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Achieving Environmental Sustainability through Economic Fitness and Energy Efficiency in OECD Countries

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ABSTRACT

As global economic and human activities, as well as energy consumption, which have increased by 44% between 1971 and 2014, continue to rise, the concentration of greenhouse gas emissions (GHG) will continue to exacerbate global warming and environmental degradation. CO_2 emissions (CO_2E) are leading source of global warming, accounting for about 80% of all GHG. Rising sea levels are a consequence of increased CO_2E. Despite the fact that OECD countries have achieved notable successes, particularly in sustainable development, through regulations and other initiatives for more than six decades, they continue to face significant environmental challenges. In addition, the economies of the OECD member States and a number of developing nations are still responsible for three-quarters of total emissions. This study analyses the influence of economic fitness (EF), energy efficiency (EE), economic growth (EG), and international trade (INT) on CO_2E. It employs the CS-ARDL, two-way fixed-effect estimation techniques, and the second-generation methods of cointegration and granger causality for the analysis. The results indicate that EF, EE, and INT are important factors in curbing CO_2E, while EG is responsible for the rising CO_2E in the short-run and the long-run. These findings imply that improving economic fitness and energy efficiency maybe a crucial component of CO_2E mitigation.

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INTRODUCTION

As Global economic and human activities together with energy consumption which has increased by 44% from 1971 to 2014 (WorldBank, 2017), continue to rise, the quantity of greenhouse gas emissions (GHG) will continue to worsen global warming and environmental deterioration. CO2E significantly contribute to the concentration of GHG in the atmosphere and to the development of life-threatening weather events (Cheema, Chiah, & Man, 2020; Makino, Chan, Isobe, & Beamish, 2007). CO_2E contributed 83% to total emission amount in 2011(Shahbaz, Shahzad, Alam, & Apergis, 2018), and the rate of global emissions has increased to about 68% since the onset of industrial revolution (IPCC, 2021). Unsuitable economic growth policies have enhanced national income and heat trapping gas emissions from an increased in human activities are imposing huge costs on environmental sustainability

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(Kirikkaleli, Adebayo, Khan, & Ali, 2021). According to the IEA, global emission of CO2 from non-renewable resource rose by 65% between 1980 and 2018.

For over six decades now, the OECD member States have recorded significant successes, especially in sustainable development, through regulations and other initiatives. According to Ozcan, Tzeremes, and Tzeremes (2020), the OECD's strategy for economic growth (EG) and energy consumption switched from fossil fuels to renewable energy resources from 2000 to 2014, resulting in less environmental decay. Sueyoshi, Mo, and Wang (2022) confirmed that due to increased efforts to adopt green technology, the level of sustainability in OECD countries was higher than in non-OECD countries between 2012 and 2014. However, the World emission statistics shows that the OECD countries and some emerging countries are still responsible for three-quarters of total emissions.

Globally, energy efficiency has been recognized in recent years as a crucial factor in tackling global CO_2E and achieving the goals of sustainable development. Some empirical papers have examined the relationship between EE and CO_2E (Akram, Majeed, Fareed, Khalid, & Ye, 2020; Chen, Song, & Wang, 2021a; U. R. Danish & Khan, 2020; Go, Lau, Yii, & Lau, 2020; Hasanbeigi, Morrow, Sathaye, Masanet, & Xu, 2013; J. Li & Li, 2020; B. Lin & Chen, 2018; Nathaniel, Barua, Hussain, & Adeleye, 2021; Ouyang, Chen, & Du, 2021; Özbuğday & Erbas, 2015; Pei, Zhu, & Wang, 2021b). Besides EE, many empirical papers have investigated the influence of FDI (Demena & Afesorgbor, 2020; Demena & Murshed, 2018; Sapkota & Bastola, 2017; H. Zhu, Duan, Guo, & Yu, 2016), urbanization (Ahmad, Jabeen, & Wu, 2021; Luqman, Rayner, & Gurney, 2023; Martínez-Zarzoso & Maruotti, 2011), financial development (Umar, Ji, Kirikkaleli, & Xu, 2020), globalization (Aslam et al., 2021; Baloch, Ozturk, Bekun, & Khan, 2021; Chien et al., 2021; Shan et al., 2021; Zhang, Wang, Bao, & Zhao, 2019), innovation (Ahmad & Satrovic, 2023; M. I. Khan, Teng, & Khan, 2020; Mongo, Belaïd, & Ramdani, 2021; Ullah, Ozturk, Majeed, & Ahmad, 2021), renewable energy consumption (Fatima, Li, Ahmad, Jabeen, & Li, 2019; H. Khan, Khan, & BiBi, 2022; Sharma & Kautish, 2020; Sharma, Shahbaz, Kautish, & Vo, 2021), the structure of the industry (Z. Khan, Shahbaz, Ahmad, Rabbi, & Siqun, 2019), and information and communication technology (H. Khan, Weili, & Khan, 2022; Usman, Ozturk, Hassan, Zafar, & Ullah, 2021) on CO_2E. Presently, one of the most significant empirically verified variables affecting CO_2E is trade. The growth of trade enhances a country's overall economic activities (Sharma, Shahbaz, Kautish, & Vo, 2023), while also significantly contributing to the negative ecological footprint (Ertugrul, Cetin, Seker, & Dogan, 2016). However, Wang and Wang (2021) opine that trade reduces the negative ecological footprint. Trade affects CO_2E via different channels such as scale, technique, and composition effect (H. Liu, Kim, & Choe, 2019; Shi, Visas, Ul-Haq, Abbas, & Khanum, 2023). These channels determine whether trade will have an inhibitory or promoting effect on CO_2E (Nasreen & Anwar, 2014).

Many studies on the environment have also examined the impact of trade on CO_2E, using the "volume of trade or the scale effect" as a measure for trade (Pan, Uddin, Saima, Jiao, & Han, 2019). Some empirical analysis have attempted to quantify the trade impact by focusing on the environmental impacts of "export product diversification (EPD)". Current thinking holds that when it concerns minimizing environmental degradation, product diversification (PD) is a better indicator than EPD (Johansson, Broberg, & Ottosson, 2021). Some empirical investigations have investigated the association between CO_2 emissions and economic complexity in industrialized nations (Can and Gozgor (2017); Doğan, Saboori, and Can (2019); Yilanci and Pata (2020); and Tacchella, Cristelli, Caldarelli, Gabrielli, and Pietronero (2012) . Ul-Haq, Visas, Can, and Khanum (2023) is one of few empirical studies that have examined how product diversification affects CO_2E. PD is only a part of economic fitness (EF), which is an all-encompassing metric than PD measure (Çınar, Korkmaz, & Şişman, 2023; İSKENDEROĞLU & AKDAĞ, 2018; Ul-Haq, Visas, Umair, Hussain, & Khanum, 2023). Therefore, in this study, not only energy efficiency which has been recognized in recent years as a crucial factor in tackling global carbon emissions is used, but also EF, as it is a more comprehensive metric that captures a more accurate representation of the environmental impact caused by economic activities.

EF is a measure of how well a country produces a variety of complex goods that are highly competitive on a global scale. High-economic-fitness countries experience predictable long-term growth, diversify their product portfolios, move into more complex product categories, and strengthen their competitive position. Low economic fitness is associated with poverty, less know-hows, lower growth, less value addition, more upgrading difficulties, and less diversity in the economy.

By introducing economic fitness as a key determinant of environmental sustainability, this study goes beyond using traditional economic indicators like the GDP, renewable energy consumption, income trade and technological innovation that have been used in existing study urbanization (Ali, Dogan, Chen, & Khan, 2021; Amin, Zhou, & Safi, 2022; Hojnik & Ruzzier, 2016; Mensah et al., 2018; Narayan & Narayan, 2010; Shahbaz et al., 2018). As Economic fitness captures the complexity and diversity of the productive capacity of countries, it could influence their abilities to adopt and benefit from energy-efficient technologies. Also, previous studies have employed standard econometric methods like ARDL and fixed effects models, which often do not fully address issues of cross-sectional dependence, heterogeneity, and long-term dynamics relationships between variables (Kartal, Ayhan, Sarıhan, & Altaylar, 2025; Rahaman, Chen, & Jiang, 2023; Raihan et al., 2025). The CS-ARDL approach, which in this context is novel, addresses these limitations by integrating cross-sectional augmentation and autoregressive distributed lag modeling (Karim et al., 2025). Finally, while studies like (M. Li et al., 2025) debate climate policy layers and fiscal tools, they failed to incorporate economic fitness into policy frameworks. This gap should not be ignored as economic fitness could inform targeted policies for OECD countries based on their economic structure and capacities.

This study therefore adds to existing empirical studies on environmental sustainability in many ways: First, it looks at the impact of EF and energy efficiency, international trade and economic growth on CO_2E in OECD countries. Second, to the best of our knowledge, this paper is the first to employ energy efficiency and economic fitness in OECD countries, which is a more comprehensive metric, compared to the PD measure employed in existing studies. Third, to compute CO_2E, we used CO_2E in metric tons per head and CO_2E (kg per 2015 US$ of GDP). Fourthly, we employ the CS-ARDL which is advantageous over other approaches as it handles structural breaks, endogeneity and heterogeneity issues (Chudik & Pesaran, 2015) and the two-way FE estimator to simultaneously adjust for unobserved unit-specific and time-specific extraneous variables.

The rest of study is arranged as following sections; literature review, data and estimation techniques, results and discussion, and the last section conclude the study and give policy recommendation.

Literature Review

The most common factors that are mostly responsible climate change as identified by existing literature include income, trade, financial deepening, energy consumption, and urbanization (Adeneye, Jaaffar, Ooi, & Ooi, 2021; Ali et al., 2021; Amin et al., 2022; Ding, Khattak, & Ahmad, 2021; Hojnik & Ruzzier, 2016; Ji et al., 2021; M. I. Khan et al., 2020; J. Li & Li, 2020; Mensah et al., 2018; Narayan & Narayan, 2010; Pei, Zhu, & Wang, 2021a; Shahbaz et al., 2018; Wahab, Zhang, Safi, Wahab, & Amin, 2021).

Recently, researchers have identified EE and other new potential factors of environmental degradation (Amin et al., 2022; Chen, Song, & Wang, 2021b; Ding et al., 2021; Hassan, Song, Khan, & Kirikkaleli, 2022; Y. He, Fu, & Liao, 2021; Pei et al., 2021b). The issue of EE has received immense attention from researchers over the years (Chen et al., 2021a; Y. He et al., 2021;

Pei et al., 2021b). In industrialized countries, technical and sustainable developments, as well as strategies involving the implementation of authorized requirements, have all increased EE which has abated GHGs levels (Mategaonkar & Eldho, 2012). In contrast, emerging economies have experienced a rise in CO_2E attributed to several factors including transportation, industry, and the services sector (Heidari et al., 2019). According to Sihwail, Omar, Ariffin, and Tubishat (2020), developing countries serve as attractive locations for fuel industries and heavily depend on alternative energy sources. However, this reliance on alternative energy sources can lead to long-term environmental concerns, including the emission of ecologically hazardous pollutants that contribute to global warming. Ozcan et al. (2020) revealed that over the past six decades, the OECD member States have recoded extraordinary success, principally in sustainable development, as a result of its strategy for EG and energy consumption, which has reduced environmental decay. According to a study conducted by Sueyoshi et al. (2022), the level of sustainability in OECD countries over the period from 2012 to 2014 was found to be greater compared to non-OECD countries. This disparity in sustainability was attributed to the greater focus on adopting green technology in OECD countries. Using data on 15 economies, Saidi and Omri (2020) found that EE promotes economic growth and also prevents environmental threats like CO_2E. The study also observed a two-way causality between EE and CO_2E. Go et al. (2020) investigated the aggregated and disaggregated level relationships between EE, carbon emissions, and EG in Malaysia, and observed a causative relationship between EE and CO_2E at the aggregate level, but no causal associations were established at the disaggregated level. According to Yang, Hao, and Feng (2021) efficiency and advancements in technology related to EE are the main variables that break the link between economic growth and CO_2E.

The impact of EPD on CO2E has been the subject of some previous studies (Apergis, Can, Gozgor, & Lau, 2018; Dou, Ul-Haq, Visas, Aslam, & Khanum, 2023; Sharma et al., 2023; Shi et al., 2023). Others have looked at how import product diversification (IPD) influences CO_2E (Hu, Can, Paramati, Doğan, & Fang, 2020; Parteka & Tamberi, 2013), while others have analyzed the impact of PD on CO_2E (Johansson et al., 2021; Ul-Haq, Visas, Can, et al., 2023). Can and Gozgor (2017), Doğan et al. (2019)), Yilanci and Pata (2020) and Tacchella et al. (2012) found a negative association between CO_2E and economic complexity in industrialized economies. Ul-Haq, Visas, Umair, et al. (2023) investigated the influence of EF on CO_2E in BRICS nations between 1995 and 2015 and found an inverted dell shaped association between EF and CO_2E. The only similar study to EF is that of Çınar et al. (2023) that examined the influence of green complexity and EF on the environment in the United States. No previous research, particularly in the context of OECD nations, has employed a holistic indicator as EF, which is a comprehensive measure of PD that captures the ability to produce complex commodities that can compete on the world stage. This study thus seeks to address this existing research gap using data from the OECD countries.

The presence of affordability promotes the occurrence of operations and economic pollution, leading to CO_2E, which intensifies the risk posed by climate change (Cheng, He, & Zhao, 2019; J. Liu et al., 2021). Furthermore, as the economy expands, consumers acquire more luxury goods, like automobiles, microwaves, and exhaust systems that possess environmental hazards (T. He et al., 2019; Ma, Shi, Ma, & Wang, 2013; Wu & Zhao, 2018). The study of Salahuddin, Alam, Ozturk, and Sohag (2018) revealed the presence of a bidirectional Granger causal relationship between EG and CO_2E. In contrast, Omri, Nguyen, and Rault (2014) identified a unidirectional Granger causation in specific countries located in Central Asia, Europe, the Caribbean, and Latin America. Controlling CO_2E poses challenges due to the diverse range of factors involved, including changes in government regulations, geographical considerations, and others. Additionally, the presence of numerous economic barriers further complicates the task of managing CO_2E. According to the findings of J. Li and Li (2020) and J. Zhu, Shi, Song, Tan, and Tao (2020), it is acknowledged that CO_2E which constitutes approximately 80% of total greenhouse gas emissions, significantly contributes in driving global warming.

DATA AND METHODOLOGY

Model and Theoretical Rationale

To empirically examine the connection between CO2E, energy efficiency, economic fitness, economic growth, and international trade in OECD economies, and following Ul-Haq, Visas, Umair, et al. (2023), and Haseeb, Xia, Saud, Usman, and Quddoos (2023), this paper uses the following specification:

$$CO2_{i,t} = \lambda_0 + \lambda_1 EE_{i,t} + \lambda_2 \mathrm{EF}_{i,t} + \lambda_3 EG_{i,t} + \lambda_4 INT_{it} + \eta_{i,t} \tag{1}$$

EE represents energy efficiency measured by the share of energy consumption in real GDP, EF is economic fitness, GDP represents gross domestic product, and INT symbolizes international trade measured by the sum of import and export as a proportion of the GDP. EG represents economic growth measured by GDP per capita (at 2015 constant USD). This study uses a consumption-based approach to measure carbon emissions. As observed by B. Lin and Chen (2018) and Mahapatra and Irfan (2021), energy efficiency contributes to less CO_2E and thus important for attaining the sustainable development goals. As a result, we expect energy efficiency to abate CO_2E in OECD countries, i.e., $\lambda 1 = \frac{\partial CO2}{\partial EE} < 0$. In line with Çınar et al. (2023) and Ul-Haq, Visas, Umair, et al. (2023), this study introduces EF as the second primary predictor variable. It has been demonstrated that EF and green EF reduce CO_2E in BRICS nations and the United States, respectively. Consequently, we anticipate that EF will reduce CO_2E in OECD countries i.e., $\lambda 2 = \frac{\partial CO2}{\partial EF} < 0$. Following Ali et al. (2021), this study introduces GDP as one of the variables. This author has demonstrated that economic growth has positive, negative and inconclusive effects on the environment in various regions of the globe, making it one of the leading environmental degradation factors. Therefore, we predict that the GDP will have either a promoting or an inhibitory effect on CO_2E, i.e., $\lambda 3 = \frac{\partial CO2}{\partial GDP} > 0$ or $\lambda 3 = \frac{\partial CO2}{\partial GDP} > 0$. While Ertugrul et al. (2016) and Sharma et al. (2023) demonstrated that international trade substantially contributes to the negative ecological footprint, Wang and Wang (2021) concluded that international trade decreases the negative ecological footprint. We incorporate international trade in this analysis with the expectation that it will reduce CO_2E.

Data Source

This study uses data from OECD countries from 1990 to 2017. The data is collected from two different sources: Organization for Economic Co-operation and Development (OECD) (2021) and World Bank (2021). Following Chen et al. (2021a), Go et al. (2020), J. Li and Li (2020), and Nathaniel et al. (2021), this study uses the ratio of output to energy used to measure EE. Energy usage is the use of energy from burnable renewables and waste. EF measures a country's diversification and aptitude to manufacture globally economical goods (Çınar et al., 2023; Ul-Haq, Visas, Umair, et al., 2023).

Econometric Techniques

To estimate the effects of EE, EF, EG and INT on environmental sustainability, this study follows a six steps analysis.

Slope heterogeneity (S.H.) and cross-sectional dependence (C.D)

For panel data, S.H and C.D can be serious issues. We therefore start by examining S.H and cross-sectional dependence (C.D). Interdependence among the world economy is brought on by some shocks. To verify the C.D, we employ the Pesaran (2015) test. To verify the S.H. in models, Pesaran. and Yamagata (2008) performed a test while assuming that a homogeneous coefficient is measured; a strong assumption that may or may not be accurate. The test statistics are:

$$\tilde{\Delta}_{SH} = \sqrt{\frac{N}{2k}} \times \left(\frac{1}{N}\tilde{S} - k\right) \tag{2}$$

$$\tilde{\Delta}_{ASH} = \sqrt{\frac{N(T+1)}{2k(T-k-1)}} \left(\frac{1}{N}\tilde{S} - 2k\right) \tag{3}$$

Where $\tilde{\Delta}_{SH}$ and $\tilde{\Delta}_{ASH}$ are delta and delta adjusted respectively.

Panel Unit Root

As the data spans for a period of 1990 to 2017, it might be characterized by random walks leading to unrealistic results. Three panel stationarity tests namely Breitung and Das (2005), Levin, Lin, and Chu (2002), and Fisher Chi-square ADF test (G. S. Maddala & Wu, 1999) are used in this work. More information on these strategies can be found in Choi (2001).

In the event of S.H and C.D, we will employ Pesaran (2007) stationarity testing, which produces reliable results even when there is variation in the S.H and C.S.D. The CIPS test method can be illustrated by the following equation:

$$\Delta Y_{i,t} = \varphi_i + \varphi_i Z_{i,t-1} + \varphi_i \bar{Y}_{t-1} + \sum_{l=0}^{p} \varphi_{il} \Delta \bar{Y}_{t-l} + \sum_{l=1}^{p} \varphi_{il} \Delta Y_{i,t-l} + \mu_{it} \tag{4}$$

The test statistics is given as:

$$\widehat{\text{CIPS}} = \text{N}^{-1} \sum_{i=1}^{n} \text{CDF}_i \tag{5}$$

Panel Cointegration

Kao (1999) employs the Augmented Dickey-Fuller (ADF) test to check for cointegration in panel data. This methodological approach is employed on the panel regressions model shown in equation 1.

$$P_{it} = K_{it} B_{it} + D_{it} \alpha_0 + \dot{o}_{it} \tag{6}$$

P and K are supposed to be non-stationary.

$$G_{it} = \sigma G_{it}^{\circ} + P_{it} \tag{7}$$

where $G_{it} = (P_{it} - K_{it} B_{it}^{\circ} - D_{it} \sigma^{\circ})$ and shows the residuals from estimating Eq6.

To validate the presence of cointegration between the variables P and K in eq (7), the null hypothesis $H_{\circ}$: $\sigma = 1$ is tested against the alternate hypothesis that P and K are cointegrated ($H_1 : \sigma < 1$). In this context, Kao (1999) developed a methodology to test for cointegration by adapting the rules of the standard ADF test. Kao's approach involves computing panel-based ADF test statistics, which pool information from the cross-sectional dimension to improve the power of the test. The resulting ADF test statistics serve as a criterion for inference: a significantly negative value means the rejection of the null hypothesis of no cointegration, thereby providing evidence in support of a stable long-run equilibrium relationship between P and K across the panel: The ADF test statistics can show the following:

$$\text{ADF} = \frac{t_{ADF+\sqrt{6N\hat{\vartheta}_v/2\hat{\vartheta}_u}}}{\sqrt{\frac{\hat{\vartheta}_v^2}{2\hat{\vartheta}_v^2}+3\hat{\vartheta}_v^2/10\hat{\vartheta}_v^2}} \tag{8}$$

Where,

N => Cross section data

$\hat{\vartheta}_v$ => SD of v

$\hat{\vartheta}_u$ => SD of u

$\hat{\vartheta}_v^2$ => Variance of v

t_{ADF} => $[\,(\rho^{\wedge}-1)(\Sigma_{i=1}^{N}(\frac{F}{Qi\ Fi}))\ ^1/_2]/S_v$

Adopting the panel cointegration testing strategy developed by Kao (1999), this paper utilizes a residual-based approach, which centers on calculating a panel ADF test statistic to examine long-run equilibrium relationships. As formally stated in the null hypothesis (Equation F1), the test determines whether the entire panel lacks cointegration. The statistical evidence for this test is aggregated from individual cross-sectional unit tests, where *I* represents the p-value for each specific unit i.

$$2\sum_{i=1}^{n} log\,(\Pi_i) \rightarrow x^2 2_n \ldots\ldots\ldots\ldots.(F1)$$

where the x^2 value shows the p-value, which is used for Johansen's cointegration maximum eigenvalue test and trace test. See eq (5) for Johansen's highest probability method.

$$\Delta P_{i\,t} = \Pi_i y_{i\,t-1} + \sum_{k=1}^{n} T_k \Delta P_{i\,t-k} + \in_{i\,t} \tag{9}$$

In the event of CD, this study will employ the Westerlund (2007) cointegration test which is a second generation test that addresses issues CD. This procedure is robust compared to the conventional cointegration tests by McCoskey and Kao (1998). The test uses the following statistics:

$$G_t = \frac{1}{N}\sum_{i-1}^{N}\frac{ά_i}{SE(ά_i)} \tag{10}$$

$$G_\alpha = \frac{1}{N}\sum_{i-1}^{N}\frac{\mathrm{T}ά_i}{ά_i(1)} \tag{11}$$

$$P_T = \frac{ά}{SE(ά)} \tag{12}$$

$$P_{\alpha} = \mathrm{T}\acute{\alpha} \tag{13}$$

The CS-ARDL and the two-way fixed effect Approachs

The CS-ARDL approach is utilized to measure the short- and long-run relationships between EF, EE, EG, and INT. This strategy is more robust and efficient than the conventional panel data techniques (Chudik & Pesaran, 2015). The primary advantages of CS-ARDL over other approaches are that it is useful for working with structural breaks, endogeneity and heterogeneity. The CS-ARDL's equation is given as:

$$\Delta CO2_{i,t} = \theta_i + \sum_{l=1}^{p} \pi_{il} \Delta CO2_{i,t-l} + \sum_{l=0}^{p} \pi'_{il} X_{i,t-l} + \sum_{l=0}^{1} \pi'_{il} \bar{Z}_{i,t-l} + \varepsilon_{i,t} \tag{14}$$

Where the cross-sectional averages are denoted by $\bar{Z}_t = (\Delta\overline{CO2}_t, \bar{X}'_t)'$..

This study also uses the TWFE estimator to simultaneously adjust for unobserved unit-specific and time-specific **extraneous variable**. The typical specification of the TWFE estimator is of the form:

$$y_{it} = X_{it}\beta + c_i + f_t + u_{it}, \qquad t = 1,\ldots\ldots,T; i = 1,\ldots\ldots,N \tag{15}$$

Where X_{it} is a $1 \times K$ vector of variables *and* β is a $K \times 1$ vector of parameters. The *ci* are unit-specific effects (heterogeneity) and *ft* are the time-specific effects.

We define the unit-specific averages over time as

$$\bar{X}_{i.} = \frac{1}{T}\sum\nolimits_{t=1}^{T} X_{it} \tag{16}$$

And the cross-sectional average for each *t* as

$$\bar{X}_{.t} = \frac{1}{N}\sum\nolimits_{i=1}^{N} X_{it} \tag{17}$$

The overall average is given by

$$\bar{\boldsymbol{x}} = \frac{1}{NT}\sum\nolimits_{i=}^{N}\sum\nolimits_{t=}^{T} x_{it} = \frac{1}{N}\sum\nolimits_{i=1}^{N} \bar{\boldsymbol{x}}_{\boldsymbol{i}.} = \frac{1}{T}\sum\nolimits_{t=1}^{T} \bar{\boldsymbol{x}}_{\boldsymbol{i}.} \tag{18}$$

Letting:

$$\ddot{x}_{it} = x_{it} - \bar{x}_{i.} - \bar{x}_{.t} + \bar{\boldsymbol{x}}\,\boldsymbol{;}\;\; \ddot{y}_{it} = y_{it} - \bar{y}_{i.} - \bar{y}_{.t} + \bar{\boldsymbol{y}}\,\boldsymbol{,}$$

As shown in Baltagi (2001) $\hat{\beta}_{TWFE}$ is the pooled OLS estimator given by:

$$\hat{\beta}_{TWFE} = \left(\sum\nolimits_{i=0}^{n}\sum\nolimits_{i=0}^{n} \ddot{X}'\ddot{X}\right)^{-1} \sum\nolimits_{i=0}^{n}\sum\nolimits_{i=0}^{n} \ddot{X}'\ddot{Y} \tag{19}$$

RELTS AND DISCUSSION

This section presents the findings of the analysis conducted in five steps.

The Slope Heterogeneity (SH) Test

We test for SH using the Pesaran and Yamagata (2008) test. The results of the SH test shown in Table 1. As delta and adjusted delta statistics are both significant at the 1% level, we conclude that the model has SH issues. To address SH issue, this study employs the second-generation CS-ARDL approach.

The Pesaran (2004) CD test for cross-section dependence

Regarding **cross-section dependence**, all the p-values associated with the explanatory variables exhibit statistical significance at the 1% level, whereas the p-value associated with the independent variable attains statistical significance at the 15% level, suggesting the presence of CD. The results of the CD test are presented in Table 2.

The FGLS estimation technique is appropriate as it accounts for CD, heteroscedasticity, and first-order autocorrelation (Beck & Katz, 1995; Davidson & MacKinnon, 1993; G. Maddala & Lahiri, 2006). In this study, we use the two-way FE as well as the CS-ARDL approach, which accounts for C.S.D, S.H, endogeneity, and non-stationarity issues (Chudik & Pesaran, 2015). The FGLS is used only for robustness check.

Panel Unit Root Tests

This study employs the Levin et al. (2002), Breitung (2001), and Fisher-type (Choi, 2001) tests, which are tests of the first generation for calculating the panel unit-roots of the variables. As S.H and C.D are present, we also applied the Pesaran (2007) stationarity test, which produces reliable results even when S.H and C.D exhibit variation. Table 3 displays the results of unit

Table 1. Slope Heterogeneity Tests

Slope Heterogeneity Test	Statistics
$\tilde{\Delta}$	23.474***
$\tilde{\Delta}^{\text{Adjusted}}$	27.775***

Note: *** *indicates P<0.01.*

Table 2. The Pesaran (2004) CD test

Variable	CD-test statistics	p-values
CO_2	.1.44	0.151
EE	11.19	0.000
EG	15.21	0.000
INT	13.37	0.000
EF	13.34	0.000

**Note: Under the null hypothesis of cross-sectional independence, CD ~ N(0,1), p-values less than 0.1 indicate data are correlated across panel groups.*

Table 3. Panel Unit Root

	Levin, Lin &Chu		Breitung lambda		ADF-Fisher Chi-square		Pesaran Panel Unit Root (CIPS)	
	Level	**Frist diff**	**Level**	**Frist diff**	**Level**	**Frist diff**	**Level**	**Frist diff**
CO_2	-0.184	-7.739***	1.139	-11.12***	72.556	98.162**	-1.697	-4.312***
EE	3.738	-2.675***	4.088	-7.634***	41.872	123.044***	-1.731	-4.484***
EG	-2.036**	-3.151***	6.801	-7.578***	52.569	287.514***	-1.419	-3.848***
INT	-1.723**	-7.596***	0.987	-9.250***	46.464	137.065***	-1.483	-4.167***
EF	-5.181***	-8.714***	2.290	-9.351***	62.467	133.177***	-2.324**	-4.746***

*Note: *, **, and *** indicate P<0.10, P<0.05, and P<0.01 significance levels, respectively.*

Table 4. Pedroni and Westerlund tests for cointegration

Pedroni		Westerlund	
Statistic	Coefficients	Statistics	Z-value
MPPerron t	3.636***	Gt	-6.578***
PPerron t	-3.169***	Ga	6.727
ADF t	-3.386***	Pt	-1.304**
		Pa	3.725

*Note: *, **, and *** indicate P<0.10, P<0.05, and P<0.01 significance levels, respectively.*

Table 5. CS-ARDL's Estimates

	Long run Coefficients	**Short-Run Coefficients**	**Two-way FE**
EE	-0.139***	-0.705***	-1.433***
	(0.003)	(.107)	(0.080)
EG	0.135***	0.511***	0.892***
	(0.003)	(0.144)	(0.016)
INT	-0.096***	0.109***	-0.132***
	(0.002)	(0.050)	(0.033)
EF	-.0001***	-0.046	-0.044*
	(0.000001)	(0.033)	(0.024)
ECM	-	-1.248***	
		(0.032)	
Obs	-	-	735
Cty			35
R^2			0.84

*Significance level of 1%, 5% and 10% are represented by ***, ** and *.*

root tests for panel data. Results of the test indicate that all variables utilized in the study are stationary at first difference.

Test for Cointegration

The results of the first and second generation cointegration are shown in Table 4. The p-value of the Gt statistics is significant at the 1% level while that of the Pt statistics is significant at the 5% level. Therefore, there is evidence against the null hypothesis of no cointegration. The p-values of the Ga and Pa statistics are however insignificant. Thus, based on the Gt and Pt statistics, we conclude that there is a long run or equilibrium relationship All of the Pedroni test statistics are significant at the 1% level. The results demonstrate a long-term equilibrium relationship between the presented variables. Hence, it is inferred that all variables are cointegrated.

The CS-ARDL and Two-Way Fixed Effect Estimates

The CS-ARDL and two-way fixed effect estimates are shown in Table 5. The long-run estimates in column 1 of Table 5 reveal a significant and negative relationship between EE and CO_2E in OECD nations in both the short and the long-run periods. A 1% improvement in EE in OECD diminishes CO_2E by 0.705% and 0139% in the short-run and the long-run respectively, with both coefficients significant at the 1% level. When the two-way fixed effects estimation strategy is employed, the mitigating effect of EE on CO_2E is even bigger as a 1% improvement in EE corresponds to a 1.433% reduction in CO_2E. Thus, energy efficiency reduces CO_2E, demonstrating that improving EE is indispensable for CO_2E mitigation in OECD countries. Therefore, policymakers must incorporate energy efficiency into their respective CO_2E -reduction strategies. These findings support those of Mategaonkar and Eldho (2012), Go et al. (2020), Saidi and Omri (2020), Chen et al. (2021a), Danish, Ulucak, and Khan (2020), and Ouyang et al. (2021).

In both the long and short run, the coefficient of lnGDP is positive and significant at the 1% level. In the long run, for every 1% increase in growth, CO2E increases by 0.135%. In the short run, the coefficient of EG is also positive and significant, implying that EG increases CO2E in OECD countries regardless of time frame. This study supports the findings of Omri et al. (2014), Cheng et al. (2019), J. Liu et al. (2021), Salahuddin et al. (2018), Mehmood (2021), Zoundi (2017), M. I. Khan et al. (2020). H. Khan, Khan, et al. (2022) also found that an increase in EG in the OECD countries increases CO2E. According to Ma et al. (2013), Wu and Zhao (2018), and T. He et al. (2019), as the economy grows, consumers purchase environmentally hazardous luxury products, increasing CO2E. N. Li, Shi, Song, and Tao (2020) and J. Zhu et al. (2020), affimed that CO2E accounting for 80% of all GHGs, are the leading cause of global warming. However, our results contradict that of Shakouri and Khoshnevis Yazdi (2017).

The coefficient of international trade is positive and significant in the short run, but negative and significant in the long run, according to the estimates of the CS-ARDL. As countries open to international trade in the short term, they may not observe the stringent international trade rules, making them pollution havens as the production, use, and disposal of polluting commodities are accelerated, causing a significant increase in CO_2E. This conclusion sanctions the results of Al-mulali and Sheau-Ting (2014), Bashir, Sheng, Doğan, Sarwar, and Shahzad (2020), Al-mulali, Weng-Wai, Sheau-Ting, and Mohammed (2015), Barrows and Ollivier (2021), Hassan et al. (2022), and Sharma et al. (2023). In the Long-term, however, international trade could have either a positive or negative effect on CO_2E. The long run coefficient of international trade is negative and statistically significant at the 1% level, as shown in column 1 of Table 5. CO_2E in OECD declines by 0.096% for every 1% increase in international trade. This result supports the findings of Wang and Wang (2021), who established that trade reduces the negative ecological footprint, but contradicts the findings of Ertugrul et al. (2016), who found that trade significantly increases the negative ecological footprint.

The dissimilarities in the short and long-run impacts of trade on environmental sustainability in OECD countries, can be explained by dominant economic effects shifting over time (M. I. Khan et al., 2020). The positive short-run coefficient indicates that initial increases in trade worsen environmental degradation (Ertugrul et al., 2016). This is mainly due to the scale effect, where a rapid growth of economic activities and transportation dependent on fossil fuel increase emissions before economies can adjust (Sharma et al., 2023). On the contrary, the negative long-run coefficient exhibits a favorable relationship, where trade eventually enhances sustainability. This is caused by the technique effect, as trade facilitates the propagation of energy-efficient technologies and knowledge spillovers (Liobikienė & Butkus, 2019; Shi et al., 2023). Furthermore, long-term structural economic changes (*composition effect*) see OECD countries shifting toward less polluting service and high-tech sectors (Liobikienė & Butkus, 2019). Additionally, as incomes rise stricter environmental regulations and greater demand for cleaner production are imposed, transforming trade into a force for environmental improvement (J. Lin, Cao, Dong, & An, 2024).

EF reduces the negative ecological footprint by reducing CO2E both in the short run and over time. The coefficient of EF, as indicated by the long run estimate in column 1 of Table 5, is negative and statistically significant at the 1% level, indicating that as a country's EF rises by 1%, CO2E decreases by 0.0001% over the long term. This result is supported by the two-way FE estimate, which indicates that CO2E decreases by 0.044% for every 1% increase in EF over the long term. This finding is consistent with those of Ul-Haq, Visas, Umair, et al. (2023) for BRICS nations, Çınar et al. (2023) for the United States, and Tacchella et al. (2012) for countries with higher Green Complexity Index.

While both economic fitness and energy efficiency exhibit a statistically significant mitigating influence on carbon dioxide emissions within OECD countries, a comparative analysis exposes a palpable disparity in their relative impact. When evaluating the magnitude and overall contribution to the improvement of environmental sustainability, the empirical evidence shows that the role of energy efficiency is considerably more pronounced and important than that of economic fitness.

Table 6. The JKS (2021) Granger non-causality Test

H_o:	HPJ Wald test	P-value
Selected covariates do not Granger-cause CO_2E	135.3725	0.000
EE does not Granger-cause CO_2E	95.7113	0.000
EG does not Granger-cause CO_2E	377.753	0.000
INT does not Granger-cause CO_2E	14.8428	0.002
EF does not Granger-cause CO_2E	8.0832	0.044

Table 7. FGLS, DKSE and FE Estimates

	FGLS	DKSE	FE
EE	-0.955***	-.955***	-1.424***
	(0.049)	(0.011)	(0.046)
EG	0.862***	.863***	0.887***
	(0.015)	(0.012)	(0.016)
INT	-0.161*	-0.162***	0.134***
	(0.039)	(0.028)	(0.034)
EF	-.016*	-0.016*	-0.048**
	(0.009)	(0.009)	(0.023)
Cons	-8.817***	-8.818***	5.217***
	(0.533)	(0.407)	(0.461)
Obs	735	735	735
Cty	35	35	35
Wald chi2(4)	5835***	-	-
R^2	-	0.89	0.87

*Note: Significance level of 1%, 5% and 10% are represented by ***, ** and *.*

Juodis, Karavias and Sarafidis (JKS) 2021 Granger non-causality Test

To examine whether causality runs from the dependent to the dependent variable collectively and individually, the Juodis, Karavias, and Sarafidis (2021) Granger non-causality test was employed. The results are shown in Table 6 below. The p-values associated with the half-panel jackknife (HPJ) Wald statistic are significant at the 1% and 5% levels, thereby rejecting the null hypothesis of no Granger causality.

Robustness Checks

For Robustness checks, we employ the FGLS, DKSE and the FE estimation approaches. The results are presented in Table 7. The FGLS estimates presented in column 1 of Table 7 shows that energy efficiency, international trade and economic fitness significantly reduce CO_2E in OECD countries. These results ae supported by the DKSE and the FE estimates which in addition suggest that 89% and 87% of the total variation in CO_2E in these countries are explained by these variables.

Conclusion and Policy Implications

This study examines the role of EF, EE, EG, and INT in the reduction of CO_2E in OECD countries from 1990 to 2017. Analyzing the long run linear association between the predictor and outcome variables, this study employs CS-ARDL and the two-way fixed effect models. In order to conduct a robustness analysis of the CS-ARDL and two-way fixed effect estimates, various techniques including FGLS, DKSE, and FE were utilized. The results indicate that EF, energy efficiency, and international trade significantly reduce CO_2E, while economic growth significantly increases them. As E.E. reduces the consumption of fossil fuels, resulting in fewer emissions, it is crucial to the global determination to tackle climate change. Therefore, OECD nations should consider raising their EE. Economic growth increases carbon emissions, indicating that OECD countries may continue to rely on nonrenewable energy to promote their economies. Utilizing innovation energy will therefore improve energy efficiency and reduce costs, while accelerating economic activity and having no negative impact on environmental quality. Improving the economic fitness of OECD nations is also essential for these nations to abate their CO_2E levels.

The study used the Pesaran (2015) CD test and the Pesaran and Yamagata (2008) SH test. The study identified the issues of CD and slope heterogeneity. In order to evaluate the stationarity of the variables under consideration, the study utilized both first-generation tests and second-generation unit root test, which addresses concerns related to CD and slope heterogeneity. The Westerlund (2007) cointegration technique validated the long run association among the variables of interest. The Granger causality test, the Juodis et al. (2021) Granger non-causality test was employed, also confirmed the causality between the dependent and the dependent variable collectively and individually.

Our study has important policy implications because it helps shape initiatives to cut down on carbon dioxide emissions. The findings of this paper underscore the importance for policymakers to prioritize energy efficiency (EE) and economic fitness (EF), both of which have been shown to significantly slow environmental degradation. Therefore, OECD member countries should adopt carbon pricing mechanisms, notably carbon taxation and emissions trading systems, to promote energy efficiency. This is particularly critical for the building sector, which is responsible for approximately 40% of energy-related CO_2E. Sector-specific strategies include supporting deep energy renovations in buildings encompassing thermal insulation and system modernizations, which can produce energy savings exceeding 60%, and promoting industrial energy efficiency through the upgrading of electric motors and manufacturing process equipment. Effective implementation requires bulletproof multi-level governance coordination between national and local authorities. Additionally, a comprehensive policy framework should integrate strategic investment in green technologies, the integration of strict environmental standards into trade contracts, and support for sectors during transitional periods to mitigate short-term negative effects while accelerating the realization of long-term gains.

Future research should build upon these findings by exploring the moderation and mediation effects of energy efficiency on the relationship between EF and environmental sustainability. Additionally, further investigation must explore the possible nonlinear relationships of both EE and EF on environmental sustainability.

ETHICS APPROVAL

Not Applicable

CONSENT TO PUBLICATION

All authors have consented to publish.

CONSENT TO PARTICIPATE

Not Applicable.

GRANT SUPPORT DETAILS

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AVAILABILITY OF DATA AND MATERIAL

Data used in this study is available upon request.

CONFLICT OF INTEREST

The authors declare that there is not any conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

LIFE SCIENCE REPORTING

No life science threat was practiced in this research.

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