infrared radiation and traps heat. Their build-up in the atmosphere poses serious threats to the global climate, with negative consequences for ecosystems, human health, and the economy. Recent events around the world demonstrate that we are already experiencing the effects, such as rising sea levels, more extreme weather, flooding, droughts, and storms (see Strauss et al., 2021). The 26th United Nations Climate Change Conference (COP26) commits countries to limiting global temperature rise to 1.5 degrees Celsius by 2030 (Jacobs, 2022). The acceptance and signing of the pact signify that all countries, at various levels of development, are to make efforts to decouple CO_2 emissions from economic and demographic trajectories.

With energy demand still increasing, getting on track with the climate-neutral target has been a major challenge for most economies. This is partly due to the important role that energy plays in driving economic growth (Liu et al., 2022a). Europe, in particular, has taken a wide range of factors into account, with the most current policy mix focusing on altering the technological composition of their consumption structure (Hainsch et al., 2022). At the moment, energy consumption (in

* Corresponding author.
E-mail addresses: nwanichinaza@gmail.com, nwani.chinazaekpere@funai.edu.ng (C. Nwani), ousman@ticaret.edu.tr (O. Usman), o.kingsley@gregoryuniversityuturu.edu.ng (K.I. Okere), fbekun@gelisim.edu.tr (F.V. Bekun).

https://doi.org/10.1016/j.resourpol.2023.103738
Received 7 October 2022; Received in revised form 10 April 2023; Accepted 18 May 2023
Available online 24 May 2023

particular fossil fuels) accounts for more than half of all greenhouse gas emissions (IEA, 2022). It is consequently critical for the countries to pay attention to developments in the energy sector if their decarbonisation target of decreasing emissions by at least 55% by 2050 is to be met (Renou-Maissant et al., 20220). The European Green Deal (EGD) released in 2019 has its focus on increasing conservation and efficiency as well as deepening the use of renewable energy technologies such as wind, solar, and biogas, which emit no CO_2 (Hainsch et al., 2022). This policy step marked a critical transition pathway towards diminishing reliance on fossil fuels. Its effectiveness, however, has generally been influenced by a combination of domestic factors, such as industrial structure, and international variables, such as the level of reliance on foreign trade. From the standpoint of dependence on imported energy, which according to the World Bank's estimates accounts for more than 50% of net energy use in Europe (WDI, 2022), there is a need to assess how the current policy framework performs under the increasing trade-induced demand for energy.

In this study, we examine the role of the technological composition of the energy mix in explaining energy use effects on CO_2 emissions in Europe. Specifically, we model an impact equation relating CO_2 emissions to population size, per capita income, and the technological structure of energy use. Based on the Kaya identity framework, the technological structure of energy use is defined using energy efficiency and carbon intensity metrics (Lin et al., 2015). The energy intensity metric is used to track the impact of technologies that allow for greater energy conservation and efficiency, whereas technologies that control pollution or lower the carbon content of energy sources lead to a reduction in carbon emissions intensity (González-Torres et al., 2021). In technical and policy contexts, the use of renewable energy can have a positive effect on the energy and carbon efficiency of the consumption structure. Taking this into consideration, we extend the model specifications to examine how changes in the technological composition of the consumption structure towards renewable energy shape the decarbonisation progress in Europe.

A number of scholars have explored how changes in the technological composition of the energy consumption mix influence environmental impacts in Europe (Pham et al., 2020; Obobisa, 2022; Frodyma et al., 2022). There are, however, noticeable gaps in these studies that limit their contribution to climate policy. In particular, their empirical models have been based on territorial estimates of energy and CO_2 emissions (production-based metrics) without adjusting for embodied components in traded goods. To address this gap, we model the environmental impacts of the countries using consumption-based metrics. Traditionally, countries are guided to report emissions using a production-based (PB) metric, indicating emissions produced within their territorial jurisdiction (Davis and Caldeira, 2010; Pan et al., 2022). With international trade, goods and services produced in other countries become intermediate inputs or final consumption in another country (Pan et al., 2022). In recognition that goods and services flowing across international borders redistribute emissions, recent computations have adjusted national historical responsibilities for CO_2 emissions using a consumption-based[1] (CB) metric (see Friedlingstein et al., 2022). Embodied CO_2 emissions in trade flows into Europe (imports) have in recent years exceeded embodied emissions in its exports, resulting in positive net CO_2 emissions from trade and higher historical estimates of CO_2 emissions in general (see Fig. 1). Between 1995 and 2019, Europe reduced its territorial emissions by 15.4%. The mitigation gains, however, were reduced to 8.4% after adjusting the estimates for emissions embodied in traded goods and services. The difference of 7%, which amounts to approximately 446.9 million metric tons of CO_2 emissions, is an indication that current policy measures have been tailored mainly to curbing territorial emissions. It is also an indication that existing empirical studies may have provided insufficient evidence on the effectiveness of and needed policy directions in mitigating CO_2 emissions in Europe. In the same way, we define energy and carbon intensities of the consumption mix using metrics that add net energy embodied in traded goods and services (i.e., trade-adjusted energy use = territorial estimates of energy use plus embodied energy in import trade minus embodied energy in export trade). The derived estimates are consumption-based, and the corresponding parameter estimates could aid efficient policies in support of the decarbonisation targets in Europe.

This study contributes to the literature on technological pathways to decarbonisation in several ways. **First,** to our knowledge, this study is one of the first empirical studies to model drivers of environmental impacts in Europe using consumption-based metrics adjusted for both emissions and energy embodied in traded goods. **Second,** given a significant increase in renewable energy, particularly in Europe, previous empirical attempts have introduced renewable energy directly into the impact equation. This has resulted in a limited understanding of how renewable energy mitigates CO_2 emissions. To address this glaring issue, we test a model formulated based on the Kaya identity framework. The added policy insight is that energy and carbon intensities of the consumption structure may shape the technological path to decarbonisation in Europe. Within this framework, we test the mediating role of renewable energy in the technology-CO_2 emissions nexus. Different from the direct linkages that have defined existing empirical attempts, we bring to the fore the technology path to understanding the role of renewable energy in the carbon mitigation model. Specifically, we show that shifts in energy technologies towards renewables are the main driver of decarbonisation progress in Europe. Third, on the methodological basis, most existing empirical attempts have often used the Dumitrescu-Hurlin (DH) approach to causality testing in analysing the causal relationships between energy transition variables and CO_2 emissions in Europe. However, this causality test does not allow for multivariate causality specifications, making the impact of controlled policy variables irrelevant in the Granger non-causality test. In this study, we address this issue by using the newly developed bias-corrected Granger non-causality test by Juodis et al. (2021), which provides both univariate and multivariate causality tests.

The next section reviews the literature and provides some theoretical support, while the third section describes the model, data and regression techniques. The fourth section presents and discusses the results, while the fifth section contains concluding remarks with some policy recommendations.

2. Literature review

This section starts with a brief discussion of theoretical framework underlining environmental impacts modelling. This is followed by a review of evidence from existing empirical studies on the nexus between the technological structure of energy mix and CO_2 emissions. The concluding discussion summaries by highlighting some research gaps to set focus for the current study.

2.1. Theoretical framework

The literature has suggested a number of analytical frameworks to aid precise understanding of anthropogenic factors shaping human environmental impacts. Ehrlich and Holdren (1971) specified a mathematical identity that relates environmental impacts (I) as a multiplicative function of population (P), affluence (A) and technology (T) (i.e., $I = PAT$). Apeaning (2021) argues that ethical concerns often undermine the effectiveness of using population control as a mitigation tool. Likewise, according to the environmental Kuznets curve (EKC) hypothesis, the effectiveness of the economic growth path (i.e., A) is a function of the level of development (Grossman and Krueger, 1991; Frodyma et al., 2022). Countries are only willing to decouple CO_2

[1] Trade adjusted (Consumption-based (CB)) CO_2 emissions = Territorial (Production-based (CB) CO_2 emissions + net CO_2 emissions embodied in traded goods (see Pan et al., 2022).

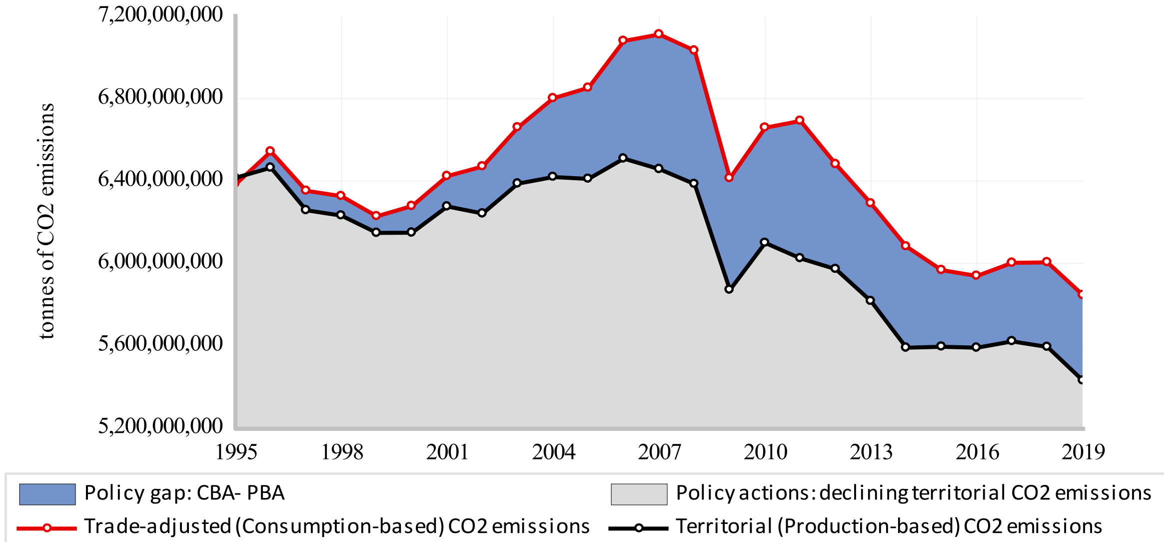

Fig. 1. CO_2 emissions in Europe based on PB and CB accounting system, 1995–2019. Data sources: Global Carbon Budget, Friedlingstein et al. (2022).

emissions from economic output after reaching a certain level of per capita income (Frodyma et al., 2022). Undeniably, the technology (T) path remains the most reliable way to mitigate CO_2 emissions (Apeaning, 2021), but was not given a specific definition in the original formulation of the IPAT equation (York et al., 2003). To give a precise definition, Waggoner and Ausubel (2002) reformulated T to encompass the technological structure of energy mix. The extended impact equation produces a 4-factor Kaya identity specification, taking anthropogenic drivers of environmental impact as a multiplicative function of population (P), affluence (A), energy intensity (EI; the amount of energy consumed per unit of GDP) and carbon intensity (CI; the amount of CO_2 emitted per unit of energy) (Lin et al., 2015).

2.2. PAT, Renewable energy and CO_2 emissions: some empirical evidence

Econometric testing of the impact of PAT on CO_2 emissions has increased recently, but much more interest has been focused on the role of renewable energy technologies. Some of the studies examined just a single country instance (see for e.g., Awan et al., 2022; Kartal et al., 2022; Azam et al., 2023; Jie et al., 2023; Hassan et al., 2023), while others focused on a group of countries, with selection classification spread across geographic, income, or economic blocs (see for e.g., Dong et al., 2019; Pham et al., 2020; Usman et al., 2021; Liu et al., 2022b; Yu et al., 2022). Dong et al. (2019) modelled an extended identity equation for global and regional CO_2 emissions using a panel data of 128 countries for 1990–2014 using Mean Group panel time-series estimators and the Dumitrescu-Hurlin (DH) Granger causality test. The results showed that positive changes in affluence, population size, fossil fuel energy use, and energy intensity increase CO_2 emissions in all regions. Although the use of renewable energy produced the smallest effect in all regions, its statistical significance in the model suggests that it remains the key path to reducing global CO_2 emissions. The use of fossil fuels was in particular identified as the main contributor to CO_2 emissions in Europe. In addition, the study showed that a unidirectional causality runs from energy indicators (per capita energy use, renewable and non-renewable energy shares of the consumption mix) to CO_2 emissions in Europe.

Similarly, Pham et al. (2020) modelled the impact of PAT on CO_2 emissions in a panel of 28 European countries from 1990 to 2014 using panel VAR and the fully modified OLS-based techniques. In support of theoretical specifications, the results showed that growth in population size and economic affluence pose a threat to the attainment of the decarbonisation targets. Another insight from the results indicates that European economies will have to rely on energy efficiency and renewable technologies to thwart the growing trend in their carbon footprints. In another study, Mohsin et al. (2022) modelled the impact equation for the period spanning from 1971 to 2016 using the autoregressive distributed lag (ARDL) model and the Engle-Granger causality test, showed that a positive causal flow runs from affluence to CO_2 emissions in the European and Central Asian countries. Using the ARDL technique, Frodyma et al. (2022) modelled an extended impact equation for 28 European countries. The results rejected the validity of inverted U-shaped curve in all the countries except Germany. In a study of the top fifty carbon intensive countries, Mirziyoyeva and Salahodjaev (2022) used data spanning from 2000 to 2015 to quantify the mitigation gains from the use of renewable energy technologies. The results from the generalised method of moments (GMM) estimator showed that for a 1% increase in the use of renewables, there is a 0.98% decrease in CO_2 emissions.

In a cross-regional study using Mean Group panel time-series estimators, Obobisa (2022) found that a 1% increase in the use of renewable energy technologies reduces CO_2 emissions by 0.01% in Europe and by 0.26% in America. Taking additional modelling step using the DH Granger causality algorithm, the study showed that the direction of causality between renewable energy and CO_2 emissions is bidirectional in Europe but unidirectional from CO_2 emissions to renewable energy in America. Liu et al. (2022b) used advanced regression and DH causality techniques to model an extended IPAT equation for CO_2 emissions in Latin America during the period 1990–2020 and reported negative relationship and bidirectional causality between renewable energy and CO_2 emissions in the region. In a cross-country of 82 countries using dynamic panel threshold model, Yu et al. (2022) showed that renewable energy contributes to achieving energy efficiency policy goals, but provide different levels of performance in different development and policy regimes. The derived estimates generated 0.22% and 0.02% decrease in energy intensity for every 1% increase in renewable energy development in the high and low regimes, respectively.

2.3. Consumption-based accounting of CO_2 emissions

One factor that complicates the selection of mitigation options from existing studies is the geographical separation of production and consumption of goods and services (Davis and Caldeira, 2010). A significant portion of one country's economic output is used to meet the demand of consumers in another country via international trade (Pan et al., 2022). As a result, recent studies have quantified the emissions embodied in global trade flows (Peters et al., 2011; Friedlingstein et al., 2022).

Friedlingstein et al. (2022) used two accounting techniques: production-based (PB), which accounts for CO_2 embodied in all goods and services created within a country's territorial jurisdiction, and consumption-based (CB), which adjusts PB estimates to embodied CO_2 in traded goods and services. The estimates suggest that many developed countries are net importers of CO_2 emissions, with their CB emissions being higher than their PB emissions, supporting prior findings by Davis and Caldeira (2010) and Peters et al. (2011). Furthermore, Harris et al. (2020) and Rocco et al. (2020) showed that PB understates emissions in Europe. Their findings suggest that CB is a more appropriate technique for quantifying the environmental impact of Europe's consumption-driven economy. The reason according to Zhong et al. (2022) is that countries with stricter environmental policies have lower emission intensity in their exports but higher emission intensity in their imports.

2.4. Research gaps

The reviewed empirical literature highlights some research gaps that need to be addressed to shape environmental policy targets in Europe. One is the use of production-based metrics in the modelling of the environmental impacts of the countries. Since trade-induced consumption lifestyles of European economies augment significantly their territorial CO_2 emissions, existing studies, including Pham et al. (2020) and Mirziyoyeva and Salahodjaev (2022), could be considered to have underestimated the environmental impacts of the economies in their analyses. This study addresses this gap by adjusting energy and CO_2 emission estimates to the consumption patterns of the economies. Second, existing studies introduced renewable energy directly into the impact equation (see, e.g., Dong et al., 2019; Pham et al., 2020; Mirziyoyeva and Salahodjaev, 2022). This allows for a limited understanding of how renewable energy mitigates CO_2 emissions. To address this gap, this study models the changes in CO_2 emissions within the Kaya identity framework (Treimikien and Balezentis, 2016). This enables the direct and indirect testing of relationships between technological factors that underlie the progress of the energy transition (i.e., energy efficiency and carbon intensity) and renewable energy consumption. Another noticeable gap in the reviewed studies is the limited causality evidence regarding the nexus between the technological structure of the energy mix and CO_2 emissions in Europe. In fact, the few existing causality tests relied on the DH technique. This technique uses univariate causality specifications and, as such, does not account for the impact of control variables in the Granger non-causality test. To address this gap, this study implements the newly developed bias-corrected Granger non-causality test by Juodis et al. (2021), which allows for both univariate and multivariate causality specifications.

3. Methodology

3.1. Model specification

The IPAT identity was redefined by Dietz and Rosa (1994) into a stochastic model, STIRPAT, for stochastic impacts by regression on P, A and T. Algebraically, the model takes the following form:

$$I_t = \eta P_t^{\varphi} A_t^{\delta} T_t^{d} \tag{1}$$

The constant, η, scales the function; φ, δ and d are the exponents of P, A and T, respectively, that are to be derived using appropriate econometric techniques to aid policy inferences. Following Pham et al. (2020) N and Waggoner and Ausubel (2002), we define T as a function of the technological structure of the energy mix. Specifically, we use energy intensity (EI, defined by the amount of energy consumed per unit of GDP) and carbon intensity (CI, defined by the amount of CO_2 emissions per unit of energy) metrics (see the formulation of ImPACT model by York et al., 2003). Thus, Eq. (1) is extended to produces a 4-factor Kaya identity specification for modelling the anthropogenic drivers of CO_2 emissions. Taking algebraic and natural logarithmic (*ln*) transformation of the 4-factor Kaya identity specification yields the following expression for empirical investigation:

$$lnCO2_{it} = \eta + \varphi lnPOP_{it} + \delta lnPCgdp_{it} + \varphi lnEI_{it} + \psi lnCI_{it} + \varepsilon_{it} \tag{2}$$

Where impacts *(I)* are represented by CO_2 emissions (CO2), population size denoted by (POP) and affluence (A) denoted by per capita GDP (PCgdp). *"it"* refers to the *ith* country in year *t* and ε is the error term. φ and ψ represent the elasticity coefficients of CO_2 emissions regarding the impacts of changes in energy intensity (EI) and carbon intensity (CI), respectively. The interactions between CO_2 emissions and PCgdp, as the economy progress along the development path, could follow an inverted U-shaped curve according to the environmental Kuznets curve (EKC) hypothesis (Grossman and Krueger, 1991). Hence, we extend Eq. (2) to include the quadratic term of per capita GDP (PCgdpSQ) in the functional equation:

$$lnCO2_{it} = \eta + \varphi lnPOP_{it} + \delta_1 lnPCgdp_{it} + \delta_2 lnPCgdpSQ_{it} + \varphi lnEI_{it} + \psi lnCI_{it} + \varepsilon_{it} \tag{3}$$

A valid inverted U-shaped curve only exists if $\delta_1 > 0$ and $\delta_2 < 0$. Further modelling consideration extends insights on the role of technology in mitigating CO_2 emissions. Offsetting the impact of large increase in GDP (and increases in population) on CO_2 emissions will depend on whether the countries could reduce their EI and CI fast enough. As clearly highlighted in the literature, trends in these two factors depend on the composition of technologies in use; particularly the rate at which fossil fuel energy is replaced by non-zero technologies (e.g., renewable energy). To extend empirical insights on the technology effect, an intermediate model is specified to track the impact of renewable energy on EI and CI:

$$EI_{it}/CI_{it} = \eth + \Omega \mathrm{lnRE_{it}} + \lambda_1 \mathrm{lnPCgdp_{it}} + \lambda_2 \mathrm{lnPCgdpSQ_{it}} + \vartheta \mathrm{lnSTU_{it}} + \varepsilon_{it} \tag{4}$$

Where Ω denotes the impact of renewable energy (RE). The functional equation controls for the influence of PCgdp, PCgdpSQ and industrial structure upgrading (STU). The introduction of STU accounts for the impact of structural shifts in the economy, in particular the shift from secondary sectors to tertiary sectors which relies on depth of technological development and tends to induce efficiency in energy use (Luan et al., 2021).

3.2. Data description

This study models the drivers of CO_2 emissions in a selection of European countries using annual time series data over the period, 1995 – 2019. Conventionally, CO_2 emissions are measured on the basis of domestic production of goods and services – indicating emissions that occur within a country's territorial jurisdiction. The limitation is that this accounting technique does not adjust for emissions embedded in traded goods, which constitute major part of aggregate consumption (Pan et al., 2022). To calculate total emissions on the basis of aggregate consumption, the estimates are adjusted for traded goods - CO_2 emissions embedded in imported goods are included, while those embedded exported goods are subtracted (Pan et al., 2022). One common feature of CO_2 emissions in Europe is that most of the countries are witnessing large increase in CO_2 emissions through the consumption path, a reflection that international trade augments their environmental

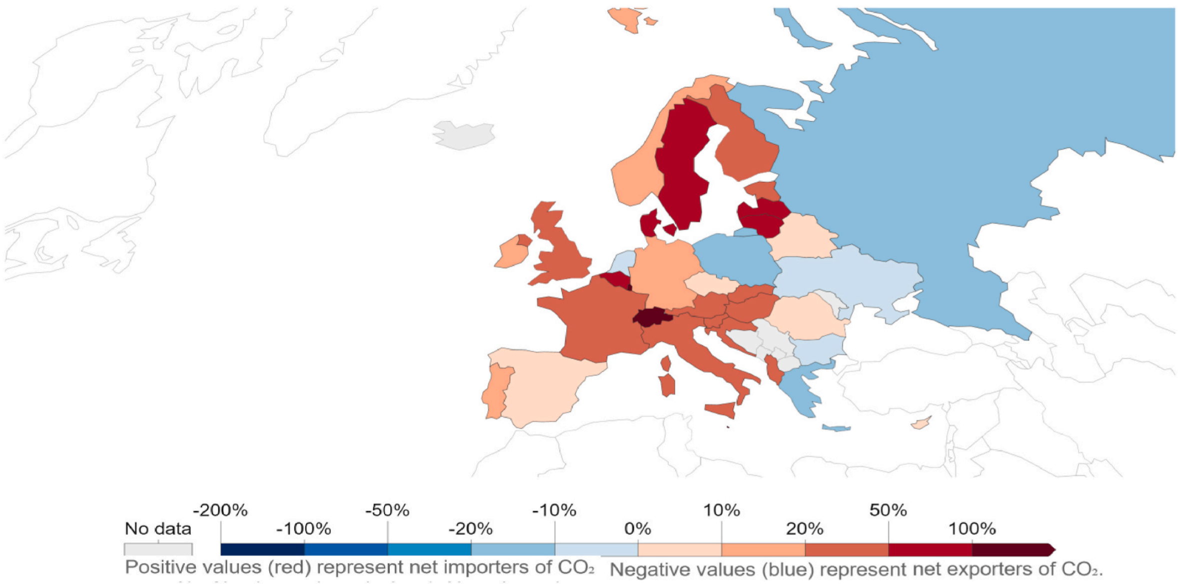

Fig. 2. CO_2 emissions embedded in trade, European Countries, 2019. Note: Positive estimates (Red) depict net importers of CO_2 while Negative estimates (Blue) depict net exporters of CO_2. *Source:* https://ourworldindata.org/grapher/share-co2-embedded-in-trade?country=~EGY.

impacts (see Fig. 2). In this context, we construct a balanced panel-data including 20 net-importers of CO_2 emissions[2] selected strictly on the basis of data availability over the study period. Because the analysis relies on a balance panel-data structure, countries without complete data on key explanatory variables of interest are excluded from the study. To aid policy formulation and extend relevant literature, consumption-based metrics are used for empirical analysis, involving adjusting the variables for emissions and energy embedded in traded goods. The variables are listed in Table 1 along with their computational definitions and data sources while basic descriptive statistics are summarised in Table 2.

3.3. Estimation techniques

The dataset has 20 countries (i.e., cross-section dimensions (N) = 20) and time-series (*T*) dimension of 25 years. Traditional econometric techniques are considered unsuitable for the dataset, since T is moderately large and greater than N (Eberhardt, 2012). For datasets with T > N, Eberhardt (2012) recommends panel time-series econometric steps, including a set of preliminary checks (cross-section (CS) dependence test, slope heterogeneity tests and unit-root tests), cointegration tests and second-generation estimation methods (the mean group (MG), the common correlated effects mean group (CCEMG) and the augmented mean group (AMG) estimators). This study, therefore, employs the macro panel framework as recommended by Eberhardt (2012).

3.3.1. Preliminary tests

Ignoring the inter-dependency among the countries could produce biased estimates. Therefore, the panel dataset needs to be screened for possible cross-section dependence (CSD). The test proposed by Pesaran (2004, 2021) is adopted for this purpose. This technique is employed to verify the existence of CSD under the hull hypothesis as: $H_o : \widehat{p}_{ik} = corr(\varepsilon_{it}\varepsilon_{kt}) = 0 \forall i \neq k$ based on the following equation:

$$CSD = \sqrt{\frac{2T}{n(n-1)}}\left(\sum_{i=1}^{n-1}\sum_{k=i+1}^{n}\widehat{p}_{ik}\right) \sim n(0,1)\ i,k \tag{5}$$

Where $T = 25$ years and $n = 20$ oil-rich countries. $\widehat{p}_{ik}$ is a component that introduces the ADF in the pairwise cross-sectional dependency.

Similarly, biased estimates could be avoided by checking the slope characteristics. This is achieved by using the Pesaran and Yamagata (2008) approach, which detects the presence of homogeneity or otherwise in panel datasets. The test is based on the following equation:

$$(\widehat{\Delta}_{SH}) = (N)^{\frac{1}{2}}(2k)^{-\frac{1}{2}}\left(\frac{1}{N}\overline{S} - k\right);\ \ (\widehat{\Delta}_{ASH}) = (N)^{\frac{1}{2}}\left(\frac{2k(T-k-1)}{T+1}\right)^{-\frac{1}{2}}\left(\frac{1}{N}\overline{S} - 2k\right) \tag{6}$$

Where, $\widehat{\Delta}_{SH}$ and $\widehat{\Delta}_{ASH}$ are respectively the delta tilde and adjusted delta tilde statistics which form the basis for testing the null hypothesis of homogeneity in the slope coefficients.

The third preliminary check examines the unit root characteristics of the variables using the cross sectional augmented Im-pesaran-Shin (CIPS) test by Pesaran (2007). The equation under the non-stationary specification is given as:

$$\Delta Y_{it} = \omega_i + \rho_i^* Y_{i,t-1} + d_0\overline{Y}_{t-1} + \sum_{j=0}^{p} d_{ij}\Delta\overline{Y}_{t-j} + \sum_{j=1}^{p} c_{ij}\Delta Y_{i,t-j} + \varepsilon_{it} \tag{7}$$

Where Δ, Y are the difference operator and the case variable, respectively. CIPS statistics are derived from Eq. (11) as:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i \tag{8}$$

The adjusted (truncated) CIPS statistic (i.e., CIPS-TR) is calculated in order to lessen the effects of issues created by T not being sufficiently large to limit extreme outcomes. The CIPS-TR given as:

$$CIPS - TR = \frac{1}{N}\sum_{i=1}^{N} CADF_i^* \tag{9}$$

3.3.2. Test for cointegration

To test for the presence of a long-run relationship between the var-

[2] Austria; Belgium; Croatia; Denmark; Estonia; Finland; France; Germany; Hungary; Ireland; Italy; Latvia; Lithuania; Portugal; Slovakia; Slovenia; Spain; Sweden; Switzerland; United Kingdom.

Table 1
Data definitions and sources.

Notation	Definition	Unit of Measurement	Database	Compilation
CO2	Consumption-based CO_2 emissions	Territorial/ Production-based emissions minus emissions embedded in exports, plus emissions embedded in imports. Data are measured in tonnes of CO_2	Global Carbon Budget - Global Carbon Project (GCB-GCP v2021)	Consumption-based Kaya Identity (CKI) Dataset, https://ourworldindata.org
POP	Population, total	Historical estimates of total number of people in a country	United Nations Population Division	CKI Dataset, https://ourworldindata.org
PCgdp	GDP per capita	GDP Per Capita, PPP (Constant, 2017 International $). This adjusts for inflation and cross-country differences.	World Development Indicators (WDI v2022)	CKI Dataset, https://ourworldindata.org
EI	Consumption-based Energy Intensity	Number of kilowatt-hours of energy used per dollar of GDP. To adjust for trade, energy use is calculated as domestic energy use minus energy embodied in exported goods, plus those embodied in imported goods. These estimates are divided by GDP (measured in 2017 international $)	EXIOBASE v3.8.2 and WDI v2022	CKI Dataset, https://ourworldindata.org
CI	Consumption-based Carbon Intensity	The quantity of CO_2 emitted per unit of energy computed as CO_2 emissions adjusted for emissions embedded in traded goods divided by energy use adjusted for energy embodied in traded goods	GCB-GCP v2021 and EXIOBASE	CKI Dataset, https://ourworldindata.org
RE	Renewable energy	Renewable energy consumption (% of total final energy consumption)	WDI v2022	World Bank, https://data.worldbank.org
STU	Industrial structure upgrading	Ratio of Services, value added (% of GDP) to Industry (including construction), value added (% of GDP)	WDI v2022	World Bank, https://data.worldbank.org

iables, we employ the error-correction-based panel cointegration tests proposed by Westerlund (2007), which significantly accounts for possible presence of CSD in the panel dataset. The equation takes the following form:

$$\Delta Y_{i,t} = \mu_i' d_t + \omega_i\left(Y_{i,t-1} - \beta_i' X_{i,t-1}\right) + \sum_{j=1}^{k} \varnothing_{ij}\Delta Y_{i,t-j} + \sum_{j=1}^{k}\gamma_{ij}\Delta X_{i,t-j} + \varepsilon_{i,t} \tag{10}$$

Y_{it} and X_{it} are the dependent and explanatory variables, respectively; ω_i is the coefficient of the error-correction term reflecting the rate of correction towards equilibrium. Accordingly, four (4) statistical can be estimated from equation (5):

$$G_t = \frac{1}{N}\sum_{i=1}^{N}\frac{\widehat{\omega_i}}{se(\widehat{\omega_i})} \tag{11}$$

$$G_a = \frac{1}{N}\sum_{i=1}^{N}\frac{T\widehat{\omega_i}}{1-\sum_{j=1}^{k}\omega_{ij}} \tag{12}$$

$$P_t = \frac{\widehat{\omega}}{se(\widehat{\omega})} \tag{13}$$

$$P_a = T\widehat{\omega} \tag{14}$$

Testing for cointegration in the full panel can be done using the P statistics (P_t and P_a,) while the G statistics (G_t and G_a,) offer the basis for verifying the existence of cointegration in at least one cross-sectional group.

3.3.3. *Parameter estimation*

This study employs three estimators developed to address heteroscedasticity, CDS and slope heterogeneity concerns in panel time-series models (Eberhardt, 2012). First, we use the Pesaran and Smith (1995) mean group (MG) estimator, in which estimates of the parameters associated to the observable variables are calculated independently for each cross-section and averaged at the end. Despite that MG estimator supports heterogeneous slope coefficients; CSD-related problems still persist. Second, we use the Pesaran (2006) Common Correlated Effects Mean Group (CCEMG) estimator. By including group-specific regression's cross-sectional averages of the dependent variable Y_{it} and the independent variable X_{it}, the CCEMG algorithm inadvertently adjusts parameters to the problems of CSD and slope heterogeneity.

$$Y_{it} = \beta_i X_{it} + \gamma_i \overline{Y}_{it} + \theta_i \overline{X}_{it} + \alpha_i + \tau_i f_t + \varepsilon_{it} \tag{15}$$

The empirical setup of the CCEMG algorithm is robust to the presence of weak unobserved common factors (e.g., local spillover effects) but limited in the presence of strong factors such as global shocks (see Pesaran and Tosetti, 2011). The algorithm estimates each panel regression by OLS. As in the MG estimator, the mean group estimates are obtained by averaging each panel unit:

$$CCEMG = \frac{1}{N}\sum_{i=1}^{N}\widehat{\beta}_i \tag{16}$$

Finally, we use the Eberhardt and Teal (2010) Augmented Mean Group (AMG) estimator, which is also resistant to CSD and slope

Table 2
Summary statistics.

Statistic	CO2	POP	PCgdp	EI	CI	RE	STU
Mean	199000000.00	19914735.00	37992.79	1.48	0.20	18.50	2.57
Median	73635762.00	8103316.00	39475.16	1.31	0.20	17.27	2.45
Maximum	1140000000.00	83517046.00	86650.01	5.40	0.44	52.88	4.08
Minimum	11702227.00	1315330.00	9600.85	0.75	0.06	0.85	1.39
Std. Dev.	265000000.00	25011165.00	13450.53	0.60	0.05	12.03	0.58
Skewness	1.79	1.32	0.20	2.34	1.03	0.52	0.55
Kurtosis	5.35	3.11	2.99	10.43	6.46	2.49	2.64
Jarque-Bera	380.60	145.00	3.42	1605.19	338.92	27.79	28.02
Probability	0.00	0.00	0.18	0.00	0.00	0.00	0.00
Observations	500	500	500	500	500	500	500

heterogeneity. In contrast to the CCMG estimator, the AMG takes into account the model configuration for unobservable common components. The AMG technique uses a first difference estimate of a pooled regression model plus time dummies (Eberhardt and Teal, 2010). The following equation expresses this first step as thus:

$$Y_{it} = \rho_i + \alpha_i \Delta X_{it} + \tau_i \delta_t + \sum_{t-1}^{T} \varphi_t D_t + \varepsilon_{it} \tag{17}$$

Where α_i denotes the slope, δ_t the unobserved common factor, τ_i the heterogeneous factor loadings, D_t the year dummies, and φ_t the coefficients. Second, we add a unit coefficient for each group unit to the group-specific regression specification and then average the group-specific parameters across the panel.

$$AMG = \frac{1}{N} \sum_{i=1}^{N} \widehat{\alpha}_i \tag{18}$$

3.3.4. Bias-correction for Granger non-causality based on Half-Panel Jackknife Wald-type test

This study performs the Granger non-causality test developed by Juodis et al. (2021) (JKS test), which uses Half-Panel Jackknife (HPJ) Wald-type test as the bias-correction estimator. The novelty of JKS test algorithm lies in the fact that it offers superior size and power performance, achieved by setting a pooled estimator with a $\sqrt{\mathrm{NT}}$ rate of convergence. These properties are required under circumstances that are empirically relevant: testing causality in both multivariate and univariate systems, checking heterogeneous nuisance parameters, and allowing for CSD and cross-sectional heteroscedasticity (Juodis et al., 2021; Xiao et al., 2022). We specify the following equation (Juodis et al., 2021):

$$y_{i,t} = \pi_{0,i} + \sum_{k=1}^{k} \delta_{p,i} y_{i,t-k} + \sum_{q=1}^{Q} \varphi_{q,i} x_{i,t-k} + + \varepsilon_{i,t} \quad \text{for country } i = 1, \ldots, N\,(=20) \text{ and years } t = 1, \ldots, T\,(=25) \tag{19}$$

In Eq. (14), $x_{i,t}$ is taken as a scalar while $\delta_{p,i}$ represents heterogeneous autoregressive effects and $\varphi_{p,i}$ represents the heterogeneous Granger causation effects. Juodis et al. (2021) assume that $y_{i,t}$ depicts an autoregressive distributed lag process under the null hypothesis (H_0), $\varphi_{q,i} = 0$, for all i and q. This permits the use of a pooled estimator for $\{\varphi_{q,i}\}_{i=1}^{N}$. To resolve the bias of the pooled estimator, the test algorithm employs the HPJ estimator of Dhaene and Jochmans (2015). In the presence of CS dependence, the variance of the HPJ estimator can be derived by bootstrapping. The bootstrap resamples across the cross-sectional dimension. The derived estimates are bias-corrected, providing Wald statistics for Granger non-causality test. In particular, the rejection of H_0 will indicate the statistical relevance of the alternative hypothesis, $H_0 = \varphi_{q,i} \neq 0$ for some i and q.

Table 3
Pesaran (2004, 2015) Cross-section dependence test.

Variable	CD-test	p-value	average joint	mean ρ	mean abs(ρ)
lnCO2	33.223***	0.000	25.00	0.48	0.55
lnPOP	9.889***	0.000	25.00	0.14	0.85
lnPCgdp	61.025***	0.000	25.00	0.89	0.89
lnPCgdpSQ	60.943***	0.000	25.00	0.88	0.88
lnEI	51.17***	0.000	25.00	0.74	0.76
lnCI	17.163***	0.000	25.00	0.25	0.47
lnRE	55.907***	0.000	25.00	0.81	0.81
lnSTU	43.869***	0.000	25.00	0.64	0.66

Note: *** indicate statistical significance at 1%.

4. Presentation and discussion of results

4.1. Results from preliminary tests

Table 3 divulges the outcome of the Pesaran (2004, 2021) Cross-section dependence test (CD-test). The result confirms the existence of cross-sectional dependence for the empirical model. In addition, Table 4 presents the result of the slope homogeneity test developed by Pesaran and Yamagata (2008). This result reveals that the null hypothesis of the homogeneity of slope coefficients is, however, rejected. This implies that the slope coefficients for this study are heterogeneous. Since the panel dataset is characterised by the presence of CSD, second-generation unit root testing test, CIPS, by Pesaran et al. (2007) is applied. These tests are conducted with a constant and again constant and trend. The result displayed in Table 5, shows that in the presence of cross-sectional dependence, the variables are not stationary in their levels. However, they become stationary in their first differences. These results, therefore, provide the basis to conclude that all the variables used for this study are integrated of I(1). In other words, they are I(1) process. Having established the integrating properties of the variables, we step further to determine whether cointegration exists among the variables or not. We use the panel cointegration test by Westerlund (2007). Results as reported in Table 6 suggest that a panel cointegration exists for all the estimated models, i.e. Kaya Identity Model and Kaya Identity Model with EKC as well as energy intensity and carbon intensity models. This is also confirmed by the robustness test using the Kaya Identity model with renewable energy for carbon intensity. As part of

Table 4
Pesaran and Yamagata (2008) slope heterogeneity test.

Model	Delta tilde ($\tilde{\Delta}$)	P-value	Adjusted delta tilde ($\tilde{\Delta}_{Adj}$)	P-Value
1. Kaya Equation	12.016***	0.000	13.783***	0.000
2. Kaya-EKC	12.870***	0.000	15.167***	0.000
3. Energy Intensity	14.884***	0.000	17.074***	0.000
4. Carbon Intensity	11.915***	0.000	13.667***	0.000
5. Robustness test (Kaya with RE)	19.822***	0.000	22.738***	0.000

Note: *** indicate statistical significance at 1%.

the preliminary tests, we use the variance inflation factors (VIFs) test to evaluate the explanatory variables for multicollinearity concerns. The test statistics show that the VIF, **1/VIF** and **Mean VIF** are all below the theoretical tolerance levels, indicating the absence of multicollinearity concerns in the linear model specifications (see Table A1 in the Appendix).

Table 7 presents the empirical results of the Kaya identity equation and the extended EKC specification. From the results, we find that population size, per capita GDP, energy intensity, and carbon identity exert significant positive impact on CO_2 emissions in the selected European countries. The coefficient estimates show that CO_2 emissions increase by 0.95% for a percentage increase in population size, by 0.97% for a percentage increase in per capita GDP, by 0.99% for a percentage increase in energy intensity and by 0.99% for a percentage increase in carbon intensity (using the AMG estimator). These findings are consistent with the concerns raised by Dong et al. (2019) and Pham et al. (2020) about environmental degradation in Europe. According to the Kaya identity model with EKC specification, the coefficient of the squared term of per capita GDP is negatively related to consumption-based CO_2 emissions for the MG and AMG estimates, but positively related to consumption-based CO2 emissions for the CCEMG estimate. Yet, regardless of the estimator chosen, the estimates are not statistically significant. This means that the sample for this study does not verify the inverted U-shaped curve predicted by the EKC hypothesis between per capita GDP and CO_2 emissions.

Results in Table 8 explain the effects of renewable energy and some control variables on consumption-based energy and carbon intensities. According to the results, increasing renewable energy reduces consumption-based intensity of energy use as well as the carbon intensity of the energy mix. A 1% increase in renewable energy use, for example, provides technological efficiency by reducing the carbon and energy intensities of the consumption mix by 0.10%–0.29%. A rise in per capita GDP has a positive influence on consumption-based energy and carbon intensities (only where it is significant), whereas per capita GDP squared has a negative effect (only where it is significant). This suggests that an inverted U-shaped relationship exists between the technological composition of the energy consumption mix and per capita GDP. Thus, the results provide another perspective to understanding the curve between affluence and environmental impact in Europe, different from the direct relationship that has defined the test in earlier research, notably the one by Frodyma et al. (2022). As regards industrial structure upgrading, the coefficient estimate show the effect is not statistically significant.

4.2. Robustness check

Furthermore, we incorporate renewable energy for carbon intensity to test the robustness of our findings. The results as reported in Table 9 reveal that population size is positively related to CO_2 emissions, however only confirmed by the AMG estimator. The results also reveal that an increase in energy intensity has a positive and significant influence on CO_2 emissions whereas an increase in renewable energy reduces CO_2 emissions significantly. There is no evidence to support that a rise in per capita GDP and its squared term impacts significantly on CO_2 emissions. Technically, the direct introduction of renewable energy into the impact equation as specified by Dong et al. (2019), Pham et al. (2020) and Mirziyoyeva and Salahodjaev (2022) provides a limited understanding of how renewable energy mitigates CO_2 emissions in Europe. In

Table 5
Cross-sectional augmented Panel Unit Root Tests.

	CIPS				CIPS-TR				
	Level I(0)		1st Difference I(1)		Level I(0)		1st Difference I(1)		
Variables	Constant	Constant and Trend	Constant	Constant and Trend	Constant	Constant and Trend	Constant	Constant and Trend	Decision
lnCO2	−1.278	−1.760	−3.779***	−3.304***	−2.268	−2.268	−3.723***	−3.146***	I(1)
lnPOP	−2.088	−2.2046	−6.941***	−8.948***	−1.899	−1.866	−4.969***	−5.395***	I(1)
lnPCgdp	−1.621	−1.621	−2.858***	−3.168***	−1.403	−1.403	−2.858***	−3.168***	I(1)
lnPCgdpSQ	−1.593	−1.593	−2.906***	−3.164***	−1.392	−1.392	−2.906***	−3.164***	I(1)
lnEI	−1.968	−1.945	−5.968***	−6.066***	−1.508	−1.508	−5.321***	−5.544***	I(1)
lnCI	−1.410	−1.410	−5.688***	−5.662***	−2.516	−2.516	−5.203***	−5.308***	I(1)
lnRE	−1.932	−1.932	−5.295***	−5.457***	−2.215	−2.215	−4.920***	−5.162***	I(1)
lnSTU	−1.841	−1.841	−4.126***	−4.323***	−1666	−1.666	−4.126***	−4.305***	I(1)

Table 6
Results from Panel cointegration tests.

				Model Specifications		
Test Statistics		Kaya Equation	Kaya-EKC	Energy Intensity	Carbon Intensity	Robustness test (Kaya with RE)
Gt	Value	−1.528	−1.523	−3.620***	−3.688***	−3.700***
	(Robust p-value)	(0.900)	(0.960)	(0.000)	(0.000)	(0.000)
Ga	Value	−5.204	−4.242	−13.869***	−12.384***	−7.551
	(Robust p-value)	0.760	0.970	(0.000)	(0.000)	(0.640)
Pt	Value	−12.216*	−13.259**	−13.118**	−14.478***	−15.057***
	(Robust p-value)	(0.070)	(0.030)	(0.010)	(0.010)	(0.000)
Pa	Value	−9.129**	−8.414**	−10.206**	−12.158***	−8.155*
	(Robust p-value)	(0.040)	(0.020)	(0.020)	(0.010)	(0.090)
Panel Cointegration		Yes	Yes	Yes	Yes	Yes

Note: Robust P-values derived from bootstrap replications of critical values; ***p < 0.01, **p < 0.05, *p < 0.1.

Table 7
Kaya Identity Equation with EKC extension.

	Kaya Identity Equation			Kaya Identity Equation with EKC		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	MG	CCEMG	AMG	MG	CCEMG	AMG
lnPOP	0.967***	0.832***	0.947***	0.964***	0.838***	0.956***
	(0.029)	(0.109)	(0.037)	(0.039)	(0.117)	(0.043)
	[32.811]	[7.652]	[25.859]	[24.465]	[7.187]	[22.084]
lnPCgdp	0.997***	0.958***	0.975***	1.355***	0.287	1.739*
	(0.005)	(0.027)	(0.015)	(0.467)	(1.075)	(1.053)
	[200.188]	[36.101]	[64.904]	[2.901]	[0.267]	[1.651]
lnPCgdpSQ				−0.018	0.031	−0.036
				(0.023)	(0.053)	(0.050)
				[-0.790]	[0.580]	[-0.711]
lnEI	1.001***	1.001***	0.996***	0.997***	0.997***	0.994***
	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
	[181.053]	[196.917]	[186.836]	[163.020]	[179.796]	[209.529]
lnCI	0.999***	1.002***	0.996***	0.998***	0.998***	0.999***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
	[184.814]	[175.755]	[184.323]	[155.161]	[157.658]	[179.397]
Constant	−6.539***	−3.482	−6.034***	−7.344	−2.342	−11.398*
	(0.484)	(3.837)	(0.615)	(5.228)	(8.354)	(6.292)
	[-13.516]	[-0.907]	[-9.815]	[-1.405]	[-0.280]	[-1.812]
Observations	500	500	500	500	500	500
Number of ID	20	20	20	20	20	20

Standard errors in (.); t-statistics in [.]; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 8
Energy and carbon intensity.

	Energy Intensity Equation			Carbon Intensity Equation		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	MG	CCEMG	AMG	MG	CCEMG	AMG
lnRE	−0.168**	−0.072	−0.004	−0.205***	−0.100*	−0.219***
	(0.066)	(0.080)	(0.055)	(0.040)	(0.059)	(0.059)
	[-2.545]	[-0.908]	[-0.066]	[-5.180]	[-1.692]	[-3.679]
lnPCgdp	5.941	−4.500	8.205*	18.686*	−0.291	−5.636
	(4.455)	(16.575)	(4.581)	(11.146)	(26.026)	(6.960)
	[1.333]	[-0.271]	[1.791]	[1.676]	[-0.011]	[-0.810]
lnPCgdpSQ	−0.304	0.216	−0.397*	−0.897*	0.028	0.257
	(0.215)	(0.800)	(0.218)	(0.525)	(1.240)	(0.334)
	[-1.415]	[0.269]	[-1.821]	[-1.709]	[0.022]	[0.769]
lnSTU	−0.188	0.052	0.074	0.126	0.202	0.140
	(0.120)	(0.150)	(0.138)	(0.129)	(0.184)	(0.163)
	[-1.569]	[0.345]	[0.538]	[0.976]	[1.098]	[0.858]
Constant	−27.697	43.860	−41.521*	−98.193*	96.076	30.737
	(22.879)	(59.990)	(23.978)	(58.975)	(120.360)	(36.172)
	[-1.211]	[0.731]	[-1.732]	[-1.665]	[0.798]	[0.850]
Observations	500	500	500	500	500	500
Number of ID	20	20	20	20	20	20

Standard errors in (.); t-statistics in [.]; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

comparison, modelling within the Kaya identity equation, as in Table 8, provides a more policy informed evidence.

4.3. Results of JKS non-causality tests

For the multivariate functions under study, we test if the selected covariates do not Granger-cause the response variable. The results obtained from the tests are reported in Panel A of Table 10. As we can see from the results, the null hypothesis (H_0) that POP, PCgdp, EI and CI do not jointly Granger-cause consumption-based CO_2 emissions in the European economies is rejected at the 1% level of significance. The H_0 that RE, PCgdp and STU do not jointly Granger-cause the technological structure of the energy consumption mix (i.e., EI and CI) is likewise rejected at the 1% level of significance. Overall, the results in Panel A reveal that the selected covariates do Granger-cause the response variables, implying that the variables have predictive potential on consumption-based CO_2 emissions in the European countries studied.

We then consider univariate equations by testing Granger non-causality for each variable separately. The results are given in Panel B of Table 10. The results show a unidirectional causality from CO_2 emissions to POP and bidirectional causality between PCgdp and CO_2 emissions. These empirical findings confirm the earlier result that population size and economic growth explains CO_2 emissions in the selected European economies. Mohsin et al. (2022) reported similar findings for the impact of economic growth in the EU region. In addition, the results also show that bidirectional causality exists between EI and CO_2 emissions while a unidirectional causality runs from CI to CO_2 emissions. These findings imply that previous values of EI and CO_2 emissions predict each other while CI is the one that has predictive power on CO_2 emissions and not vice versa. The extended specifications show that renewable energy does Granger-cause changes in CI and EI. While the reverse causality is rejected for CI, it is accepted for EI, indicating bidirectional causality with EI and a unidirectional causality from renewable energy to CI. Similarly, the results show that bidirectional

Table 9
Robustness test incorporating RE for CE.

	(1)	(2)	(4)
VARIABLES	MG	CCEMG	AMG
lnPOP	−0.364	0.860	0.781**
	(0.907)	(1.406)	(0.348)
	[-0.401]	[0.612]	[2.243]
lnPCgdp	4.485	−6.629	8.059
	(8.444)	(13.189)	(5.617)
	[0.531]	[-0.503]	[1.435]
PCgdpSQ	−0.180	0.324	−0.349
	(0.401)	(0.622)	(0.267)
	[-0.448]	[0.521]	[-1.309]
lnEI	0.245***	0.119**	0.119***
	(0.079)	(0.053)	(0.038)
	[3.088]	[2.248]	[3.100]
lnRE	−0.219***	−0.152***	−0.166***
	(0.060)	(0.038)	(0.033)
	[-3.651]	[-4.003]	[-5.007]
Constant	−15.235	59.525	−47.443
	(56.408)	(100.886)	(32.722)
	[-0.270]	[0.590]	[-1.450]
Observations	500	500	500
Number of ID	20	20	20

Standard errors in (.); t-statistics in [.]; ***p < 0.01, **p < 0.05, *p < 0.1.

Table 10
Results of JKS non-causality test.

Panel A: Multivariate non-causality test					
H_0: Selected covariates do not Granger-cause lnCO2	Lags	HPJ Wald test	p-value	Decision	Conclusion
Kaya Equation	2	37.612***	0.000	Reject H_0	Selected covariates do Granger-cause lnCO2
Kaya Equation extended with EKC	2	54.237***	0.000	Reject H_0	Selected covariates do Granger-cause lnCO2
Energy Intensity	1	17.078***	0.002	Reject H_0	Selected covariates do Granger-cause lnCO2
Carbon Intensity	2	30.021***	0.000	Reject H_0	Selected covariates do Granger-cause lnCO2
Robustness test (Kaya with RE)	2	44.704***	0.000	Reject H_0	Selected covariates do Granger-cause lnCO2
Panel B: Univariate non-causality test					
H_0: x does not Granger-cause ($\nRightarrow$) y	Lags	HPJ Wald test	p-value	Decision	Conclusion
lnPOP $\nRightarrow$ lnCO2	1	0.071	0.790	Accept H_0	Unidirectional
lnCO2 $\nRightarrow$ lnPOP	1	31.221***	0.000	Reject H_0	lnCO2 $\Rightarrow$ lnPOP
lnPCgdp $\nRightarrow$ lnCO2	1	3.938**	0.047	Reject H_0	Bidirectional
lnCO2 $\nRightarrow$ lnPCgdp	1	6.945***	0.008	Reject H_0	lnCO2 $\Leftrightarrow$ lnPCgdp
lnEI $\nRightarrow$ lnCO2	1	3.847**	0.050	Reject H_0	Bidirectional
lnCO2 $\nRightarrow$ lnEI	1	10.276***	0.001	Reject H_0	lnCO2 $\Leftrightarrow$ lnEI
lnCI $\nRightarrow$ lnCO2	1	10.820***	0.001	Reject H_0	Unidirectional
lnCO2 $\nRightarrow$ lnCI	1	1.515	0.218	Accept H_0	lnCI $\Rightarrow$ lnCO2
lnRE $\nRightarrow$ lnEI	2	5.170*	0.075	Reject H_0	Bidirectional
lnEI $\nRightarrow$ lnRE	2	7.086**	0.029	Reject H_0	lnEI $\Leftrightarrow$ lnRE
lnRE $\nRightarrow$ lnCI	2	6.177**	0.046	Reject H_0	Unidirectional
lnCI $\nRightarrow$ lnRE	2	1.656	0.437	Accept H_0	lnRE $\Rightarrow$ lnCI
lnRE $\nRightarrow$ lnCO2	1	3.908**	0.048	Reject H_0	Bidirectional
lnCO2 $\nRightarrow$ lnRE	1	17.995***	0.000	Reject H_0	lnCO2 $\Leftrightarrow$ lnRE

***, ** and * denote 1%, 5% and 10% significance levels, respectively; $\Leftrightarrow$ denotes bidirectional causality; $\Rightarrow$ denotes unidirectional causality.

causality exists between RE and CO_2 emissions, indicating that renewable energy has predictive power on CO_2 emissions and vice versa. These findings are consistent with Dong et al. (2019) who found that positive changes in energy use and energy intensity stimulate CO_2 emissions in 128 countries around the world. Also, the significant predictive power of renewable energy on CO_2 emissions is consistent with the findings of Obobisa (2022) and Mirziyoyeva and Salahodjaev (2022).

4.4. Discussion of the key findings

The results of this study show that per capita GDP, energy and carbon intensities of the consumption structure have significant positive causal impact on consumption-based CO_2 emissions in European countries. Although the coefficients of per capita GDP and its squared term are respectively positive and negative, as expected for the case of the EKC hypothesis, the coefficient of the squared term is not statistically significant. This shows that increases in per capita GDP have a positive monotonic relationship with CO_2 emissions in the countries studied. However, the EKC hypothesis is confirmed in the case of consumption-adjusted EI and CI models. While per capita GDP increases energy and carbon intensity metrics, per capita GDP square decreases them. In other words, at the early stages of development, both per capita GDP and energy and carbon intensities have a positive relationship; however, after a certain level of development is reached, the relationship becomes negative as further increases in per capita GDP induce cleaner consumption and production patterns, thereby reducing the intensity of energy use and the carbon contents of the consumption mix. According to Frodyma et al. (2022), the income-environment relationship in the European Union is not defined by an inverted U-shaped curve. As a result, this aspect of our findings highlights the relevance of energy transition in turning the EKC curve in European economies.

Furthermore, the positive and significant effect of trade-adjusted energy and carbon intensity metrics on consumption-based CO_2 emissions in the countries studied suggests that deepening clean energy transition remains the path to decarbonising Europe in the post-COP26 era. From policymaking point of view, altering the environmental effects of the consumption pattern in Europe requires deepening energy transition away from fossil fuels and towards the more environmentally friendly renewable technologies. It has been scientifically acknowledged that fossil fuels generate some environmental externalities leading to global warming and other existential environmental challenges. These challenges remain a threat to ecosystems, economic development, and human lives. Therefore, our results support the earlier finding of Dong et al. (2019) who found energy intensity as part of the factors that contribute to CO_2 emissions at the global level. Also, the mitigation effect of renewable energy on consumption-based energy and carbon intensities implies that energy transition towards deepening the use of renewables provides the technological path to improving economic efficiency – reducing the amount of energy used for a unit GDP and the amount of CO_2 emitted per unit of energy used. In view of the high affluence and high consumption pattern of the European economies, a shift in the energy consumption structure to the more environmentally friendly renewable energy provides the technological path to decoupling consumption demands from trade-induced CO_2 emissions. This is because renewable (clean) energy consumption does not emit CO_2 and hence it is generally accepted as an antidote to environmental degradation which has posed a great existential challenge to human existence. Therefore, our results are consistent with the findings of Obobisa (2022) and Mirziyoyeva and Salahodjaev (2022).

5. Conclusion, policy remarks and future directions

5.1. Conclusion

Europe has a high level of affluence and consumption. Taking this into account, this study uses data from 1995 to 2019 to examine the relationship between technological trajectories defining the energy transition progress, namely energy and carbon intensities of the consumption mix, and CO_2 emissions in a panel of 20 European countries. The variables are adjusted for cross-border effects on domestic consumption by adding net emissions and energy embodied in traded goods and services. To avoid skewed parameter values, the study applies the Common Correlated Effects Mean Group (CCEMG) and Augmented Mean Group (AMG) panel estimators, which are robust to cross-sectional dependence and allow for heterogeneous slope coefficients. According to the findings, population size, per capita GDP, energy intensity, and carbon intensity all have a positive effect on CO_2 emissions, whereas the use of renewable energy technologies has a negative (decreasing) effect on both energy and carbon intensities, resulting in reduced CO_2 emissions. Although the estimated effects of per capita GDP and its squared term are respectively positive and negative, only the effect of the squared term is found to be statistically significant. In the case of consumption-adjusted EI and CI models, however, an inverted U-shaped curve is confirmed. These findings validate the EKC hypothesis in the selected European countries through the technological composition of their energy mix.

Using the JKS non-causality test, we show that under multivariate specifications, population, per capita GDP, and the technological composition of the energy structure jointly have predictive power on consumption-based CO_2 emissions. Similarly, renewable energy, per capita GDP, and industrial structure upgrading demonstrate joint predictive power on the technological composition of the energy structure. Univariate tests show that a unidirectional causality runs from population size and the carbon intensity of the energy structure to CO_2 emissions, and bidirectional causality exists between CO_2 emissions and per capita GDP and energy intensity. Additional univariate specifications show a unidirectional causality from renewable energy to the carbon intensity of the energy structure and bidirectional causality between renewable energy and energy intensity. Conclusively, the results show that renewable energy has predictive power over the technological composition of the energy structure and, by implication, provides the path to mitigating consumption-based CO_2 emissions in the selected European countries.

5.2. Policy implications

There are at least three policy implications from the findings that could improve the effectiveness of post-COP26 climate mitigation initiatives. First, the results show that the environmental impacts of the countries increase when energy and carbon intensity metrics describing the technological composition of their consumption structure increase. This implies that Europe may further reduce its environmental impacts by shifting its energy mix towards lower carbon intensity and increasing energy efficiency. The current energy composition indicates that three-quarters of final energy consumption comes from fossil fuels. As a result, a strategic adjustment in policy composition is required. Continuing with the current strategy will only make a minor contribution to the post-COP26 targets unless significant steps are taken to raise the proportion of green energy sources in the consumption mix. Making buildings more energy efficient, mobilising private financing for energy investments and phasing out the sale of new gasoline and diesel cars are key policy steps to take.

Second, the results show that the technological capacity of the countries to mitigate CO_2 emissions improves with an increase in renewable energy consumption. This implies that renewable energy clearly points the way to decarbonisation. Europe can accelerate its energy transition by promoting the marketability and development of renewable energy technology. This approach is consistent with the EU's Renewable Energy Directive (RED), which strives for a minimum of 20% renewable energy sources (RES) in the final energy mix. However, if the region is to fulfil its decarbonisation goal of decreasing emissions by 80%–95% by 2050, the energy transition must advance far faster than the current targets. From a policy standpoint, increased incentives in the form of tax credits and research grants can spur investment in renewable energy development.

Three, the EKC path to carbon mitigation is only validated through the technological composition of the energy structure. Based on this finding, this study suggests that reducing the energy and carbon intensities of the consumption structure are prerequisites to bending the curve between per capita GDP and environmental impacts in Europe. As a region with high affluence and high consumption, current economic policies must be adjusted to integrate clean energy transition if the countries are to mitigate the cross-border consequences of their consumption patterns. Energy conservation programs and incentives can help raise awareness of energy efficiency in key industries as well as in the residential and commercial sectors. Increased usage of renewable energy technology, as part of the policy options outlined in this study, can reduce embodied emissions in traded goods and services while preserving the economic gains obtained from trade demands. A further reduction in the cost of efficient and renewable energy technologies is necessary to make them not only environmentally friendly but also an economically viable option for economic entities.

Beside the above-highlighted policy implications, the cross-border environmental impacts of Europe's consumption pattern underline the importance of collaboration in the transition to a more sustainable global society. To develop an optimal mitigation approach, the path to meeting post-COP26 targets will involve a combination of national, regional, and international cooperation. As a result, European countries with advanced research capabilities in efficient and renewable energy technologies could help other countries that are struggling technologically. The benefit is that many of these countries will be able to skip a critical step in their energy transition by replacing "dirty" production relying on fossil fuel energy with "green" output created using renewable energy sources. Embodied emissions in cross-border trade flows can be lowered with such a policy approach.

5.3. Limitations and future directions

This study has some limitations, but it also opens up new avenues for future research. To begin, this study is based on a sample of European countries. As a result, future studies could concentrate on other countries or regions. Second, this study estimated energy and CO_2 emissions using consumption-based metrics. Thus, the impact equation may also be useful in understanding production-based emissions in Europe and can be extended to analyse environmental impacts in other regions for comparative evidence. Finally, using energy and carbon intensity indicators, this study specifies the technological structure of the energy consumption mix. Future research can investigate more disaggregated energy structures to better understand the environmental implications of oil, natural gas, solar, wind, nuclear, and other energy sources.

CRediT authorship contribution statement

Chinazaekpere Nwani: Conceptualization, Writing – original draft, Methodology, Investigation, Formal analysis. **Ojonugwa Usman:** Validation, Interpretation and Discussion of Results. **Kingsley I. Okere:** Software, Methodology, Methodology, Formal analysis. **Festus Victor Bekun:** Supervision, Writing – review & editing.

Declaration of competing interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix 1

Table A1
Correlation matrix and VIF test

Variables	lnCO2	lnPOP	lnPCgdp	lnEI	lnCI	lnRE	lnSTU
lnCO2	1.000						
lnPOP	0.963	1.000					
lnPCgdp	0.525	0.385	1.000				
lnEI	−0.449	−0.454	−0.699	1.000			
lnCI	0.144	−0.002	0.097	−0.277	1.000		
lnRE	−0.497	−0.418	−0.070	0.000	−0.388	1.000	
lnSTU	0.371	0.419	0.290	−0.449	−0.027	0.058	1.000

Variance inflation factors (VIFs) test for the presence of multicolinearity in linear model specification

Model Specifications	**VIF**	**1/VIF**	**Mean VIF**
Kaya Equation	2.380	0.888	1.710
Energy Intensity	1.100	0.988	1.070
Carbon Intensity	1.100	0.988	1.070
Kaya with RE	2.240	0.778	1.790

Note: In theory, multicollinearity concerns arise when VIF ≥10 and the Mean VIF ≥6.

References

Apeaning, R.W., 2021. Technological constraints to energy-related carbon emissions and economic growth decoupling: a retrospective and prospective analysis. J. Clean. Prod. 291, 125706.

Awan, A., Sadiq, M., Hassan, S.T., Khan, I., Khan, N.H., 2022. Combined nonlinear effects of urbanization and economic growth on CO2 emissions in Malaysia. An application of QARDL and KRLS. Urban Clim. 46, 101342.

Azam, W., Khan, I., Ali, S.A., 2023. Alternative energy and natural resources in determining environmental sustainability: a look at the role of government final consumption expenditures in France. Environ. Sci. Pollut. Control Ser. 30 (1), 1949–1965.

BP, 2022. BP Statistical Review of World Energy June 2022. Available online: http://www.bp.com/statisticalreview.

Davis, S.J., Caldeira, K., 2010. Consumption-based accounting of CO2 emissions. Proc. Natl. Acad. Sci. USA 107 (12), 5687–5692.

Dong, K., Dong, X., Dong, C., 2019. Determinants of the global and regional CO2 emissions: what causes what and where? Appl. Econ. 51 (46), 5031–5044.

Dhaene, G., Jochmans, K., 2015. Split-panel Jackknife estimation of fixed-effect models. Rev. Econ. Stud. 82 (3), 991–1030.

Dumitrescu, E.I., Hurlin, C., 2012. Testing for Granger non-causality in heterogeneous panels. Econ. Modell. 29 (4), 1450–1460.

Eberhardt, M., 2012. Estimating panel time-series models with heterogeneous slopes. STATA J. 12 (1), 61–71.

Eberhardt, M., Teal, F., 2010. Productivity Analysis in Global Manufacturing Production. Department of Economics, University of Oxford. Discussion Paper 515. http://www.economics.ox.ac.uk/research/WP/pdf/paper515.pdf.

Friedlingstein, P., Jones, M.W., O'Sullivan, M., Andrew, R.M., Bakker, D.C., Hauck, J., et al., 2022. Global carbon budget 2021. Earth Syst. Sci. Data 14 (4), 1917–2005. https://doi.org/10.5194/essd-14-1917-2022.

Frodyma, K., Papież, M., Śmiech, S., 2022. Revisiting the environmental Kuznets curve in the European Union countries. Energy 241, 122899.

González-Torres, M., Pérez-Lombard, L., Coronel, J.F., Maestre, I.R., 2021. Revisiting Kaya Identity to define an emissions indicators pyramid. J. Clean. Prod. 317, 128328.

Grossman, M.G., Krueger, B.A., 1991. Environmental Impacts of A North American Free Trade Agreement (No. W3914). National Bureau of Economic Research. https://www.nber.org/papers/w3914.

Hainsch, K., Löffler, K., Burandt, T., Zwickl-Bernhard, S., 2022. Energy transition scenarios: what policies, societal attitudes, and technology developments will realize the EU Green Deal? Energy 239, 122067.

Harris, S., Weinzettel, J., Bigano, A., Källmén, A., 2020. Low carbon cities in 2050? GHG emissions of European cities using production-based and consumption-based emission accounting methods. J. Clean. Prod. 248, 119206.

Hassan, S.T., Wang, P., Khan, I., Zhu, B., 2023. The impact of economic complexity, technology advancements, and nuclear energy consumption on the ecological footprint of the USA: towards circular economy initiatives. Gondwana Res. 113, 237–246.

Jacobs, M., 2022. Reflections on COP26: international diplomacy, global justice and the greening of capitalism. Polit. Q. 93 (2), 270–277.

Jie, H., Khan, I., Alharthi, M., Zafar, M.W., Saeed, A., 2023. Sustainable energy policy, socio-economic development, and ecological footprint: the economic significance of natural resources, population growth, and industrial development. Util. Pol. 81, 101490.

Juodis, A., Karavias, Y., Sarafidis, V., 2021. A homogeneous approach to testing for Granger non-causality in heterogeneous panels. Empir. Econ. 60 (1), 93–112.

Kartal, M.T., Depren, S.K., Kirikkaleli, D., Depren, Ö., Khan, U., 2022. Asymmetric and long-run impact of political stability on consumption-based carbon dioxide emissions in Finland: evidence from nonlinear and Fourier-based approaches. J. Environ. Manag. 321, 116043.

Lin, S.J., Beidari, M., Lewis, C., 2015. Energy consumption trends and decoupling effects between carbon dioxide and gross domestic product in South Africa. Aerosol Air Qual. Res. 15 (7), 2676–2687.

Liu, H., Khan, I., Zakari, A., Alharthi, M., 2022a. Roles of trilemma in the world energy sector and transition towards sustainable energy: a study of economic growth and the environment. Energy Pol. 170, 113238.

Liu, H., Alharthi, M., Atil, A., Zafar, M.W., Khan, I., 2022b. A non-linear analysis of the impacts of natural resources and education on environmental quality: green energy and its role in the future. Resour. Pol. 79, 102940.

Luan, B., Zou, H., Chen, S., Huang, J., 2021. The effect of industrial structure adjustment on China's energy intensity: evidence from linear and nonlinear analysis. Energy 218, 119517.

Mirziyoyeva, Z., Salahodjaev, R., 2022. Renewable energy and CO2 emissions intensity in the top carbon intense countries. Renew. Energy 192, 507–512.

Mohsin, M., Naseem, S., Sarfraz, M., Azam, T., 2022. Assessing the effects of fuel energy consumption, foreign direct investment and GDP on CO2 emission: new data science evidence from Europe & Central Asia. Fuel 314, 123098.

Obobisa, E.S., 2022. Achieving 1.5° C and net-zero emissions target: the role of renewable energy and financial development. Renew. Energy 188, 967–985.

Pan, X., Wang, H., Lu, X., Zheng, X., Wang, L., Chen, W., 2022. Implications of the consumption-based accounting for future national emissions budgets. Clim. Pol. 1–13.

Pesaran, M.H., 2006. Estimation and inference in large heterogeneous panels with a multifactor error structure. Econometrica 74, 967–1012.

Pesaran, M.H., 2004. General diagnostic tests for cross section dependence in panels. CESifo Working. Paper No. 1229.

Pesaran, M.H., 2007. A simple panel unit root test in the presence of cross-section dependence. J. Appl. Econom. 22, 265–312.

Pesaran, M.H., 2021. General diagnostic tests for cross-sectional dependence in panels. Empir. Econ. 60, 13–50. https://doi.org/10.1007/s00181-020-01875-7.
Pesaran, M.H., Smith, R., 1995. Estimating long-run relationships from dynamic heterogeneous panels. J. Econom. 68 (1), 79–113.
Pesaran, M.H., Tosetti, E., 2011. Large panels with common factors and spatial correlation. J. Econom. 161, 182–202.
Pesaran, M.H., Yamagata, T., 2008. Testing slope homogeneity in large panels. J. Econom. 142 (1), 50–93.
Peters, G.P., Minx, J.C., Weber, C.L., Edenhofer, O., 2011. Growth in emission transfers via international trade from 1990 to 2008. Proc. Natl. Acad. Sci. USA 108 (21), 8903–8908.
Pham, N.M., Huynh, T.L.D., Nasir, M.A., 2020. Environmental consequences of population, affluence and technological progress for European countries: a Malthusian view. J. Environ. Manag. 260, 110143.
Renou-Maissant, P., Abdesselam, R., Bonnet, J., 2022. Trajectories for energy transition in EU-28 countries over the period 2000–2019: a multidimensional approach. Environ. Model. Assess. 27 (3), 525–551.
Rocco, M.V., Golinucci, N., Ronco, S.M., Colombo, E., 2020. Fighting carbon leakage through consumption-based carbon emissions policies: empirical analysis based on the World Trade Model with Bilateral Trades. Appl. Energy 274, 115301.
Soeder, D.J., 2021. Fossil fuels and climate change. In: Fracking and the Environment. Springer, Cham, pp. 155–185.
Strauss, B.H., Orton, P.M., Bittermann, K., Buchanan, M.K., Gilford, D.M., Kopp, R.E., et al., 2021. Economic damages from Hurricane Sandy attributable to sea level rise caused by anthropogenic climate change. Nat. Commun. 12 (1), 1–9.
Štreimikienė, D., Balezentis, T., 2016. Kaya identity for analysis of the main drivers of GHG emissions and feasibility to implement EU "20–20–20" targets in the Baltic States. Renew. Sustain. Energy Rev. 58, 1108–1113.
Usman, O., Iorember, P.T., Jelilov, G., Isik, A., Ike, G.N., Sarkodie, S.A., 2021. Towards mitigating ecological degradation in G-7 countries: accounting for economic effect dynamics, renewable energy consumption, and innovation. Heliyon 7 (12), e08592.
Waggoner, P.E., Ausubel, J.H., 2002. A framework for sustainability science: a renovated IPAT identity. Proc. Natl. Acad. Sci. USA 99 (12), 7860–7865.
Westerlund, J., 2007. Testing for error correction in panel data. Oxf. Bull. Econ. Stat. 69, 709–748.
World Bank, 2022. World Development Indicators, World Bank. Available online: https://databank.worldbank.org/home.aspx.
Xiao, J., Juodis, A., Karavias, Y., Sarafidis, V., Ditzen, J., 2022. Improved tests for Granger noncausality in panel data. In: Swiss Stata Conference 2022. Stata Users Group. No. *06)*.
York, R., Rosa, E.A., Dietz, T., 2003. STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. Ecol. Econ. 46 (3), 351–365.
Yu, S., Liu, J., Hu, X., Tian, P., 2022. Does development of renewable energy reduce energy intensity? Evidence from 82 countries. Technol. Forecast. Soc. Change 174, 121254.
Zhong, S., Goh, T., Su, B., 2022. Patterns and drivers of embodied carbon intensity in international exports: the role of trade and environmental policies. Energy Econ., 106313