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DO ENVIRONMENTAL INNOVATIONS, TRADE, AND ECONOMIC GROWTH AFFECT THE ECOLOGICAL FOOTPRINT IN INDUSTRIALIZED COUNTRIES? PANEL AUGMENTED MEAN GROUP AND COMMON CORRELATED EFFECT ESTIMATIONS

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ABSTRACT

This study assessed the environmental technological innovation (ETI) of the 13 countries with the highest industrial added value (China, the United States, Japan, Germany, India, the United Kingdom, South Korea, France, Russia, Italy, Mexico, Brazil, Indonesia) over the period between 1992 and 2019. The objective is to evaluate the impact of carbon dioxide (CO_2) emissions, trade openness (TO), and economic growth (EG) on the ecological footprint (EFP). In this study, a panel data analysis was conducted utilizing the second-generation PANIC unit root test, the Westerlund cointegration test, the Dumitrescu-Hurlin causality test, and the common correlated effect mean group (CCEMG) and augmented mean group (AMG) estimator methods. The results of the analysis demonstrate that, according to the CCEMG, ETI exerts a mitigating influence on EFP in Indonesia. In numerous countries, CO_2 has been observed to increase EFP, whereas in a select few countries, EG has been found to have a similar effect. Conversely, in China and South Korea, TO has been identified as a factor contributing to an increase in EFP, while in the United States, it has been identified as a factor that contributes to a decrease in EFP. The AMG indicates that ETI results in a decrease in EFP in Brazil and Indonesia, while simultaneously producing an increase in Mexico. While CO_2 is observed to increase EFP in numerous countries, EG is seen to increase EFP in many countries, although this is only the case in India. TO is found to decrease EFP in China, India, South Korea, and Brazil, while simultaneously increasing it in Germany. The empirical evidence suggests that policies aimed at limiting uncontrolled economic growth, prioritising

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environmentally friendly technological innovations, improving international trade processes and policies with the objective of reducing emissions, and developing environmentally friendly processes and products in production are likely to be effective.

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1. INTRODUCTION

Increasing social welfare is undoubtedly one of the main objectives of national economies. Improvements in social welfare are possible with sustainable economic growth (EG). EG, which can be defined as an increase in output, represents a fundamental transformation in social life. EG is a driving force behind societal change, facilitating the transition from an agricultural to an industrial society, industrialization, population growth, urbanization and increased consumption. While EG offers numerous benefits to society, the expansion of production scale has a detrimental impact on the ecosystem, leading to a decline in natural capital (Islam, 2021). The acceleration of economic activities and growth has resulted in increased output across a range of sectors, including agriculture, industry, and mining. While technological advancement has been a key driver of this expansion, it is not a standalone factor. The utilization of existing resources more than their current levels is also a necessary condition for continued output growth. In this context, previous periods of EG neglected sustainable growth processes, and economic progress and welfare improvements through growth-oriented policies also cause environmental problems (Destek and Manga, 2020, 21991).

Rapid expansion and development of economic practices increase the strain on natural resources and accelerated waste generation (Sarkodie, 2021). As economic activities expand, the environment is exposed to an increasing number of hazardous residues resulting from human actions. While the environment has the capacity to resist pollution, exceeding the the pollution load has a detrimental impact on environmental quality (Islam, 2021). Climate change, global warming and carbon dioxide (CO_2) emissions result from advances in agriculture, industry and mining and the increased use of natural resources.

In the context of the environmental impacts of EG, the factor of trade openness (TO), which is a principal determinant of growth, is a key area of focus. The role of TO in accelerating industrialization is of particular significance. The substantial expansion in international TO, when assessed in terms of imports and exports, has led to a notable shift in the global trade balance, increasing from 10% in the 19th century to 50% in the present era. The TO of countries plays a supportive role in terms of economic progress and development, particularly by facilitating mutual trade. The improvement in living standards, especially in developing countries, contributes to the perception that trade is a significant factor in enhancing economic power (Appiah et al., 2022). On the other hand, the liberalization of international trade and the adoption of an open economy model facilitate acceleration of industrial production. This increased production, however, also leads to adverse environmental consequences, including air pollution and the greenhouse gas effect (Islam and Rahaman, 2023).

The accelerated environmental degradation resulting from human activities has caused a significant deterioration of the ecosystem, adversely affecting both the natural world and humanity (Chu, 2022a, 23779; Chu, 2022b). The deterioration of the natural environment has a detrimental impact on human well-being and the functioning of ecosystems. A degraded environment endangers the physical and mental health of individuals, predisposing them to a range of health issues. Disease proliferation impairs production efficiency, leading to lower economic prosperity. Furthermore, environmental degradation contributes to extinction of animal species (Islam, 2022; Islam, 2021). Destruction of the environment increases both climate change and global warming. The rising sea and ocean levels due to global warming, the extinction of some living species, and the melting of ice in polar regions are examples of negative environmental impacts (Ali et al., 2016). In this context, Berstein et al. (2007) predict a sea level rise of 18-59 cm and a global average temperature increase of 1.1-6.4°C by 2100.

The global impact of climate change and environmental pollution is becoming increasingly evident. Given that human and economic activities have contributed to global warming for approximately 200 years, reducing environmental pollution has become a key objective of the Sustainable Development Goals (SDGs) (Islam, 2024). Growing environmental problems threaten both developed and developing countries. To address this threat, several international meetings have been held. These include the Kyoto Conference (1997) and the Paris Conference (2015). The main themes of these meetings are the transition from the consumption of non-renewable energy to renewable energy and increasing the use of renewable energy, controlling CO_2 emissions, protecting natural water resources and forest areas, and implementing green and technological innovations to protect the environment (Görmüş and Aydın, 2020, 279-90; Twum et al., 2020, 20-21; Danish, Ulucak and Khan, 2020, 1; Rees, 1992) The desire for rapid EG leads to the overuse and misuse of natural resources, reducing the biological capacity of the environment and increasing the ecological footprint (EFP).

Ecological footprint (EFP) in its shortest definition expresses human pressure on the environment (Baabou et al., 2017, 94). One indicator of environmental sustainability is EFP. It expresses the need for natural capital for the productive environment, which is defined as carrying capacity. On the other hand, the EFP measures biocapacity related to carrying out economic activities according to the SDGs. In this context, the EFP does not ignore other human activities detrimental to ecological sustainability, unlike emissions, which can limit the focus on ecological sustainability among major industrial activities (Destek and Sinha, 2020). The EFP measures environmental problems and damage in this respect. It is possible to find an unlimited number of studies that measure the negative impact of human and economic activities on the environment through CO_2 emissions. The CO_2 emissions, however, measure only a certain part of environmental damage (Öcal et al., 2020, 668).

Only a limited number of studies measure environmental damage using the EFP as a key indicator. Hence, a more realistic and comprehensive perspective is to use the EFP as a measure of environmental damage instead of CO_2 emissions. This is because the EFP fully captures environmental dynamics such as rangelands, fisheries, plantations, settlements, and CO_2 emissions (Sarkodie, 2021). The world's growing population and accelerating urbanization are putting pressure on the EFP. The United Nations estimates that by 2030, the world's population will be around 8.5 billion, and by 2050, the urban population is expected to reach 68%. The total world population will be 10.4 billion in 2100. The concentration of population in cities and the expectation that this concentration will increase over the years will also affect the environment.

Because of the climate change emerging after industrialisation gave rise to significant challenges and an ever-increasing necessity for energy, all countries are contemplating implementing measures designed to reduce greenhouse gas emissions (Jiang et al, 2022). To achieves sustainable growth and development, both developed and developing countries have reached consensus on the necessity of mitigating the negative environmental impacts of economic activities. Furthermore, there is agreement on the importance of a green transition and the adoption of innovative technologies. It is essential to protect the environment from the harmful effects of conventional production methods by prioritizing technological advances for environmental sustainability (Twum et al., 2021, 17119). Besides technological innovations, the impact of environmental protection policies on the environment is undeniable. As a result, Porter and Claas (1995) state that environmental regulations play an important role in creating environmentally friendly (green innovation) technological innovations. R&D studies and innovative approaches, especially in the energy field, effectively reduce environmental negativities and increase environmental quality (Sinha and Sengupta, 2020).

Technology innovations enable reduced emissions per unit of output produced, reduced environmental pollution costs, and introduce new environmentally friendly and environmentally protective products to the market (Carraro, 2000, 271). On the other hand, technology innovations are the active factor in converting energy consumption, one of the important determinants of EF, from fossil sources to renewable energy sources. Technology innovations save energy and reduce emissions per unit by increasing energy efficiency. Again, while innovations enable cost reduction, they also facilitate the introduction of environmentally friendly green products to the market. When evaluated in terms of renewable energy production, technology innovations are again a factor in developing renewable energy processes (Lin and Zhu, 2015: 1505, Carraro, 2000, 270). Ultimately, improving environmental quality allows individuals to live in better conditions and improve their living standards (Chien et al., 2022:2). Environmental innovations are acknowledged as technological advancements that enhance environmental quality by reducing energy consumption and detrimental emissions. Consequently, environmental innovation is regarded by economists and policymakers as a potent instrument for curbing environmental contamination. Given the efficacy of environmental innovations in addressing environmental concerns, many countries are pursuing environmental innovation and environmentally friendly technologies (Islam et al., 2024).

This study examines the relationship between ecological footprint (EFP) and environmental technological innovation (ETI). The other independent variables in the study are Gross Domestic Product (GDP), CO_2, and trade. The study differs from previous studies in a number of ways. Studies investigating the role of ETI on EFP are limited, and further research is required in this area. Previous literature frequently utilises CO_2 emissions as a metric for environmental degradation; however, EFP can be regarded as a more comprehensive measure. Additionally, no studies have been conducted on the group of countries with the highest industrial value added. This study addresses an existing research gap in the relevant country group by measuring the impact of ETI on EFP with the help of other control variables in 13 countries with the highest industrial added value. Finally, EFP as a variable in assessimg environmental degradation represents a novel approach that provides a comprehensive evaluation of the ecological impacts of pollution in countries with the highest industrial added value. The following sections of the study include a literature review, a description of the methodology and data set, the compilation and interpretation of results, and a conclusion and discussion section, which provides an overall assessment and policy recommendations.

2. LITERATURE REVIEW

In the post-World War II era, a widespread belief in the positive impact of EG and development on societal well-being drove the expansion of economic activity. However, in recent decades, the global drive for EG has accelerated environmental damage. Rapid and uncontrolled EG threatens sustainability by causing climate change and global warming (Öcal et al., 2020, 668). This has led scientists to question and study EG environmental impact. The literature includes various theoretical and empirical studies on ETI, EG and TO. Theoretical studies in the literature are based on a number of hypotheses. The relationship between environmental degradation and economic activities is associated with the hypothesis initially proposed by Kuznets (1955), which postulates an inverted U-shaped relationship between EG and income inequality. Indeed, Grossman and Krueger (1991) renamed the hypothesis as the Environmental Kuznets Curve Hypothesis (EKC) and interpreted the relationship between EG and the environment. The hypothesis postulates that environmental degradation occurs in the initial phase of the EG process, but that improvements in the economy limit environmental degradation by improving environmental quality (Islam, 2022). Similarly, the effect of TO on environmental degradation is also included in the theoretical literature. In particular, the pollution haven hypothesis (Antweiler et al., 2001) posits that as underdeveloped and developing countries engage in international commercial activities, their environmental quality will decline. Specifically, trade liberalization will prompt multinational companies to relocate pollution-intensive industrial production to underdeveloped and developing countries where costs and environmental controls are less stringent. Over time, these countries will become havens for pollution-intensive industries. The factor endowment hypothesis (FEH) considers the impact of endowments and technology on trade, rather than focusing on the role of policies. While a capital-rich country may increase pollution within its own borders through capital-intensive production, a capital-deprived country will experience a decrease in pollution due to the inability to support capital-intensive production. Therefore, the effects of trade on the environment, both nationally and globally, are contingent upon the distribution of comparative advantages among countries (Temurshoev, 2006).

It is imperative to leverage technological progress to sustain EG while concurrently minimizing environmental degradation. Technological progress depends on generating technological innovations (TI) through research and development (R&D) activities. These innovations give rise to new industries, products, and production processes, which in turn enhance existing industrial capabilities. From an economic perspective, the advancement of productivity and the development of new products and production processes not only facilitate accelerated growth but also present opportunities for creating employment and improving living standards. Endogenous growth theories posit that technological advancements facilitate sustainable EG and development by enhancing productivity (Romer, 1990). The expectation that technological advances will be used to protect the environment is based on the premise that these developments will benefit society in other ways. This issue, which was previously the focus of scientists and policymakers in developed economies, has also been brought to the attention of developing countries over time.

Various empirical studies in the literature cover the environmental effects of technological innovations. Studies evaluate factors impacting the EFP, which expresses environmental damage more comprehensively, EG process, natural resources, globalization, human capital, urbanization, and so forth. Socio-economic factors are associated with the environment and the environmental effects of these factors are analyzed. Some studies analyzie the impact of ecological activities on the environment through the environmental Kuznets curve (EKC). For example, Destek et al. (2018) suggest that the environmental Kuznets curve, which explains the relationship between real income and EFP, takes a U shape. The study concluded that non-renewable energy consumption harms the environment, while renewable energy and TO reduce environmental damage.

In their 2015 study, Al-Mulali et al. examined the environmental Kuznets curve (EKC) hypothesis across a range of income levels, including 16 low-income, 26 lower middle-income, 26 upper middle-income, and 31 high-income countries. They employed EFP as a proxy for environmental degradation. In the study, the relationship between EFP and GDP takes an inverted U shape in countries with high, middle, and high-income groups. In addition, energy consumption, urbanization and TO are among the factors that increase the EFP for all country groups. Destek and Sarkodie (2019) investigated the validity of the environmental Kuznets curve hypothesis by examining the relationship between EG, energy consumption, financial development and EFP in 11 newly industrialized countries for the period 1977-2013. In order to achieve this, both the augmented mean group (AMG) estimator and the heterogeneous panel causality method were employed in the study.

The results of the estimator demonstrate that there is an inverted U-shaped relationship between EG and EFP. The causality test results indicate that there is bidirectional causality between EG and EFP. Ali et al. (2016) examined the relationship between CO_2 emissions and the determinants of EG, energy consumption, financial development and TI in Malaysia between 1985 and 2012. The findings of the study, which employed the lag distributed autoregressive (ARDL) model, indicate that there is a negative but statistically insignificant correlation between TI and environmental pollution in Malaysia. Furthermore, the findings indicate that elevated EG enhances environmental quality over the long term, aligning with the Environmental Kuznets Curve (EKC) hypothesis. Similarly, the results indicate that financial sector development will result in reducing CO_2 emissions, thereby improving environmental quality in Malaysia. The Granger causality approach employed in the study identifies bidirectional causality between EG and CO_2 emissions, as well as between TI and CO_2 emissions in the long run. Furthermore, the results demonstrate existence of bidirectional causality between energy consumption and EG, as well as between EG and TI in the short run.

Islam (2024) analyzed the impact of environmental innovations on environmental quality in Saudi Arabia for the period between 1990 and 2020 using the NARDL method. The findings indicate that the positive aspects of environmental technologies exert a relatively limited influence on environmental pollution, largely due to the relatively modest share of environmental technology patents within the total technology landscape in Saudi Arabia. Conversely, the negative aspects of environmental technologies are responsible for an increase in pollutant emissions, both in the long and short term, due to the low level of environmental technology. It is important to note, however, that EG, energy consumption and trade volume also contribute to an increase in pollutant emissions.

In another study for Saudi Arabia, Islam, Rehman, and Khan (2024) examined the impact of environmental technology on CO_2 emissions by examining the influence of information and communication technologies, energy use, energy intensity, and financial development over the period between 1990 and 2020. The NARDL method was employed in the study, and the findings indicated that the deficiency of environmental technologies in Saudi Arabia fosters environmental contamination. It was demonstrated that ICT stimulates environmental contamination due to its limited scope in comparison to the technological foundation of the Kingdom. Information and communication technologies enhance environmental quality, whereas energy consumption impairs environmental quality. The NARDL test also suggests that energy intensity and financial development have deleterious effects on emissions.

Ersin et al. (2024) conducted an analysis of the long- and short-run relationships between EFP, environmental technology patents, high technology exports and EG in four major high technology exporters (the USA, Germany, France and China) over the period between 1988 and 2019. The results obtained from the study, which employed the Fourier ARDL method, underscore the significance of environmental technology innovations in mitigating the EFP and environmental impacts in the USA, Germany, and France. The expansion of high-tech exports in international trade has the potential to exacerbate the EFPs in these countries, particularly when considered alongside the adverse effects of EG in all countries, including China. Jiang et al. (2022) employed the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) framework to analyze the impact of environmental technologies, coal consumption, EG and population density on consumption-based CO_2 in BRICS (Brazil, Russia, India, China and South Africa) countries for the period between 1985 and 2018. The long-term empirical findings indicate that environmental technologies exert a negative influence on consumption-based CO_2 emissions, whereas GDP per capita and coal consumption exert a positive influence. The empirical evidence suggests that environmental technologies are of significant importance for the BRICS countries. Furthermore, the findings suggest that energy intensity and financial development have a detrimental effect on emissions.

Another study, Islam et al. (2024a) analyzed the relationship between remittances and environmental quality in Saudi Arabia for the period between 1990 and 2020. This analysis employed the use of information and communication technologies, environmental innovation, and energy consumption control variables. The study employed nonlinear autoregressive distributed lag (NARDL) and autoregressive distributed lag (ARDL) methods, which yielded evidence of a long-run relationship between the variables. In this context, the overall effect of remittance flows on CO_2 emissions is negative. Furthermore, the effect of negative shocks significant, while the effect of positive shocks is insignificant. The introduction of positive shocks in information and communication technologies has been found to significantly reduce environmental pollution. Pollution levels tend to decline in line with increased investment in environmental technologies, but conversely, they tend to rise in line with decreased investment. Given that the majority of energy consumed in the Kingdom is derived from non-renewable sources, it can be argued that energy use is a significant contributor to environmental degradation. Ozkan et al. (2023) employed the dynamic ARDL method to analyze the interrelationship between green technology innovation and EFP in Turkey over the period between 1990 and 2018. The results of the dynamic ARDL test indicate that green TI exert a mitigating influence on the EFP, both in the long and short term. In the short term, positive shocks in TO have a detrimental impact on environmental quality, whereas negative shocks have a beneficial effect. In the long run, the opposite is true.

Alola et al. (2019) analyzed the driving forces for achieving the SDGs on reducing environmental pollution in EU member states, and examined the relationship between EFP, real gross domestic product, TO, fertility rate, and renewable and non-renewable energy consumption in 16 EU countries between 1997 and 2014. The application of PMG-ARDL analysis revealed that non-renewable energy consumption has a detrimental impact on environmental quality, whereas renewable energy utilization has beneficial effect on environmental sustainability. Additionally, the observed long-run fertility-EFP link is associated with disparate fertility rate data across EU Member States.

Studies in the literature have examined the relationship between technological innovations and the environment in the context of CO_2 emissions. For example, Ahmad et al. (2020) researched the interconnections between natural resources, TI, EG and the resulting EFP in emerging economies. In the study, the second generation panel cointegration test was employed using data from 1984 to 2016. The cointegration results substantiate the existence of a stable and long-run relationship between the EFP, natural resources, TI and EG. In the long term, the expansion of natural resources and EG contribute to increased EFP, whereas TI facilitate the reduction of environmental degradation. Findings from the CS-ARDL are corroborated by the Augmented Mean Group (AMG) method. Furthermore, the Dumitrescu-Hurlin Granger causality test indicates that natural resources, TI and EG-oriented policies exert a significant influence on the EFP, and vice versa.

Ahmad et al. (2023) applied the autoregressive distributed lag method (ARDL) to examine the influence of technological advancement on China's sustainable development from 1982 to 2018. Their objective was twofold: to ascertain the extent to which TI contributes to sustainable development and to identify how this occurs. The findings indicate that TI is a key driver of sustainable development, while also supporting EG without causing environmental degradation. The results also demonstrate that financial development plays a pivotal role in China's sustainable development, particularly through the reduction of CO_2 emissions. Furthermore, EG accelerates the sustainability process by further reducing CO_2 emissions. Chu (2022a) studied how environmental technologies influenced EFP of 20 OECD countries between 1990 and 2015. The findings substantiate the existence of a long-term relationship between EFP and several key variables, including green technologies, renewable energy, international trade, energy intensity, and real income.

Chien et al. (2021) examined the impact of CO_2 emissions and PM2.5 on the largest Asian economies between 1990 and 2017. They investigate the influence of various energy sources, environmental taxation, and ecological innovation on these emissions. This study considers a number of analytical techniques, including cross-sectional dependence analysis, unit root tests with and without structural breaks, slope heterogeneity analysis, Westerlund and Edgerton panel cointegration analysis, Banerjee and Carrion-i-Silvestre cointegration analysis, long- and short-run CS-ARDL results, and AMG and CCEMG, to ensure robustness of the findings. The empirical evidence from both the short and long run confirmed the negative and significant impact of renewable energy, ecological innovation and environmental taxes on CO_2 emissions and PM2.5. The analysis revealed that non-renewable energy sources cause environmental degradation in the Asian economies included in the study. Destek and Manga (2021), evaluated the relationship between technologic innovations and EF, considering CO_2 emissions in BEM (Argentina, Brazil, China, India, Indonesia, Mexico, Poland, S. Africa, S. Korea and Turkey) countries for the period between 1995-2016. The results show that increasing the use of renewable energy results in a reduction of CO_2 emissions and EFP but increasing non-renewable energy use results in expansion of CO_2 emissions and EFP. On the other hand, technology innovations reduce CO2 emissions in these countries but do not impact their EFP. In addition to all these, it is claimed that financialization negatively affects both CO_2 emissions and EFP in the case of large developing economies. Koseoglu et al. (2022) examinesd the relationship between green innovation and EFP in the top 20 green innovator countries. In order to test for horizontal cross-section dependence, panel unit roots and panel cointegration, the study employs tests covering the period from 1993 to 2016. The results indicate that EG is the primary driver of environmental degradation. Renewable energy consumption exerts a moderate influence on the EFP, while environmental technologies have a statistically significant impact.

The findings suggest that environmental protection and EG can coexist. However, the analysis revealed a concerning trend of degradation in the Asian economies included in the study. The literature shows a consensus that technological and environmental innovations generally reduce CO_2 emissions and environmental pollution, but some other studies suggest that innovations increase CO_2 emissions. The starting point of the argument is that decrease in energy prices resulting from innovations reduces energy costs and triggers CO_2 emissions by increasing energy consumption in the production process due to the cost advantage. The results of studies generally suggest that R&D expenditures, which form the basis of innovation in developing countries, increase CO_2 emissions contrary to expectations, while they often reduce CO_2 emissions in developed economies (Fernandez et al. 2018, Dauda et al., 2019). Another article with similar results argues that technological innovations increase environmental damage. In this context, Aydın et al. (2023) analyzed the impact of environmental innovation on the EF of 26 European countries using the PSTR model. The results indicate that below a certain threshold, environmental pressure on per capita EF increases with environmental innovations; however, after the threshold is exceeded, the pressure decreases. The study also suggests that environmental innovations alone are insufficient to reduce the pressure on the Earth's ecosystem. Additional resources are required to achieve this goal.

3. RESEARCH DESIGN AND METHODOLOGY

3.1 EMPIRICAL MODEL

In line with the above explanations, we aim at examining the effects of some variables on the EF in industrialized countries. In this context, the top 14 countries in terms of industrial added value were selected. The study covers the period from 1992 to 2017. Canada, however, was not included in the analysis due to a lack of data. Therefore, the 13 countries included in the analysis are China, the USA, Japan, Germany, India, the UK, Korea, France, Russia, Italy, Mexico, Brazil, and Indonesia. The model examined is defined as follows:

$$\text{Ecofoot} = f\,(\text{Envtech}, \text{Log}CO_2, \text{Trade}, \text{LogGDP})$$

Table 1 defines variables, data sources, and some descriptive statistics. Accordingly, each variable has 364 observations, and this is balanced panel data. In addition, the moderate instability in the variables is due to the low standard deviation value.

Finally, the expectations about the sign of the variables should be mentioned. The Envtech variable represents the eco-friendly technologies and environmentally related technologies data were used to represent technological innovations. The variable in question reveals the environmental effects of technological progress. An increase in this variable is anticipated to decrease in EF, meaning it is expected to have a negative sign, since an increase in CO_2 emissions leads to an increase in EF due to positive sign expectation between CO_2 emissions and EF. The sign of the Trade variable may be positive or negative based on the overriding effect on EF. Trade relations between countries are closely related to logistics activities, and these activities increase pollution. If this effect is high, the sign of this variable is expected to be positive. However, given the increased specialization and efficient production as a result of trade, the sign of this variable is expected to be negative. Finally, the Loggdp variable is expected to have an increasing effect on the EF. Therefore, the sign of this variable is expected to be positive.

TABLE 1
Variables, Definitions, and Descriptive Statistics

Variables	Description	Data source	Number of obs.	Mean	Std. Dev.
Ecofootprint	EFP (per capita hga)	GFN*	364	4.4172	2.2558
Envtech	ETI	OECD	364	6.5442	9.0840
Logco$_2$	Logarithm of CO_2 (kiloton)	World Bank	364	5.9190	0.4262
Trade	Share of trade in GDP (%) (TO)	World Bank	364	47.6880	18.5365
Loggdp	Logarithm of GDP per capita (EG)	World Bank	364	12.2972	0.3883

Note: * Global Footprint Network

3.2 ECONOMETRIC METHODOLOGY

Based on the model described, we first examined the cross-sectional dependence (CSD) of the series and based on the results from this examination, we applied the Panic unit root test as a second-generation unit root test. After detecting that all variables become stationary at the first difference, we applied Westerlund (2007) cointegration tests. Based on the presence of cointegration, we finally estimated the long-run coefficient with AMG and CCEMG methods. The methodological explanation is given in this section of the study.

3.2.1 PANEL UNIT ROOT TESTS

Bai and Ng (2004, 2010) put forth a series of tests based on examination of stationarity in the residue and the factors on an individual basis. This test is referenced in the academic literature as the Panel Analysis of Nonstationarity, Idiosyncratic and Common Components (PANIC). The PANIC test is one of the second-generation tests. PANIC test, is as follows:

(1) $X_{i,t} = D_{it} + \lambda_i' F_t + e_{i,t}$

Where D_{it} polynomial trend function, F_t is an rx1 dimensional vector of common factors, λ_i is a vector of factor loadings. The series $X_{i,t}$ is the sum of deterministic component D_{it}, a common component $\lambda_i' F_t$, and an error $e_{i,t}$ that is largely idiosyncratic. At the same time;

(2) $e_{i,t} = p_i \, e_{it-1} + e_{i,t}$ i=1……..,N

However, the deterministic components are represented by the following equation, $D_{it} = \sum_{j=0}^{p} \delta_{ij} t^j$ when p=0, $D_{it} = \delta_i$ the outcome has been determined. If p=1 in equation (1) above, there is an individual time trend. If P=-1, there is no deterministic term $(D_{it} = 0)$ In this case, the first difference model.

(3) $y_{it} = \lambda_i' F_t + z_{it}$

In equation (3), the abbreviations are $y_{it} = \Delta y_{it}$, $F_t = \Delta f_t$ and z_{it} =Δe_{it}. In the event that P = 1, the mean of the first difference data set is to be eliminated. In the final instance a definitive outcome will be reached.

$$y_{it} = \Delta Y_{it} - \Delta \overline{Y}_i, \;\; F_t = \Delta F_t - \Delta \overline{F} \text{ and } z_{it} = \Delta e_{it} - \Delta \bar{e}_i$$

When the PC method is applied to first differenced data y_{it}), factors $(\hat{f}_t)$, and factor loadings $(\hat{\lambda}_i)$, $\hat{z}_{it}$ $(= \hat{y}_{it} - \hat{\lambda}_i' f_t)$ are obtained. In the PANIC test, the stationarity of the residue is evaluated subsequent to the assessment of the stationarity of the common factors. Two stages are employed to ascertain the stability of the residue. Initially, the hypothesis that $\hat{e}_{it}$ is individually stationary is evaluated through ADF regression. Subsequently, the stationarity of the entire panel is assessed by aggregating the p-values of the individual tests (Tatoğlu, 2017).

3.2.2 PANEL COINTEGRATION ANALYSIS

The subsequent stage is to undertake a review of the cointegration relationship among the series. The long-term relationship between the series is investigated by using cointegration tests. Cointegration tests are classified into two categories: the first and second generation tests. The former are employed in scenarios where there is no cross-sectional dependence, whereas the latter are utilized where cross-sectional dependence exists. This test is designed to accommodate cross-sectional dependency and slope heterogeneity among the panel units (Islam, 2022). This study employed the panel cointegration test proposed by Westerlund (2007), which accounts for cross-sectional dependence between units.

$$\Delta Y_{it} = \delta_i' d_t + \alpha_i(Y_{it-1} - \beta_i' X_{it-1}) + \sum_{j=1}^{p_i} \alpha_{ij}\, \Delta Y_{it-j} + \sum_{j=-qi}^{p_i} y_{ij}\, \Delta X_{it-j} + e_{it} \tag{4}$$

t=1…… T is the time dimension; I = 1…….N is the unit dimension and d_t is the deterministic components. d_t=0 means the situation without deterministic term (without constant and trend); d_t=1 is the situation with constant; and finally, d_t = (1,t) is the situation with constant and trend. Upon readjustment of the error correction model, the following equation can be formulated:

$$\Delta Y_{it} = \delta_i' d_t + \alpha_i Y_{it-1} + \lambda_i' X_{it-1} + \sum_{j=1}^{p_i} \alpha_{ij}\, \Delta Y_{it-j} + \sum_{j=-qi}^{p_i} y_{ij}\, \Delta X_{it-j} + e_{it} \tag{5}$$

Here is the equation of λ_i'=$-\alpha_i\beta_i'$. α_i The term 'parameter' is used to describe the speed of return to equilibrium following a sudden shock. The possibility of an error correction is also under discussion. if α_i < 0; this position means a cointegration relation between y_{it} and x_{it}. There is no correction if α_i =0; namely, there is no cointegration relation. The null hypothesis (H_0: $\alpha_i = 0$) in the Westerlund cointegration relation indicates that no cointegration relation exists for all i. However, this depends on the assumption regarding the homogeneity of the alternative hypothesis, α_i. The initial two cointegration tests are designated as the ensemble average test. This test evaluates the H_0 hypothesis for a minimum of one i value in opposition to H_i^g: $\alpha_i < 0$, obviating the necessity for an equation of α_i. Two further tests, known as panel tests, assume that the α_i values are equal for all i. Once again, the H_0 hypothesis is tested for all i values against H_i^g: $\alpha_i = \alpha < 0$ as outlined by Persyn and Westerlund (2008:233). Westerlund cointegration tests comprise two groups of statistics: ensemble average variance and panel variance statistics. The following equation can be written for each unit with reference to the group mean statistics of the variance least squares method.

(6) $$\Delta y_{it} = \hat{\delta}'_i d_t + \hat{\alpha}_i y_{it-1} + \hat{\lambda}'_i x_{it-1} + \sum_{j=1}^{pi} \hat{\alpha}_{ij} \Delta y_{it-j} + \sum_{j=0}^{pi} \hat{\gamma}_{ij} \Delta x_{it-j} + \hat{e}_{it}$$

Subsequently, the ensemble average variance statistics (Gt and Ga) are calculated.

(7) $$G_t = \frac{1}{N}\sum_{i=1}^{N} \frac{\hat{\alpha}_i}{SE(\hat{\alpha}_i)} \; and \; G_a = \frac{1}{N}\sum_{i=1}^{N} \frac{T\hat{\alpha}_i}{\hat{\alpha}_i(1)}$$

In the second phase, the common error correction parameter (α) and its standard error are estimated using the following formula: $\Delta \tilde{y}_{it}$ and $\tilde{y}_{it-1}$.

(8) $$\hat{\alpha} = \left(\sum_{i=1}^{N}\sum_{t=2}^{T} \tilde{y}_{it-1}^2\right)^{-1} \sum_{i=1}^{N}\sum_{t=2}^{T} \frac{1}{\hat{\alpha}_{(1)}} \tilde{y}_{it-1} \Delta \tilde{y}_{it}$$

In the final stage, the Pa and Pt statistics are calculated in accordance with the following procedure.

(9) $$P_t = \frac{\hat{\alpha}}{SE(\hat{\alpha})} \; and \; P_a = T\hat{\alpha}$$

The rejection of the null hypothesis for both group tests indicates the absence of a cointegration relationship across the entire panel (Tatoğlu, 2017: 202).

3.2.3 COMMON CORRELATED EFFECT MEAN GROUP (CCEMG) AND AUGMENTED MEAN GROUP (AMG) ESTIMATORS

Once the co-integration has been established in the panel data, the final step is estimation of the long-run coefficients. At this juncture, the CCEMG estimator, as developed by Pesaran (2006), and the AMG estimator, as introduced by Eberhardt and Bond (2009), are employed.

The Common Correlated Effect mean group (CCEMG) method, developed by Pesaran (2006), is employed in the case of CSD in the model's residuals. The model used by Pesaran (2006), i=1,2,…,N and t=1,2,…,T where i refers to cross-section units and t to time.

$$(10) \qquad y_{it} = \alpha'_i d_t + \beta'_i x_{it} + e_{it}$$

In this context, d_t represents the observed common effect vector, which has an nx1 dimension. Similarly, x_{it} denotes the explanatory variables vector, which has a kx1 dimension. It is notable that the error vector exhibits a multifactor property.

$$(11) \qquad e_{it} = \gamma'_i f_t + \varepsilon_{it}$$

In Equation (11), f_t represents an unobserved common factor vector with a m x 1 dimension, while ε_{it} denotes error terms specific to cross-section units. The coefficient of the long-run relationship is estimated as follows (Pesaran, 2006):

$$(12) \qquad \hat{\beta}_{MG} = N^{-1} \sum_{i=1}^{N} \hat{\beta}_i$$

In Equation (12), $\hat{\beta}_i$ represents the estimation for cross-section i. The long-run coefficient for the overall panel is obtained by averaging the coefficients of the cross-section units.

The AMG employs an estimation method incorporating the CSD through a 'common dynamic effect' within the regression for each country. Furthermore, it is assumed that the observable inputs x_{it} and output y_{it}, as well as the unobserved common factors f_t and g_t, are a priori non-stationary (Eberhardt and Bond, 2009, 2). To enhance precision of this methodology, two key steps are undertaken (Eberhardt and Bond, 2009: 3). The initial step involves a standard FD-OLS regression with T-1 year dummies in first differences. The authors then collected the year dummy coefficients and relabelled them as $\hat{\mu}_t$. Second, this variable was incorporated into each of the N standard country regressions with linear trend terms representing omitted idiosyncratic processes (Eberhardt and Bond, 2009: 3). As a result, the AMG estimator offers a number of significant advantages. Primarily, it permits the utilization of variables exhibiting disparate stationary levels, while also accommodating CSD and parameter heterogeneity (Eberhardt and Teal, 2010: 4).

3.2.4 PANEL CAUSALITY ANALYSIS

The final step is to test the causal relationship between the variables. While potential exists for a unidirectional causal relationship between economic variables, it is also possible to observe a mutual causality relationship between the variables. In some cases, there may be no discernible causal relationship. The Dumitrescu and Hurlin test, which is one of the causality tests used in models where all parameters are heterogeneous, was employed in the model. Dumitrescu and Hurlin extended the Granger causality test for heterogeneous panels (Tatoğlu, 2017:154). For stationary x and y values, the linear model for each unit in the case of i=1…..N and t = 1…….T is as follows (Dumitrescu and Hurlin, 2012:1451);

(13)

$$Y_{it} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} Y_{it-k} + \sum_{k=1}^{K} \beta_i^{(k)} X_{it-k} + \varepsilon_{i,t}$$

The aforementioned equation is employed to ascertain whether the x variable is the causal factor behind the y variable. The fundamental premise is that if the preceding values of x are a significant predictor of the current value of y, even when the preceding values of y are incorporated into the model, then x is the causal factor behind y (Lopez and Weber, 2017: 2). The causality in question is tested with the following hypothesis:

$$H_0: \beta_i = 0 \quad i=1,\ldots..N$$

The fundamental assumption is that β_i is equal to zero. Concurrently, the null hypothesis (H_0) posits the absence of homogeneous panel causality from x to y. The alternative hypothesis is:

$$H_1: \beta_i = 0 \qquad i=1,\ldots..N \quad \text{ve} \quad \beta_i \neq 0 \qquad i=N_1+1, N_2+2,\ldots.N$$

In accordance with the alternative hypothesis, the inequality N1 < N signifies the absence of causality from x to y. Despite the uncertainty surrounding N1, it is constrained by the condition $0 \leq N1/N < 1$. In the event of N1 = N, the conclusion that no causality exists within the panel is reached, a scenario analogous to that of the basic hypothesis. When N_1 is equal to zero, the variable x is identified as the causal factor for y across all units within the panel. If H_0 is accepted, it can be concluded that the variable x does not cause the variable y for all units of the panel. In contrast, the null hypothesis (H_0) is rejected, and when $N_1 = 0$, the variable x is found to cause the variable y for all units in the panel. In this case of causality, a homogeneous result is obtained. Conversely, if $N_1>0$, the causality relationship is heterogeneous (Dumitrescu and Hurlin, 2012). For the basic hypothesis i = 1, ..., N, which asserts that there is no causality, the average of Wald statistics specific to each unit is used (Tatoğlu, 2017: 155).

$$\bar{W}_{N,T} = \frac{1}{N} \sum_{i=1}^{N} W_{i,T} \quad (14)$$

In the aforementioned equation, the unit-specific Wald test statistic, denoted as W_i,T, is employed to test the null hypothesis, H_0: $\beta_i = 0$, at the level of unit i.

3.2.5 EMPIRICAL RESULTS

It is crucial to assess the stationarity of the variables before applying econometric techniques, to prevent occurrence of spurious regressions. The existing literature on this subject identifies two principal categories of unit root tests: the first and the second generation. The former is employed when there are no CSD, whereas the latter is utilized when CSD are present (Brooks, 2014: 547). Consequently, the CSD tests were initially applied to all variables (see Annex A). Based on these results, all variables were found to exhibit CSD. Consequently, the PANIC test, a second-generation test, was applied to all variables. The results of the unit root test are presented in Table 2.

The results presented in Table 2 indicate that the null hypothesis cannot be rejected for any of the variables. This implies that all of the variables exhibit a unit root at the level. Nevertheless, all variables are stationary at first differencing. If all the variables are I(1), then they are likely to be related to each other in the long run. Cointegration tests are applied to detect this kind of relationship. Therefore, we have summarized the cointegration test results and some diagnostics in Table 3.

TABLE 2
Unit Root Test

Variables	Level		1st difference	
	PCe_Choi	PCe_MW	PCe_Choi	PCe_MW
Ecofoot	-0.2526	24.1785	7.5128***	80.1758***
	(0.5997)	(0.5658)	(0.000)	(0.000)
Envtech	-1.1218	17.9109	7.1934***	77.8724***
	(0.8690)	(0.8790)	(0.000)	(0.000)
LogCO_2	-2.5985	7.2620	7.0853***	77.0926***
	(0.9953)	(0.9999)	(0.000)	(0.000)
Trade	-2.7710	6.0182	9.3053***	93.1018***
	(0.9972)	(1.0000)	(0.000)	(0.000)
Loggdp	-2.6151	7.1422	2.8740***	46.7248***
	(0.9955)	(0.9999)	(0.0020)	(0.0076)

Note: *** and ** refer to 1% and 5% significance levels. The values in parenthesis are p-values.

TABLE 3
Cointegration Tests

Westerlund Cointegration Test				
	Test stat.			p-value
G_t	10.690***			(0.001)
G_a	6.994			(0.500)
P_t	-17.794***			(0.000)
P_a	5.801***			(0.000)
Diagnostics				
CSD for the Model				
	CDLM 1	p-value	Lmadj	p-value
Model	10.23***	(0.0000)	20.69***	(0.0000)
Pesaran-Yamagata Homogeneity Test				
	Delta	p-value	Delta adj	p-value
Model	20.106***	(0.000)	22.683***	(0.000)

Note: *** and ** refer to 1% and 5% significance levels.

Second-generation Westerlund (2007) panel cointegration tests were applied under lagged (2) constant and trend assumptions. The results are recorded in Table 3. The Gt, Pt and Pa statistics are significant at the 1% level, indicating that the null hypothesis of no cointegration is rejected. Consequently, it is possible to discuss the existence of a long-term cointegration relationship between the variables. Certain diagnostics, however, are employed to determine the most suitable estimator. One such diagnostic is the CSD test for the residuals of the model in question. The results presented in Table 3 indicate that the p-values are less than 0.05, thus rejecting the null hypothesis that there is no CSD. Consequently, a second-generation estimator is necessary if the CSD is present in the residuals generated from the model. Therefore, we used CCEMG and AMG estimators to measure the coefficients. Before examining the coefficients, however, we need to test the homogeneity of slope coefficients. In Table 3, there is also the result of the Pesaran-Yamagata test, which is used to examine the homogeneity of coefficients among the cross-section units. It is observed that we reject the null hypothesis of homogeneity if the p-value is lower than 0.05. Hence, we estimated long-run coefficients for each cross-section unit separately.

One more issue to consider before estimating the coefficients is multicollinearity. The method to examine multicollinearity in the model examined is to analyze the bivariate correlations of the explanatory variables. The bivariate correlations must be lower than 0.80 to avoid multicollinearity issues (Senaviratna and Cooray, 2019: 3). Another way to detect multicollinearity is to examine the Variance Inflation Factor (VIF) values. Accordingly, if the VIF value of any variable has a high correlation with other explanatory variables this causes a multicollinearity problem (Kim, 2019: 559). Depending on the bivariate correlations (see Appendix 2) and the VIF values (see Appendix 3), it is observed that there is no multicollinearity problem in the model. The estimation results are given in Table 4.

TABLE 4

Long-Run Coefficient Estimation Results

	CCEMG Estimation Results				AMG Estimation Results			
	envtech	logco2	loggdp	trade	envtech	logco2	loggdp	trade
CHN	0.008	5.271***	-0.639	-0.012***	0.004	4.606***	-0.315	-0.011***
	(0.469)	(0.000)	(0.587)	(0.000)	(0.560)	(0.000)	(0.171)	(0.000)
USA	0.004	11.213**	18.071**	0.072*	-0.031	13.627***	5.188*	-0.014
	(0.888)	(0.015)	(0.017)	(0.054)	(0.257)	(0.000)	(0.062)	(0.496)
JPN	-0.019	7.348***	1.767	0.003	0.012	5.497***	3.563	-0.007
	(0.504)	(0.009)	(0.724)	(0.868)	(0.551)	(0.002)	(0.370)	(0.661)
DEU	0.018	6.388**	3.026	0.009	0.029	5.953***	-0.7079	0.017***
	(0.614)	(0.024)	(0.625)	(0.633)	(0.303)	(0.002)	(0.756)	(0.001)
IND	-0.053	1.504***	0.100	0.001	-0.009	1.598***	-0.654***	-0.002**
	(0.194)	(0.000)	(0.771)	(0.339)	(0.844)	(0.000)	(0.000)	(0.011)

TABLE 4 (*continued*)

	CCEMG Estimation Results				AMG Estimation Results			
	envtech	logco2	loggdp	trade	envtech	logco2	loggdp	trade
GBR	0.006	10.803***	5.274	-0.008	0.045	8.490***	8.840***	-0.002
	(0.980)	(0.000)	(0.247)	(0.680)	(0.851)	(0.000)	(0.000)	(0.890)
KOR	-0.005	13.667***	-2.794	-0.025***	-0.009	7.598***	3.373***	-0.012***
	(0.889)	(0.000)	(0.427)	(0.000)	(0.807)	(0.000)	(0.007)	(0.000)
FRA	0.011	1.760	7.530	0.022	0.153	4.393**	7.901***	0.010
	(0.919)	(0.554)	(0.221)	(0.315)	(0.129)	(0.027)	(0.002)	(0.482)
RUS	-0.505	4.380	5.364*	0.003	-0.338	3.769*	5.623***	0.0049
	(0.432)	(0.315)	(0.053)	(0.689)	(0.537)	(0.071)	(0.000)	(0.236)
ITA	-0.114	3.827	14.305**	-0.012	-0.203	4.438***	13.27***	-0.010
	(0.559)	(0.154)	(0.022)	(0.255)	(0.175)	(0.001)	(0.000)	(0.293)
MEX	3.694	-8.784	14.441	0.009	4.776**	2.049	3.398	0.009
	(0.177)	(0.275)	(0.117)	(0.467)	(0.049)	(0.373)	(0.296)	(0.401)
BRA	-0.443	1.185	5.420***	-0.012	-0.864**	1.558**	1.351	-0.023***
	(0.296)	(0.277)	(0.007)	(0.136)	(0.028)	(0.046)	(0.256)	(0.000)
IDN	-1.790*	1.044***	1.028***	-0.002	-2.291*	0.196	1.003***	0.000
	(0.096)	(0.005)	(0.003)	(0.115)	(0.060)	(0.387)	(0.008)	(0.754)

Note: ***, ** and * refer to 1%, 5% and 10% significance levels, respectively. The values in parenthesis correspond to p-values.
(CHN: China, USA: United States, JPN: Japan, DEU: Germany, IND: India, GBR: United Kingdom, KOR: South Korea, FRA: France, RUS: Russia, ITA: Italy, MEX: Mexico, BRA: Brazil, IDN: Indonesia)

The results of the CCEMG indicate that the impact of ETI on the EFP is significant only in Indonesia. The AMG results, however, suggest that this is also the case in Mexico, Indonesia and Brazil. In contrast, results from other countries are not statistically significant. The CCEMG and AMG results both indicate that ETI reduce the EFP. The mitigating effects of TI are consistent with the results of Ali et al. (2016) for Malaysia, Islam (2024) for Saudi Arabia, and Ozkan et al. (2023) for Turkiye. However, the AMG results also indicate that in Mexico, these innovations have the opposite effect, increasing the EFP. The advent of ETI in Mexico has led to an increase in the country's EFP. This suggests that Mexico is currently undergoing industrialization, is in the initial stages of developing environmental technologies, and that the developed technologies are not yet fully implementable or commercially viable. These findings also prompt the question of how these technologies can be effectively utilized in Mexico.

The CCEMG results indicate that CO_2 emission has an increasing effect on the EFP in China, the USA, Japan, Germany, India, the UK, Korea and Indonesia. The AMG results indicate that EFP expansion is associated with growth in CO_2 emissions in China, the USA, Japan, Germany, India, the UK, Korea, France, Russia, Italy and Brazil. The analysis results demonstrate that CO_2 emission has a detrimental impact on EFP in most countries, endangering the environment and future generations through its role in environmental degradation. The CCEMG results indicate that the loggdp variable exerts an increasing influence on the EFP in the US, Russia, Italy, Brazil, and Indonesia. Similarly, the AMG results demonstrate that in the United States, India, the UK, South Korea, France, Russia, Italy, and Indonesia, the loggdp variable also has a positive effect on the EFP. Results are consistent with that in Destek and Sarkodie (2019) for 11 newly industrilized countries, and Alola et al. (2019) for EU countries. The findings indicate that the initial tenets of the EKC hypothesis remain pertinent in the present era, even in nations that have attained the final stage of industrialization. In other words, the EG process continues to have a detrimental impact on the environment, even in developed countries.

The CCEMG results indicate that trade has decreasing effect on the EFP in South Korea and China. However, it has an enhancing effect in the USA. The results of AMG indicate that while trade contributes to a reduction in China, India, Korea and Brazil's EFP, it concurrently leads to an increase in Germany's. According to CCEMG and AMG, the results suggesting that TO reduces the EFP coincide with the results of Destek and Sinha's (2020) study for OECD countries and with Aydın and Turan (2020) for BRICS countries. International trade has the potential to facilitate technology transfer to other countries. This could allow nations to access cleaner technologies, which could reduce the adverse impact on the environment and improve environmental quality. The results of the two tests (CCEMG and AMG) demonstrate that trade is responsible for an increase in the EFP in both Germany and the USA. The results indicate that the impact of trade on the EFP is statistically limited in terms of both its increasing and decreasing effects.

The Dumitrescu-Hurlin panel causality test results are outlined in Table 5, which provide two bidirectional (Envtech ↔ ecofootprint; Trade ↔ ecofootprint) and two unidirectional (Ecofootprint → logco2kt ; loggdp → ecofootprint) causalities. The bidirectional causality between envtech and ecofootprint confirms that envtech causes ecofootprint vice versa. These result indicate that any policy targeting the ecofootprint, will accelerate envtech and any change in envtech will affect ecofootprint. The outcome confirms the finding of Ahmad et al. (2020). Technological progress and the adaptation of innovations to the environment contribute positively to environmental sustainability. The bidirectional causality between trade and ecofootprint reveals that trade causes environmental damage vice versa. The bilateral causality relationship between TO and EFP is analogous to the causality relationships obtained from Zhou et al. (2024). The results of the causality test indicate a unidirectional relationship from loggdp to ecofootprint, which lends support to the findings of Chu (2022b). The expansion of economic activity causes the EFP. Finally, a one-way causal relationship was detected from ecofootprint to logco2kt. This relationship explains that approaches to reduce the EFP are the reason for the decrease in logco2kt, one of the harmful emissions to the environment.

TABLE 5
Dumitrescu-Hurlin Panel Causality Test Results

Null Hypothesis	W-Bar	Z-Bar	Prob	Decision
envtech does not Granger-cause ecofootprint	8.8979	1.8289	0.0674*	Envtech ↔ ecofootprint
ecofootprint does not Granger-cause envtech	17.8297	10.4358	0.0000***	
logco2kt does not Granger-cause ecofootprint	1.4261	1.0863	0.2773	Ecofootprint → logco2kt
ecofootprint does not Granger-cause logco2kt	10.2857	3.1662	0.0015***	
trade does not Granger-cause ecofootprint	12.7983	5.5874	0.0000***	Trade ↔ ecofootprint
ecofootprint does not Granger-cause trade	8.9648	3.0858	0.0020***	
loggdp does not Granger-cause ecofootprint.	8.7359	1.6727	0.0944*	loggdp → ecofootprint.
ecofootprint does not Granger-cause loggdp	1.5765	1.4698	0.1416	

Note: ***, ** and * refer to 1%, 5% and 10% significance levels, respectively.

4. DISCUSSION AND CONCLUSION

Today, the attempt to enhance social welfare in terms of national economies has entailed pursuit of sustainable EG. In this process, where EG efforts become the main goal, environmental sustainability is ignored. Pursuit of economic progress and increased prosperity has resulted in environmental challenges, including global warming, climate change, and an increase in CO_2 emissions. Concurrently, the rise in consumption driven by urbanization and population growth has significantly increased energy consumption, reaching envionmentally threatening levels for both developed and developing countries.

In this study, the concept of exclusively focusing on CO_2 emissions for assessing environmental damage was deemed insufficient. In this framework, the EF approach was employed, which is a more comprehensive indicator that examines environmental sustainability in a broader context and includes CO_2 emissions. In essence, a heightened awareness of environmental degradation among policymakers and academics engaged with this subject area has prompted a shift in focus from an exclusive emphasis on CO_2 emissions to a more encompassing examination of the EF.

The CCEMG and AMG results indicate that in countries such as Indonesia and Brazil, where TI reduces the EFP, it is advisable for policymakers and governments to strengthen ETI policies with the aim of decreasing the EFP and solving the environmental pollution problems. In this instance, it is crucial to increase the proportion of environmental technology within the technological landscape and to provide a range of financial and investment incentives aimed at fostering environmental technology advancement. In addition to all this, in a country like Mexico, where ETI are increasing the EFP and environmental degradation is occurring, policymakers must take responsibility. Furthermore, in conjunction with advances in environmental technologies, it is of paramount importance for governments to formulate effective implementation strategies for environmental policies. In most countries included in the study, the impact of CO_2 emissions on EFP is incorporated into the analysis of CCEMG and AMG results. The implementation of measures such as using alternative energy sources, particularly for industrial production, the expansion of public transportation opportunities and the increased use of hybrid vehicles, the development of environmentally-friendly and environmentally conscious smart city plans, and the incorporation of environmentally friendly components in agricultural production will contribute to reducing CO_2 emissions.

The results of CCEMG and AMG analyses indicate that the EG process has a detrimental impact on the EFP in numerous countries. The findings demonstrate that countries tend to prioritize EG over environmental considerations in their production processes. In light of these findings, it is recommended that countries consider implementing measures aimed at promoting environmentally conscious practices within their production processes. This could entail adopting environmentally-friendly techniques and transitioning to more sustainable products and production methods. The production of environmentally friendly products and services in the EG process is more costly and time-consuming. It is important to utilize economic incentives in producing such products and services. On the other hand, a combination of effective policy interventions is needed to ensure sustainable growth, improve living standards and foster technological advances. Global co-operation summits should be established to address issues related to economic activity impact on the environment. Additionally, policies aimed at reducing excessive consumption may prove beneficial in this regard. The results of the CCEMG and AMG indicate the necessity for more rigorous trade policy implementation in both exports and imports in countries where trade intensifies the EFP. The creation of trade policies should encompass an assessment of the potential negative impacts of commercial activities on the environment. Furthermore, prioritizing environmentally friendly products in export and import processes, coupled with incentive factors for these products, is crucial in formulating effective environmental policy.

It should be noted that the study is subject to a number of limitations. The present study encompasses 13 countries with the highest added value. The number of countries included in the study could be further expanded by including additional data sets. Furthermore, data from the years 1992 to 2019 were employed in this study. Data to be published in the future, particularly with regard to the EFP, will extend the time period of future studies. The study was conducted using four independent variables: ETI, CO_2 emissions, GDP and trade. In future studies, institutional and social data, in addition to economic data, can also be used for this group of countries.

REFERENCES

Ahmad, N., L. Youjin, S. Zikovi, and Z. Belyaeva. “The Effects of Technological Innovation on Sustainable Development and

Environmental Degradation: Evidence From China." *Technol. Soc.* 72 (2023): 102184.

Ahmad, M., P. Jiang, A. Majeed, M. Umar, Z. Khan, and S. Muhammad. "The Dynamic Impact of Natural Resources, Technological Innovations and Economic Growth on Ecological Footprint: An Advanced Panel Data Estimation." *Resour. Policy* 69 (2020): 101817.

Ali W, A. Abdullah, and M. Azam. "The Dynamic Linkage Between Technological Innovation and Carbon Dioxide Emissions in Malaysia: An Autoregressive Distributed Lagged Bound Approach." *Int J Energy Econ Policy* 6, no. 3 (2016): 389–400.

Al-Mulali, U., C. Weng-Wai, L. Sheau-Ting, and A.H. Mohammed. "Investigating The Environmental Kuznets Curve (EKC) Hypothesis by Utilizing the Ecological Footprint as an Indicator Of Environmental Degradation." *Ecological Indicators* 48 (2015): 315-23.

Alola, A., F. Bekum, S. Sarkodie. "Dynamic Impact of Trade Policy, Economic Growth, Fertility Rate, Renewable and Non-Renewable Energy Consumption on Ecological Footprint in Europe." *Sci. Total Environ* 685 (2019): 702-09.

Antweiler, W., B.R. Copeland, and M.S. Taylor. "Is Free Trade Good For The Environment?" *American Economic Review* 91, no. 4 (2001): 877–908.

Appiah K, T.A. Worae, B. Yeboah, and M. Yeboah. "The Causal Nexus Between Trade Openness And Environmental Pollution in Selected Emerging Economies." *Ecological Indicators* 138 (2022): 108872

Aydin, M., and Y.E. Turan. "The Influence of Financial Openness, Trade Openness, and Energy Intensity on Ecological Footprint: Revisiting the Environmental Kuznets Curve Hypothesis For BRICS Countries." *Environ Sci Pollut Res* 27, no. 34 (2020): 43233–3245.

Aydın, C., Ö. Esen, Ö., and Y. Çetintaş. "Environmental Innovation, Ecological Footprint, and Environmental Rebound Effects: A Solution for or a Cause of Environmental Degradation?" *Research Square* (2023): 1-22.

Baabou, W., N. Grunewald, C.O. Plamondon, M. Gressot, and A. Galli. "The Ecological Footprint of Mediterranean Cities: Awareness Creation and Policy Implications." *Environmental Science & Policy* 69 (2017): 94-104.

Bai, J., and S. Ng. "A PANIC Attack on Unit Roots and Cointegration." *Econometrica* 72, no. 4 (2004): 1127-177.

______, and S. Ng. "Panel Unit Root Tests With Cross-Section Dependence: A Further İnvestigation." *Econometric Theory* 26, no. 4 (2010): 1088-114.

Brooks, Chris. *Introductory Econometrics for Finance.* Cambridge: Cambridge University Press, 2014.

Carraro, Carlo. "Environmental Technological Innovation and Diffusion: Model Analysis." In *Innovation-Oriented Environmental Regulation*, edited by Jens Hemmelskamp, Fabio Leone and Klaus Rennings, 269-97, 2020.

Chien, F., C.C. Hsu, A. Sibghatullah, V.M. Hieu, T.T.T. Phan, and N.H. Tien,. "The Role of Technological Innovation and Cleaner Energy Towards the Environment in ASEAN Countries: Proposing a Policy for Sustainable Development Goals." *Economic Research-Ekonomska Istraživanja* 35, no. 1 (2022): 4677-692.

______, M. Sadiq, M.A. Nawaz, M.S. Hussain, T.D. Tran, and T.L. Thanh. "A Step Toward Reducing Air Pollution in Top Asian Economies: The Role of Green Energy, Eco-innovation, and Environmental Taxes." *Journal of Environmental Management,* 297 (2021): 113420.

Chu, L.K. "Determinants of Ecological Footprint in OCED Countries: Do Environmental-Related Technologies Reduce Environmental Degradation?" *Environmental Science and Pollution Research* 29 (2022a): 23779–3793.

______. "The İmpact of Informal Economy on Technological Innovation–Ecological Footprint Nexus in OECD Countries: New Evidence from Panel Quantile Regression." *J. Environ. Stud. Sci*. (2022b): 1–19.

Danish, R. Ulucak, and S.U. Khan. "Determinants of The Ecological Footprint: Role of Renewable Energy, Natural Resources, and Urbanization." *Sustainable Cities and Society* 54 (2020): 1-10.

Dauda, L., X. Long, C.N. Mensah, and M. Salman. "The Effects of Economic Growth and Innovation on CO2 Emissions in Different Regions." *Environmental Science and Pollution Research,* 26, no. 15 (2019): 15028–5038.

Destek, M. A., and A. Sinha. "Renewable, Non-Renewable Energy Consumption, Economic Growth, Trade Openness and Ecological Footprint: Evidence from Organisation for

Economic Cooperation and Development Countries." *Journal of Cleaner Production,* 242 (2020): 118537.

______, and M. Manga. "Technological Innovation, Financialization, and Ecological Footprint: Evidence from BEM Economies." *Environmental Science and Pollution Research,* 28 (2020): 21991–2001.

______, and S.A. Sarkodie. "Investigation of Environmental Kuznets Curve for Ecological Footprint: The Role of Energy and Financial Development." *Science of The Total Environment* 650 (2019): 2483-489.

______, R. Ulucak, and E. Doğan. "Analyzing the Environmental Kuznets Curve for The EU Countries: The Role of Ecological Footprint." *Environmental Science and Pollution Research,* 25, no. 29 (2018): 29387–9396.

______, and M. Manga. "Technological Innovation, Financialization, and Ecological Footprint: Evidence From BEM Economies." *Environmental Science and Pollution Research* 28 (2021): 21991–2001.

Dumitrescu, E.I., and C. Hurlin. "Testing for Granger Noncausality in Heterogeneous Panels." *Economic Modelling* 29, no.4 (2012): 1450-460.

Eberhardt, M., and S. Bond. "Cross-Section Dependence in Nonstationary Panel Models: A Novel Estimator." *MPRA Paper* (2009): 17692.

______, and F. Teal. "Productivity Analysis in Global Manufacturing Production." Discussion Paper in University of Oxford Department of Economics no. 515 (2010).

Ersin, O.O., A. Ustabas, and O. Usman. "The Role of Environmental Innovation on Ecological Footprint in Nations with High Technology Exports Concentrations in İnternational Trade." *Technological Forecasting & Social Change* 208 (2024): 123703.

Fernández, Y., M.A. Fernández Lopez, and B. Olmedillas Blanco. "Innovation for Sustainability: The Impact of R&D Spending on CO2 Emissions." *Journal of Cleaner Production* 172 (2018): 3459–467.

Görmüş, S., and M. Aydın. "Revisiting the Environmental Kuznets Curve Hypothesis Using Innovation: New Evidence from the Top 10 Innovative Economies." *Environmental Science and Pollution Research* 27 (2020): 27904–7913.

Grossman, G.M., and A.B. Krueger. "Environmental Impacts of a North American Free Trade Agreement." Working Paper in National Bureau of Economics no. 3914 (1991).

Islam, M.S. "Influence of Economic Growth on Environmental Pollution in South Asia: A Panel Cointegration Analysis." *Asia-Pacifc Journal of Regional Science* 5 (2021): 951–73.

______, A. Rehman, I. Khan, and S.H. Rahaman. "Remittance Outflow and Environmental Quality Nexus in Saudi Arabia: The Role of ICT, Environmental İnnovation, and Energy Consumption." *Environment, Development and Sustainability,* 26 (2024a): 12843–2862.

______. "Does Financial Development Cause Environmental Pollution? Empirical Evidence from South Asia." *Environmental Science, and Pollution Research* 29, no.3 (2022): 4350–362.

______. "Linking Green Innovation to Environmental Quality in Saudi Arabia: An Application of the NARDL Approach." *Environment, Development and Sustainability* (2024).

______, and S.H. Rahaman. "The Asymmetric Effect of ICT on CO2 Emissions in the Context of an EKC Framework in GCC Countries: The Role of Energy Consumption, Energy Intensity, Trade, and Financial Development." *Environmental Science and Pollution Research* 30 (2023): 77729–7741.

______, A. Rehman, and I. Khan. "Assessing The Impact of Environmental Technology on CO2 Emissions in Saudi Arabia: A Quantile-Based NARDL Approach." *Mathematics* 12 (2024): 2352.

Jiang, Q., Z. Rahman, X. Zhang, and M.S. Islam. (2022). "An Assessment of the Effect of Green Innovation, Income, and Energy Use on Consumption-Based CO2 Emissions: Empirical Evidence from Emerging Nations BRICS." *Journal of Cleaner Production* 365 (2022): 132636.

Kim, J.H. "Multicollinearity and Misleading Statistical Results." *Korean Journal of Anesthesiology* 72, no. 6 (2019): 558-69.

Koseoglu, A., A.G. Yucel, and R. Ulucak. "Green Innovation and Ecological Footprint Relationship for a Sustainable Development: Evidence from Top 20 Green Innovator Countries." *Sustainable Development* (2022): 1–13.

Kuznets, S. (1955). "Economic Growth and Income Inequality." *Am Econ Rev* 49 (1955): l–28.

Lin, B., and J. Zhu. "The Role of Renewable Energy Technological Innovation on Climate Change: Empirical Evidence from China." *Science of the Total Environment* 659 (2019): 1505-512.

Lopez, L., and S. Weber. "Testing for Granger Causality in Panel Data." Working Paper in IRENE University of Neuchatel Institute of Economic Research no. 17-03 (2017).

Ozkan, O., N. Khan, and M. Ahmed. "Impact of Green Technological innovations on Environmental Quality for Turkey: Evidence from the Novel Dynamic ARDL Simulation Model." *Environ. Sci. Pollut. Res.* 30 (2023): 72207–2223.

Öcal, O., B. Altınöz, and A. Aslan. "The Effects of Economic Growth and Energy Consumption on Ecological Footprint and Carbon Emissions: Evidence from Turkey." *Journal of Research in Economics, Politics & Finance* 5, no. 3 (2020): 667-81.

Persyn, D., and J. Westerlund. "Error-Correction–Based Cointegration Tests for Panel Data." *The Stata Journal* 8, no. 2 (2008): 232–241.

Pesaran, M.H. "Estimation and Inference in Large Heterogeneous Panels with A Multifactor Error Structure." *Econometrica* 74, no. 4 (2006): 967-1012.

Porter, M.E, and V. L. Claas. "Toward a New Conception of the Environment-Competitiveness Relationship." *J Econ Perspect* 9, no. 4 (1995): 97–118.

Rees, W.E. "Ecological Footprints and Appropriated Carrying Capacity: What Urban Economics Leaves Out." *Environ. Urbanization* 4, no. 2 (1992): 121-30.

Romer, P.M. "Endogenous Technological Change." *Journal of Political Economy* 98, no. 5 (1990): 71-102.

Sarkodie, S.A. "Environmental Performance, Biocapacity, Carbon & Ecological Footprint of Nations: Drivers, Trends and Mitigation Options." *Science of the Total Environment* 751 (2021): 141912

Senaviratna, N.A.M.R., and T.M.J.A. Cooray. "Diagnosing Multicollinearity of Logistic Regression Model." *Asian Journal of Probability and Statistics* 5, no. 2 (2019): 1-9.

Sinha A, and T.A. Sengupta. "Interplay Between Technological Innovation And Environmental Quality: Formulating The SDG Policies for Next 11 Economies." *J Clean Prod.* 242 (2020): 118549

Tatoğlu, Ferda Yerdelen. *Panel Zaman Serileri Analizi: Stata uygulamalı*. Beta: İstanbul, 2017.

Temurshoev, U. "Pollution Haven Hypothesis or Factor Endowment Hypothesis: Theory and Empirical Examination for the US And China." Working Paper in Center for Economic Research and Graduate Education Academy of Sciences of the Czech Republic Economics Institute (2006).

Twum, F.A., X. Long, M. Salman, C.N. Mensah, W.A. Kankam, and A.K.Tachie. "The Influence of Technological Innovation and Human Capital on Environmental Efficiency among Different Regions in Asia-Pacific." *Environ Sci Pollut Res Int* 28, no. 14 (2021): 17119-7131.

Westerlund, J. "Testing for Error Correction in Panel Data." *Oxford Bulletin of Economics and Statistics* 69, no. 6 (2007): 709-48.

Zhou, D., M. Kongkuah, A.K. Twum, and I. Adam. "Assessing the Impact of International Trade on Ecological Footprint in Belt and Road Initiative Countries." *Heliyon* 10 (2024): e26459.

APPENDIX 1
CSD Test for the Residuals of the Model

Variables	CDLM	LM adj
Ecofoot	3.388	118.620
	(0.000)	(0.000)
envtech	1.909	112.528
	(0.028)	(0.000)
LogCO2 emissions	4.403	106.358
	(0.000)	(0.000)
Trade	9.059	67.090
	(0.000)	(0.000)
Loggdp	16.678	114.527
	(0.000)	(0.000)

APPENDIX 2
Bivariate Correlation Matrix for Explanatory Variables

	Logenv	LogCO2 emissions	Trade	Loggdp
Logenv	1	-	-	-
LogCO2 emissions	0.4444	1	-	-
Trade	0.6975	0.6999	1	-
Loggdp	-0.2910	-0.2648	-0.2755	1

APPENDIX 3
Variance Inflation Factor Values for Explanatory Variables

Variables	VIF
envtechinov	2.01
logco2kt	2.00
loggdpc2015	3.09
tradeofgdp	1.12
Mean VIF	2.06