IJEEP
INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY
EJ EconJournals
ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2023, 13(1), 454-464.

EJ EconJournals

Impact of Economic Growth, Energy use and Research and Development Expenditure on Carbon Emissions: An Analysis of 29 OECD Countries

Aisha Sheikh[1]*, Owais Ibin Hassan[2]

[1]Department of Economics, Miranda House, University of Delhi, New Delhi 110016, India, [2]Department of Economics, Jamia Millia Islamia, Okhla 110025, India.
*Email: aisha.sheikh@mirandahouse.ac.in

Received: 03 September 2022 **Accepted:** 25 December 2022 **DOI:** https://doi.org/10.32479/ijeep.13647

ABSTRACT

This study attempts to investigate the impact of economic growth, energy use and research and development expenditure on carbon dioxide emissions for a panel of 29 Organisation for Economic Development and Cooperation (OECD) countries over 1995-2019. We employ two sets of econometric techniques.The first set of estimation techniques assumes cross sectional independence in the panel (also known as the first generation tests). The first generation tests include the panel unit root tests- Levin et al. (LLC), Im et al. (IPS) ADF-Fisher and PP-Fisher unit root tests, Pedroni (1999) and Kao cointegration tests and the Fully Modified Ordinary Least Square (FMOLS) for computing output elasticities. The second set of econometric tests are performed after checking for cross sectional dependence using the second generation tests. These include Pesaran CD test, Breusch Pagan CD test, to establish cross sectional dependence followed by Cross-sectional augmented Im-Pesaran-Shin (CIPS) panel unit root test developed by Pesaran (2007) to test for panel stationarity followed by the error correction based panel cointegration test proposed by Westerlund and Edgerton (2007) with bootstrap. Augmented Mean Group (AMG) is performed to estimate output elasticities while Dumitrescu-Hurlin (DH) Panel Causality tests is done to ascertain causality between variables. We obtain the same results for the effect of GDP and energy use on carbon emissions from the two strategies but conflicting results for the impact of research and development spending on carbon emissions, although there is evidence of stronger cointegration under the first generation tests. Based on findings from the two approaches, we conclude that with a rise in GDP, carbon emissions fall in OECD but increase with a rise in energy use. Aggregate research and development expenditure has a positive effect on carbon emissions under cross sectional independence but a neutral effect when estimated using cross-sectional dependence tests giving inconclusive results.

Keywords: Carbon Emissions, Cross-Sectional Dependence, OECD, Energy, GDP, Westerlund, Augmented Mean Group
JEL Classifications: Q430, O13, P28, Q540

1. INTRODUCTION

There has never been a collective human endeavour more ambitious than stabilising the climate (Economist October 30th, 2021). The environmental outcomes of a warmer earth are too well documented to need another review. There is no doubt that anthropogenic activities have contributed significantly to this situation, primarily through the burning of fossil fuels among other factors.The recently concluded 26th conference of parties (CoP26) at Glasgow may not have been able to garner the expected commitments and outcomes yet it remains the only multilateral framework for negotiating global climate policy and for keeping the quest alive. The resolve and capabilities of nations and regions to decarbonise are asymmetric. The Organisation for Economic Co-operation and Development (OECD) block is relatively more politically committed and proactive in the common quest for attaining carbon neutrality. Nevertheless, the global trajectory of climate action is short of warranted action to achieve the Paris temperature goals.

A vast body of income-pollution literature addresses this issue, with carbon dioxide being the most studied pollutant. The determinants of carbon dioxide emission have been widely investigated for different regions using a variety of functional forms and econometric techniques. As a block of countries, OECD is the second largest carbon emitter in the world, first being Asia (Ritchie and Roser, 2020). However recent trends indicate that greenhouse gas emissions (GHG) per capita of GDP, from OECD countries are decreasing (International Energy Agency, 2018, OECD Climate report 2015). The energy sector is the leading source of greenhouse gas emissions globally (World Energy Outlook, 2018). A strand of literature identifies energy and income (gross domestic product) as the principal sources of carbon emissions (Zhang and Gao (2016); Dogan and Turkekul (2016); Javid and Sharif (2016); Farhani and Ozturk (2015); Al-Mulali et al. (2015); Seker et al. (2015); Tang and Tan (2015); Dogan et al. (2015); Shahbaz et al. (2014); Lean and Smyth (2010, Kasman and Duman (2015); (Soytas et al. (2007). Global energy demand has been consistently rising and increased by nearly 2% in 2017. This fastest rise in the decade is attributable to changes in consumer behaviour and economic prosperity (World Energy Outlook, 2018). 81% of the global energy needs are met by fossil energy sources, the primary source of carbon dioxide emissions.

The relationship between GDP and environmental degradation has been explained by Grossman and Kruegner (1991) by scale, composition and technique effects. Scale effect is the situation where growth in output leads to greater pollution emissions because of increased use of energy and resources. The composition effect is structural in nature implying that as the economy advances, the cleaner service sector has a greater share in the output. The third is the technique effect which means that with economic advancement cleaner technologies replace pollution intensive technologies that environmental stress.This phenomenon of an initial rise and subsequent fall in pollution with economic growth can be depicted as an inverted u-shaped curve also called the environmental kuznets curve (EKC) (Grossman and Kruegner 1991; 1995).

The theoretical perspective on the effect of aggregate research and development spending on carbon emissions postulates that research and development spending tends to mitigate carbon emissions expectedly through the development and dissemination of energy saving technologies. However empirical evidence does not uphold this view and produces mixed results Petrovic and Lobanov (2019) cite the discovery of the Higgs boson, which involved large scale investments in particle accelerators in the European Organization for Nuclear Research. The discovery however did not lead to a reduction in carbon emission.

The investment was colossal and the accelerator was energy intensive. In all likelihood, it increased carbon emissions from greater fossil fuel consumption. Research and development spending also comprises research outlay on medical, pharmaceutical and other areas which don't have a direct bearing on increasing energy efficient research output. Overall the impact of research and development spending on carbon emissions can range from positive, negative to neutral and the empirical experience of different countries vary (Churchill et al., 2019).

We articulate a model that incorporates energy use and research and development spending as additional explanatory variables besides GDP. Our motivation is to analyse the behaviour of carbon emissions with an increase in GDP and research and development spending for the OECD countries post 1995. Besides GDP, our second variable of interest is aggregate research spending (as a percentage of GDP) as empirical evidence about the effect of R&D spending is, at best, ambiguous in available literature.Energy use is the leading source of carbon emissions, we have included it in our model to avoid potential omitted variable bias.

The income-pollution literature prior to 2010 relied mostly on first-generation tests which assume cross sectional independence. An emerging section of literature addressed cross-sectional dependence (CSD) in panel data. CSD is a correlation that arises from common shocks with heterogeneous impacts across different countries, like the oil shock of 1970's and the global financial crisis of 2007. Local spillover effects between regions and economies, spatial effects and interactions among economies are other reasons for cross-correlated errors (Atasoy, 2017).

This paper investigates the role of gross domestic product, energy consumption and research and development spending (as a percentage of gross domestic product) on carbon dioxide emissions for a group of 29 OECD countries over the span of 1995-2019 using estimation techniques that assume cross sectional independence and a second set of techniques designed for accommodating cross sectional dependence.The econometric techniques employed an their sequence is discussed in detail in the Methodology section.

The rest of the paper is organised as follows. Section two consists of a review of literature. The data and methodology is described in section 3. Estimation results are discussed in section 4 and the conclusion is presented in section 5.

2. LITERATURE REVIEW

The determinants of carbon emissions in general and for the OECD block in particular (for the post 90's period) have been widely investigated. However findings are sensitive to econometric techniques, functional forms, choice of regressors and even the time period studied. Broadly, trade, financial development, energy use, technology and urbanization have been studied as explanatory variables in the OECD-carbonisation literature.

The STIRPAT model (Stochastic Impacts by Regression on Population, Affluence and Technology) posits that population, income and technology are the principal sources of environmental degradation. (Shafiei and Salim 2014; Poumayvong and Kaneko, 2010; Zhang and Lin, 2012; Liddle, 2011; Wang et al., 2012; Liddle and Lung 2010; Lin et al., 2009; York et al.) and the EKC framework (Dogan and Seker, 2016; Ahmad et al., 2017; Zhang et al., 2014) have been tested widely to analyse the relationship between carbon emissions and factors causing them.

Hamilton and Turton (2002) analysed the causes of greenhouse gas emissions over 1982-1997 using the decomposition formula.The study concludes that growth in emissions are principally driven by increase in population and GDP per capita.

Chiu and Chang (2009) used a panel threshold regression model and confirmed a significant and positive relationship between real GDP and carbon dioxide emissions. Menz and Welsch (2012) analysed the data from 1960 to 2005 using the augmented version of standard macroeconomic emissions regressions for a panel of 26 OECD countries. Their findings indicate that a shift in the composition and age of the population positively affected carbon dioxide emissions.

Energy consumption has been widely treated as an explanatory variable in the growth-carbonisation literature, since it is a principal determinant of carbon dioxide emissions. (Say and Yucel (2006); Apergis and Payne, (2009); Soytas et al. (2007); Ang, (2007); Halicoglu, (2009); Atici, (2009); Acaravci and Ozturk (2010); Lean and Smyth, (2010); Pao and Tsai, (2011); Pao et al. (2011); Hossain (2011); Jalil and Feridun (2011); Nasir and Rehman (2011); Park and Hong (2013); Alam et al. (2012); Lau et al. (2014); Omri (2013); Farhani et al. (2014); Shahbaz (2013, 2014); Kasman and Duman (2015); Yavuz (2014); Dogan (2015); Serker (2015); Baek (2015); Shahbaz et al. (2015); Al-Mulali et al. (2015); Tang and Tan (2015); Farhani and Ozturk (2015); Dogan and Turkekul (2016); Javed and Sharif (2016) and Zhang and Gao (2016).

Another section of literature has explored the relationship between carbon dioxide and it's determinants for the OECD block. Zaidi et al. (2021) examine the dynamic linkages between carbon emissions and financial inclusion for 21 OECD countries over 2004-2017. Corruption, infrastructure and economic growth are also used as control variables. The study finds that financial inclusion negatively impacts carbon emissions. Iqbal et al. (2021) investigate the role of carbon neutrality, scal decentralization, eco-innovation for achieving carbon neutrality target for 37 OECD economies from 1970 to 2019.

The study applies second generation tests and the augmented mean group (AMG) to determine the long run dynamic equilibrium. Findings show that export diversification, scale, GDP and scale decentralization positively affect carbon emissions. Environmentally friendly technological improvements and renewable energy improve environmental outcomes.

The study recommends that OECD partner countries emphasize on growing renewable energy and expand environment friendly technological innovation. Ahmed (2020) explored if environmental regulations have the potential to mobilize technological innovation that can lead to carbon abatement. The paper empirically investigates the role of environmental rules in affecting environmentally compatible technological innovations, carbon emissions exports, imports and GDP for a sample of 20 OECD countries. Findings reveal that stricter environmental regulations in combination with environmentally compatible technological innovations are effective in carbon abatement. International trade does not have a meaningful impact on green innovation though in the short run imports are found to be emission intensive while exports are emission reducing. The paper suggests that OECD countries should reconsider trade related environmental regulations.

Bashir et al. (2020) explore the contribution of export diversification (using the indicators of export diversification, extensive margin and intensive margin) for energy intensity and carbon intensity in 29 OECD countries over 1995-2015 by using alternative panel data estimations, sequential estimations, panel quantile regression, GMM and difference GMM. The paper concludes that export diversification helps in reducing energy intensity. Pan X, et al. (2019) use the symbolic regression method to find the determinants of carbon dioxide emissions intensity using six regressors-population, GDP, foreign direct investment, industrialization, technological innovation and urbanization.

for 34 OECD countries during 1995-2014. Although factors influencing carbon dioxide emissions are different for different countries, the most common influencer is gross domestic product. Technological innovation is found to be the third important factor in countries with low population density, a low amount of average FDI but high rate of urbanization. Paramati et al (2021) investigated the role of financial deepening, foreign direct investment (FDI), green technology, trade openness and per capita income on carbon dioxide emissions for a panel of 25 OECD countries from 1991 to 2016.

Green technology is represented by the use of energy efficient technology (used in the process of production and consumption). Findings reveal that FDI and green technology are major factors that help in reducing carbon dioxide emissions, while per capita income and financial deepening increase carbon dioxide emissions.

Petrovic and Lobanov (2019) analyze the effect of research and development expenditure in 16 OECD countries during 1981-2014. The other regressors included in the analysis are GDP, foreign trade and gross fixed capital formation. The study applies parametric techniques for testing the cross sectional dependence of the dataset.

Common Correlated Effects Mean Group (CCEMG) and Augmented Mean Group (AMG) are used to calculate the coefficient elasticities. Estimates of the long run regression model show that the long run average effect of research and development expenditure on carbon dioxide emissions is negative. However, the short run nonparametric time varying coefficient panel data show that the effect of research and development expenditure on carbon dioxide emissions is insignificant over years. In cases where it is significant it can be either negative or positive. Such ambiguous findings imply that country wise empirical estimates should be obtained for purposeful policy making.

Ganda (2019) analyzed technology investments and innovation influenced carbon emissions in select OECD countries using the Generalized Method of Moments (GMM's). The indicators for innovation and technology investment are renewable energy consumption, research and development expenditure, number of researchers and the number of triadic patent families. Results of the study are as follows: Research and development spending negatively affects carbon emissions whereas the number of triadic patent families, number of researchers and human capital positively affects carbon emissions. Hashmi and Alam (2019) studied the effect of environmental regulation and innovation on carbon abatement over the span of 1999-2014 using the modified STIRPART framework.The augmented model articulated by Hashmi and Alam incorporates regulation as an additional regressor. The augmented model is tested using a generalized method of moments, panel fixed effects and random effects using Driscoll-Kraay corrected robust standard errors performed under condition of cross-sectional dependence, time and panel fixed effects. Findings of the analyses reveal that growth in environmentally friendly patents as well as enlarging the environmental tax facilitates carbon abatement.

The study emphasises the necessity for the implementation of instruments like carbon pricing and patents. Gozgor (2017) analyzed the impact of trade openness, per capita energy consumption and per capita income on the level of per capita carbon emissions in a panel dataset of 35 OECD countries over 1960-2013. The paper confirms the existence of a conventional EKC (inverted U shaped) between income and carbon dioxide emissions.

The study supports the extensively reported finding that energy consumption increases carbon emissions while both trade indices have a mitigating effect on carbon emissions.

Dogan and Serker (2016) examined the effect of trade openness, financial development and energy consumption and real income on carbon emissions for OECD using homogenous panel econometric techniques within the EKC framework.

Main findings suggest that energy consumption contributes to carbon emissions and confirms the existence of an EKC for the sample.Trade openness and financial development reduce carbon emissions. Saboori et al. (2014) studied the long run association between GDP, transport sector energy consumption and CO_2 emissions in OECD countries over 1960-2008 by applying Fully Modified Ordinary Least Squares (FMOLS).

The study reports a positive, significant and bi-directional relationship between CO_2 emissions, road sector energy consumption and GDP.

The paper also uses the generalized impulse response approach to detect the response of each variable to shocks in the values of other variables. Results show that the initial response of CO_2 emissions is shorter to economic growth compared to road transport energy consumption. The authors advocate a transition to renewable energy.

Wang et al. (2015) explored the nature of the relationship between urbanization and carbon emissions using the STIRPAT framework using a semi-parametric panel fixed effects regression estimator. The paper attempts to check for the presence of an urbanization-carbon emissions EKC. Results detect a more pronounced conventional inverted U shaped EKC using the semi-parametric panel fixed effects regression estimator. Jebli et al. (2016) examine a panel of 25 OECD countries by employing panel cointegration techniques for the period 1980-2010 to infer that increase in the volume of trade reduces CO_2 emissions.

This paper modestly contributes to the OECD-carbonisation literature by examining the impact of research and development spending (research and development spending as a percentage of GDP), energy use and gross domestic product on carbon emissions. While these variables have been studied formerly as determinants of carbon emissions in OECD, this functional form has not been examined previously. Secondly, to the best of our knowledge this is the first study to make this analysis in the context of OECD using two estimation strategies, with and without the assumption of cross dependence and heterogeneity. Jardon et al. (2017) performed a similar comparative analysis using cross sectional independent and cross sectional dependent techniques for countries of Latin America and Caribbean.Finally, we use the most updated dataset spanning from 1995 to 2019.

3. DATA AND METHODOLOGY

3.1. Data

Annual frequency data from 1995 to 2019 for 29 OECD countries is used in this study. The countries included in the panel are: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Netherlands, New Zealand, Norway, Portugal, Slovak Republic, Sweden, Spain, Turkey, United Kingdom, United States. The data for carbon dioxide emissions, gross domestic product, research and development spending (R&D expenditure) and energy use is taken from World Development Indicators (WDI), the database of World Bank (2021). All variables have been taken at their natural logarithm form.

3.2. Definition of the Variables

Variables	Definition
Gross Domestic Product (GDP)	GDP is defined as the sum of gross value added generated in an economy calculated at factor cost, without adjusting for depreciation or environmental degradation
R&D expenditure	Gross domestic expenditure on research and development is expressed as a percent of GDP. It includes expenditure on basic research, experimental development and applied research by government, businesses, higher education and private non-profit on both current and capital account
Carbon dioxide emissions	Carbon dioxide emissions emanate for the production of cement and burning of fossil fuels (solid, liquid and gas fuels)
Energy use	Energy use refers to the use of primary energy before conversion to end use fuels. This includes the indigenous production, net exports, changes in stock and fuel supplied to ships and aircrafts for international travel

Source: World development ındicators

3.3. The Model

To study the impact of income, energy use and R&D expenditure on carbon emissions, we articulate the following model:

$$LnCO_{it} = \beta_0 + \beta_{1LnG} + \beta_{LnEU} + \beta_{3LnRD} + e_{it} \tag{1}$$

Where LnCO is carbon emissions, the dependent variable. The independent variables are

In the above equation, the dependent variable is carbon emissions (LnCO). The independent variables are LnG (GDP), LnEU (energy use) and LnRD (R&D expenditure). The subscripts *i* and *t* denote country and year respectively, β_0 is the intercept term and e_{it} denotes the error term.

3.4. Methodology

This paper uses two parallel estimation strategies, commonly known as the first and second generation tests. The first generation estimation method consists of the following steps: (i) Determining the stationarity properties of the series using conventional panel unit root tests (ii) performing the Pedroni and Kao cointegration tests (iii) Computing the coefficient elasticities using FMOLS. The second generation tests are performed in the following sequence: (i) The Pesaran (2007) cross sectional dependence test (ii) the augmented cross sectional dependence panel unit root test to examine the stationarity properties of the variables (iii) the Westerlund (2007) cointegration test (iv) AMG is employed to compute the elasticities of the coefficients.

3.5. Panel Unit Root

The first part of the estimation strategy entails the panel unit root tests to check for stationarity properties under the assumption of cross sectional independence.

The procedure includes performing the Levin et al. (LLC), Im et al. (IPS) ADF-Fisher and PP-Fisher unit root tests. To evaluate the stationarity properties of the series under the assumption of cross-sectional independence the following panel unit root test is conducted:

$$\Delta y_{it} = \varphi_{it\beta_{i,i-1}} + p^* y_{i,t-1} + \sum_{j=1}^{ni} \varphi_{ij\Delta_{yi,t-j}} + \in_{it} \tag{2}$$

(Balsalobre-Lorente et al. 2019).

3.6. Panel Cointegration Test

After establishing the stationarity properties of the variables and rejecting the null hypothesis of unit root, the next step is to determine if a long run relationship exists between the variables of interest by performing the appropriate panel cointegration tests.

The Pedroni (1999) and Kao cointegration tests extend the Engle-Granger framework to test for panel cointegration.

The Pedroni cointegration test given below accommodates heterogeneous intercepts and trend coefficients within cross-sections.

$$y_{it} = \alpha_{it} + \delta_{it} + \beta_{1i} X_{1,it} + \beta_{2i} X_{2,it+} \ldots\ldots + \beta_{Mi} X_{M,it} + \varepsilon_{it}$$

Where t = 1.,T; i = 1.,N, m = 1.,M, where y and x are expectedly integrated of I(I). The parameters α_{it} and δ_{It} indicates individual and trend effects. The objective is to compute the residuals from equation 2 to ascertain whether the residuals are I(I) according to the auxiliary regression.

$$\varepsilon_{it} = \rho_{i\varepsilon i,t-1} + u_{it}$$

$$\varepsilon_{it} = \rho_{i\varepsilon i,t-1} + u_{it} + \sum_{j=1}^{p} \varphi_{ij\Delta\varepsilon i,t-j} + v_{it}$$

Pedroni (1999) proposes several methodologies to construct statistics for testing the null hypothesis of no cointegration ($\rho_i = 1$). Two alternate hypothesis in this test are: (a) the within-dimension test or panel statistic test which is also the homogenous alternative ($p_i = p) < 1$ for all *i*. (b) the between dimension or group statistic is the heterogeneous alternative, $p_i < 1$ for all. The Pedroni cointegration test includes seven different statistics, four within-dimension of the panel and three along between dimensions of the panel. All test statistics are normalized to be distributed under N (0,1).

The Kao cointegration test is based on the same methodology. However in case of the Kao test, the cross sectional intercepts and homogeneous coefficients are specified on the first stage regressors. Following os the bivariate case in Kao:

$$y_{i,t} = a_1 + \beta_{1iX1,t} + \varepsilon_{it}$$

$$y_{i,t} = y_{1,t-1} + u_{i,t}$$

$$x_{i,t} = x_{1,t-1} + \varepsilon_{i,t}$$

Where *t* = 1., *T*; *i* = 1., *N*. The first stage regression is done lacking the a_1 to be heterogeneous, β_i to be homogenous through cross-sections, and setting all the trend coefficients ρ_i to zero. (Balsalobre-Lorente et al., 2019).

3.7. Fully Modified Ordinary Least Square (FMOLS)

The FMOLS technique is applied as it handles endogeneity issues. FMOLS is a nonparametric approach through which optimal results can be obtained from cointegrating regression. It handles serial correlation and endogeneity due to the presence of cointegrating relationships. The following equation is articulated:

$$W_{i,t} = \alpha_i + \beta_{iX_{i,t}} + \varepsilon_{i,t}, \qquad \forall t = 1,2,\ldots.T, \qquad i = 1,,\ldots,N$$

Allowing for W_i and $X_{i,t}$ are cointegrated with slopes β_i

Where

$$W_{i,t} = \alpha_i + \beta_{iX_{i,t}} + \sum_{k=-Ki}^{Ki} \gamma_{i,k\Delta X_{i,t-k}} + \varepsilon_{i,t}, \ \forall t = 1,2,\ldots,T, \ i = 1,2,\ldots,N$$

The assumption is: $\xi_{i,t} = (\rho\hat{\varepsilon}_{i,t}\Delta X_{i,t})$. and $\Omega_{i,t} = \lim E\,(\Sigma_{i=1}^{T}\xi_{i,t})(\Sigma_{i=1}^{T}\xi_{i,t})]$

The long covariance is divided into $\Omega_i = \Omega_i^0 + \Gamma_i + \Gamma_i^{'}$, where Ω_i^0 is the simultaneous covariance and $+ T_i^{'}$ is the weighted sum of autocovariance. FMOLS is obtained as follows:

$$\hat{\beta}^*_{FMOLS} = \frac{1}{N} \sum_{i=1}^{N} \left[\left(\sum_{i=1}^{T} (X_{i,t} - X)_i \right) \left(\sum_{i=1}^{T} (X_{i,t} - X)_i W^*_{i,t} - T_{yi} \right) \right]$$

Where,

$$W^*_{i,t} = W^*_{i,t} W_i - \frac{\Omega 2,\hat{1},i}{\Omega 2,\hat{2},i} \Delta X_{i,t} \text{ and } \hat{\gamma}_i = \hat{\Gamma}_{2,1,i} + \hat{\Omega}^0_{2,1,i}$$

$$-\frac{\hat{\Omega}02,1,i}{\hat{\Omega}02,2,i}\left(\hat{\Gamma}_{2,2,i} + \hat{\Omega}_{2,2,i}\right)$$

(Balsalobre-Lorente et al., 2019).

3.8. Cross-Sectional Dependence Test

Panel datasets tend to have the disadvantage of cross-sectional dependence which can lead to inconsistent estimates (Zhao et al., 2020). Cross-sectional dependence in panel data sets implies the existence of a correlation between individual units. Global economic integration is likely to make countries considerably interdependent. It can also arise from a common exogenous shock suffered by all countries with spillover effects between countries (Mania, 2019).

As a prerequisite to choosing the appropriate econometric techniques, a preliminary step is to check for cross-sectional dependence in the panel dataset. Breusch-Pagan Lagrange multiplier (LM) test, Pesaran scaled LM test and Pesaran Cross-Sectional Dependence (CD) test are the most widely applied cross sectional dependence tests. This paper employs all the aforementioned cross-sectional dependence tests.

The Pesaran CD test developed by Pesaran (2004) can be expressed as follows:

$$CD_{Pesaran(2004)} = \sqrt{\frac{2}{i(i-1)}} \sum_{j=k+1}^{i-1} \sum_{j=k+1}^{i} T_{k,jPk,j \sim N(0,1)} \tag{2}$$

3.9. Panel Unit Root Test (Cross-Sectional Dependent)

In the second part of the analysis, we perform the panel unit root tests for cross sectional dependence. The Pesaran (2007) Cross-sectional augmented Im-Pesaran-Shin (CIPS) panel unit root test developed by Pesaran (2007) is performed to test for panel stationarity. This technique is known to produce rather consistent and reliable stationarity properties by accommodating cross-sectional dependence(Wang et al., 2020).The null hypothesis in CIPS is non-stationarity.

The test statistic for Pesaran CIPS is given as follows:

$$\Delta Y_{it} = \gamma_i + \alpha_i Y^{i,t-1} + \beta^i Y^{t-1} + \sum_{i=0}^{P} \gamma^{i1} \Delta Y_{t-1} + \varepsilon^{it} \tag{3}$$

In equation 3 Y_{t-1} and ΔY_{t-1} are the cross sectional averages of lagged levels and first differences of respective series. The CIPS test statistic is derived from the cross sectional augmented dickey fuller (CADF) as follows:

$$CIPS = \frac{1}{N} \sum_{I=1}^{N} CADF^i \tag{4}$$

In equation 4, $CADF^i$ is the t-statistic in the CADF regressions.

3.10. Cross-Sectional Dependent Panel Cointegration Test

The panel unit root tests are followed by error correction based panel cointegration test proposed by Westerlund and Edgerton (2007) with bootstrap to check for the presence of a long run cointegrating relationship among carbon emissions, gross domestic product, technology and energy use. The Westerlund and Edgerton (2007) cointegration test accounts for cross-sectional dependence (Ali et al., 2020) and includes four statistics: Two group statistics (G_a and G_t) and two-panel statistics (P_a and P_t). This technique effectively predicts the cointegrating properties in a cross-sectionally dependent homogenous panel dataset and computes four error-correction-based panel non cointegration test statistics under the null hypothesis of no cointegrating relationship (Khan et al., 2021).

The test equation for the four statistics are expressed below:

$$G_t = N^{-1} \sum_{i-1}^{N} \frac{a}{SE(\alpha)} \tag{5}$$

$$G_t = N^{-1} \sum_{i-1}^{N} \frac{Ta}{\alpha(1)} \tag{6}$$

$$P_a = \frac{a}{SE(a)} \tag{7}$$

$$P_a = T_a \tag{8}$$

3.11. Augmented Mean Group (AMG)

Once the presence of a cointegration relationship among the variables is confirmed we proceed to estimate the long run coefficients using Augmented Mean Group (AMG).

Eberhardt and Bond (2009) formulated the AMG estimator which takes both cross-sectional dependence and heterogeneity into consideration.

$$y_{it} = \beta_{i,x,it} + u_{it}, \quad u_{it} = \alpha_i + \lambda_i f_i + \varepsilon_{it} \tag{9}$$

$$x_{mit} = \pi_{mi} + \delta'_{migration} + \rho_{imi} f_{1mt} + \ldots + \rho_{nmi} fnmtv_{mit} \tag{10}$$

$$f_t = \varphi f_{t-1} + \varepsilon_t \quad and \quad g_t = \omega g_{t-1} + \varepsilon_t \tag{11}$$

x_{it} is a vector of covariates and f_t and g_t denote observed common factors. λ_i indicates unit-specific factor loadings.

The AMG estimator was developed by Eberhardt and Bond (2009).

$$AMG - Stage(i)\Delta y_{it} = b\Delta x_{it} + \sum_{t=2}^{T} C_{tDt} + e_{it} \tag{12}$$

$$AMG - Stage(i)\Delta y_{it} = a_i + b\, x_{it} + c_{it+di\mu t} + e_{it} \tag{13}$$

The heterogeneous-based approach included in the second set of analyses done by this study has certain advantages. It is more impeller than de-facto regressions. It generates more robust results in the presence of different stationary regressors and does

Table 1: Panel unit roots test

Variable	Level				First difference			
	LLC	IPS	ADF-Fisher	PP-Fisher	LLC	IPS	ADF-Fisher	PP-Fisher
LnGDP	−4.409	0.0063	55.280	181.72	6.9215	−9.2263	195.511	751.47
	(0.000)	(0.502)	(0.577)	(0.000)	(1.000)	(0.000)	(0.000)	(0.000)
LnCO	1.0030	4.2369	28.548	27.507	−7.382	−10.959	238.13	549.05
	(0.842)	(1.000)	(0.999)	(0.999)	(0.000)	(0.000)	(0.000)	(0.000)
LnRD	−3.8165	0.285	59.910	52.993	−7.3020	−9.839	208.66	387.10
	(0.000)	(0.612)	(0.406)	(0.661)	(0.000)	(0.000)	(0.000)	(0.000)
LnEU	0.11261	2.426	33.730	55.610	−9.578	−11.993	255.24	569.60
	(0.544)	(0.992)	(0.995)	(0.564)	(0.000)	(0.000)	(0.000)	(0.000)

Parentheses shows P-value. Source: Authors` own calculations

not preclude the possibility of cointegrating modeling and takes a fuller account of all-time variant information (Liddle, 2014).

4. ESTIMATION RESULTS

4.1. OECD

Table 1 shows the results from the LLC, IPS, ADF-Fisher, and PP-Fisher Panel unit root tests. LnGDP is found stationary at level according to the LLC and PP-Fisher unit root tests (at intercept). LnGDP, LnCO, LnRD, LnEU are stationary at their first difference according to all four-panel unit root tests. It can be concluded that the series LnGDP, LnCO, LnRD, LnEU are integrated of order (1).

Once we have determined that the variables are *I*(I), next we ascertain whether a long run relationship exists between the variables by applying the cointegration tests. Results of the Pedroni cointegration test (1999, 2004) are reported in Tables 2 and 3 reports the results of the Kao (1999) cointegration tests.

According to the Pedroni test, the null hypothesis of no cointegration is rejected by two out of the four panel statistics and two out of the four group statistics (taken at intercept).

The Kao test (reported in Table 3) strongly rejects the null of no integration. In general, considering the results of both cointegration tests we can infer that the variables in question LnGDP, LnCO, LnEU, LnRD exhibit a long-run relationship.

The long run elasticities are estimated by employing Pedroni's (2000, 2001) Fully Modified Ordinary Least Square (FMOLS). The FMOLS results are presented in Table 4.

The coefficients of all three variables are found to be statistically significant. The coefficient for LnGDP is negative and significant (−0.854) while the coefficients for LnEU (0.479) and LnRD (0.768) are positive and significant. This can be interpreted as follows: A 1% increase in GDP reduces the carbon dioxide emissions by 0.85% approximately, while a 1% increase in energy use will increase carbon dioxide emissions by 0.47% approximately, and a 1% increase in LnRD will increase carbon dioxide emissions by 0.76%.

4.2. Second Generation Tests

Table 5 and show the findings of the cross-sectional dependence tests. Cross sectional dependence in the panel data is established by all three cross-sectional dependence tests-Breusch Pagan LM, Pesaran scaled LM, and the Pesaran CD test.The null hypothesis of cross sectional independence is rejected by all three tests.

Table 2: Pedroni Cointegration test results LnCO {LnGDP, LnEU, LnRD}

Test	Statistic	P-value
Panel v	25.258	0.000
Pane lRHO	−3.897	0.000
Panel PP	−0.278	0.390
Panel ADF	−1.610	0.053
Group RHO	1.080	0.861
Group PP	−4.687	0.000
Group ADF	−3.585	0.000

Above computations are done at intercept. Source: Authors` own calculations

Table 3: Kao residual cointegration test

Model	t-statistic
LnCO {LnGDP, LnEU, RD}	4.624 (0.000)

Parentheses shows probability values. Source: Authors` own calculations

Table 4: FMOLS estimation results

Model/Variables	LnCO {LnGDP, LnEU, LnRD}
LnGDP	−0.854 (0.004)
LnEU	0.4798 (0.000)
LnRD	0.768 (0.000)

Parentheses shows probability values. Source: Authors` own calculations

Table 6 contains the findings of the Pesaran (2007) cross-sectional dependence test, providing more evidence of strong rejection of the null hypothesis of no cointegration. It can be inferred that the panel dataset of 29 OECD countries employed in this study exhibits cross-sectional dependence or homogeneity.

After establishing the existence of cross-sectional dependence of the panel of 29 OECD countries used in this study, we proceed to perform a sequence of econometric tests designed for accommodating cross-sectional dependence.

Table 7 presents the Pesaran (2007) CIPS panel unit root test results which account for cross-sectional dependence. LnCO, LnRD, and LnEU contain a unit root at the level when considered with and without trend. The variables LnCO, LnRD, and LnEU are found stationary at their first difference whereas LnGDP is found stationary at level, both at the "with" and " no trend" options. Since the variables are integrated of order (I) the possibility of obtaining spurious regressions is eliminated.

Table 5: Results of cross-sectional dependence test

Test	Statistics	P-value
Breusch Pagan LM	4936.34	0.0000
Pesaran scaled LM	158.984	0.0000
Pesaran CD	47.914	0.0000

Source: Authors` own calculations

Table 6: Results of cross-sectional dependence test: Pesaran (2007)

Variables	Statistics	P-value
LnCO	4694.255	0.000
LnGDP	258.117	0.000
LnEU	4063.529	0.000
LnRD	3960.501	0.000

Source: Authors own calculations

Table 7: Results of pesaran unit root test

Variables	I (0)		I (I)	
	No trend	With trend	No trend	With trend
LnCO	−1.860	−2.325	−4.405*	−4.565*
LnGDP	−3.003*	−3.821*	−5.207*	−5.272*
LnRD	−1.808	−1.759	−3.947*	−4.123*
LnEU	−0.916	−2.250	−4.091*	−4.053*

*1% significance level, **5% significance level, ***10% significance level.
Source: Authors` own calculations

Having established that the variables are I(I) the next step is to apply the Westerlund (2007) cointegration test to check for the existence of cointegration among the variables.

Westerlund and Edgerton (2007) cointegration results are given in Table 8. The group statistics strongly reject the null hypothesis of no cointegration for the model LnC {LnGDP, LnEU, LnRD}. We infer that a long run association exists between the variables LnC, LnGDP, LnEU, LnRD.

In the next step, we compute the long-run coefficients of the independent variables that affect carbon dioxide emissions.

Table 9 shows the AMG estimation results. The AMG estimators show that the coefficient for LnGDP is negative and significant (−0.224), the coefficient for LnEU is positive and significant (0.143) while that of LnRD is negative and insignificant. These results can be interpreted as follows: A 1% increase in GDP will reduce carbon dioxide emissions by 0.224%, a 1% increase in energy use will increase carbon dioxide emissions by 0.143%. Our findings regarding LnGDP and LnEU are consistent with the results obtained from FMOLS, both sets of tests suggest the same results that an increase in GDP will reduce carbon emissions. An increase in energy use will increase carbon emissions for the sample of OECD countries over 1995-2019. However, it's worth noting that once we account for the issues of cross-sectional dependence and homogeneity (using the AMG estimator) the elasticities obtained for income and energy use are smaller than the elasticities obtained through FMOLS.

The statistically significant negative coefficient of the GDP can be explained by the *technique and composite effect.* Technique

Table 8: Results of Westerlund cointegration test for the model LnCO {LnGDP, LnEU, LnRD}

Value	G_t	G_a	P_t	P_a
Z-value	−0.796	2.359	1.085	1.095
P-value	0.213	0.991	0.061	0.863
Robust P-value	0.000	0.000	0.600	0.200

Parentheses shows probability values. Source: Authors` own calculations

Table 9: AMG estimation results LnC {LnGDP, LnEU, LnRD}

Variables	Coefficient	
LnGDP	−0.224	0.006
LnEU	0.143	0.000
LnRD	−0.073	0.363

Parentheses shows probability values. Source: Authors` own calculations

and composite effect is the phenomenon that sets it at later stages of economic growth (after attaining a certain threshold level of "income") when a greater share in the GDP belongs to the cleaner service sector and pollution intensity of manufacturing reduces owing to cleaner and more sophisticated technologies.

Our findings regarding the impact of GDP on carbon emissions is consistent with the findings of the reports of the International Energy Agency 2018 and OECD 2015.

The positive and statistically significant coefficient for energy consumption is consistent with the findings of Say and Yucel (2006); Apergis and Payne (2009); Soytas et al., (2007); Ang (2007); Atici (2009); Acaravci and ozturk (2010); Lean and Smyth (2010); Pao and Tsai (2011); Pao et al. (2011); Hossain (2011); Jalil and Feridun (2011); Nasir and Rehman (2011); Park and Hong (2013); Alam et al. (2012); Lau et al. (2014); Omri (2013); Farhani et al. (2014); Shahbaz (2013, 2014); Kasman and Duman (2015); Yavuz (2014); Dogan (2015); Serker (2015); Shahbaz et al. (2015); Tang and Tan (2015); Farhani and Ozturk (2015); Dogan and Turkekul (2016); Javed and Sharif (2016) and Zhang and Gao (2016).

A probable reason for the positive role of energy use in increasing CO_2 emissions is the heavy dependence of the OECD region on fossil fuel energy sources. The share of fossil fuel sources in total energy sources for the OECD were 91% in 2000 and reduced marginally to 87% in 2015 (IEA 2018).

However, we find conflicting results for the impact of research and development spending on carbon emissions. The AMG results suggest that research and development spending is statistically insignificant with a negative sign in sharp contrast with the results produced by FMOLS which suggests that an increase in R&D spending increases carbon emissions. Petrovic and Lobanov (2019) report similar mixed results about the impact of research and development expenditure on carbon emissions.The results that research and development spending is statistically insignificant when analyzed as a determinant of carbon emissions (also coined as the "neutrality hypothesis") supports the findings of Garronen and Grilli (2010); Cheng et al. (2017); Amri (2018).

Table 10: Dumitrescu-hurlin (DH) panel causality tests

Null hypothesis	W-stat	Zbar-Stat	Prob
GDP does not homogeneously cause CO	8.259	12.684	0.000
CO does not homogeneously cause GDP	5.564	6.674	0.175
EU does not homogeneously cause CO	4.001	3.679	0.000
CO does not homogeneously cause EU	4.8444	5.455	5.E-08
RD does not homogeneously cause CO	4.543	4.820	1.E-06
CO does not homogeneously cause RD	5.564	6.995	3.E-12

Source: Authors` own calculations

While the findings from FMOLS that indicate that research and development spending increases CO_2 emissions is consistent with the conclusions of Danish and Baloch 2018, Park et al. 2018; Jardon et al. (2017) also report conflicting findings from estimation techniques with and without the assumption of cross-sectional dependence.

Table 10 reports the results of DH Panel causality tests. Results show a unidirectional causal relationship between GDP and CO_2 suggesting that an increase in income causes carbon dioxide emissions. (Pan et al., 2019). A unidirectional causal relationship is also confirmed between energy use and carbon dioxide emissions indicating that increased energy use causes carbon dioxide emissions.

5. CONCLUSION

This paper examines the impact of income, technology, and energy use on carbon dioxide emissions for 29 OECD countries over the span of 1995-2019 using two parallel estimation strategies. The first, under the assumption of cross-sectional independence, is more commonly known in the literature as the first generation tests, and the second under the assumption of cross-sectional dependence, also known as the second generation tests. The first strategy entails-the panel unit root tests (ADF-Fisher, PP-Fisher, LLC, and IPS), Pedroni and Kao panel cointegration tests, Pedroni's FMOLS for calculating elasticity of coefficients. Under the second strategy, we perform the Pesaran cross-sectional dependence test, CIPS unit root test, Westerlund cointegration test, and the augmented mean group to estimate coefficient elasticities.

When we juxtapose the results of the two strategies we notice that we get the same results for the impact of income and energy use on carbon dioxide emissions. Both the methods suggest that with an increase in GDP, carbon dioxide emissions reduction. We can infer that the empirical evidence of declining carbon emissions with GDP growth is fairly robust. The same results are obtained from both the strategies for the impact of energy use on carbon emissions. Both the first and second-generation tests indicate that energy use positively and significantly impacts carbon emissions.

However, when we probe the impact of research and development spending on carbon emissions we get conflicting results from the two strategies. The first generation tests indicate that technology has a positive and significant coefficient whereas the second generation tests suggest that technology has a negative and insignificant coefficient. Though it's worth mentioning that the first-generation tests produce evidence of stronger cointegration results compared to the second-generation tests.

Overall, we can conclude that our results show that for OECD countries over the span of 1995-12019 the increase in GDP has reduced carbon emissions while the increase in energy use has increased carbon emissions. The mixed results obtained for research and development spending warrant further research to explore the impact of research and development spending on carbon emissions.

OECD's 2015 report. "Climate Change mitigation: Policies and progress (2015) observed the climate change mitigation in 44 countries (including the OECD nations) and the European Union. It observed that almost all the analyzed nations showed a decrease in greenhouse gas emissions per unit of GDP, although achieving decarbonization targets will require radical acceleration of effort. The report also noted that the introduction and implementation of carbon-pricing instruments, slashing of fossil fuel subsidies, investment in research efforts for green technology, reduction of emissions from factories, landfill sites, and farms have contributed to the reduction of greenhouse gas emissions. The report emphasized that these efforts showed progress but were clearly insufficient to meet mitigation targets.

It's noteworthy that the political commitment for achieving carbon neutrality is asymmetric across the world and the OECD is relatively more politically committed to climate action.

America's 45Q tax incentives for carbon capture show some promise and can be copied in Europe. In the European Union, electricity generators and an increasing number of other businesses face penal costs for burning fossil fuels (Economist, 31st Oct 2021).

World Energy Outlook report 2015 identified five the following opportunities that could facilitate an early peak in energy-related greenhouse gas emissions: Boosting end-use energy efficiency, growing investment in renewables, phasing out inefficient fossil fuel subsidies, phasing out inefficient coal power plants, controlling methane emissions from oil and gas production.

The global trajectory is far from what is required to achieve the Paris temperature targets. Though in the most optimistic scenario of sustained progress, emissions reductions are unlikely to be drastic enough to keep the warming as low as 1.5°. Decarbonization efforts need to be supplemented by "negative emissions" or carbon withdrawal, mechanisms for which are at best embryonic. Ambitious and transformative changes are needed to meet climate targets.

This study sets the direction for further research, in the particular country-wise analysis of the OECD members. A country-wise analysis of the determinants of CO_2 and their coefficients will be more revealing and insightful for policy formulation.

REFERENCES

Acaravci, A., Ozturk, I. (2010), On the relationship between energy consumption, CO2 emissions and economic growth in Europe.

Energy, 35(12), 5412-5420.
Ahmad, N., Du, L., Lu, J., Wang, J., Li, H.Z., Hashmi, M.Z. (2017), Modelling the CO2 emissions and economic growth in Croatia: Is there any environmental Kuznets curve? Energy, 123, 164-172.
Ahmed, K. (2020), Environmental policy stringency, related technological change and emissions inventory in 20 OECD countries. Journal of Environmental Management, 274, 111209.
Ali, S., Dogan, E., Chen, F., Khan, Z. (2020), International trade and environmental performance in top ten emitter countries: The role of eco-innovation and renewable energy consumption. Sustainable Development, 29, 378-387.
Al-Mulali, U., Ozturk, I. (2015), The effect of energy consumption, urbanization, trade openness, industrial output, and political stability on environmental degradation in the MENA (Middle East and North African) region. Energy, 84, 382-389.
Amri, F. (2018), Carbon dioxide emissions, total factor productivity, ICT, trade, financial development, and energy consumption: Testing environmental Kuznets curve hypothesis for Tunisia. Environmental Science and Pollution Research International, 25, 33691-33701.
Ang, J. B. (2007), CO2 emissions, energy consumption, and output in France. Energy policy, 35(10), 4772-4778.
Apergis, N., Payne, J. E. (2009). Energy consumption and economic growth in Central America: evidence from a panel cointegration and error correction model. Energy Economics, 31(2), 211-216.
Atasoy, B.S. (2017), Testing the environmental Kuznets curve hypothesis across the US: Evidence from panel mean group estimators. Renewable and Sustainable Energy Reviews, 77, 731-747.
Atici, C. (2009), Carbon emissions in central and Eastern Europe: environmental Kuznets curve and implications for sustainable development. Sustainable Development, 17(3), 155-160.
Balsalobre-Lorente, D., Shahbaz, M., Jabbour, C.J.C., Driha, O.M. (2019), The role of energy innovation and corruption in carbon emissions: Evidence based on the EKC hypothesis. In: Energy and Environmental Strategies in the Era of Globalization. New York City: Springer International Publishing.
Bashir, M.A., Sheng, B., Doğan, B., Sarwar, S., Shahzad, U. (2020), Export product diversification and energy efficiency: Empirical evidence from OECD countries. Structural Change and Economic Dynamics, 55, 232-243.
Cheng, Z., Li, L., Liu, J. (2017), The emissions reduction effect and technical progress effect of environmental regulation policy tools. Journal of Cleaner Production, 149, 191-205.
Chiu, L.C., Chang, T.H. (2009), What proportion of renewable energy supplies is needed to initially mitigate CO2 emissions in OECD countries? Renewable and Sustainable Energy Reviews, 13, 1669-1674.
Churchill, S., Inekwe, J., Smyth, R., Zhang, X. (2019), R and D intensity and carbon emissions in the G7: 1870-2014. Energy Economics, 80, 30-37.
Danish, K., Baloch, M. (2018), The effect of ICT on CO2 emissions in emerging economies: Does the level of income matters? Environ Sci Pollut Res, 25, 22850-22860.
Dogan, E., Seker, F. (2016), An investigation on the determinants of carbon emissions for OECD countries: Empirical evidence from panel models robust to heterogeneity and cross-sectional dependence. Environmental Science and Pollution Research, 23(14), 14646-14655.
Dogan, E., Seker, F. (2016), Determinants of CO2 emissions in the European Union: The role of renewable and non-renewable energy. Renewable Energy, 94, 429-439.
Dogan, E., Seker, F., Bulbul, S. (2015), Investigating the impacts of energy consumption, real GDP, tourism and trade on CO2 emissions by accounting for cross-sectional dependence: A panel study of OECD countries. Current Issues in Tourism, 20, 1701-1719.
Dogan, E., Turkekul, B. (2016), CO2 emissions, real output, energy consumption, trade, urbanization and financial development: Testing the EKC hypothesis for the USA. Environmental Science and Pollution Research, 23(2), 1203-1213.
Eberhardt, M., Bond, S. (2009), Cross-Section Dependence in Nonstationary Panel Models: A Novel Estimator (No. 17692: MPRA Paper). Germany: University Library of Munich.
Farhani, S., Ozturk, I. (2015), Causal relationship between CO2 emissions, real GDP, energy consumption, financial development, trade openness, and urbanization in Tunisia. Environmental Science and Pollution Research, 22, 15663-15676.
Ganda, F. (2019), The impact of innovation and technology investments on carbon emissions in selected organisations for economic Co-operation and development countries. Journal of Cleaner Production, 217, 469-483.
Garronen, P., Grilli, L. (2010), Is there a relationship between public expenditures in energy R and D and carbon emissions per GDP?An empirical investigation. Energy Policy, 38, 5600-5613.
Global Energy and CO2 Status Report 2017. (2017), Available from: https://www.iea.org/reports/global-energy-co2-status-report-2017
Gozgor, G. (2017), Does trade matter for carbon emissions in OECD countries? Evidence from a new trade openness measure. Environmental Science and Pollution Research, 24(36), 27813-27821.
Grossman, G., Krueger, A. (1991), Environmental İmpacts of a North American Free Trade Agreement. United States: National Bureau of Economic Research, Inc.
Grossman, G.M., Krueger, A.B. (1995), Economic growth and the environment. Quarterly Journal of Economics, 110(2), 353-377.
Hamilton, C., Turton, H. (2002), Determinants of emissions growth in OECD countries. Energy Policy, 30(1), 63-71.
Hashmi, R., Alam, K. (2019), Dynamic relationship among environmental regulation, innovation, CO2 emissions, population, and economic growth in OECD countries: A panel investigation. Journal of Cleaner Production, 231, 1100-1109.
Hossain, M.S. (2011), Panel estimation for CO_2 emissions, energy consumption, economic growth, trade openness and urbanization of newly industrialized countries. Energy policy, 39(11), 6991-6999.
IEA (2018), Global Energy and CO_2 Status Report 2017, IEA, Paris https://www.iea.org/reports/global-energy-co2-status-report-2017
IEA (2018), World Energy Outlook 2018, IEA, Paris.
Im, K., Persaran, M., Shin, Y. (2003), Testing for unit roots in heterogeneous panels. Journal of Econometrics, 115, 53-74.
Iqbal, N., Abbasi, K.R., Shinwari, R., Guangcai, W., Ahmad, M., Tang, K. (2021), Does exports diversification and environmental innovation achieve the carbon neutrality target of OECD economies? Journal of Environmental Management, 291, 112648.
Jalil, A., Feridun, M. (2011), The impact of growth, energy and financial development on the environment in China: a cointegration analysis. Energy economics, 33(2), 284-291.
Javed, M., Sharif, F. (2016), Environmental Kuznets curve and financial development in Pakistan. Renewable and Sustainalbe Energey Reviews, 54, 406-414.
Jebli, M.B., Youssef, S.B., Ozturk, I. (2016), Testing environmental Kuznets curve hy-pothesis: The role of renewable and non-renewable energy consumption and trade in OECD countries. Ecological Indicator, 60, 824-831.
Kao, C. (1999), Spurious regression and residual-based tests for cointegration in panel data. Journal of Econometrics, 90, 1-44.
Kasman, A., Duman, Y. (2015), CO2 emissions, economic growth, energy consumption, trade and urbanization in new EU member and candidate countries: A panel data analysis. Economic Modelling, 44, 97-103.
Khan, Z., Murshed, M., Dong, K., Yang, S. (2021), The roles of export diversification and composite country risks in carbon

emissions abatement: Evidence from the signatories of the regional comprehensive economic partnership agreement. Applied Economics, 53(41), 4769-4787.

Lau, L.S., Choong, C.K., Eng, Y.K. (2014), Investigation of the environmental Kuznets curve for carbon emissions in Malaysia: do foreign direct investment and trade matter?. Energy policy, 68, 490-497.

Lean, H.H., Smyth, R. (2010), CO2 emissions, electricity consumption and output in ASEAN. Applied Energy, 87(6), 1858-1864.

Levin, A., Lin, C., Chu, C. (2002), Unit root tests in panel data: Asymptotic and finite sample properties. Journal of Econometrics, 108, 1-24.

Liddle, B. (2011), Consumption-driven environmental impact and age structure change in OECD countries: A cointegration-STIRPAT analysis. Demographic Research, 24, 749-770.

Liddle, B. (2015), What are the carbon emissions elasticities for income and population? Bridging STIRPAT and EKC via robust heterogeneous panel estimates. Global Environmental Change, 31, 62-73.

Liddle, B., Lung, S. (2010), Age-structure, urbanization, and climate change in developed countries: Revisiting STIRPAT for disaggregated population consumption-related environmental impacts. Population and Environment, 31(5), 341-347.

Lin, S., Zhao, D., Marinova, D. (2009), Analysis of the environmental impact of China based on the STIRPAT model. Environmental Impact Assessment Review, 29(6), 341-347.

Mania, E. (2020), Export diversification and CO2 emissions: An augmented environmental Kuznets curve. Journal of International Development, 32(2), 168-185.

Menz, T., Welsch, H. (2012), Population aging and carbon emissions in OECD coun-tries: Accounting for life-cycle and cohort effects. Energy Economics, 34(3), 842-849.

Nasir, M., Rehman, F.U. (2011), Environmental Kuznets curve for carbon emissions in Pakistan: an empirical investigation. Energy policy, 39(3), 1857-1864.

Omri, A. (2013), CO_2 emissions, energy consumption and economic growth nexus in MENA countries: Evidence from simultaneous equations models. Energy economics, 40, 657-664.

Pan, X., Uddin, M.K., Ai, B., Pan, X., Saima, U. (2019), Influential factors of carbon emissions intensity in OECD countries: Evidence from symbolic regression. Journal of Cleaner Production, 220, 1194-1201.

Pao, H.T., Tsai, C.M. (2011), Modeling and forecasting the CO_2 emissions, energy consumption, and economic growth in Brazil. Energy, 36(5), 2450-2458

Paramati, S.R., Mo, D., Huang, R. (2021), The role of financial deepening and green technology on carbon emissions: Evidence from major OECD economies. Finance Research Letters, 41, 101794.

Park, Y., Meng, F., Baloch, M. (2018), The effect of ICT, financial development, growth, and trade openness on CO2 emissions: An empirical analysis. Environmental Science and Pollution Research, 25, 30708-30719.

Pedroni, P. (1999), Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxford Bulletin of Economics and Statistics, 61, 653-678.

Pedroni, P. (2000), Fully modified OLS for the heterogeneous cointegrated panels. Advances in Econometrics, 15, 93-130.

Pesaran, H. (2004), General Diagnostic Tests for Cross-Sectional Dependence in Panels. (No. 435: Cambridge Working Papers in Economics), United Kingdom: University of Cambridge.

Pesaran, M. (2007), A simple panel unit root test in the presence of cross-section dependence. Journal of Applied Economics, 22(2), 265-312.

Petrović, P., Lobanov, M.M. (2020), The impact of R and D expenditures on CO2 emissions: Evidence from sixteen OECD countries. Journal of Cleaner Production, 248, 119187.

Poumayvong, P., Kaneko, S. (2010), Does urbanization lead to less energy use and lower CO2 emissions? A cross-country analysis. Ecological Economics, 70(2), 434-444.

Ritchie, H., Roser, M. (2020), CO□ and Greenhouse Gas Emissions. United Kingdom: Our World in Data.

Saboori, B., Sapri, M., Baba, M.B. (2014), Economic growth, energy consumption and CO2 emissions in OECD (Organization for Economic Co-operation and Development)'s transport sector: A fully modified bi-directional relationship approach. Energy, 66, 150-161.

Say, N. P., Yücel, M. (2006), Energy consumption and CO_2 emissions in Turkey: Empirical analysis and future projection based on economic growth. Energy policy, 34(18), 3870-3876.

Seker, F., Ertugrul, H., Cetin, M. (2015), The impact of foreign direct investment on environmental quality: A bounds testing and causality analysis for Turkey. Renewable and Sustainable Energy Reviews, 52, 347-356.

Shafiei, S., Salim, R. (2014), Non-renewable and renewable energy consumption and CO2 emissions in OECD countries: A comparative analysis. Energy Policy, 66, 547-556.

Shahbaz, M., Khraief, N., Uddin, G., Ozturk, I. (2014), Environmental Kuznets curve in an open economy: A bounds testing and causality analysis for Tunisia. Renewable and Sustainable Energy Reviews, 34, 325-336.

Soytas, U., Sari, R., Ewing, B. (2007), Energy consumption, income, and carbon emissions in the United States. Ecological Economics, 62(3), 482-489.

Tang, C.F., Tan, B.W. (2015), The impact of energy consumption, income and foreign direct investment on carbon dioxide emissions in Vietnam. Energy, 79, 447-454.

Wang, L., Chang, H.L., Rizvi, S.K.A., Sari, A. (2020), Are eco ınnovation and export diversification mutually exclusive to control carbon emissions in G-7 countries? Journal of Environmental Management, 270, 110829.

Wang, Y., Zhang, X., Kubota, J., Zhu, X., Lu, G. (2015), A semi-parametric panel data analysis on the urbanization-carbon emissions nexus for OECD countries. Renewable and Sustainable Energy Reviews, 48, 704-709.

Wang, Z., Yin, F., Zhang, Y., Zhang, X. (2012), An empirical research on the influencing factors of regional CO2 emissions: Evidence from Beijing city, China. Applied Energy, 100, 277-284.

Westerlund, J., Edgerton, D. (2007), A panel bootstrap cointegration test. Economics Letters, 97(3), 185-190.

Yavuz, N.Ç. (2014), CO_2 emission, energy consumption, and economic growth for Turkey: evidence from a cointegration test with a structural break. Energy Sources, Part B: Economics, Planning, and Policy, 9(3), 229-235.

York, R., Rosa, E.A., Dietz, T. (2003), STIRPAT, IPAT and ImPACT: Analytic tools for unpacking the driving forces of environmental impacts. Ecological Economics, 46(3), 351-365.

Zaidi, S.A.H., Hussain, M., Zaman, Q.U. (2021), Dynamic linkages between financial inclusion and carbon emissions: evidence from selected OECD countries. Resources, Environment and Sustainability, 4, 100022.

Zhang, C., Lin, Y. (2012), Panel estimation for urbanization, energy consumption and CO2 emissions: A regional analysis in China. Energy Policy, 49, 488-498.

Zhang, L., Gao, J. (2016), Exploring the effects of international tourism on China's economic growth, energy consumption and environmental pollution: Evidence from a regional panel analysis. Renewable and Sustainable Energy Reviews, 53, 225-234.

Zhao, J., Jiang, Q., Dong, X., Dong, K. (2020), Would environmental regulation improve the greenhouse gas benefits of natural gas use? A Chinese case study. Energy Economics, 87, 104712.