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Research article

Toward achieving zero-emissions in European Union countries: The contributions of trade and overseas direct investments in consumption-based carbon emissions

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Abstract: To achieve the ideal emissions reduction goals, several studies have suggested that carbon emissions should be examined in the framework of both territorial and consumption-based emissions. Nevertheless, the European Union (EU) SDGs targets aimed at mitigating carbon emissions based on the United Nation (UN) Kyoto Protocol structure, only appears to be concerned with the reduction of territorial-based emissions whilst emissions embodied on imported goods and services receive very little attention. To this end, this study examines the contributions of outward foreign direct investment (OFDI) and disaggregate trade flows toward consumption-based sustainability in twenty-one (21) EU countries for the period 1995–2019. The study utilizes the STIRPAT model (Stochastic Impacts by Regression on Population, Affluence, and Technology) and battery of advanced econometric techniques such as the Cross-Sectional Autoregressive Distributed Lag (CS-ARDL), Common Correlated Effects (CCE) and the Cross-Sectional Distributed Lags (CS-DL) to examine the short-and long-run dynamics of OFDI and trade on consumption-based emissions. Finding reveals that EU exports and OFDI spillover reduces consumption-based emission, whilst import of goods and services promote emissions both in the short-run and long-run. This suggests that the progress report on carbon emissions reduction for most EU countries under the greenhouse gas accounting systems are merely

carbon emissions outsourced to low-income countries whilst consumption-based emission continues to increase. These findings are robust to several econometric problems with set of policy implications provided for policymakers and governments to formulate more efficient strategies toward the mitigation of consumption-based carbon emissions among EU countries.

Keywords: consumption-based emission; production-based emission; carbon emission; import outward FDI; trade; CS-ARDL; STIRPAT, CS-DL; European Union

1. Introduction

The greenhouse gas emissions (GHGs) have significantly increased over the last century (since 1900) due to rapid industrialization brought about by unprecedented economic growth and development, which has triggered serious environmental problems. Thus, discussions on the mitigation of global warming attributed to GHGs emissions have become one of the top-burner in global issues, and a central objective for policy initiatives. For this reason, large numbers of international bodies and countries including EU have signed different international environmental laws and partnership agreements on cooperation toward the reduction of carbon emission. Some of these agreements include the "Paris Agreement", "Kyoto Protocol", and "the World Environmental Pact", promulgated to address environmental pollution and global climate change. In 2015, the United Nation (UN) established the Stainable Development Goals (SDGs) with a clarion call to eradicate poverty, preserve the environment, as well as the assurance that each person lives in prosperity and peace by 2030 [1]. Thus, countries or group of countries with similar environmental objective needs to be more proactive and strategized in developing their nationally determined contributions (NDCs) toward attaining the 2030 sustainability goals [2].

The European Union (EU) countries are some of most dynamic and proactive countries that has made tremendous "progress" towards achieving SDGs goals. The European Green Deal clearly aimed at transforming all EU countries into more modern, resource efficient and competitive economy where GHGs emissions and other environmental challenges are adequately addressed and turned into opportunity. Strategizing to achieve these SDGs goals, the EU countries are committed to reducing GHGs emissions to 20% by 2020, thereafter by 80% by 2050 [3]. However, as of 2019, the EU has already "achieved" its 2020 SDGs target with the reduction of emission by 26% [4], and the overall reduction of GHGs in 2020 was 34% compared to 1990 based year. This indicates that the EU appears to be "on track" to achieving its environmental sustainability goals. Recently, the EU adopted 55% reduction target by 2030 which include mitigation of carbon emission from forestry activities, paving the way to achieve carbon neutrality by 2050. Nevertheless, despite the "progress" and pledge by EU members to reduce the GHGs emissions and attain the environmental SDGs goals [5]. The pace of progress among the EU-27 member countries still differs and the GHGs emission accounting system (the UNFCCC, 2016) used in assessing the perceive progress has been heavily criticized by both economics and environmental scholars.

Under the United Nations Framework Convention for Climate Change (UNFCCC, 2016), most countries report production-based emissions (PBA) which computes emissions due to fossil fuel combustion within territorial boundaries. Thus, GHGs emissions records for countries is only based on PBA approach. However, when goods are traded, the emissions linked with the products (or embodied emissions) are also traded but not reported in the consumer country's emissions statistics. This distort and mislead the true national emission records as reported emissions are only linked to the exporting countries [6,7]. Reports on "carbon loophole" by [8,9], shows that EU "full lifecycle" accounting carbon emissions which include emissions due to consumption of imported goods are not accounted for in the current GHGs accounting system, thus EU emissions is revealed to have grown by 11%. Trend on embodied carbon emissions associated with the consumption of imported goods in the EU region continue to increase, cancelling out the carbon reduction gains achieved by individual countries [8]. Therefore, the emission reduction achievements and progress reported in EU countries under the Kyoto Protocol framework only appear as emissions exported to developing countries. According to Becqué et al. [8]. report based on 2009 data, Luxembourg (79%), Austria (48%), France (44%), Sweden (44%), Ireland (42) and Italy (29%) were EU's top net importers of carbon emission, while the top importers of carbon in absolute terms were Germany (402 Mt), France (254 Mt), United Kingdom (246 Mt), Italy (215 Mt), Spain (147 Mt), and Netherlands (105 Mt).

Several scientific research papers have examined both the territorial and consumption-based carbon emissions, but handful studies have focused on EU consumption-based emissions (see, Table 1A) using exploratory approach (a non-econometric methods) which are not robust to econometric problems such as heterogeneity, cross-sectional dependency, heteroscedasticity etc. Failure to account for these econometric problems lead to bias and inconsistent estimates. Whilst complete and adequate study examining EU's consumption-based carbon emissions nexus using advanced econometric methods is yet to be explored, the role of outward FDI spillover toward the reduction of consumption-based emission remain unexamined. To the best of our knowledge, no study has examined whether the combine effects (joint impact) of trade and OFDI spillover bring about sustainable consumption. FDI can increase domestic markets competition, stimulate technological innovation, and disseminate management policy [10,11]. But as facilitator of the global economy, FDI has become a major source of environmental pollution, as production section of firms link with pollution may be exported abroad. This promotes the redistribution of pollution and pollutants products. However, many existing research on FDI and CO_2 emissions have focused primarily on production-based emissions, whilst studies on reversed technology due to effect OFDI spillover on consumption-based emissions remained unexplored. To this end, this study investigates the aforementioned research gaps by examining the impact of disaggregate international trade (export and import) and OFDI spillovers on consumption-based emissions in twenty-one (21) EU counties spanning 1995 to 2019. For efficient and complete policy strategies toward achieving 2030 SDGs target in EU region., the study considered the results of both the short-run and long-run dynamics.

This study contributes to literature in several ways: (i) The study utilized variables selected based on the STIRPAT model which assesses human impact on the environment and predict a non-monotonic and non-proportional functional relationship among the selected emission determinants. (ii) The study utilizes advanced econometrics techniques such as Cross-Sectional Autoregressive Distributed Lag (CS-ARDL), Common Correlated Effects (CCE) estimator, and cross-sectional distributed lags (CS-DL) robust to cross sectional dependency to evaluates the long-run effect and short-run dynamics of trade and investments on consumption-based emission. (iii) Unlike many other studies that examined territorial-based emission such as Halicioglu and Ketenci [12], Dogan and Seker [13], etc., this study examines the impact of disaggregate trade and OFDI spillover on consumption-based carbon emission among EU countries which to the best of our knowledge has not been investigated. (iv) Most likely, this study is the first to examine the role of OFDI spillover on consumption-based CO_2 emission in 21 selected EU countries. Examining OFDI-Consumption-based emission nexus will be interesting given the technique effects of OFDI spillover toward attaining sustainable consumption. (v) Up to this present study, no study has examined the combine effects of disaggregate trade and OFDI spillover toward achieving cleaner environment among EU countries. Thus, the study is first to examine the interactions of trade and OFDI toward achieving consumption sustainability

The structure of this paper is essentially based on five sections: Section 2 is devoted to the study's theoretical background including review of previous literatures on the relationship between trade, investment, and the environment. Section 3 describes the data and methodology of the study. Section 4 discusses the empirical results of the study. Section 5 summarizes and conclude the study with policy recommendations as well as direction for future research.

2. Theoretical background and review of related literature

Debate on "the country that takes responsibility for carbon emissions" are being explored along production- and consumption-based emissions accounting approach. The production-based accounting method probably the most widely used, allocates the responsibility of emissions on the actors (country) who operates the production process (economy). This type of carbon emissions are merely emissions contributed within a country's territory and indicate the production-based emission at country level, initiated by the international carbon accounting systems as part of effort aimed at reducing carbon emissions reached at the Paris Agreement (UNFCCC, 2008; 2015). Nevertheless, the criticism that trails the production-based accounting approach shows that the method only explains territorial emission as countries may falsely reduce their emissions level by outsourcing carbon intensive industries whilst ignoring inbound emissions via imported products. This led to the recommendation of the consumption-based accounting approach, calculated as territory-based emissions plus the emissions embodied in imports (CO_2) minus the emissions embodied in exports [14]. Numerous studies have examined the emission level of individual countries or group of countries using either the production or consumption-based accounting approach or both. Some of the notably studies include [12–18], etc., Recently, the extraction-based carbon emission approach has also been utilized and suggested that CO_2 emission are caused by the use of fossil fuels, placing emission burden on the producers that benefit financially from the extraction and sales of these fossil fuel. Related to the extraction-based carbon emission is the more general income-based approach [19].

Recently, a growing body of empirical literature has examined consumption-based carbon emission. For instance, Liddle [14] paper found that imports decrease territorial emissions and increase consumption-based carbon emissions for 102 countries for the period 1990 to 2013. The study examined the effects of international trade, industry value added, energy prices, and fossil fuel consumption on both territory and consumption-based CO_2 emissions. Bhattacharya et al. [20] paper investigated the production and consumption-based carbon emissions for 70 countries spanning from 1990 to 2014. Examining the club convergence, their findings revealed two clubs convergent for consumption-based and three club convergence for territory-based emissions. However, imports and income showed to enhance consumption-based carbon emissions, while exports mitigate consumption-based CO_2 emissions in G7 countries from 1990 to 2017 when several determinants of consumption-based emissions were investigated [12]. Similarly, consumption-based emissions and international trade relationship for oil-exporting countries from 1995 to 2013 was examined by Hasanov et al. [16]. The study revealed that whilst exports was negatively related to consumption-based carbon emissions, import and GDP were found to be positively related. Contrarily, imports and exports showed to decrease territory-based carbon emissions. Dong and Wang [21] study investigated the consumption and production-based carbon emissions for the global panel Environmental Kuznets Curve (EKC) hypothesis. Findings indicate the absence of EKC hypothesis for consumption-based carbon emissions. Gyam [22] paper examined the impact of FDI, natural resources, economic advancement and urbanization on consumption-based carbon emission in Sub-Saharan Africa countries for the period 1990 to 2018. The paper utilized panel econometrics approach such as AMG, CCEMG and the Driscoll–Kraay (DK) OLS techniques. Findings revealed positive linkage between all explanatory variables and the consumption-based carbon emission.

However, scholars such as Yang and Liu [23], Mohanty and Sethi [24], Borghesi et al. [25], Zhang et al. [26] examined outward FDI-Carbon emission relationship for different home country. For instance, Yang and Liu [23] utilized the Japanese data to explore the relationship between outward FDI and carbon emission using the Granger causality test approach, and their findings revealed that the Japanese outward FDI improves the environment. Mohanty and Sethi [24] paper found that outward FDI spillovers, energy consumption and environmental quality relationship in BRICS countries help reduce carbon emission. Borghesi et al. [25] evaluates 22,000 firms' outward FDI for Italian manufacturing enterprise and examines the role played by the European Union's Emissions Trading System. Their empirical results revealed that EU ETS had a weak effect on firm's outward FDI flow. These papers only examined territorial-based carbon emission which do not account for emissions induced by imported products.

So far, there is dearth of literature on OFDI spillover and consumption-based emissions relationship, but studies on EU's OFDI spillover on consumption-based carbon emissions remain unexamined. Similarly, study examining the combined effects of trade and OFDI spillover toward mitigating consumption-based emissions have also not been considered.

EU countries plays a major role in the flow of international trade and accounts for the second largest share of global imports and exports of goods in 2016. This increase in trade may cause emission especially imported goods. This shows that through imported products, the EU countries dissipate much more emission to the rest of the world, compared to the emission emitted to EU from other countries [27,28]. However, for to matter with respect to emissions, the consumption-based rather than territory-based emissions should be considered [8, 14–17], etc. So far, literature survey on EU's consumption-based carbon emissions is shown in Table 1A and the approaches employed are mostly exploratory which are inadequate in the presence of cross-sectional dependency and heterogeneity. To this end, this study employs advanced panel data econometric technique such CS-ARDL, CS-DL and CCE which account for cross-sectional dependency and heterogeneity to investigate the long- and short-term effect of the impact of disaggregate international trade (import and export) and OFDI spillover on consumption-based carbon emissions for EU countries for the period of 1995 to 2019. In addition, this study examines the links between EU's consumption-based emissions and other variables such as the total fossil fuel (Tff), industry added share (Ind) and the population growth to mitigate CO_2 emission.

Table 1A. A survey of existing literature focusing on production and consumption based CCO2 emissions in EU region.

S/N	Authors	Titles	Emission accounted	Methods	Findings
1	Karstensen et al. [29]	Trends of the EU's territorial and consumption-based emissions from 1990 to 2016	Territorial and consumption-based emissions	A Kaya identity decomposition	Decline in CCO2 is partly due to decreasing TCO2
2	Dogan and Seker [13]	Determinants of CO_2 emissions in the European Union: The role of renewable and non-renewable energy	Territorial-based emissions	DOLS, FMOLS, and D-H causality	Renewable energy mitigates CO_2 emissions.
3	Sandström et al. [6]	The role of trade in the greenhouse gas footprints of EU diets	Consumption-based emissions	Quantities	Plant-based diets may mitigate climate change
4	Fezzigna et al. [30]	Revising Emission Responsibilities through Consumption-Based Accounting: A European and Post-Brexit Perspective	Consumption-based emissions	National Carbon Intensity (NCI) method	EU embodied in imports is higher than in exports
5	Liobikiene and Dagiliute [31]	The relationship between economic and carbon footprint changes in EU: The achievements of the EU sustainable consumption and production policy implementation	Territorial and consumption-based emissions	Exploratory analysis (Observation)	EU CCO2 footprint exceeded the level TCO2 emissions
6	Valodka et al. [32]	Impact of the International Trade on the EU Clothing Industry Carbon Emissions	Consumption-based emissions	MRIO and triangulation method	Financial crisis reduces EU imports of CO_2 emissions

3. Methodology and data

3.1. Data description

This study explores the contributions of international trade and outward FDI in 21 European union countries toward sustainable consumption for the period 1995–2020. The timeframe adopted is driven by data availability. Table 1 (see Appendix) shows the list of countries in sample for the study analysis. As reported in Table 2, the sample data are derived from the world bank database, and Global Carbon Budget. This study transformed the selected data from their raw form into natural logarithmic to obtain elasticity of CO_2 emissions with respect to the independent variables. To avoid the problem associated with logarithm of negative numbers, a constant number of 88.0 and 4.0 were added to the OFDI and POP variables respectively before taking logarithm. Thus, the OFDI variable used in this study is the log (88.0 + OFDI), whilst the negative numbers in population growth are dealt with in the same way, that is log (4.0 + pop growth rate). The collated data are strongly balanced panel without gaps, which is more desirable for the application of reliable estimation techniques. However, Figure 1 shows the combined sample plots of the main variables (CCO2, OFDI, EXP and IMP) for the selected twenty-one (21) EU countries spanning 1995 to 2019. Regarding the scatter plots shown in Figures 2A–F, both InEXP and InIMP variables shows to be negatively related to CCO2 variable, while the Ind variable is positively linked (plot 2C). Contrarily, plots 2A and 2F indicates no correlation between the dependent variables (CCO2) and the response variables (OFDI and POP).

Table 2. Definitions of variables and data sources.

Code	Variables	Description	Sources
CCO2	Consumption-based CO_2 Emissions	This denotes the EU's countries consumption-based CO_2 emission (metric tons per capita).	Friedlingstein et al. [33]
TCO2	Territorial- based CO_2 Emissions	This denotes the EU's countries territorial-based CO_2 emission (metric tons per capita).	Friedlingstein et al. [33]
OFDI	Outward FDI	Foreign Direct Investment net outflows as percentage of Gross Domestic Product (% of GDP).	World Bank [34]
EXP	Export share	Export of goods and services as percentage of Gross Domestic Product (% of GDP).	World Bank [34]
IMP	Import share	Import of goods and services as percentage of Gross Domestic Product (% of GDP).	World Bank [34]
Tff	Total fossil fuel share	Fuel energy consumption as a share of total energy consumption (% of total).	World Bank [34]
Ind.	Industry share	It comprises values added in mining, manufacturing, construction, electricity, water, and gas.	World Bank [34]
POP	Population growth	Population growth (annual %) is derive from total population of respective EU countries.	World Bank [34]

Note: 1). Sources: author's compilation, 2020. Note Global Carbon Budget [33] is available at https://doi.org/10.5194/essd-11-1783 2019; 2). https://databank.worldbank.org/source/world-development indicators.

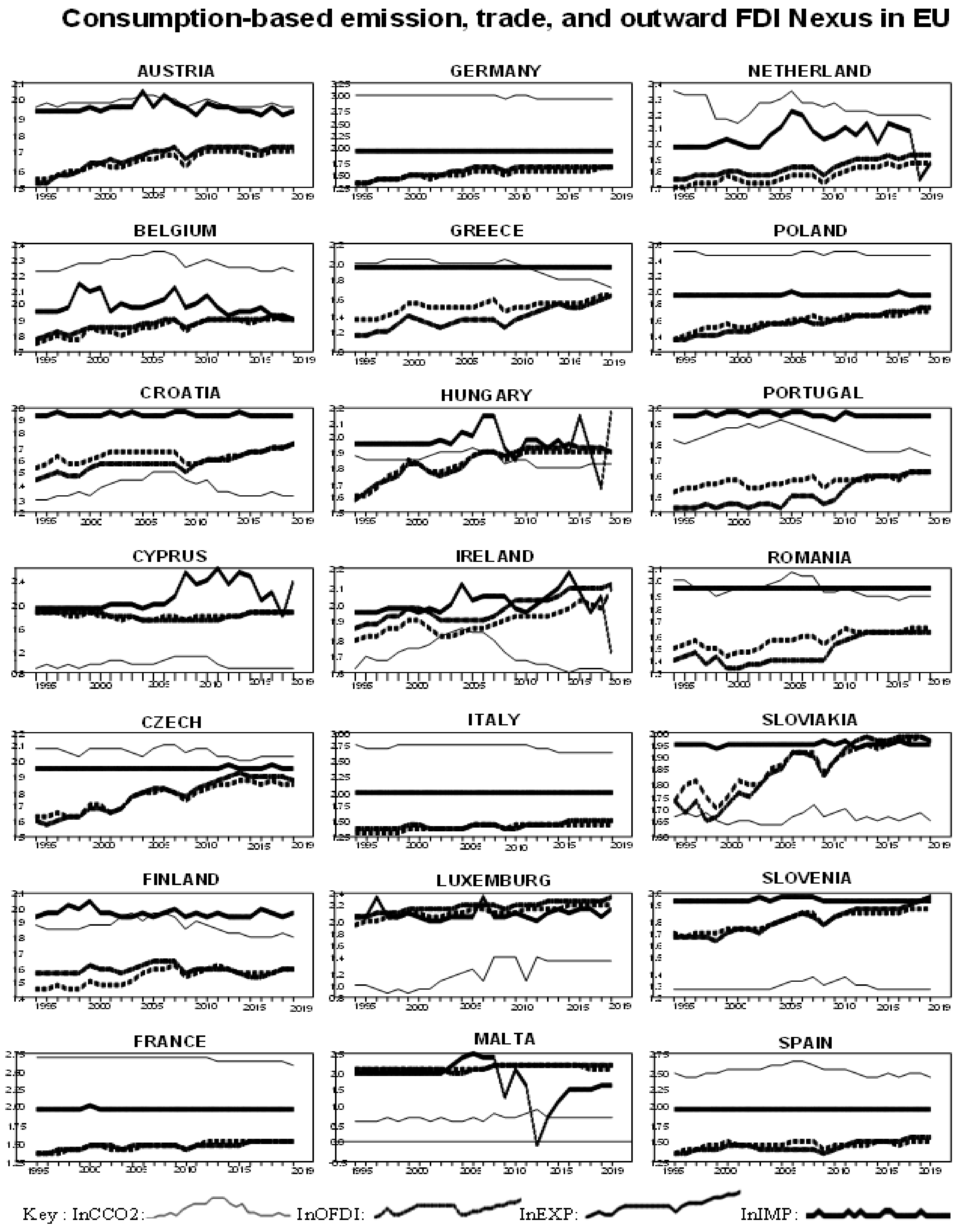

Figure 1. Plots showing log of variables in European Union (EU) 21 countries.

Source: Authors evaluation using global carbon budget and world bank data.

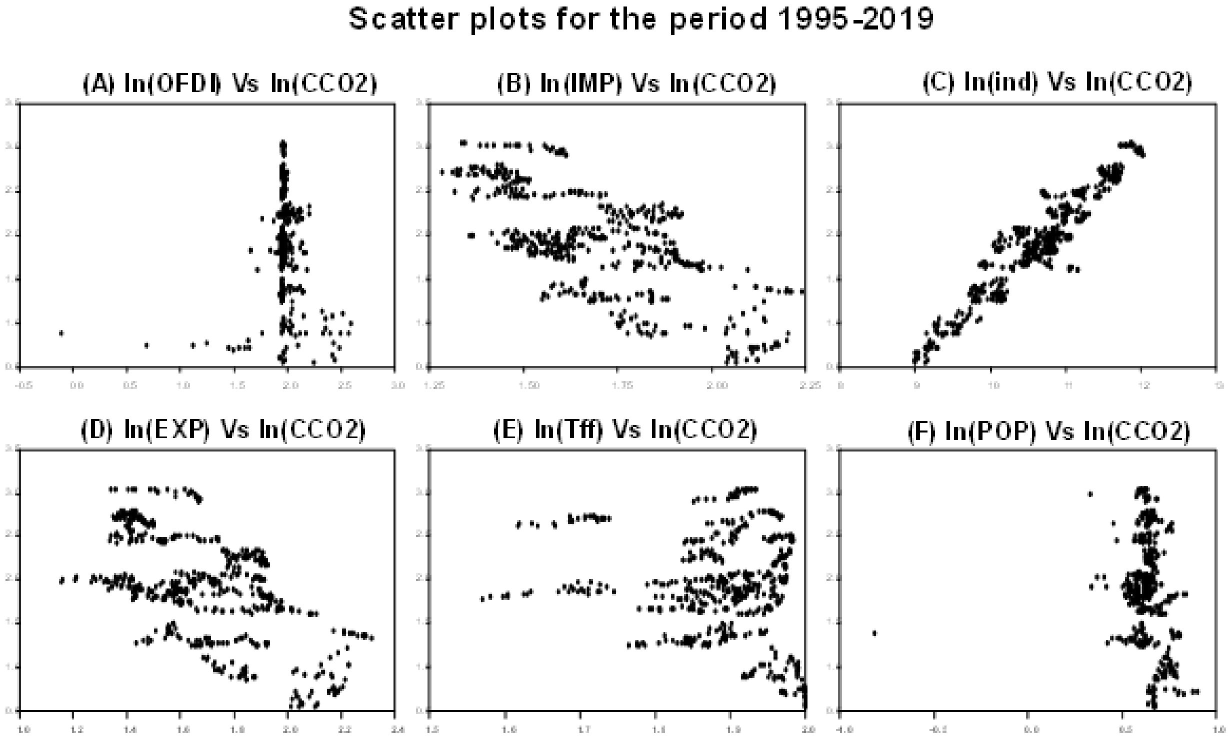

Figure 2. Note that Figures 2A–F are the panel scatter plots of consumption-based emission and other utilized variables. That is, the horizontal axes represent the log variables of OFDI, EXP, IMP, Tff, ind. and POP and the vertical axes represent the log of consumption-based emission.

Source: Authors evaluation using Global Carbon Budget and world bank data.

3.2. Econometric model techniques and model specifications

3.2.1. The IPAT and STIRPAT model

Ehrlich and Holdren [35] developed the IPAT model to examine the relationship between the environment and home country economic activities. Specifically, they showed that the growth of population, wealth and technology are collectively responsible for environmental degradation. The formulation of the relation was given as,

$$I = PAT, \tag{1}$$

where IPAT indicates Impact, Population, Wealth, and Technology respectively

More so, the IPAT equation results suggested that population growth negatively impact the environment and that affluence is a major driver of the CO_2 emissions. Early researchers such as [36] also applied the IPAT model in examining carbon emission. However, the use of the model by econometrist revealed that the model does not consider some crucial determinants, which may give rise to non-proportional and non-monotonic effects [37].

$$I_{it} = \delta P_{it}^{\varphi} A_{it}^{\alpha} T_{it}^{\beta}. \tag{2}$$

York et al. [37] and Dietz and Rosa [38] developed a random version of the IPAT model, known as the STIRPAT "Stochastic Impacts by Regression on Population, Affluence, and Technology" model showed in Eq (2). Taking the logarithmic transformation of the linear regression with a stochastic random error term leads to Eq (3). The improved model (STIRPAT) has become a crucial interdisciplinary model linking the ecological accounting equation with social sciences [38]. Thus, the linear form is given as,

$$lnI_{it} = ln\delta_{it} + \varphi lnP_{it} + \alpha lnA_{it} + \beta lnT_{it} + \varepsilon_{it}. \tag{3}$$

The STIRPAT model may be expanded by adding other important variables such as social, political, cultural and economic via disaggregating 'T', whilst Other T can represent any other factors. This study introduces the OFDI and international trade as part of the disaggregated items from T, to examine carbon emissions among European Union member countries taking into consideration the role of other variables, thus:

Model-I

$$\left.\begin{aligned} InCCO2_{it} = {} & \beta_0 + \beta_1 In(OFDI_{it}) + \beta_2 In(EXP_{it}) + \beta_3 In(IMP_{it}) + \beta_4 In(Tff_{it}) \\ & + \beta_5 In(Ind_{it}) + \beta_6 In(POP_{it}) + \varepsilon_t \end{aligned}\right\}. \tag{4}$$

Subscripts i = 1, 2… N and t = 1, 2… T denote 21 EU countries and year respectively, β_0 to β_8 are the unknown parameters to be estimated while ε is an error term. All the variables are expressed in natural logarithm.

Model-II

$$\left.\begin{aligned} InCCO2_{it} = {} & \beta_0 + \beta_1 In(OFDI_{it}) + \beta_2 In(EXP_{it}) + \beta_3 In(IMP_{it}) + \beta_4 In(Tff_{it}) \\ & + \beta_5 In(Ind_{it}) + \beta_6 In(POP_{it}) + \beta_7 ln(EXP_{it} \times OFDI_{it}) + \varepsilon_t \end{aligned}\right\}. \tag{5}$$

In this study, we construct the joint impact of international trade (IMP) and OFDI variable. Thus, Eq (4) is extended by addition the interaction term $(EXP_{it} \times OFD_{it})$ to form Eq (5).

Model-III

$$\left.\begin{aligned} InCCO2_{it} = {} & \beta_0 + \beta_1 In(OFDI_{it}) + \beta_2 In(EXP_{it}) + \beta_3 In(IMP_{it}) + \beta_4 In(Tff_{it}) \\ & + \beta_5 In(Ind_{it}) + \beta_6 In(POP_{it}) + \beta_7 ln(IMP_{it} \times OFDI_{it}) + \varepsilon_t \end{aligned}\right\}. \tag{6}$$

In model III, we construct the joint impact of international trade (EXP) and OFDI variable to examines environmental pollution. Thus, Eq (4) is also extended by addition the interaction term $(IMP_{it} \times OFD_{it})$ to form Eq (7).

3.3. Estimation strategy

3.3.1. Cross-sectional dependence (CSD) test

Cross-sectional dependence (CSD) of countries in panel analysis may lead to bias estimates and inconsistence results due to unobserved shocks [39], hence it is considered as the most critical test in panel analysis. The standard panel unit-root approaches assume cross-sectional independent in series and non-occurrence of spill-over effect among the cross countries, but in practice, cross-sectional dependency may arise due to numerous factors such as common financial integration, trade as well as other unobserved factors [40,41]. Thus, the presence of the CSD assumption in panel analysis is not appropriate for empirical investigation. To address this CSD issue, this study employs the CSD test introduced by Pesaran [42] under the null hypothesis of cross-sectional independence, with the alternative hypothesis of cross-sectional dependence. To investigate the interdependence, four (4) CDS tests are performed in this study, and these are the Breusch & Pagan Lagrange Multiplier (LM), the Pesaran Scaled Lagrange Multiplier (LM), Bias-corrected (LM) and the Pesaran Cross-sectional Dependence (CD). The CSD test equation is given as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right), \tag{7}$$

where T indicates the period, N represents the cross-section in the panel, and $\hat{\rho}_{ij}$indicates the pair-wise correlation residual sample estimates.

3.3.2. Slope homogeneity test

In addition to CSD test, this study also examines whether or not the slope coefficients of the cointegration equation in the cross section are homogenous. Swamy [43] developed the homogenous tests and improved by Pesaran and Yamagata [44]. Given a cointegration equation $y_{it} = \alpha + \beta_i x_i + \varepsilon_{it}$, and tested whether β_i slope coefficient is different between cross section units [44]. The null hypothesis ($H_0\colon \beta_i = \beta$) is that the slope coefficients are homogenous, and the alternative hypothesis ($H_0\colon \beta_i \neq \beta$) that slope coefficients are not homogenous. The standard F test is the most widely used techniques to investigate the null hypothesis of slope homogeneity, and the formed test statistics are:

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\bar{S}-k}{\sqrt{2k}}\right) \sim \chi_k^2, \tag{8}$$

$$\tilde{\Delta}_{\text{adj}} = \sqrt{N}\left(\frac{N^{-1}\bar{S}-k}{v(T,k)}\right) \sim N(0,1), \tag{9}$$

N indicates the numbers of cross-sectional unit; S represent the Swamy test statistic; k indicates the independent variables. If the null hypothesis is accepted, then the cointegrating coefficients is considered homogenous.

3.3.3. Panel unit-root test

Standard panel technique, such as the [45] and [46] tests, may yield misleading results in the presence of cross-sectional dependence. In addition, testing stationarity properties may give rise to low power in unit root analyses which can lead to poor panel investigation in cross-section dependence [47,48]. To address this problem, Pesaran [49] combined both the augmented Dickey-Fuller and IPS tests under cross-sectional dependence to examine panel stationarity. Thus, in this study more efficient panel unit root test of Cross-Sectional Augmented Dickey-Fuller (CADF) and Cross-Sectional Im-Pesaran-Shin (CIPS) tests are utilized to address the cross-sectional dependence issue. The CADF test are given as:

$$\Delta Y_{i,t} = \varphi_i + \varphi_i z_{i,t-1} + \varphi_i Y_{t-1}^{-} + \sum_{I=0}^{p} \varphi_{i,t} Y_{t-1}^{-} + \sum_{I=0}^{P} \varphi_{i,t} Y_{i,t-1} + u_{i,t}, \quad (10)$$

where $Y_{i,t}$ is the determinant to be analyzed, $Y_{i,t-1}$ and Y_{t-1}^{-} represents the cross-sectional averages, Δ indicates the difference, φ_i indicates the individual intercepts, $u_{i,t}$ represents the white noise error term. The Akaike Information Criterion (AIC) are utilized in selecting the optimal lag lengths. However, the Cross-Sectional Im-Pesaran-Shin (CIPS) tests statistic is obtained as illustrated by Eq (11).

$$\widehat{CIPS} = \frac{1}{N} \sum_{i=1}^{N} CDF_i. \quad (11)$$

The null hypothesis is "there is unit root" and the alternative hypothesis indicates "there is no unit root".

3.3.4. Westerlund (2007) panel cointegration test

This study applies the Westerlund [50] dynamic panel cointegration test to determine whether there exists long run cointegrating relationship among the variables under consideration due to cross-sectional dependency and heterogeneity. The test can be applied on the condition that the dependent variable is I (1) and the independent variables are at different integration levels. The test results are robust, hence reliable with the null hypothesis of no cointegration in the error-correction term (ECT). For instance, Eq (12) illustrates the cointegrating relationship between the dependent variable $y_{i,t}$ and the independent variables $x_{i,t}$. Thus, error-correction model is estimated as,

$$\Delta y_{i,t} = \acute{\delta}_i d_t + \alpha_i \left(y_{i,t-1} - \acute{\beta}_i x_{i,t-1} \right) + \sum_{j=1}^{P_i} \alpha_{i,j} \Delta y_{i,t-1} + \sum_{j=0}^{P_i} \gamma_{i,j} \Delta x_{i,t-1} + \varepsilon_{i,t}, \quad (12)$$

where d_t represents the deterministic element, α measures the degree of velocity of adjustment, cointegration is expressed by $y_{i,t-1} - \acute{\beta}_i x_{i,t-1} = 0$, assured by $\alpha_i < 0$, whereas $\alpha_i = 0$, and β_i indicates the error correction coefficient. The test statistics are separated in two - group statistics (G_α, G_τ) and panel statistics (P_α, P_τ). Whilst the panel statistic pools information along the cross-sectional dimension, the group statistic does not require the information of panel of error-correction. The test is illustrated as:

$$G_\tau = \frac{1}{N} \sum_{i=1}^{N} \frac{\hat{\alpha}_i}{SE(\hat{\alpha}_i)} \qquad P_\tau = \frac{\hat{\alpha}_i}{SE(\hat{\alpha}_i)}$$

$$G_\alpha = \frac{1}{N} \sum_{i=1}^{N} \frac{T\hat{\alpha}_i}{\hat{\alpha}_i(1)} \qquad P_\alpha = T_{\hat{\alpha}}$$

where $SE(\hat{\alpha}_i)$ is the conventional standard error of $\hat{\alpha}_i$.

3.3.5. Cross-sectionally augmented autoregressive distributed lags (CS-ARDL)

The panel autoregressive distributed lags (ARDL) model is considered as one of the most desired heterogeneous panel data estimators, but the model inability to address potential cross-sectional dependence error remain major drawback [51,52]. Similarly, the application of the first generation cointegration techniques such as the Fully Modified Ordinary Least Squares (FMOLS) and the Dynamic Ordinary Least Squares (DOLS) may give rise to bias and inconsistence estimates in the presence of heterogeneity and cross-sectional dependence in panel data. In these estimators, the unobserved factors may be correlated with errors among cross-sectional units and distort true parameters [53]. In addition, other more relevant EU consumption-based emission determinants may have been omitted during the selection of the explanatory variables. This may cause endogeneity problem derived from omitted variables. Similarly, EU trade and OFDI variables in the right-hand side of the model, may lead to endogeneity issue as trade may cause OFDI. For this reason, Chudik and Pesaran [51] proposed the cross-sectional autoregressive distributed lags (CS-ARDL) model, which is robust to cross-sectional dependency, heterogeneity, endogeneity etc., but not efficiently estimated by the DOLS and FMOLS estimators. Given the level of interrelationship among EU countries, this study examines model I-III using the CS-ARDL techniques and the equation is given as follow:

$$CCO2_{i,t} = \alpha_i + \sum_{j=1}^{py} \delta_{i,t}\, CCO2_{i,t-j} + \sum_{j=0}^{px} \varphi_{i,t}\, x_{i,t-j} + \sum_{j=0}^{p} \grave{\lambda}_{i,t}\, \bar{Z}_{i,t-j} + \varepsilon_{i,t}, \tag{13}$$

where $\bar{Z}_{i-j}$ is the lagged cross-sectional average, $\bar{Z}_{i-j}$ indicates $CO2_{i,t-j}$, $x_{i,t-j}$ denotes a vector of the regressors, py and px are the optimal lag lengths of $CO2_{i,t-j}$ and each variable in $x_{i,t-j}$

$$\hat{\theta}_{cs-ADRL,i} = \frac{\sum_{j=0}^{px} \hat{\varphi}_{i,t}}{1-\sum_{j=1}^{py} \hat{\delta}_{i,t}}. \tag{14}$$

The mean group

$$(\mathrm{MG}) = \sum_{i=1}^{N} \hat{\theta}_i\ . \tag{15}$$

The CS-ARDL specification of error correction model is given by:

$$\left.\begin{aligned} \Delta CCO2_{i,t} &= \psi_i\left[CCO2_{i,t-1} - \hat{\theta}_i x_{i,t}\right] - \alpha_i + \sum_{j=1}^{py-1} \delta_{i,t}\Delta CCO2 + \sum_{j=0}^{px-1} \varphi_{i,t}\Delta x_{i,t} \\ &\quad + \sum_{j=0}^{p} \grave{\lambda}_{i,t}\Delta\bar{Z}_{i,t-j} + \varepsilon_{i,t} \end{aligned}\right\}. \tag{16}$$

3.3.6. Common correlated effects (CCE)

Pesaran [54] seminal paper proposed a new estimator known as the Common Correlated Effects (CCE) estimator, which assume common factor representation within the cross-sectional dependence. The CCE estimator accounts for cross-sectional dependence by approximating linear combinations of the unobserved common factors using the cross-sectional averages of the dependent and explanatory variables which are included in a panel OLS regression [51]. That is, the CCE technique is advantageous, by augmenting the basic regression with cross-section averages of the observed regressors and dependent variables. Previous studies such as Liu et al. [55], Hussain and Khan [56]. Chaudhry et al. [57] applied the CCE estimator as presented in Eq (18).

Given that,

$$CCO2_{i,t} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{i,t}. \tag{17}$$

The CCE model regression equation augments the OLS baseline estimator with $\bar{z}_t = \bar{y}_{i,t}, \bar{x}_{i,t})$. Therefore, the CCE estimator is given as

$$CCO2_{i,t} = \alpha_i + \beta_i x_{i,t} + y\bar{z}_t + \varepsilon_{i,t}. \tag{18}$$

The regression equation for the CCE model augments the baseline OLS estimator with $\overline{zt}$ = ($\overline{yit}$,$\overline{xit}'$), representing a vector of the cross-sectional averages.

3.3.7. Cross-sectionally augmented distributed lag (CS-DL) approach

This study also applied the cross-sectional distributed lags (CS-DL) techniques as robustness check to the results of CS-ARDL approach in examining the role of outward FDI and international trade (exports and imports) on consumption-based carbon emission in twenty-one (21) European union countries. The cross-sectional units among the EU countries are heterogeneous due to the differences in OFDI and trade flows, carbon emission intensity and the levels of development and technology. Therefore, the assumption of homogeneity leaves much to be desired. Thus, the likelihood of error cross-sectional dependence is high due to common unobserved factors among EU countries. The CS-DL method eliminates cross-sectional error dependence and yields similar results compared to other classical methods such as CS-ARDL technique. The CS-DL technique directly estimates the long-run coefficients by adding the differences of the explanatory variables and their lags without first estimating the short-run coefficients [58]. Thus, the technique is unaffected by the compulsory speed of adjustment coefficient between −1 and 0 in order for the error-correction approach to be appropriate as in the case of CS-ARDL model. In line with Ditzen [58] and Chudik et al. [59] papers, the CS-DL specification is given as,

$$\Delta CCO2_{i,t} = c_i + \acute{\theta} x_{i,t} + \sum_{l=0}^{p_x-1} \beta_{i,t}\, x_{i,t-l} + \gamma CCO2_{,i} \Delta\overline{CCO2}_t \sum_{l=0}^{3} CCO2x_{,i,l}\, \bar{x}_{i,t-l} + \varepsilon_{i,t}, \tag{19}$$

where $y_{i,t}$ is the log of consumption-based carbon emission, $x_{i,t}$ represent vector of explanatory variables in natural logarithm.

4. Results and discussion

4.1. Descriptive statistics and correlation test

Table 3 reports the descriptive and summary statistics of the variables used in this study. Both the IMP and EXP values has a mean rate of about six times larger than the direct investment abroad (OFDI), and the average value of consumption-based carbon emissions is 181.522. For the variables Tff, Ind., and POP, the mean values are 79.132, 1.290×10^{11} and 0.380 respectively. The standard deviation of CCO2 for the selected countries is 238.54 suggesting that EU countries carbon emissions consumption rates are highly different, but the population growth deviation (0.746) appears almost similar. Similarly, the deviation of 35.051, 36.314 and 30.880 for IMP, EXP and OFDI respectively shows the presence of trade and investment diversity among EU countries. In the panel, OFDI and POP growth variables have the least values with −87.227 and −3.847 respectively, whilst the maximum value is from the Ind variable with 1.09×10^{12}. As shown in Table 4, the study examines the correlation patterns among the variables. Column 1 shows that there is a positive association between CCO2, and the other variables listed in the panel. Except the Ind. (0.9497) variable with high correlation, none of the correlated coefficients has value in excess of 0.7 [60].

Table 3. Descriptive statistics for European Union countries (1995–2019).

Variable	Observation	Mean	Std. Dev.	Min	Max
CCO2	525	181.522	238.54	3.538	1135.38
OFDI	525	9.500	35.051	−87.227	301.250
EXP	525	58.544	36.314	14.287	205.482
IMP	525	56.506	30.880	19.174	174.622
Tff	525	79.132	13.764	37.207	100.000
Ind	525	1.290×10^{11}	2.03×10^{11}	9.70×10^{8}	1.09×10^{12}
POP	525	0.380	0.746	−3.847	3.931

Table 4. Correlation matrix for European Union countries (1995–2019).

S/N	Variables	1	2	3	4	5	6	7
1	InCCO2	1						
2	InOFDI	0.0037	1					
3	InEXP	0.5923	0.0056	1				
4	InIMP	0.6831	0.0091	0.4706	1			
5	InTff	0.1945	0.0181	0.1740	0.2420	1		
6	InInd	0.9497	0.0266	−0.4960	0.6096	−0.3011	1	
7	InPOP	0.1714	0.0169	0.3503	0.3188	0.1207	−0.1143	1

Using the data shown in Table 2, new data series are created and reported in Table 4A: C/T (Mt CO_2) indicates the mean ratios of consumption-based emissions to territorial-based carbon emissions, T/C (Mt CO_2) represents the mean ratios of territorial-based carbon emission to consumption-based emission, and C−T(Mt CO_2) indicates the difference of consumption-based emissions to territorial-based emissions. A country with the ratio of C/T (Mt CO_2) less than 1 or T/C (Mt CO_2) greater than 1 indicates net emission exporters. However, positive difference of C−T(Mt CO_2) represents net emission importer while negative value indicates net emission exporter. Therefore, results of the analysis reported Table 4A shows that Czech Republic, Greece, Poland, and Romania are some of the few countries in EU that are net emission exporter, whilst every other country among the twenty-one (21) EU country are net importer of emission for the period 1995–2019. However, countries such as Malta, Belgium, Portugal, and Austria show to be top emissions importers.

Table 4A. The ratios of consumption-production based emission in EU for the period 1995–2019.

Countries	C/T (Mt CO_2)	T/C (Mt CO_2)	C−T(Mt CO_2)
Austria	1.4006	0.7139	27.9492
Belgium	1.7578	0.5688	87.5905
Croatia	1.1842	0.8444	3.7170
Cyprus	1.1502	0.8693	1.1039
Czech Republic	0.9694	1.0314	−3.6280
Finland	1.2760	0.7836	15.8009
France	1.3041	0.7668	115.0432
Germany	1.1804	0.8471	153.8471
Greece	0.9199	1.0869	−7.5449
Hungary	1.2935	0.7730	16.1309
Ireland	1.3127	0.7617	13.0803
Italy	1.2564	0.7958	111.0429
Luxembourg	1.0727	0.9321	0.7284
Malta	2.4750	0.4040	3.5381
Netherlands	1.0962	0.9122	16.4029
Poland	0.9413	1.0622	−19.3711
Portugal	1.4487	0.6902	25.8830
Romania	0.9763	1.0242	−2.2550
Slovakia	1.1428	0.8749	5.6730
Slovenia	1.2390	0.8070	3.7742
Spain	1.0953	0.9129	28.3732

Note: 1). Authors own calculation based on data gleaned from Global Carbon Atlas database; 2). C/T indicates the ratio of consumption to production-based carbon emission; 3). T/C represent the ratio of production to consumption-based carbon emission; 4). C−T is the differences in emission.

4.2. Cross-sectional dependence and slope homogeneity

This study examines whether there is heterogeneity between the countries, and cross-sectional dependence between the variables. Table 5 shows the slope homogeneity test by Pesaran and Yamagata [44] using the null hypothesis that the slope coefficients are homogeneity. However, both the delta ($\tilde{\Delta}$ test) and delta adjusted ($\tilde{\Delta}_{adj}$ test) tests statistic rejects the null hypothesis at 1% level of significance, thus, the results indicates that the three (3) models under consideration are heterogeneous and highly significant. Before examining the stationary of the series, the cross-sectional dependence of the series is considered given that EU countries are highly interlinked economically, geographically, and culturally. To this end, this study performs four (4) CSD tests viz the Breusch-Pagan Lagrange Multiplier (LM), Bias-corrected Lagrange Multiplier (LM), the Pesaran Scaled Lagrange Multiplier (LM) and the Pesaran Cross sectional Dependence (CD) tests.

Table 6 reports indicate that the null hypothesis of no cross-sectional dependence is rejected among the series at 1%, 5% and 10% significance level. This suggests the existence of cross-sectional dependence in the selected EU variables, and the presence of heterogeneity among the EU countries significantly.

Table 5. Pesaran-Yamagata homogeneity test for European Union countries (1995–2019).

	Model-I		Model-II		Model-III	
Tests	Statistic	p-value	Statistic	p-value	Statistic	p-value
$\tilde{\Delta}$ test	4.063***	0.000	7.116***	0.000	2.782***	0.001
$\tilde{\Delta}_{adj}$ test	9.217**	0.000	13.225***	0.001	8.841***	0.000

Note: 1). Author's calculation; 2). Significance: * p < 0.1, ** p < 0.05, *** p < 0.01; 3). H0: slope coefficients are homogenous.

Table 6. Cross sectional dependence test for European Union countries (1995–2019).

Variables	Breusch-Pagan LM		Pesaran Scaled LM		Bias-corrected LM		Pesaran CD test	
	Test stat.	Prob.	Test stat.	Prob.	Test stat.	Prob.	Tests stat	Prob.
InCCO2	187.45**	0.000	66.05**	0.004	51.00***	0.000	9.72**	0.001
InOFDI	203.38**	0.000	51.25***	0.020	50.37***	0.000	18.94***	0.000
InEXP	96.24***	0.000	32.38***	0.000	31.56**	0.004	4.11***	0.000
InIMP	81.33**	0.006	37.22*	0.002	36.83**	0.002	3.20**	0.005
InTff	126.10**	0.000	73.62**	0.010	702.48***	0.001	4.71*	0.008
InInd.	83.97***	0.000	61.84**	0.003	43.58***	0.000	17.04**	0.000
InPOP	492.13*	0.001	113.07**	0.000	97.81*	0.00	17.69**	0.037

Note: 1). Author's calculation; 2). Significance: * p < 0.1, ** p <0 .05, *** p < 0.01.

4.3. Panel unit root tests and cointegration test

The presence of cross-sectional dependence in series and heterogeneous among EU countries can give rise to spurious results. This study examines the stationary properties among the series using the Cross-Sectional Augmented Dickey-Fuller (CADF) proposed by Pesaran [49], and Cross-Sectional Im-Pesaran-Shin (CIPS) tests. In the unit root testing procedure, this study considers the constant and constant plus trend terms at both level and first differenced form of variables. Table 7 reports the panel unit root results. Finding indicates that except for GCF and POP variables which appears stationary at level and first difference, all other variables are non-stationary both at constant and constant plus trend using the CADF and CIPS tests. This shows that the variables are non-integrated (stationary) of order I (0). More so, the first difference of the variables is examined and the result shows that the series are stationary both at constant and 'constant plus trend' at different levels of statistical significance. This implies that most of the study data are integrated of order I (1) which suggests the use of an advanced econometric technique such as ARDL to examine the long run analysis of the parameters.

Table 7. Second-generation panel unit root test outcomes.

Variables	Unit Root Tests	At level		At first difference	
		Constant	Const. & Trend	Constant	Const. & Trend
InCCO2	CADF	39.77	16.18	64.11***	–11.78*
	CIPS	–2.04	–0.65	–0.38**	–3.10***
InOFDI	CADF	28.64	32.12	33.81*	41.04**
	CIPS	–0.69	–0.40	–0.86***	–3.53**
InEXP	CADF	33.07*	42.99	41.73*	–34.75*
	CIPS	9.13	–13.76	13.06*	–28.20*
InIMP	CADF	61.22*	56.05	66.37**	45.56***
	CIPS	–11.74	18.34	–15.38*	–19.04**
InTff	CADF	23.19	42.05	28.99***	33.01**
	CIPS	–1.08	–10.96	11.87*	–22.17*
InInd.	CADF	18.02	19.63	63.72*	34.16***
	CIPS	–3.74	0.88	–2.03**	–1.62***
InPOP	CADF	36.12	26.06**	39.41*	–31.19**
	CIPS	–0.21*	–0.79	–0.43***	–12.45*

Note: 1). Author's calculation; 2). Significance: * p < 0.1, ** p < 0.05, *** p < 0.01; 3). CADF indicates Cross-Sectional Augmented Dickey-Fuller, CIPS indicates Cross-Sectional Im-Pesaran-Shin test.

Table 8. Westerlund (2007) panel cointegration tests for European Union countries (1995–2019).

	Model-I			Model-II			Model-III		
Sta	Value	Z-value	p-value	Value	Z-value	p-value	Value	Zvalue	pvalue
G_t	9.82**	1.46	0.03	11.84**	10.06	0.02	8.18**	2.38	0.00
G_a	7.34*	0.89	0.05	17.37*	3.25	0.06	11.36**	0.75	0.02
P_t	5.08**	2.36	0.00	9.59**	5.01	0.03	9.74*	1.61	0.05
P_a	4.02**	1.02	0.02	3.36**	1.48	0.00	6.27**	2.03	0.03

Note: 1). Significance: * p < 0.1, ** p < 0.05, *** p < 0.01; 2). Author's calculation.

In contrast to Pedroni [61,62] papers on seven tests statistics which assumed heterogeneity and rely on residual based approach, the Westerlund [50] cointegration test approach assumes the presence of cross-sectional dependence and heterogeneity among variables. The test provides p-values that are quite robust and consistent both in the dependent and independent variables through bootstrapping. Whist the group mean statistics (G_τ and G_α) test the null hypothesis of cointegration among selected EU countries in our sample, the panel statistics (P_τ and P_α) test the null hypothesis of no cointegration among all the countries considered in our sample. Table 8 shows the results of the Westerlund [50] error correction model panel cointegration test which examines the null hypothesis of no cointegration.

The null hypothesis of no cointegration is rejected at 1%, and 5% significance level for all the four test statistics (cases). This indicates the existence of an error correction for group mean (G_τ and G_α) and for panel (P_τ and P_α) among the variables under consideration, suggesting long-run cointegration between carbon emission and the other variables listed in Table 1. This supports the existence of the long-run relationship among the selected EU determinants. However, cointegration test doesn't estimate the long-run coefficients, hence the need to employ an econometric technique to evaluate the parameterization of the long-run and short-run relationship. On this account, this study adopts the Chudik and Pesaran [51] CS-ARDL model, which is robust to cross-sectional dependency and heterogeneity to examine the long-run relationship between carbon emission and environmental determinants in EU.

4.4. Short- and long-run dynamics between OFDI, trade and CCO2 emission in EU

This section discusses the short-run and long-run results from the three different models described in Section 3.2.1 shown in Table 9 panel A (short-run) and B (long-run). Model I describe the direct impact of some selected CCO2 emission determinants, whilst model II seeks to capture both the direct and indirect (joint effects) of EXP and OFDI on CCO2 emission. Model III examines the nexus between CCO2 emission and the explanatory variables with the inclusion of the interaction term of IMP and OFDI. Preliminary results reported in Tables 5–8 shows cointegrating relationship which provides support for the use of an error correction model mechanism to examines the long-run dynamics. The result of CCO2 emission determinants for EU countries estimated using CS-ARDL technique proposed by Chudik and Pesaran [51] are reported in Table 9. Expectedly, the coefficients of ECM(-1) for model I-III are negative and statistically significant which suggests that the whole system (EU CCO2 emission model) quickly converge back to long term equilibrium after short term shock at the speed of 71.3%, 87.3%, and 62.9% respectively for the different models. Thus, the short-run disturbance will be corrected after 1-year to return to long-run equilibrium level.

The impact of OFDI spillover on CCO2 emission in EU countries is examine in the three different model. In the short term, finding reveals that OFDI spillover from EU countries have negative and statistically significant impact on CCO2 emission. Thus, a 1% increase in OFDI spillover reduces CCO2 emission by –0.57%, –0.33% and –0.41% in EU countries. Similarly, within the range of (–0.27) to (–0.39)%, CCO2 emission is decreased if there is 1% increase in OFDI in the long-run. This may be due to years of reversed spillover of green and advanced technologies. This suggests that overseas investment by EU countries may give rise to reverse technology spillover which involves the transfer of advanced or green environmentally friendly technology to EU countries which reduces emission. This indicates that EU countries investment policies support domestic enterprises to "go global" and enter international fields such as advanced manufacturing and new technology which has a spillover effect that build domestic capacity in reducing carbon multiplier effects due to import of material products. This indicates that the emission abating effect of OFDI spillover associated with technique effect reduces environmental pollution more in the long run than in the short run (see model I, II, and III), which suggests that previous years of pollution management and the use of environmentally friendly technologies in EU countries pays in the long run.

The results for the disaggregate trade (IMP and EXP) varies but appears statistically significant. The coefficient of EXP is negative and statistically significant, indicating that increase in EU's exports of goods and services leads to the reduction of consumption-based emissions in the short run. Thus, a

1% increase in export leads to the reduction of CCO2 emission by –0.81%. –0.79% and –0.88% in the short-run, implying that exports from EU countries decreases consumption-based emission and improves environmental quality. This emissions reduction effects of EXP is similar in the long-run by –0.68%, –0.63% and –0.64% respectively for models I–III. The rationale behind these results may suggests EU economies being energy intensive market supports cleaner production domestically by further exporting consumption-based emission abroad (pollution halo hypothesis). These finding supports Leitão and Balogh [63], Yasmeen et al. [64] studies that trade plays an important role in lowering domestic carbon dioxide emissions.

Nevertheless, the IMP-CCO2 emission nexus is positive and promotes emission in EU countries, implying that, a 1% increase in the importation of good and services, increases consumption-based carbon emission within the range of 2.36%–3.70% in the short-run, whereas in the long-run consumption-based emission increases within the range of 0.48%–0.53%. Crude petroleum products, chemical products, machinery & electrical equipment remains EU top importing product which are majorly consume in the manufacturing sector, transportation sector, etc., which promotes carbon emission and deteriorate the environmental quality. This indicates that import of goods and services in EU countries is a source of carbon leakage both in the short run and long-run. However, EU emissions shows a decreasing rate in the long run.

Table 9. The CS-ARDL estimation outcome for European Union countries (1995–2019).

Panel A: Short run estimates				Panel B: Long run estimates			
Parameter	Model I	Model II	Model III	Parameter	Model I	Model II	Model III
ΔInOFDI	−0.005***	−0.0033**	−0.004**	InOFDI	−0.0038*	−0.002**	−0.0039
	(0.002)	(0.001)	(0.002)		(0.002)	(0.0009)	(0.008)
ΔInEXP	0.0081**	−0.007***	−0.0088*	InEXP	−0.0068	−0.0063*	−0.0064*
	(0.004)	(0.000)	(0.003)		(0.005)	(0.0037)	(0.004)
ΔInIMP	0.0236*	0.0371	0.030***	InIMP	0.0048**	0.0053***	0.0049
	(0.014)	(0.028)	(0.012)		(0.002)	(0.002)	(0.004)
ΔInTff	0.0863*	0.0941*	0.0676**	InTff	0.0110**	0.0128**	0.0133**
	(0.047)	(0.053)	(0.033)		(0.005)	(0.006)	(0.007)
ΔInInd.	0.131***	0.1095**	0.1107*	InInd.	0.011***	0.0144**	0.0101*
	(0.027)	(0.048)	(0.061)		(0.004)	(0.007)	(0.006)
ΔInPOP	0.970	1.0490*	1.1034*	InPOP	0.995**	0.9452	0.8976
	(0.582)	(0.624)	(0.652)		(0.502)	(0.631)	(0.876)
Δ (EXP×OFDI)		−0.0019***		EXP×OFDI		−0.00096**	
		(0.0002)				(0.0001)	
Δ (IMP×OFDI)			−0.0026**	IMP×OFDI			−0.0016**
			(0.0013)				(0.0008)
ECM(-1)	−0.71***	−0.873***	−0.62***				
	(0.137)	(0.252)	(0.148)				

Note: 1). Author's calculations; 2). Values in the parentheses are the standard errors; 3). Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

However, the results of emissions-population elasticity in the short-run appears positive, unitary, and significant, implying that population growth in EU countries may increase consumption-based emissions and undermine climate goals particularly SDGs targets both in the short-run and long-run. Although this finding is emissions specific which focuses on population growth and consumption-based emissions, but the result aligns with the view of Weber and Sciubba [65], Shi [66], and Bongaarts [67], that population growth affects EU environment. More so, findings from other body of research (Such as Liddle [68], etc.) that examined population size (level) and environmental pollution nexus supports POP-CCO2 emissions result of this study. Our finding is also in line with MacKellar et al. [69] paper that carbon emission is unlikely to be curbed since increase in the numbers of household and consumption are likely to increase consumption-based emission. Expectedly, the industrial value added (Ind) and the total energy fossil fuel (Tff) in the EU region are positive and significant in the short run.

The joint impact of the main explanatory variables of the study are further examined. Thus, the combine effects are captured in Models II and III for EXP×OFDI and IMP×OFDI respectively both in the short and long run. Regarding the interaction of EXP×OFDI, finding reveals that EU's EXP complements OFDI spillover at 1% significance level to decrease CCO2 emission by –0.19% in the short run, and –0.096% in the long-run to promotes sustainable environment. This shows that export of goods and service including domestic firms "going abroad" may bring about more relocation of investment returns to home country which are further re-invested in the promotion of cleaner environment among EU countries. Notwithstanding the positive link of IMP to CCO2 emission, the joint effect of IMP and OFDI (IMP×OFD) has negative impact on CCO2 emission, implying that a 1% increase in the joint effect reduces CCO2 emission by –0.26% in the short term and –0.16% in the long-run. This shows that the spillover effects of OFDI neutralizes the negative effect of IMP to reinforce sustainability via green and advanced technology to EU countries both in the short-term and long term. This promotes environmental sustainability. However, the impact of the interactions shows to be more enhanced in the long run than in the short run.

4.5. Robustness check

To check model robustness estimated by the CS-ARDL techniques, this study re-examines the parameter estimates of the long-run coefficients using the cross-sectionally augmented distributed lag (CS-DL) and the common correlated effects (CCE) methods. Although the magnitude of the estimated coefficients by CCE and CS-DL techniques reported in Table 10 are not the same with the coefficients of CS-ARDL estimations, but the values are stable and consistent across the three models, indicating the robustness of CS-ARDL estimator, and the adequacy of the utilized models. To be specific, the long elasticities of the natural logarithm of OFDI and EXP are negative in the estimation by three different techniques which decreases consumption-based emission and promotes sustainability. In the same vein, the estimated coefficients of InIMP, Tff, InInd, and InPOP are positive and appears to be one of EU sources of CCO2 emissions which promotes pollution in the long run (Table 10). Results of the joint impact of EXP×OFD and IMP×OFD using CCE and CS-DL techniques strengthens the emission-abating effects toward achieving cleaner environmental which re-affirms the reduction of EU's CO_2 emission significantly via complementary effects.

Table 10. The results of robustness check for long run estimates for the period (1995–2019).

Parameters	CCE			CS-DL		
	Model I	Model II	Model III	Model I	Model II	Model III
InOFDI	−0.029*	−0.073**	−0.068*	−0.084***	-0.093**	-0.066***
	(0.016)	(0.036)	(0.039)	(0.0018)	(0.004)	(0.001)
InEXP		−0.0303*	−0.027***	−0.037***	-0.063***	-0.0609*
	−0.031**	(0.018)	(0.005)	(0.0013)	(0.0017)	(0.003)
	(0.013)					
InIMP		0.0389**	0.0475**	0.0428**	0.0520**	0.0597
	0.0324*	(0.017)	(0.023)	(0.002)	(0.002)	(0.012)
	(0.018)					
InTff		0.0348**	0.0288*	0.0394**	0.0446***	0.0288**
	0.0172	(0.013)	(0.015)	(0.009)	(0.012)	(0.012)
	(0.015)					
InInd.		0.1136*	0.2745**	0.1127**	0.0643	0.0994**
	0.2063*	(0.059)	(0.137)	(0.008)	(0.018)	(0.010)
	(0.118)					
InPOP		0.995***	1.1008	1.3041	1.0045**	1.0271
	1.0062*	(0.352)	(0.741)	(0.839)	(0.489)	(0.687)
	(0.562)					
In(EXP×OFDI)		-0.026**			−0.0202**	
		(0.013)			(0.0006)	
In(IMP×OFDI)			−0.0538*			−0.0477**
			(0.032)			(0.00095)

Note: 1). Author's calculations; 2). Values in the parentheses are the standard errors; 3). Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5. Conclusions and policy implications

This study examined the impact of outward FDI spillover and disaggregate international trade on consumption-based emissions in twenty-one (21) European Union countries for the period 1995–2019. The study utilized the STIRPAT model which provides a fundamental understanding of the dynamic couplings, linking human activities and the environment (ecological system). The selected determinants are estimated by advanced econometric techniques such as CS-ARDL estimator, checked by the common correlated effects (CCE) and the cross-sectional distributed lags (CS-DL) techniques.

Examining the results of the short-run and long-run elasticity, finding reveals that EU's outward FDI plays a significant role in the mitigation of consumption-based emission through reverse technology spillover which bring about advanced environmentally and eco-friendly technology that increases energy-saving and reduces emission induced by consumption. Thus, EU's OFDI spillover facilitates cleaner technologies which generates positive effects that mitigate consumption-based emissions. Similarly, results indicates that export of goods and services from EU member states reduce consumption-based carbon emissions. This implies that the consumption-based emissions in most EU countries are further exported or transferred to other countries particularly developing and low-income countries which supports domestic sustainable consumption both in the short-run and long run. Nevertheless, import of goods and services increase consumption-based carbon emissions, and appear to be a source of carbon leakage for EU countries, both in the short run and long-run. This shows that EU countries import high emission material products used for domestic production which promotes carbon emission. Specifically, finding shows that most EU countries are net importer of carbon emission, except for countries such as Czech Republic, Greece, Poland and Romania which are net exporter of emission for the period 1995–2019. This suggests that most EU countries experience consumption-based carbon emissions which may be due to the importation of significant portion of material product for manufacturing. Thus, the EU progress on carbon emissions is only limited to production-based emission as full lifecycle of their carbon emission indicates that most countries in the union are heavily linked with emission via imported products.

Furthermore, the joint effects of OFDI and disaggregate trade among EU countries mitigate consumption-based emissions by strengthening the carbon emission abating effects toward achieving the United Nation SDGs goal of '5Ps' 2030 Agenda: People, Planet, Prosperity, Peace, and Partnership. This implies that the EU's OFDI spillover complements international trade to reduce consumption-based emissions by stimulating innovations toward emission reduction, facilitating the reversed environmental and eco-friendly technologies, dissemination of firms' management policies toward preventing import induced emission to home countries, etc. In addition, the complementary effect of OFDI and trade may bring about relocation of investment returns to home country which are further re-invested in the promotion of cleaner environment in EU countries.

Based on these findings, this study put forward some policy recommendations to mitigate consumption-based emissions among EU countries. (i) There is the need to get the true EU emission records with a view to proffering solutions. For this reason, countries should measure and report consumption-based carbon emission annually, which should also be extended to firms that imports material for local production. Thus, the disclosure of companies' data on emissions must be a mandatory reporting. (ii) EU countries need to swiftly introduce new policy instruments or expand existing policy instruments to include the mitigation of consumption-base emission associated with imports. (iii) In order to quickly control the continuous rise in consumption-based emission in EU region, policies makers and government must cooperate to set emissions reduction target for imported carbon. (iv) EU countries should adopt a proactive measure in tackling the rise of imported carbon: For instance, the introduction of subsidy for products with low carbon to consumer, whilst imported products linked with embodies carbon emission should be banned. High carbon emission embodied tax should be introduced to discourage the importation of products laced with carbon emission. This implies the introduction of tax on imported energy intensive goods, and the promotion of home country's renewable energy production.

This study is limited to the present variables selected in the STIRPAT model, the econometric techniques applied, the sample of countries used, and the period analyzed. Therefore, other environmental pollution determinants, econometric methods, larger sample (if possible) and different groups of countries which may influence the impact of trade and investments on consumption-based emission worth future investigation.

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Conflict of interest

The Authors declares that there is no potential conflict of interest.

References

1. Spaiser V, Scott K, Owen A, et al. (2019) Consumption-based accounting of CO_2 emissions in the sustainable development Goals Agenda. *Int J Sust Dev World* 26: 282–289. https://doi.org/10.1080/13504509.2018.1559252
2. Rahman MM, Ahmed R, Mashud AHM, et al. (2022) Consumption-based CO_2 emissions on sustainable development goals of SAARC Region. *Sustainability* 14: 1467. https://doi.org/10.3390/su14031467
3. European Commission (2011) A Roadmap for moving to a competitive low carbon economy in 2050. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. Available from: https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2011:0112:FIN:en:PDF.
4. European Commission (2021) How has the EU progressed towards the sustainable development goals. Available from: http://ec.europa.eu/eurostat/web/products-eurostat-news.
5. European Commission (2015) Intended nationally determined contribution of the EU and its member states, UNFCCC. Available from: http://www4.unfccc.int/submissions/INDC/Published.
6. Sandström V, Valinb H, Krisztin T, et al. (2018) The role of trade in the greenhouse gas footprints of EU diets. *Glob Food Secur* 19: 48–55. https://doi.org/10.1016/j.gfs.2018.08.007
7. Kastner T, Erb K H, Haberl H (2014) Rapid growth in agricultural trade: Effects on global area efficiency and the role of management. *Env Res Lett* 9: 034015. https://doi.org/10.1088/1748-9326/9/3/034015
8. Becqué R, DubskY E, Hamza-Goodacre D, et al. (2017) Europe's carbon loophole. Draft report for consultation. Available from: https://www.climateworks.org/wp-content/uploads/2017/09/EU-carbon-loophole_final-draft-for-consultation.pdf.
9. Moran D, Hasanbeigi A, Springer C (2018) The carbon loophole in climate policy: Quantifying the embodied carbon in traded products. Available from: https://www.climateworks.org/wp-content/uploads/2018/09/Carbon-Loophole-in-Climate-Policy-Final.pdf.
10. Bloom NC, Genakos R, Sadun J, et al. (2012) Management practices across firms and countries. *AMP* 26: 12–33. https://doi.org/10.5465/amp.2011.0077
11. Branstetter L (2006) Is foreign direct investment a channel of knowledge spillovers? *J Int Econ* 68: 325–344. https://doi.org/10.1016/j.jinteco.2005.06.006
12. Halicioglu F, Ketenci N (2016) The impact of international trade on environmental quality: The case of transition countries. *Energy* 109: 1130–1138. https://doi.org/10.1016/j.energy.2016.05.013

13. Dogan E, Seker F (2016) Determinants of CO_2 emissions in the European Union: The role of renewable and non-renewable energy. *Renew Energ* 94: 429–439. https://doi.org/10.1016/j.renene.2016.03.078
14. Liddle B (2018) Consumption-based accounting and the trade-carbon emissions nexus in Asia: A heterogeneous. common factor panel analysis. *Sustainability* 10: 3627. https://doi.org/10.3390/su10103627
15. Liddle B (2018) Consumption-based accounting and the trade-carbon emissions nexus. *Energ Econ* 69: 71–78. https://doi.org/10.1016/j.eneco.2017.11.004
16. Hasanov F, Liddle B, Mikayilov C (2018) The impact of international trade on CO_2 emissions in oil exporting countries: territory vs consumption emissions accounting. *Energ Econ* 74: 343–350. https://doi.org/10.1016/j.eneco.2018.06.004
17. Fernandez-Amador O, Francois J, Oberdabernig D, et al. (2017) Carbon dioxide emissions and economic growth: An assessment based on production and consumption emission inventories. *Ecol Econ* 135: 269–279. https://doi.org/10.1016/j.ecolecon.2017.01.004
18. Knight K. Schor J (2014) Economic growth and climate change: A cross-national analysis of territorial and consumption-based carbon emissions in high-income countries. *Sustainability* 6: 3722–3731. https://doi.org/10.3390/su6063722
19. Marques A, Rodrigues J, Lenzen M, et al. (2012) Income-based environmental responsibility. *Ecol Econ* 84: 57–65. https://doi.org/10.1016/j.ecolecon.2012.09.010
20. Bhattacharya M, Inekwe J N, Sadorsky P (2020) Consumption-based and territory-based carbon emissions intensity: Determinants and forecasting using club convergence across countries. *Energ Econ* 86: 104632. https://doi.org/10.1016/j.eneco.2019.104632
21. Dong BM, Wang F, Guo YB (2016) The global EKCs. *Int Rev Econ Financ* 43: 210–221. https://doi.org/10.1016/j.iref.2016.02.010
22. Gyam AB (2021) Consumption-based carbon emission and foreign direct investment in oil production sub-Sahara african countries: The role of natural resources and urbanization. *Environ Sci Pollut Res* 29: 13154–13166. https://doi.org/10.1007/s11356-021-16509-3
23. Yang LG, Liu YN (2013) Can Japan's outwards FDI reduce its CO_2 emissions? A new thought on polluter haven hypothesis. *Adv Mater Res* 807–809: 830–834. https://doi.org/10.4028/www.scientific.net/AMR.807-809.830
24. Mohanty S, Sethi N (2021) The energy consumption-environmental quality nexus in BRICS countries: The role of outward foreign direct investment. *Environ Sci Pollut Res* 29: 19714–19730. https://doi.org/10.1007/s11356-021-17180-4
25. Borghesi S, Franco C, Marin G (2020) Outward foreign direct investment patterns of Italian firms in the European Union's emission trading scheme. *Scand J Econ* 122: 219–256. https://doi.org/10.1111/sjoe.12323
26. Zhang QX, Naqvi SAA, Shah SAR (2021) The contribution of outward foreign direct investment, human well-being, and technology toward a sustainable environment. *Sustainability* 13: 11430. https://doi.org/10.3390/su132011430
27. Wood R, Stadler K, Simas M (2018) Growth in environmental footprints and environmental impacts embodied in trade: Resource efficiency indicators from EXIOBASE3. *J Ind Ecol* 22: 553–564. https://doi.org/10.1111/jiec.12735

28. Steen-Olsen K, Weinzettel J, Cranston G (2012) Carbon, land, and water footprint accounts for the European Union: Consumption, production, and displacements through international trade. *Environ Sci Technol* 46: 10883–10891. https://doi.org/10.1021/es301949t
29. Karstensen J, Peters GP, Andrew RM (2018) Trends of the EU's territorial and consumption-based emissions from 1990 to 2016. *Climatic Change* 151: 131–142. https://doi.org/10.1007/s10584-018-2296-x
30. Fezzigna P, Borghesi S, Caro D (2019) Revising emission responsibilities through consumption-based accounting: A european and post-brexit perspective. *Sustainability* 11: 488. https://doi.org/10.3390/su11020488
31. Liobikien G, Dagiliut R (2016) The relationship between economic and carbon footprint changes in EU: The achievements of the EU sustainable consumption and production policy implementation. *Environ Sci Policy* 61: 204–211. https://doi.org/10.1016/j.envsci.2016.04.017
32. Valodka I, Snieska V, Mihi-Ramirez A (2020) Impact of the international trade on the EU clothing industry carbon emissions. *Inzinerine Ekon-Eng Econ* 31: 314–322. https://doi.org/10.5755/j01.ee.31.3.25012
33. Friedlingstein P, O'Sullivan M, Jone MW et al. (2020) Supplemental data of the Global carbon Budget 2020, Carbon Portal. Available from: https://doi.org/10.18160/gcp-2020.
34. World bank (2020) World bank indicators, World bank group Archives, Washington, D.C. United States. Available from: https://databank.worldbank.org/source/world-development-indicators.
35. Ehrlich PR, Holdren JP (1971) Impact of population growth. *Science* 171: 1212–1217. https://doi.org/10.1126/science.171.3977.1212
36. Commoner B, Corr M, Stamler PJ (1971) The causes of pollution. *Environ Sci Policy Sustain Dev* 13: 2–19. https://doi.org/10.1080/00139157.1971.9930577
37. York R, Rosa EA, Dietz T (2003) Footprints on the earth: the environmental consequences of modernity. *Am Sociol Rev* 68: 279–300. https://doi.org/10.2307/1519769
38. Dietz T, Rosa EA (1994) Rethinking the environmental impacts of population, affluence and technology. *Human Ecol Rev* 1: 277–300.
39. Phillips P, Sul D (2003) Dynamic panel estimation and homogeneity testing under cross section dependence. *Econometrics J* 6: 217–259. http://doi.org/10.1111/1368-423X.00108
40. Jalili Z, Bishak MRS, Azad MAM, et al. (2019) Resource economic growth nexus, role of governance, financial development, globalization, and war: A dynamic approach. *J Econ Integr* 34: 520–545.
41. Hsiao C (2003) *Analysis of panel data*, Cambridge: Cambridge university press.
42. Pesaran MH (2004) General diagnostic tests for cross section dependence in panels. Available from: https://ideas.repec.org/p/ces/ceswps/_1229.html.
43. Swamy PAVB (1970) Efficient inference in a random coefficient regression model. *Econometrica* 38: 311–323.
44. Pesaran MH, Yamagata TY (2008) Testing Slope homogeneity in large panels. *J Econometrics* 142: 50–93. https://doi.org/10.1016/j.jeconom.2007.05.010
45. Im KS, Pesaran MH, Shin Y (2003) Testing for unit roots in heterogeneous panels. *J Econometrics* 115: 53–74. https://doi.org/10.1016/S0304-4076(03)00092-7
46. Levin A, Lin CF, Chu CSJ (2002) Unit root tests in panel data: asymptotic and finite sample properties. *J Econometrics* 108: 1–24. https://doi.org/10.1016/S0304-4076(01)00098-7

47. Bhattacharya M, Paramati SR, Ozturk I, et al. (2016) The effect of renewable energy utilization on economic growth: Evidence from top 38 countries. *Appl Energ* 162: 733–741. https://doi.org/10.1016/j.apenergy.2015.10.104
48. Paramati SR, Ummalla M, Apergis N (2016) The effect of foreign direct investment and stock market growth on clean energy use across a panel of emerging market economies. *Energ Econ* 56: 29–41. https://doi.org/10.1016/j.eneco.2016.02.008
49. Pesaran MH (2007) A simple panel unit root test in the presence of cross-section dependence. *J Appl Econ* 22: 265–312. https://doi.org/10.1002/jae.951
50. Westerlund J (2007) Testing for error correction in panel data. *Oxford Bull Econ Stat* 69: 709–748. https://doi.org/10.1111/j.1468-0084.2007.00477.x
51. Chudik A, Pesaran MH (2015) Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *J Econometrics* 188: 393–420. https://doi.org/10.1016/j.jeconom.2015.03.007
52. Wooldridge J (2002) *Econometric analysis of cross section and panel data*, Cambridge: MIT Press.
53. Azam M, Haseeb M (2021) Determinants of foreign direct investment in BRICS- does renewable and non-renewable energy matter? *Energ Strateg Rev* 35: 100638. https://doi.org/10.1016/j.esr.2021.100638
54. Pesaran MH (2006) Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica* 74: 967–1012. https://doi.org/10.1111/j.1468-0262.2006.00692.x
55. Liu Z, Pang P, Fang W, et al. (2022) Dynamic common correlated effects of pandemic uncertainty on environmental quality: Fresh insights from East-Asia and Pacific countries. *Air Qual Atmos Health* 15: 1395–1411. https://doi.org/10.1007/s11869-022-01164-5
56. Hussain M, Khan JA (2021) The nexus of environment-related technologies and consumption-based carbon emissions in top five emitters: Empirical analysis through dynamic common correlated effects estimator. *Environ Sci Pollut Res*. https://doi.org/10.1007/s11356-021-15333-z
57. Chaudhry IS, Ali S, Bhatti SH, et al. (2021) Dynamic common correlated effects of technological innovations and institutional performance on environmental quality: Evidence from East-Asia and Pacific countries. *Environ Sci Policy* 124: 313–323. https://doi.org/10.1016/j.envsci.2021.07.007
58. Ditzen J (2018) Estimating long-run effects in models with cross-sectional dependence using xtdcce2. Available from: https://ideas.repec.org/p/bzn/wpaper/bemps81.html.
59. Chudik A, Mohaddes K, Pesaran MH, et al. (2013) Debt, inflation and growth robust estimation of long-run effects in dynamic panel data models. Available from: https://ideas.repec.org/p/fip/feddgw/162.html.
60. De Vita G, Li C, Luo Y (2021) The inward FDI-Energy intensity nexus in OECD countries: A sectoral R&D threshold analysis. *J Environ Manag* 287: 112290. https://doi.org/10.1016/j.jenvman.2021.112290
61. Pedroni P (2004) Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis, *Econometric Theory*, 20: 597–625. https://doi.org/10.1017/S0266466604203073
62. Pedroni P (1999) Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bull Econ Stat* 61: 653–670. https://doi.org/10.1111/1468-0084.0610s1653
63. Leitão NC, Balogh JM (2020) The impact of intra-industry trade on carbon dioxide emissions: The case of the EU. *Agric Econ* 66: 203–214. https://doi.org/10.17221/312/2019-AGRICECON

64. Yasmeen R, Li Y, Hafeez M, et al. (2018) The trade-environment nexus in light of governance: A global potential. *Environ Sci Pollut Res* 25: 34360–34379. https://doi.org/10.1007/s11356-018-3390-3
65. Weber H, Sciubba JD (2019) The effect of population growth on the environment: Evidence from european regions. *Eur J Population* 35: 379–402. https://doi.org/10.1007/s10680-018-9486-0
66. Shi A (2013) The impact of population pressure on global carbon dioxide emissions, 1975–1996: Evidence from pooled cross-country data. *Ecol Econ* 44: 29–42. https://doi.org/10.1016/S0921-8009(02)00223-9
67. Bongaarts J (1992) Population growth and global warming. *Population Dev Rev* 18: 299–319. https://doi.org/10.2307/1973681
68. Liddle B (2013) Population, affluence, and environmental impact across development: Evidence from panel cointegration modeling. *Environ Model Software* 40: 255–266. https://doi.org/10.1016/j.envsoft.2012.10.002
69. MacKellar L, Lutz W, Prinz C, et al. (1995) Population, households and CO_2 emissions. *Population Dev Rev* 21: 849–865. https://doi.org/10.2307/2137777

Appendix

Table 1. List of countries in sample.

Austria	Cyprus	France	Hungary	Luxemburg	Poland	Slovakia
Belgium	Czech Rep.	Germany	Ireland	Malta	Portugal	Slovenia
Croatia	Finland	Greece	Italy	Netherland	Romania	Spain

Note: Data for countries such as Bulgaria, Demark, Estonia, Latvia, Sweden, and Lithuania are unavailable or/and insufficient.

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