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RESEARCH ARTICLE

Measuring How AI Innovations and Financial Accessibility Influence Environmental Sustainability in the G-7: The Role of Globalization with Panel ARDL and Quantile Regression Analysis

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Abstract
This study investigates the impact of AI innovation on environmental sustainability in the G-7 region from 2010 to 2022. Additionally, it tests the Load Capacity Curve (LCC) hypothesis in relation to financial accessibility, globalization, and urbanization. Cross-sectional dependence and slope homogeneity tests reveal the presence of cross-sectional dependence and heterogeneity issues. Panel unit root and panel cointegration tests confirm that the variables are free from unit root problems and are cointegrated in the long run. To identify significant factors influencing environmental sustainability, this study employs Panel ARDL and Quantile Regression methods. Both methods confirm the LCC hypothesis in the G-7 region, demonstrating a U-shaped relationship between income and the load capacity factor. The results indicate that AI innovation and financial accessibility are significantly positively correlated with the load capacity factor, while globalization and urbanization are negatively correlated, leading to lower environmental sustainability. To validate the robustness of the Panel ARDL and Quantile Regression results, Driscoll-Kraay standard errors, Augmented Mean Group, and Common Correlated Effects Mean Group estimation approaches are applied, all of which support the initial findings. Furthermore, the D-H causality test reveals unidirectional causality from economic growth, financial accessibility, globalization, and urbanization to the load capacity factor, and bidirectional causality between AI innovation and the load capacity factor.

Keywords: Artificial Intelligence; Financial Accessibility; Globalization; LCC Hypothesis; G-7 region

Introduction

The sustainability of natural assets of the G-7 countries is a notable and ongoing concern, given that all of the members, except Canada, have environmental imbalances (Global Footprint Network, 2019). As the G-7 countries contribute to more than 60% of the world's net global wealth through their extensive economic activity, it is obvious that emissions from fossil fuels, coal, and conventional cooking fuels are the major cause of pollution (Alola et al., 2022a). While several G-20 and G-7 states continued to grow commercially during the last ten years, the serious threat that climate change possess to ecosystem integrity continues to be one of the most significant challenges (Alola et al.,2022b; Hossain et al.,2023). According to UNEP (2019), mitigation in pollutions below 25% and 55%, respectively, is necessary to meet the goal of global humidity level less than 2 °C and 1.5 °C by 2030. The worldwide average temperature has spiked by 0.4 to 0.8 degrees Celsius over the past several decades, and by 2100, it could climb by 1.4 to 5.8 degrees Celsius (Danish et al. 2020). As the G7 contributes to 27.3% of global emission of carbon, they do, address enormous environmental difficulties. Remarkably, the inquiry finds that the United States, Germany, the United Kingdom, and Japan are the G7's biggest pollutants (Zheng et al., 2019). The Group-7 territory offered a major improvement to the management of the globe's climate and attempted to diminish the rate of climate change by putting different policies into place through public and commercial institutions (Song et al.,2021). In light of this, this research intends to explore the consequences for load capacity factor (LCF) in the G-7 areas of GDP, Financial Accessibility (FA), Artificial Intelligence Innovation (AI), Globalization (GOB), and Urbanization (URBA). G-7 was selected for several considerations. With a considerable 39% share of the global economic output and 10.981 billion tons of emissions of carbon dioxide, the nations of the G-7 possess a major influence on the global economy. Nonetheless, figuring out what causes global warming is essential (Dastgeer et al., 2023). As a result, the economies of these nations bear a considerable degree of responsibility for environmental degradation. In addition, environmental damage continues to remain a risk to the G-7 countries even with their progress toward a green economy (Khan et al. 2020). For example, the group generated around 38% of the total world emissions between 1960 and 2014 (World Bank 2017). Thirdly, among the numerous elements that contribute to environmental contamination in the region, the ongoing advancements in the global value chain provide further grounds for concern (Ibrahim & Ajide, 2021; Mithun et al.,2023; Faruk et al.,2023). A more accurate environmental evaluation can be obtained by the LCF (Siche et al., 2010). It reflects a country's ability or capacity to sustain its people following their contemporary lifestyles (Xu et al., 2022). Thus, an ecosystem is considered sustainable when its LCF is larger than one and unsustainable when it is less than one (Pata et al., 2021). Consequently, implementing consideration of the aforementioned rationale, this research will hold significant policy implications for decision-makers concerning sustainable development goals (SDGs). Concerns addressing the possible negative effects on human development emerge as technological developments, particularly in artificial intelligence (AI), transform the community (Qin et al., 2023). Artificial intelligence (AI) is a general term for several kinds of devices and platforms that replicate human intelligence and perform activities without human intervention (Sohail et al.,2018a; Sohail et al.,2018b; Saba & Monkam, 2024). It is a powerful instrument for boosting efficiency, effectiveness, and creativity because of its possible advantages in areas like automation, data analysis, and decision-making (Makridakis 2017). Artificial intelligence-driven commercialization is projected to reach $3.9 trillion in 2022, up from $1.2 trillion in 2018, which marked a 70% growth from 2017 (Richards et al., 2019). The G-7 countries actively made investments in AI technologies, enacting regulations, establishing institutes for research, and assisting startups because they acknowledge the potential of AI in industries like medical sector, farming, finance, and others (Cyman et al. 2021; Dukhi et al. 2021).Understanding the interplay among all these factors in this particular environment is crucial for designing modern strategies that focus on capitalizing on the advantages of AI integrated progress in the G-7 countries. The widespread prevalence of globalization illustrates the interdependence of nations, with foreign direct investment and international commerce significantly influencing the economic dynamics (Jahanger et al. 2022; Ozturk and Ullah 2022). Numerous environmental consequences of globalization are visible on an interpersonal and global scale. Technological innovation can develop as an outcome of globalization and lessens the ecological impact (Akadiri et al., 2020). However, a key contributing element to inadequate green growth is the uncertainty underlying economic policy (Khan et al., 2019). The GDP of the G-7 nations is expected to reach 60.1 trillion US dollars (USD) in 2021, accounting for 44.1% of the world's GDP (WB, 2022). Out of all the G7 nations, the United States has the greatest GDP with a wide margin. In addition, the GDP of the United States rose almost continuously between 2000 and 2022, surpassing the GDPs of the other six countries combined to reach an estimated 25 trillion dollars in 2022. Before China, the United States had the greatest economy in the world. At over 4.2 trillion US dollars, Japan's GDP was the second biggest among the G7 (Dyvik, 2023). Several studies have been done to figure out the factors that contribute to environmental pollution, and many of them point to economic expansion as an important variable in the degrading of the natural world (Ozcan and Ozturk 2019; Schröder and Storm 2020). According to Bhattacharyya (2018), Ahmed et al. (2020), Shah et al. (2019), and Wu et al. (2020), decreasing economic growth has lowered carbon emissions since 2012. This investigation provides numerous important contributions to the existing body of knowledge. First off, most of the research that is currently available to assess the effects of LCF has merely looked at one or two of the consequences of globalization, artificial intelligence innovation, or financial accessibility, neglecting to take all three into account. Second, when assessing ecological damage, the LCF offers a more sophisticated approach than the Ecological Footprint (EF). Due to this, we decided to employ the LCF as an endogenous variable. Furthermore, there is a shortage of information in the literature about the applicability of the LCC hypothesis in developing countries, such as the G-7 nations. Our work fills this grasp by exploring the LCC hypothesis' applicability to the G-7 countries, which makes it a special contribution to the field. This might be partially explained by the inconsistent findings of the earlier empirical research. Third, even with the theoretical and empirical data supporting the idea that innovation in AI regulates the adverse effects of various toxins in the environment, these types of concerns are still relatively new, especially for developed countries such as the G-7. Fourth, by endeavoring to investigate the tripartite effects of GOB, FAI, and AI on environmental quality, this research is also novel. Lastly, we use a strong and contemporary econometric approach by using the most recent data available for long- and short-term estimations from 1990 to 2019 and performing panel unit root tests based on first- and second-generation methods, quantile regression, cross-section dependence tests, and the ARDL method. Additionally, we used AMG, CCEMG, and DKSE estimates to confirm their robustness.

Following is the structure of the relevant study sections: In part 2, there is a thorough representation of the literature comprising related investigation summarized extensively. The third portion covers the topics and methodology; the fourth subsection includes the outcomes and discussions; and the final part contains the conclusion and its policy proposal.

Literature Review

Many empirical analyses have addressed at the consequences of globalization, financial accessibility, AI innovation, and economic development on the load capacity factor (LCF). The majority of research has concentrated on how urbanization, green energy use, and advances in technology affected environmental quality; however, numerous analyses have made use of the ARDL framework. The link between financial globalization, financial advancement, economic growth, and LCF has been examined in other research; nonetheless, the quantile regression approach has attracted less attention in those investigations. The literature on ecological deterioration in the G-7 countries is still in the early stages and lacks comprehensive research. However, a few earlier studies have provided direction for the factors and research techniques chosen. A handful of such inquiries will be examined in this section. A rising income level will allow the expansion of the LCF, improve environmental quality, and maintain the LCF CURVE within the ASEAN region (Dai et al., 2024). Lin and Ullah (2024) performed an analysis in Pakistan using the time-series data from 1970 to 2021 and an advanced dynamic

Autoregressive Distributed Lag (DARDL) approach. They discovered that the LCF decreases by 0.027 % for each 1% boost in economic development. In the top nuclear power economies, growth in GDP has a detrimental impact on the LCF dynamics that drive ecological degradation (Teng et al., 2024). Using methodologies for second-generation panel data, Sun et al. (2024) investigate the factors that impact the LCF in 17 APEC countries. The results of this research imply that ecological health declines with economic growth. In their analysis of G7 and E7 countries between 1997 and 2018, Khan et al. (2023) observed a link within economic growth and a decline in the LCF. According to multiple studies (Huilan et al.,2024; Ozcan et al.,2024; Du et al.,2024; Awosusi et al.,2022; Pata and Isik,2021; Das and Sethi,2023; Ahmad et al.,2024), GDP growth has a detrimental influence on LCF and lowers the quality of biodiversity. But when Solarin et al. (2021) employed the ARDL approach for Nigeria between 1977 and 2016, they discovered that although growth in the economy initially degrades the environment, it eventually improves it over time. However, Jahanger et al. (2023) discovered that LCF is favorably influenced by GDP expansion in the top SDG countries. Between 2007 and 2014, Ameyaw and Yao (2018) investigated that here was no evidence of causation between CO2 emissions and gross fixed capital creation, based on the study. Similar to this, Nathaniel et al. (2020) investigated how growth in the economy affected the EFP in CIVETS territory by utilizing the AMG estimator. They concluded that GDP growth isn't harmful to biodiversity. Moreover, Raihan et al. (2024a) also observed similar outcomes in India. On the other hand, Onwe et al.(2024) revealed that economic development has varied consequences on environment condition in Japan. Digital technology and artificial intelligence are being utilized progressively to enhance strategies for lowering CO2 emissions from human activity. A variety of industries, including CO2 disposal, depend on machine learning models for improved productivity. Because classical approaches are obscure and hard to understand, bankers continue to utilize them despite advances in artificial intelligence (Ferdous et al.,2023; Shiam et al.,2024a; Arif et al.,2024). A variety of industries, including CO2 disposal, depend on machine learning models for improved productivity (Shiam et al.,2024b; Rana et al.,2024). Several investigations (like Rahman et al.,2024; Abir et al.,2024) expressed that the major effect of artificial intelligence (AI) technology on raising standards for sustainability and effective marketing, particularly machine learning (ML), deep learning (DL), and big data. AI encourages sophisticated, efficient, and environmentally friendly industrial structures (Sohail et al.,2019) which have an influence on CO2 emissions (Yuan et al., 2016). Shiam et al.(2023c) considered an examination in Nordic region from 1990 to 2020 to analyze the association between AI innovation, urbanization, GDP, stock market capitalization and banking improvement. By incorporating the STIRPAT framework they concluded that advancement in AI has inverse association with ecological footprint in the selected area. Similarly, Ridwan et al.(2024b) performed an analysis in USA from 1990 to 2019 to check the implication of AI on natural health. They made use the ARDL technique and illustrates that AI related technology can ensures ecosystem sustainability. In G-7 area Ridwan et al.(2024c) conducted another research by using MMQR method to see how AI innovation affect the LCF. Their result demonstrated that application of AI has advantageous consequences on the ecosystem level. Additionally, Akther et al.(2024) explored a study in USA by adopting the ARDL bound test covering data from 1990 to 2019. They observed that private funds in AI has favorable link with LCF. Furthermore, Hossain et al.(2024) in Nordic region also aligned with this findings.

Using a variety of econometric methods, an in-depth examination of the complex connection between globalization and its implications on ecosystems has been carried out extensively. Utilizing a long-run time series dataset spanning from 1970 to 2021, Wang et al. (2023) demonstrated that environmental deterioration is negatively and severely impacted by globalization in China. When Hasseb et al. (2018) examined an insignificant but negative correlation between the two factors. Usman et al. (2020) explore how environmental damage is caused by globalization within the framework of South Africa's EKC and discovered that ecological damage is reduced as a result of GOB. Shahbaz et al. (2017) employed the ARDL bounds test technique from 1970 to 2012 together with the Bayer and Hanck combined cointegration analysis. They discovered that China's CO2 emissions are significantly lower as a result of globalization. In opposition to the findings of these inquiries, Ulucak and Erdogan, (2022) claimed that in the cases of 78 developing and OECD nations, the GOB had a detrimental effect on environmental pollution. Using an examination of the implications of globalization, GDP, and digitization, Li et al. (2023) observed at how the next eleven countries boosted their LCF between 1990 and 2018. Using the CS-ARDL approach, the long-term outcomes illustrate that reliance on globalization reduced LCF. Wenlong et al. (2022) showed through the use of the QARDL technique that GOB leads to an acceleration of ecological excellence in the United States. Additionally, several investigations have demonstrated that globalization has an encouraging effect on ecosystem damage (Jahanger et al., 2022; Sadiq and Khan, 2022; Sheraz et al., 2022; Wen et al., 2021). The foundation of all other types of advancements and businesses is a robust financial expansion, all of which is required to generate revenue for the finance sector. On the other hand, it has been demonstrated that there is a statically uncertain association between ecological and financial expansion (Sharif et al., 2024). Scholars assume that an even more expanded financial sector might potentially enhance the standard of living for individuals globally. The number of financing possibilities that become accessible could grow as the banking sector develops larger (Tamazian et al. 2009; Tamazian & Rao 2010). To investigate the effect of financial accessibility on CO2 emissions from 1990 to 2019, Raihan et al. (2024b) carried out research in the G-7 territory. The results of the Panel ARDL model indicate that financial accessibility (FA) worsens the environment and raises CO2 emissions in the G-7 region. Additionally, FA boosts assets and earnings by generating affordable financing, boosting diversification of risks, and promoting company stability that leads to job creation. This expansion in turn increases the consumption of power which causes to CO2 emissions and degrades the environment (Acheampong 2019; Sadorsky 2010). Boussaidi and Hakimi (2024) suggest that policymakers must enhance the standards of their institutions to promote growth, avert the detrimental effects of accessibility in finances, and safeguard ecological diversity in the MENA area. On the other hand, Gao et al. (2024) evaluate the importance of financial accessibility in the context of environmental pollution for the E-7 nations. The results highlight the positive effects of financial inclusion on carbon emissions and the significance of this policy for the sustainability of the environment. In five South Asian economies, Islam (2022) discovered that because there is a direct link between financial development and CO2 emissions but the latter does not diminish with the development of financial accessibility. The goal of people transferring from rural to urban locations is to have typical lives while working in industries that generate revenue (Ruel et al., 2008). Urbanization encourages the need for transport and manufacturing, increases the use of oil and gas, and enhances the environmental impact (EFP) (Ulucak and Khan 2020). Within the context of the LCC theory, Fang et al. (2024) examine the impact of political risk, biomass utilization, and natural resources on the LCF in ASEAN nations. The ARDL estimator's output demonstrates how urbanization lessens LCF, and the LCC curve is verified in Thailand. The ARDL approach is used by Raihan et al. (2023b) to do research in Mexico using data spanning from 1971 to 2018. The findings show that urbanization lowers Mexico's LCF, which reduces the quality of the environment. Additionally, they advocate for Mexican authorities to endorse an ecologically conscious socioeconomic strategy and promote sustainable urban growth. Moreover, urbanization may boost residents' spending power, which will influence their desire for renewable energy sources and decrease EFP (Danish and Wang 2019). Lin and Ullah (2024) observed that in Pakistan, a one percent rise in urbanization improves the LCF by 0.029 %. The relationship between CO2 emissions and urbanization in the BRICS economies was analyzed by Zhu et al. (2018). According to their results, urbanization lowers emissions and enhances the quality of the natural world. Furthermore, Danish et al. (2020) agreed with the findings that urbanization enhances the standard of ecosystems in the BRICS area using the FMOLS and DOLS methodologies. Multiple studies, including Ali et al. (2017) within Singapore, Raggad (2018) in Saudi Arabia, and Saidi and Mbarek (2017) for 19 nations, corroborate the aforementioned conclusions. However, Raihan et al.(2022a) and Voumik and Ridwan (2023) opposed this findings and concluded that population growth harms the biodiversity.

In the end, our review of previous research has demonstrated that there aren't lots of works that particularly investigate the LLC hypothesis for the G-7 nations while accounting for the consequences of globalization, financial accessibility, and AI advancement. Although the LLC hypothesis has been examined in developing nations by various studies, their analysis has been limited and has not considered the effects of other areas of the economy. Given that the G-7 countries are a rapidly emerging territory with distinctive macroeconomic and environmental features, it is sense to test the LLC hypothesis. Moreover, improvements in AI might support sustainable behaviors, minimize problems with the environment, promote energy efficiency, and assist agriculture all of which in turn could decrease the danger of climate change. From the G-7 perspective, these features make artificial intelligence (AI) an entirely novel area for study. This strategy makes it possible to estimate panel data models efficiently, which enhances the methodological understanding in the field. By examining these procedures, the selected nations might be able to assess if utilizing innovations in technology, financial cooperation, and sustainable development might offer the possibility to improve its LCF and improved sustainability. Therefore, filling in this gap in the literature might enhance our knowledge of how economic progress and environmental damage interplay in the group seven countries while having an enormous effect on the long-term sustainability of the region's policies.

Methodology

Data and Variables

This study sought to explore the intricate connections between GDP, urbanization, financial accessibility, artificial intelligence (AI), globalization, and LCF for the G-7 countries. By adopting sophisticated econometric techniques, the investigation intended to evaluate the LCF hypothesis and get an understanding of the intricate interactions that exist across these variables. LCF, the dependent variable in the study, was taken from the reliable Global Footprint Network (GFN, 2022). The World Development Indicators (2022) provided the GDP, GDP squared, and urbanization data, while trustworthy resources such as Our World in Data, the Global Financial Inclusion Index, and the KOF Globalization Index provided the information on artificial intelligence, financial accessibility, and globalization. To provide a thorough summary of all characteristics examined, including their definitions, sources, and units of measurement, Table 1 is extremely crucial. The goal of this meticulous paperwork was to ensure the research's consistency and clarity, which would reinforce the approach's integrity and transparency.

Theoretical Framework

The LCF is a dependent variable that is employed to capture the relevant elements for ecosystem condition in the quickly growing G-7 areas. The LCF first came up in the literature by Siche et al. (2010), and Pata (2021) was the first to do empirical research on the factors that influence the LCF. The LCC theory is centered on the LCF indicator, which considers opportunities for ecological provision and manmade environmental pressures into account (Pata et al., 2023). Since the LCF includes both EFP and biocapacity in the denominator, a greater LCF is suggestive of a healthier environment (Pata and Kartal, 2024). The LCF offers a more thorough analysis of the environment by contrasting ecological footprint and biological resources (Dogan & Pata, 2022; Islam et al.,2024). To improve the understanding of the foregoing study, we have created the following equation (1) for LCC theory:

$$Load\ Capacity\ Factor = f(GDP, GDP^2, K_t) \qquad (1)$$

In equation (1), the variables for economic growth are GDP and GDP^2 , whereas the variable for other factors influencing the load capacity factor is K_t. Equation (2) seeks to provide an expanded view of the elements changing the LCF by including additional relevant variables such as globalization, urbanization, financial accessibility, innovation in AI, and economic growth.

$$LCF = f(GDP, GDP^2, AI, FA, GOB, URBA) \quad (2)$$

Table 1. Data and Variables

Variables	Description	Logarithmic Form	Unit of Measurement	Source
LCF	Load Capacity Factor	LLCF	Gha per person	GFN
GDP	Gross Domestic Product	LGDP	Current US$	WDI
GDP^2	Gross Domestic Product Square	$LGDP^2$	Current US$	WDI
AI	Artificial Intelligence Innovation	LAI	Patent Application in AI field	Our World in Data
FA	Financial Accessibility	LFA	Automated teller machines (ATMs) (per 100,000 adults)	Global Financial Inclusion
GOB	Globalization	LGOB	Globalization Index	KOF Globalization index
URBA	Urbanization	LURBA	Urban Population (% of total population)	WDI

The load capacity factor (LCF), economic growth (GDP), artificial intelligence (AI) innovation, financial accessibility (FA), globalization (GOB), and urbanization (URBA) are the abbreviations used in equation (2). The economic explanation of this equation can be obtained by equation (3).

$$LCF_{it} = \partial_0 + \partial_1 GDP_{it} + \partial_2 GDP_{it}^2 + \partial_3 AI_{it} + \partial_4 FA_{it} + \partial_5 GOB_{it} + \partial_6 URBA_{it} \quad (3)$$

In equation (4), the variables' logarithmic values are demonstrated. It increases understanding and enables the formulation of implications based on statistics by breaking down complex intersections into simpler linear forms. The logarithmic scale allows for data of different dimensions and aids in alleviating heteroscedasticity when broad ranges need to be reduced.

$$LLCF_{it} = \partial_0 + \partial_1 LGDP_{it} + \partial_2 LGDP_{it}^2 + \partial_3 LAI_{it} + \partial_4 LFA_{it} + \partial_5 LGOB_{it} + \partial_6 LURBA_{it} \quad (4)$$

Econometric Framework

The present research uses the Pesaran test to assess cross-sectional connections among economies. Then, to guarantee data stationarity, it utilizes both second-generation tests like CIPS and CADF and first-generation tests like Levin, Lin & Chu (LLC) and IPS. Then, Pedroni panel cointegration tests are applied in the study to verify long-term connections. With the use of ARDL and quantile regression tests, it further investigates both short- and long-term links. Next, the DKSE, AMG, and CCEMG approaches are adopted to validate the long-run estimates' robustness. With the goal to check out the causative association among the variables, the D-H causalty analysis is finally executed.

Cross-Sectional Dependency Test

As economies grow increasingly integrated and dependent on one another, industrialization is making CSD greater a problem in panel data (De Hoyos and Sarafidis, 2006). Moreover, Tufail et al. (2022) suggest that as a consequence of variables including reduced obstacles to trade, improved socioeconomic connectivity, the usage of CSD in panel data econometrics is growing. The authors of this research utilize the Pesaran's (2015) analysis for weakly exogenous CSD in large panel data econometrics to find whether CSD exists.

$$CSD = \sqrt{\frac{2T}{N(N-1)N}\left(\sum_{i=1}^{N-1}\sum_{m=i+1}^{N}\widehat{Corr_{\iota,t}}\right)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (5)$$

Panel Unit root Test

To explore if stationarity existed in our panel data, our research investigated unit root test techniques from both the first and second generations. We used the Im et al. (2003)-introduced IPS test and the Levin, Lin, and Chu (LLC) test, which is a first-generation unit root examination invented by Levin et al. (2002). In contrast, second-generation unit root assessments that account for slope fluctuation and CSD include CIPS and CADF, which were developed by Pesaran (2007). The CIPS test is the extension of the IPS examination (Polcyn et al.,2023). Voumik and Sultana (2022) claim that the unit-root series forms the basis for the theory. Before estimating the parameter, the test also recommends doing a cointegration test when the variable reaches first-difference stationarity. The below formula can be applied to represent the IPS test:

$$\Delta y_{it} = \delta_i + \alpha_i t + \beta y_{it-1} + \rho_i \Delta y_{it-1} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (6)$$

The LLC test statistics is given below:

$$\Delta \mathrm{y_{it}} = \delta_i \mathrm{y_{it-1}} + \sum_{\mathrm{j=1}}^{\rho\mathrm{i}} \mathrm{d_{ij}} \Delta \mathrm{y_{it-1}} + \mathrm{X'_{it}} \eta + \mu_{\mathrm{it}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Here, X'_{it} means the column vector of the independent variable and in regression η indicates the vector of parameters. The CIPS unit root test is a modified version of the IPS method that looks at unit roots in individual time series. Within the academic community, CIPS is becoming increasingly popular because of its efficaciousness in handling CSD and heterogeneity. This test equation takes the following form:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} t_i\,(N,T) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (8)$$

The CADF method is adopted to gather the statistics required by CIPS. The following equation describes the CADF statistics.

$$\Delta Y_{it} = \beta_i + \rho_i Y_{i,t-1} + \vartheta_i \bar{Y}_{t-1} + \sum_{j=1}^{p} \gamma_{ij} \Delta Y_{i,t-1} + \varepsilon_{it} \ldots\ldots\ldots\ (9)$$

Where, $\bar{Y}_{t-1}$ and $\Delta Y_{i,t-1}$ are average for lagged and first difference of each cross-sectional series.

Panel Cointegration Test

According to Anser et al. (2024), cointegration denotes a reliable, long-term link between the panel's variables. The Pedroni (1999) panel cointegration assessment is employed to figure out if cointegration prevails, assuming panel heterogeneity. This approach was adopted in the study; in contrast to Kao (1999), it permits the AR coefficients to vary between panels. Two separate tests were developed by Pedroni (1999, 2004). Four statistical measures are applied in the initial test, which uses a within-dimension approach: panel v-statistics, panel rho-statistics, panel PP-statistics, and panel ADF-statistics. The following analysis utilizes a between-dimension methodology using group rho-statistics, group PP-statistics, and group ADF-statistics as its three statistical measures. It is carried out in this manner:

$$sh_{it} = \vartheta_0 + \mu_i t + \delta_{1i} bkd_{it} + \beta_{2i} ib_{it} + \rho_{3i} ihr_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots \quad (10)$$

Where, i=1... N for each firm in the panel and t=1,..., T denotes the time period. The estimated residuals reveal how far the long-run association deviates from expectations.

Panel ARDL Model

Using the panel ARDL framework, Pesaran et al. (1999) established the pooled mean group (PMG) technique. Pesaran et al. (1999) propose that the inconsistency situation, common technological advances, or the development of institutions that each group encountered constitute a few explanations for the homogeneity in the long-term connection. Additionally, by considering lag duration for both exogenous and endogenous variables, the ARDL model (Attiaoui and Boufateh,2019). Furthermore, this approach has the advantage of effectively managing autocorrelation, heteroscedasticity, and multicollinearity difficulties in models, as illustrated by Wang et al. (2021). In this study, the short- and long-term effects of GDP development, artificial intelligence (AI) innovation, financial accessibility, globalization, and urbanization on LCF were investigated using the PMG-ARDL model. The PMG estimator relies on the ARDL model and assumes that the panel as a whole has the same long-run coefficients, whereas each group has unique short-term coefficients, intercepts, and error parameters.
The ARDL simulation, which is considered relevant in this context if it can be specified as an error correction model when the underlying variables are somewhat integrated (I (0) and I (1)), with the restriction that the dependent variable is limited to just I (1) (Voumik et al.,2023b; Ridwan, 2023). Nevertheless, this method is not applicable when variables are integrated for order 2 removes endogeneity issues and provides reliable and effective estimators (Pesaran et al.,1996, 2001). The long-term association models for PMG are presented below:

$$\Delta \mathrm{Y}_{1,\mathrm{it}} = \vartheta_{1\mathrm{i}} + \beta_{1\mathrm{i}} \mathrm{Y}_{1,\mathrm{it}-1} + \sum_{\mathrm{l}=2}^{\mathrm{k}} \beta_{1\mathrm{i}} \mathrm{X}_{1,\mathrm{it}-1} + \sum_{\mathrm{j}=1}^{\mathrm{p}-1} \lambda_{1\mathrm{ij}} \Delta \mathrm{Y}_{1,\mathrm{it}-\mathrm{j}} + \sum_{\mathrm{j}=0}^{\mathrm{q}-1} \sum_{\mathrm{l}=2}^{\mathrm{k}} \lambda_{\mathrm{lij}} \Delta \mathrm{X}_{1,\mathrm{it}-\mathrm{j}} + \varepsilon_{1\mathrm{i,t}} \quad (11)$$

Here, Y_i refers the dependent variable and X_i are independent factors where l=1,2, 3,4. ε_{it} and Δ are residual & first difference operator accordingly.

We found the following long-term ARDL simulation for LCF as the dependent variable:

$$\Delta LLCF_{it} = \vartheta_{1i} + \beta_{1i} LLCF_{i,t-1} + \beta_{2i} LGDP_{i,t-1} + \beta_{3i} LGDP_{i,t-1}^2 + \beta_{4i} LAI_{i,t-1} + \beta_{5i} LFA_{i,t-1} + \beta_{6i} LGOB_{i,t-1} + \beta_{7i} LURBA_{i,t-1} + \sum_{m=1}^{q} \lambda_{1i} \Delta LCF_{i,t-m} + \sum_{i=0}^{p} \lambda_{2i} \Delta LGDP_{i,t-m} +$$

$$\sum_{i=0}^{p} \lambda_{3i} \Delta LGDP_{i,t-m}^{2} + \sum_{i=0}^{p} \lambda_{4i} \Delta LAI_{i,t-m} + \sum_{i=0}^{p} \lambda_{5i} \Delta LFA_{i,t-m} + \sum_{i=0}^{p} \lambda_{6i} \Delta LGOB_{i,t-m} + \sum_{i=0}^{p} \lambda_{7i} \Delta LURBA_{i,t-m} + \varepsilon_{1i,t} \quad (12)$$

The ECT and short-term correlations are examined using the Engle and Granger (1987) ECM model after long-term relationships have been established (Voumik et al.,2023c). Equation (14) utilizes the ARDL estimate with error correction representation to explain the short-term link across the variables:

$$\Delta \mathrm{LLCF}_{\mathrm{it}} = \sum_{\mathrm{m}=1}^{\mathrm{q}-1} \alpha_{1\mathrm{im}} \Delta \mathrm{LLCF}_{\mathrm{i,t-m}} + \sum_{\mathrm{i}=0}^{\mathrm{p}-1} \alpha_{2\mathrm{im}} \Delta \mathrm{LGDP}_{\mathrm{i,t-m}} + \sum_{\mathrm{i}=0}^{\mathrm{p}-1} \alpha_{3\mathrm{im}} \Delta LGDP_{i,t-m}^{2} + \sum_{\mathrm{i}=0}^{\mathrm{p}-1} \alpha_{4\mathrm{im}} \Delta \mathrm{LAI}_{\mathrm{i,t-m}} + \sum_{\mathrm{i}=0}^{\mathrm{p}-1} \alpha_{5\mathrm{im}} \Delta \mathrm{LFA}_{\mathrm{i,t-m}} + \sum_{\mathrm{i}=0}^{\mathrm{p}-1} \alpha_{6\mathrm{im}} \Delta \mathrm{LGOB}_{\mathrm{i,t-m}} + \sum_{\mathrm{i}=0}^{\mathrm{p}-1} \alpha_{7\mathrm{im}} \Delta \mathrm{LURBA}_{\mathrm{i,t-m}} + \mu_{1\mathrm{i}} \mathrm{ECT}_{1,\mathrm{it}-1} + \varepsilon_{1\mathrm{i,t}} \quad (13)$$

Quantile Regression

Additionally, this research adopted quantile panel regression analysis for several reasons. Quantile analysis delivers a major benefit over conventional regression approaches as it enables one to figure out regression conditional quantiles and forecast how specific points within the conditional distribution will develop (Alharthi et al., 2021). The study employed the panel quantile regression model proposed by Koenker and Bassett (1978) as an illustration as it permits users to utilize the values of the explanatory factors to judge the change in the dependent variable and the conditional mean (Masiero et al., 2015). This offers vital details on the links between variables in numerous situations or quantiles (Kilinc-Ata et al.,2024). Academics from a wide range of subjects, such as environmental research (Carfora et al., 2017), economics (Shahzad et al., 2017), and clinical studies (Olsen et al., 2017), are embracing QR widely due to its numerous advantages. The QR can be shown by the following equation-

$$\mathrm{Q}_{LRCY_{\mathrm{it}}} \left(\partial \mid \emptyset_0, \mathrm{x}_{\mathrm{it},} \mu_{\mathrm{i}}\right) = \emptyset_0 + \mu_{\mathrm{it}} + \emptyset_{1\,\partial} \mathrm{LGDP}_{\mathrm{it}} + \emptyset_{2\,\partial} LGDP^{2}{}_{\mathrm{it}} + \emptyset_{3\,\partial} LAI_{\mathrm{it}} + \emptyset_{4\,\partial} \mathrm{LFA}_{\mathrm{it}} + \emptyset_{5\,\partial} \mathrm{LGOB}_{\mathrm{it}} + \emptyset_{6\,\partial} \mathrm{LURBA}_{\mathrm{it}} + + \varepsilon_{\mathrm{it}} \quad \ldots\ldots\ldots\ldots\ldots (14)$$

Here,$\left(\partial \mid \emptyset_0, \mathrm{x}_{\mathrm{it},} \mu_{\mathrm{i}}\right)$ is the ∂ th conditional quantile. Moreover, the notion ∂ and X_{it} indicates the quantile measure and independent factors accordingly.

Robustness Check

This stage involves running the DKSE, AMG, and CCEMG procedures to confirm the results' robustness. To obtain the values of explanatory variables, we implemented three distinct estimators to find the long-run hyperlink. The average values of the findings for the explanatory variable are used in addition to the residuals in the Driscoll and Kraay (1998) Standard Error. When there is cross-sectional reliance, Driscoll-Kraay standard errors are employed because they are heteroscedastic, autocorrelation consistent, as well as resistant to typical forms of cross-sectional and temporal dependency (Hoechle, 2007). Teal and Eberhardt (2010) included the production function in their revised augmented mean group (AMG) panel estimator. The primary advantage of this method is that it can aid in the correction of outcomes when panel heterogeneity and multifaceted error terms are present (Nathaniel & Iheonu, 2019). In conclusion, Pesaran (2006) developed this estimate model to replace the CCEMG estimator. This method generates reliable figures, allows time-varying unobserved factors with varying influences across panel members and robust against CSD problem. This approach can handle both an infinite number of "weak" factors and a finite number of "strong" unobserved common elements (Anshasy and Katsaiti, 2014; Addae et al.,2023).

D-H casuality Test

Causality tests are required to identify the relevant policy implications for managing the emergence of the LCF. A technique for evaluating causal linkages between the components was presented by Granger (1969); however, it has drawbacks and cannot be applied when panel data has a CSD problem. The cointegration connection suggests all factors are in a long-term equilibrium. Thus, we use the pane causality test of Dumitrescu et al. (2021) to examine their causative relationship. Because it can determine both N > T and T > N samples, this strategy can be flexible and beneficial for getting precise outcomes throughout CD (Ahmed and Le, 2021). By comparing each of the N factors to a minimum of one causal link in the panel, this method evaluates the null hypothesis of non-causality in each instance. In particular, the alternative hypothesis claims that at least a causality might be discovered in the panel (Hurtado et al., 2024).

Result and Discussion

Table 1 illustrates the statistical outcome of several measures of normality, such as skewness, probability, kurtosis, and the Jarque-Bera test. The dataset covers the G-7 nations from 1990 to 2019 and contains 91 observations for each variable. Using the following descriptive statistics, the seven variables (LLCF, LGDP, LGDPSQ, LAI, LGOB, LFA, and LURBA) are characterized.

Table 2. Summary Statistics

Statistic	LLCF	LGDP	LGDP^2	LAI	LFA	LGOB	LURBA
Mean	-0.943801	10.69067	114.3221	5.522956	4.873562	4.428334	4.387441
Median	-1.121269	10.67368	113.9275	5.513429	4.803375	4.426225	4.397432
Maximum	0.723357	11.24282	126.4009	9.709417	5.907974	4.493778	4.521299
Minimum	-2.038284	10.317	106.4405	1.609438	4.375432	4.292134	4.224305
Std. Dev.	0.779588	0.178842	3.840701	2.003691	0.373498	0.053247	0.075888
Skewness	0.811059	0.519595	0.575074	0.220978	0.879703	-0.72077	-0.260761
Kurtosis	2.868482	3.496751	3.583357	2.426018	2.993025	2.734066	3.070021
Jarque-Bera	10.04246	5.030319	6.306099	1.989793	11.73734	8.147367	1.049867
Probability	0.006596	0.08085	0.042722	0.369762	0.002827	0.017015	0.591595
Sum	-85.88593	972.851	10403.31	502.589	443.4941	402.9784	399.2571
Sum Sq. Dev.	54.69818	2.878612	1327.589	361.3301	12.55509	0.255174	0.51831
Observations	91	91	91	91	91	91	91

All selected variables have positive means, except for LLCF, as can be observed in the table. Additionally, most of the variables' estimated standard deviations are quite small, suggesting that the data points are a little temporally changeable and concentrated around the mean. The data for each variable, including the mean, standard deviation, lowest and maximum values, and the number of observations, will be shown in the box below. Other than LGOB and LLCF, which have a negative skew, the majority of the variables have a positive skew. Furthermore, each variable in this research was verified to have a normal distribution using the Jarque-Bera normality test. Given that it takes into account both skewness and any anomalous kurtosis, this test is suitable.

The Pesaran (2004) CSD evaluation findings are displayed in Table 03 below. The p-values presented above conclusively indicate that at 1% significance levels, all of the variables (LLCF, LGDP, LGDPSQ, LAI, LFA, LGOB, and LURBA) have statistical significance. In our research, cross-sectional dependency is accepted as the alternate hypothesis of the CD test. This suggests that our data collection contains CSD.

Table 3. Results of CSD test

Variables	CD-Statistics	P-Value
LLCF	5.84***	0.000
LGDP	5.36***	0.000
$LGDP^2$	5.37***	0.000
LAI	13.33***	0.000
LFA	3.96***	0.003
LGOB	11.46***	0.000
LURBA	16.61***	0.000

Before doing a cointegration inquiry, it is essential to conduct extensive unit root testing to see whether the variables are stationary. The outcomes of these unit root analyses are displayed in Table 04. In this research, LLC, and IPS, first-generation unit root tests were utilized in conjunction with CIPS and CADF, second-generation tests. The variables LAI, LFA, and LGOB are the only variables that show stationary behavior at the first difference, based on the LLC test findings. At the I(1) difference, the other variables likewise exhibit stationarity. At the 1% significance thresholds, each of these factors is significant. However, the findings of the IPS test indicate that only LFA and LGOB stay stable at their initial level all other variables (LLCF, LGDP, LGDPSQ, LAI, and LURBA) are similarly significant at the 1% significance level and are stationary at the first difference (I(1)).

The stationarity characteristics of the variables were further investigated utilizing the CIPS and CADF tests to guarantee more dependable findings. By adding cross-sectional averages of lag values and initial differences, these tests extend the capabilities of first-generation tests. Moreover, Table 05 demonstrates that, with the exception of LAI and LGOB, all variables are stationary following the first difference based on the CIPS test. In contrast, the findings of the CADF test indicate that all other variables are stationary at the first difference I(1), except for the LAI and LFA, which are stationary at their level form. The outcome of this investigation indicates that the components have undergone considerable cointegration, hence removing the possibility of a unit root issue.

Table 4. Panel Unit Root Test

Variables	Levin, Lin &Chu		IPS		CIPS		CADF		Decision
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
LLCF	-2.496	-5.071***	-0.702	-3.754***	-0.629	-3.869***	-1.230	-3.651***	I(1)
LGDP	-0.843	-5.947***	-1.622	-4.604***	-1.835	-3.392***	-1.469	-3.722***	I(1)
$LGDP^2$	-0.657	-5.957***	-1.614	-4.600***	-1.882	-3.498**	-1.516	-3.584***	I(1)
LAI	-5.346***	-5.705***	-1.229	-4.262***	-2.895**	-4.634***	-3.023**	-3.838***	I(0)
LFA	-5.687***	-6.087***	-3.255**	-4.740***	-1.098	-3.562***	-2.985**	-3.812***	I(0)
LGOB	-5.109***	-4.415***	-3.888***	-4.436***	-3.098**	-5.462***	-1.530	-3.480***	I(0)
LURBA	-0.132	-4.267***	-2.599	-7.924***	-0.659	-3.859***	-0.882	-3.087**	I(1)

Table 05 illustrates the Pedroni panel cointegration test findings, encompassing both within- and between-dimension investigation. There is no indication of cointegration because the p-values for the Panel v-Statistic and Panel rho-Statistic (0.5186 and 0.9987, respectively) are higher than the conventional significance threshold. Nonetheless, the Panel PP-Statistic and Panel ADF-Statistic p-values are less than the traditional significance criteria, indicating that the null hypothesis of no cointegration is rejected. Cointegration appears to be present based on these figures. The Group rho-statistic in the between-dimension analysis displays a very high p-value of 0.9381, suggesting that there is not enough evidence for cointegration in any of the panels. The Group ADF-Statistic and the Group PP-Statistic, on the other hand, both reveal evidence of cointegration across the panels, with p-values of 0.000. Consequently, all of the variables are cointegrated over the long run, based on Pedroni's cointegration techniques.

Table 5. Panel Cointegration Test

Alternative hypothesis: common AR coefs. (within-dimension)				
	Statistic	Prob.	Weighted Statistics	Prob.
Panel v-Statistic	1.30446	0.0960	-0.04653	0.5186
Panel rho-Statistic	2.79995	0.9974	3.00827	0.9987
Panel PP-Statistic	-2.50037	0.0000	-2.08538	0.0000
Panel ADF-Statistic	-3.82612	0.0000	-4.08531	0.0000
Alternative hypothesis: individual AR coefs. (between-dimension)				
	Statistic	Prob.		
Group rho-Statistic	4.47852	0.9381		
Group PP-Statistic	-2.40568	0.0000		
Group ADF-Statistic	-4.01587	0.0000		

The conclusions obtained from the Panel ARDL model, as illustrated in Table 06, shed light on the intricate dynamics affecting LCF in the G-7 nations. For LGDP as a starting point, the long-run coefficient is -0.048, statistically significant at traditional levels. GDP has a negative coefficient of -0.045 in the short term, which is statistically insignificant with a p-value over the usual level. It demonstrates that GDP has a considerable implication on LCF in the chosen area, suggesting that in this particular context, economic growth alone may be a major contributor to environmental degradation. According to Ang (2007) and Raihan et al.(2023a) economic expansion contributes to environmental degradation and has an advantageous effect on the emissions of CO_2. It was discovered that economic expansion posed a challenge to the reduction in emissions (Liu et al.,2020; Liu et al.,2016; Chen et al.,2022; Raihan et al.,2022b; Pattak et al.,2023; Voumik et al.,2023a; Raihan et al.,2023c; Ridwan et al.,2023; Ridwan et al.,2024a; Raihan et al.,2024c; Raihan et al.,2024d). Furthermore, Arouri et al. (2012) added that the main factor contributing to environmental deterioration in MENA nations is GDP growth. However, Acheampong et al. (2022) observed that Australia's CO_2 emissions are not heavily impacted by fluctuations in GDP.

In the short and long terms, there is an encouraging link between LGDP2 and LCF, with statistically significant coefficients. These results demonstrate that rising GDP has a beneficial long-term impact on the environmental conditions in the G-7 economies. The study shows that, in both cases, Artificial Intelligence (LAI) and LCF have a substantial positive link. Over the short and long terms, an extra one percent in LAI causes an equivalent rise in LCF of 0.029% and 0.142%, respectively. These findings highlight the need for AI innovation to guarantee the

G-7 region's ecological viability over time. In a similar vein, LFA and LCF have a positive correlation over the short and long terms, suggesting that having access to money can have a good environmental impact. With p-values less than 0.05 in each scenario, these results are statistically significant. This might be because immediate environmental surveillance strengthens the utilization of resources, and the application of AI can boost energy conservation in numerous areas, including residential electricity usage, travel, and manufacturing.. Moreover, novel technologies should be encouraged by policymakers to safeguard the environment and advance biodiversity (Alavijeh et al.,2023). The table indicates that there is a negative correlation between globalization (LGOB) and LCF in both the short and long term; however, the effect is statistically significant in the long term and negligible in the short term. This shows that while globalization promotes increased commerce and energy demand, it is not potentially good for biodiversity. The growing need for commodities and amenities across national borders made accessible by global commerce has led to a spike in greenhouse gas emissions due to globalization (Kirikkaleli et al.,2023). Study by Shahbaz et al.(2018) in Japan and Sharif et al.(2022) in G-& area also discovered that globalization is harmful for the ecosystem. However, globalization aids in resolving this problem and enhancing the environment (Adebayo et al., 2022). Furthermore, Khurshid et al. (2024) demonstrate that environmental sustainability is positively impacted by globalization.

Similarly, urbanization (LURBA) has a negative connection with LCF in both short- and long-term assessments. Over time, a 1% spike in LURBA generates a small but statistically significant 0.044% drop in LCF at conventional levels. With a p-value above 0.05, the findings, however, are not significant in the short run. Furthermore, a significant short-term reduction of 0.222% in LCF is linked to a 1% rise in LURBA. One possible reason for this outcome can be the loss of forests and the destruction of natural environments for construction are common consequences of growth in urban areas, which decrease diversity and disturb ecology. This conclusion defies those of Aye et al. (2017), who claimed that economic expansion tends to cut CO2 emissions in low-growth regimes and spikes in high-development regimes.

We used the quantile regression (QR) approach to explore the factors influencing the LCF in the G-7 economies. Five quantile points the fifth, 25th, 50th, 75th, and 95th were chosen especially for this study's regression calculation. First, for all quantiles, there is a negative correlation between the variable LGDP and LLCF. This finding suggests that in the chosen area, economic expansion had a positive impact on environmental standards. In the first and fifth quantiles, the coefficient is significant at the 1% significance thresholds; in the remaining quantiles, it is significant at the 5% significance level. These indicate that GDP might have a detrimental effect on the environment of G-7 region.

Second, across all quantiles, LGDP2 has an upward association with LCF which is statistically significant at different levels. The first quantile has the lowest coefficient value, while the second quantile has the greatest. This investigation has taken into account LAI, the third important component impacting LCF. Except for the fourth quantile, which is significant at the 5% level, the outcomes illustrated that the LAI coefficients are positively related to LCF and statistically significant at the 1% level for all quantiles. Interestingly, the second quantile has the most effect; at the 25th percentile, an additional 1% in AI corresponds to a 0.094% increase in LCF. This indicates that adoption of AI is beneficial for G-7 area.

The findings show an upward trend between the LFA variable and LCF, which is significant at the 1% level for all quantiles. A 1% rise in LFA causes an LLCF increase of 0.84% in the first quantile and 2.11% in the final quantile. Stated differently, financial accessibility in the G-7 economies fosters circularity and improves ecological conditions. It is noteworthy that there is a considerable rise in impact intensity throughout the quantiles. Likewise, there is a beneficial relationship between the dependent variable, LLCF and the variable LGOB. The intensity rises through the upper quantiles, reaching 11.18 in the fifth quantile, with the exception of the second quantile, where the coefficient value is 2.775.

Table 6. Panel ARDL Model

Long-run Estimation				
Variable	Coefficient	Std. Error	t-Stat	p-Value
LGDP	-0.048	0.0298	-2.8743	0.0234
LGDP2	0.069	0.0689	2.8604	0.0471
LAI	0.142	0.0930	1.5359	0.0034
LFA	0.793	0.0574	2.3248	0.0258
LGOB	-1.822	0.1019	-2.3949	0.0221
LURBA	-0.044	0.0218	-2.1418	0.0393
Short-run Estimation				
Variable	Coefficient	Std.Error	t-stat	P-value
COINTEQ01	-0.039	0.1887	-1.207399	0.0369
D(LGDP)	-0.045	0.0046	-2.403889	0.0689
D(LGDP2)	0.121	0.0571	1.393902	0.0219
D(LAI)	0.029	0.0595	2.182761	0.0057
D(LFA)	0.088	0.9665	0.091868	0.0273
D(LGOB)	-0.671	1.2798	-0.857848	0.0967
D(LURBA)	-0.222	0.4836	-0.934931	0.0561

Finally, with a single instance of the last quantile, the coefficient values for the indicator LURBA are negative for every quantile. The discoveries demonstrate statistical significance at the 1% level in the first, second, and fifth quantiles; however, the finding is not significant in the third and fourth quantiles. It is clear from observation that the final quantile has the biggest coefficient value (3.66). The outcome suggests that urbanization in the chosen area has greater adverse impacts on the natural landscape.

A number of estimating techniques, including DKSE, AMG, and CCEMG, were used to further examine the accuracy of quantile regression estimates and ARDL findings. Table 08 contains information on the DKSE, AMG, and CCEMG results. The projected LGDP values for the three tests are, respectively, -0.123, -0.049, and -0.054. These results indicate that economic expansion advantages the environment quality in the G-7 countries. The DKSE and CCEMG estimators have a significant coefficient value at 1%, but the AMG estimator has a significant coefficient value at the 5% level. The outcome is aligns with the panel ARDL model and quantile regression conclusions.

Conversely, the LCF variable has a positive correlation with LGDP2, LAI, and LFA. The LGDP2 coefficient values are significant at the 10% level in the AMG test and identical at the 1% significance level in the DKSE and CCEMG tests. In particular, a boost of 1% in AI innovation drives LCF to go up by 0.0077%, 0.0466%, and 0.0129%, in that sequence. This suggests that the G-7 countries' ecosystems may be improved by implementing AI technology. These results align with inferences made from the Panel ARDL and QR estimations. On the other hand, the LCF variable reveals adverse associations for LGOB and LURBA, suggesting that growing urbanization and globalization are detrimental to biodiversity in the chosen places. At the 1% level in the DKSE estimation, the 10% level in the AMG estimation, and the 5% level in the CCEMG estimation, LGOB and LURBA are both statistically significant. The LGOB result contradicts the conclusions of the ARDL model and only agrees with the QR results. In the meanwhile, the Panel ARDL and QR findings agree with the LURBA result. Thus QR and ARDL model, which serve as the main estimated method in this work, are validated by the outcomes obtained.

Table 7. Quantile regression approach

VARIABLES	(1) Q0.05	(2) Q0.25	(3) Q0.50	(4) Q0.75	(5) Q0.95
LGDP	-0.683***	-0.072**	-0.282**	-0.031**	-0.039***
	(0.0718)	(0.6018)	(0.8215)	(0.2439)	(0.0845)
LGDP2	0.017***	0.499**	0.226**	0.106**	0.178
	(0.0268)	(0.0115)	(0.0971)	(0.9761)	(0.0799)
LAI	0.047***	0.094***	0.020***	0.019**	0.089***
	(0.0086)	(0.0325)	(0.0675)	(0.0636)	(0.0257)
LFA	0.846***	0.648***	2.184***	2.282***	2.111***
	(0.0424)	(0.160)	(0.332)	(0.313)	(0.127)
LGOB	2.902***	2.775***	7.968***	10.27***	11.18***
	(0.233)	(0.879)	(1.824)	(1.719)	(0.695)
LURBA	-2.219***	-3.871***	-1.945	-0.0655	3.666***
	(0.208)	(0.786)	(1.632)	(1.538)	(0.622)
Constant	-45.419***	-92.712**	-29.123***	-15.765**	-52.836
	(10.822)	(20.723)	(13.712)	(7.323)	(29.081)
Observations	91	91	91	91	91

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The findings of the D-H causality assessment for the LCF of the G-7 economy are summarized in Table 9. The null hypothesis, which claims that the factor under investigation does not consistently cause another variable, can be rejected if the p-value approaches significant values of 1%, 5%, or 10%. Based on the research, the p-value of 0.0039 demonstrates that the effect of LGDP on LLCF is statistically significant at the 1% level. As a result, the null hypothesis can be rejected, guiding us to the conclusion that there is only one way of causality from LGDP to LLCF. Conversely, as the p-value is higher than the expected values, there is not a significant correlation between LLCF and LGDP. This result suggests a one-way connection and illustrates how ecological health in the G-7 countries can be affected by economic expansion.

Table 8. Robustness check

VARIABLES	(1) DKSE	(2) AMG	(3) CCEMG
LGDP	-0.123***	-0.049**	-0.054***
	(0.0090)	(0.0264)	(0.0813)
LGDP2	0.021***	0.068*	0.199***
	(0.0102)	(0.1210)	(0.0531)
LAI	0.00770***	0.0466***	0.0129***
	(0.0215)	(0.0656)	(0.223)
LFA	0.284***	0.493**	0.685**
	(0.009)	(0.0464)	(3.927)
LGOB	-0.912***	-0.546*	0.420**
	(0.0532)	(0.799)	(0.267)
LURBA	-0.502***	-0..971*	-0.552**
	(1.294)	(11.74)	(45.70)
Constant	20.218**	17.604**	12.981**
	(0.2671)	(0.5019)	(0.8765)
Observations	91	91	91
Number of groups	7	7	7

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9. D-H Casuality Test

Null Hypothesis	Observation	Prob.
LGDP ≠ LLCF	91	0.0039
LLCF ≠ LGDP		0.1135
LGDP2 ≠ LLCF	91	0.0062
LLCF ≠ LGDP2		0.1163
LAI ≠ LLCF	91	0.0208
LLCF ≠ LAI		0.0409
LFA ≠ LLCF	91	0.0527
LLCF ≠ LFA		0.5953
LGOB ≠ LLCF	91	0.0148
LLCF ≠ LGOB		0.9493
LURBA ≠ LLCF	91	0.0609
LLCF ≠ LURBA		0.5379

Further examination exposes a similar unidirectional link between LLCF and LGDP2. Furthermore, as we are unable to exclude the null hypothesis in this instance, the results indicate fluctuations in LLCF have no effect on LGDP2. The LCF and LAI, on the other hand, have a bidirectional hyperlink, evidenced by statistically significant p-values across all studies. Furthermore, as the suggested p-values are greater than traditional levels, there prevails no association from LFA to LLCF, LCF to LFA, LURBA to LLCF and LLCF to LURBA. Nevertheless, there exists a substantial unidirectional causal connection between LGOB and LLCF as the p-value is 0.0148 and it is significant at 1% significance level. This outcome reveals that we can reject the null hypothesis and come to the conclusion that globalization degrade the ecosystem.

Conclusion

This comprehensive study discusses the complex relationships among globalization, urbanization, financial accessibility, AI innovation, economic growth, and LCF in the G-7 territory between 1990 and 2019. The LCC hypothesis is used in this research to determine how such significant variables affect LCF dynamics. Data stationarity was observed using both first and second-generation unit root examinations to guarantee accurate estimation and to establish that the dataset was free of unit root problems. The panel cointegration test was also utilized in the inquiry to clarify the heterogeneous coefficients and demonstrate long-term cointegration across the factors under consideration. The Panel Autoregressive Distributive Lag Model (ARDL) in conjunction with quantile regression techniques enables an expanded examination of the complicated interactions between the dependent and explanatory variables. The results underscore the vital role of urbanization, GDP, and globalization in the higher rates of environmental pollution in the G-7 region. However, the quality of the ecosystem benefits from financial accessibility and AI innovation. To guarantee the correctness of the analytical framework, rigorous steps including DKSE, AMG, and CCEMG were implemented. The robustness of the quantile regression and panel ARDL studies was confirmed by all these techniques. Furthermore, Dumitrescu and Hurlin (D-H) causality tests were used to explore the causal links between each variable. The findings demonstrated a unidirectional causal association between LLCF and LGDP, LAI, and LGOB. In addition, it was discovered that none of the three factors financial accessibility, urbanization, and load capacity factor drives the other. Our investigation delivers fascinating insights into the complexities of changing LCF patterns in the G-7, which has major implications for stakeholders and decision-makers who are committed to promoting green policies and equitable growth in those nations.

Creating policies that support both environmental sustainability and financial advancement is crucial to addressing the G-7 region's U-shaped link between wealth and load capacity factor. To lessen the negative effects on environmental sustainability as wealth grows, stricter regulations on resource use and pollution must be implemented. Early on in the economic growth process, environmental degradation may be successfully stopped by offering tax breaks and subsidies to encourage sustainable practices and green technologies. Furthermore, funding programs for awareness and education might encourage long-term client behavior. The promotion of advanced clean technologies and renewable energy sources must be the focus of policy given the continuous rise in wealth (Raihan et al.,2024e). This will ensure that increasing income levels have more detrimental effects on the environment. Encouraging corporate responsibility and integrating sustainability metrics into financial reporting have the potential to significantly accelerate companies' transition to greener practices. The G-7 nations' cooperation and idea sharing can increase the effectiveness of these programs even further. The G-7 area may attain a healthy balance between environmental sustainability and economic growth through the implementation of a progressive and adaptable plan. The results draw attention to important policy implications for the G-7 countries that want to improve environmental sustainability. Governments ought to give AI research and development top priority, concentrating on innovations that track, forecast, and lessen environmental effects. Promoting public-private partnerships may hasten the utilization of AI solutions in sectors including transportation, energy, and agriculture, maximizing resource efficiency and cutting emissions. Furthermore, financial institutions must to be encouraged to offer easily available capital for environmentally friendly solutions so that small and beginning businesses may support the sustainability agenda. Broader adoption can be facilitated by implementing tax credits, subsidies, and low-interest loans for initiatives that benefit the environment. In order to promote inclusive growth and fair access to sustainable technology, policymakers must also make sure that underprivileged people are included in the financial accessibility framework. Financial strategy integration with AI may improve decision-making even more, resulting in environmental policies that are more flexible and successful. All things considered, a cooperative strategy that blends financial accessibility with AI innovation may greatly advance the G-7's pursuit of sustainability and spearhead international efforts to tackle climate change. The outcomes presents substantial policy frameworks for tackling the decreasing load capacity factor in the G-7 area caused by globalization and urbanization. Policymakers must to adopt measures to effectively handle urban expansion in a manner that is environmentally responsible, with a particular focus on promoting the establishment of eco-friendly infrastructure and intelligent urban initiatives to optimize the use of resources. Encouraging the implementation of mixed-use projects and public transit can help mitigate the environmental impact of urbanization. In addition, it is imperative for governments to enforce regulations and provide incentives to encourage firms to embrace sustainable practices in their global supply chains, therefore reducing their impact on the environment. Promoting local production and consumption can mitigate the environmental consequences of globalization. In order to sustain the carrying capacity, it is imperative to enforce more stringent environmental rules and standards for both local and foreign businesses. Furthermore, allocating resources to renewable energy sources and energy-efficient technology might aid in reducing the negative impacts of growing urbanization and global economic activity. Facilitating global collaboration to exchange optimal methodologies and technology for promoting sustainability will be essential. In order to preserve the ecological equilibrium and assure long-term sustainability in the G-7 region, it is imperative to adopt a comprehensive policy strategy that tackles the environmental consequences of globalization and urbanization.

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References

Abdulla Al Shiam, S., Mohammad Ridwan, Mahdi Hasan, M., Akhter, A., Shamsul Arefeen, S. M., Hossain, M. S., Abir, S. I., & Shoha, S. (2024c). Analyzing the Nexus between AI Innovation and Ecological Footprint in Nordic Region: Impact of Banking Development and Stock Market Capitalization using Panel ARDL method. Journal of Environmental Science and Economics, 3(3), 41–68. https://doi.org/10.56556/jescae.v3i3.973

Abir, Shake Ibna, "Parameter Estimation for Stroke Patients Using Brain CT Perfusion Imaging with Deep Temporal Convolutional Neural Network," Masters Theses & Specialist Projects, Paper 3755, 2024.

Acheampong AO (2019) Modelling for insight: does financial development improve environmental quality? Energy Econ 83:156–179

Acheampong AO, Dzator J, Amponsah M (2022) Analyzing the role of economic globalization in achieving carbon neutrality in Australia. Int J Sustain Dev World Ecol 0(0):1–20. https://doi.org/10.1080/13504509.2022.2056771

Addae, E.A., Sun, D. & Abban, O.J. Evaluating the effect of urbanization and foreign direct investment on water use efficiency in West Africa: application of the dynamic slacks-based model and the common correlated effects mean group estimator. Environ Dev Sustain 25, 5867–5897 (2023). https://doi.org/10.1007/s10668-022-02284-9

Adebayo TS, Awosusi AA, Rjoub H, Agyekum EB, Kirikkaleli D (2022) The influence of renewable energy usage on consumption-based carbon emissions in MINT economies. Heliyon 8(2):e08941

Ahmad, S., Raihan, A., & Ridwan, M. (2024). Role of economy, technology, and renewable energy toward carbon neutrality in China. Journal of Economy and Technology. https://doi.org/10.1016/j.ject.2024.04.008

Ahmed Z, Zafar MW, Ali S, Danish (2020) Linking urbanization, human capital, and the ecological footprint in G7 countries: an empirical analysis. Sustain Cities Soc 55:102064. https://doi.org/10.1016/j.scs.2020.102064

Ahmed, Z., & Le, H. P. (2021). Linking Information Communication Technology, trade globalization index, and CO2 emissions: evidence from advanced panel techniques. Environmental Science and Pollution Research, 28(7), 8770-8781.https://doi.org/10.1007/s11356-020-11205-0

Akadiri SS, Alola AA, Olasehinde-Williams G, Etokakpan MU (2020) The role of electricity consumption, globalization and economic growth in carbon dioxide emissions and its implications for environmental sustainability targets. Sci Total Environ 708:134653. https://doi.org/10.1016/j.scitotenv.2019.134653

Akhter, A., Sarder Abdulla Al Shiam, Mohammad Ridwan, Abir, S. I., Shoha, S., Nayeem, M. B., Choudhury, M. T. H., Hossain, M. S., & Robeena Bibi. (2024). Assessing the Impact of Private Investment in AI and Financial Globalization on Load Capacity Factor: Evidence from United States. Journal of Environmental Science and Economics, 3(3), 99–127. https://doi.org/10.56556/jescae.v3i3.977

Alharthi, M., Dogan, E., & Taskin, D. (2021). Analysis of CO 2 emissions and energy consumption by sources in MENA countries: evidence from quantile regressions. Environmental Science and Pollution Research, 28, 38901-38908.

Ali HS, Abdul-Rahim AS, Ribadu MB (2017) Urbanization and carbon dioxide emissions in Singapore: evidence from the ARDL approach. Environ Sci Pollut Res 24(2):1967–1974

Alola, A. A., Doganalp, N., & Obekpa, H. O. (2023). The influence of renewable energy and economic freedom aspects on ecological sustainability in the G7 countries. Sustainable Development, 31(2), 716-727.https://doi.org/10.1002/sd.2414

Alola, A.A., Alola, U.V., Akdag, S. et al. The role of economic freedom and clean energy in environmental sustainability: implication for the G-20 economies. Environ Sci Pollut Res 29, 36608–36615 (2022). https://doi.org/10.1007/s11356-022-18666-5

Ameyaw B, Yao L (2018) Analyzing the impact of GDP on CO2 emissions and forecasting Africa’s total CO2 emissions with non-assumption driven bidirectional long short-term memory. Sustainability 10(9):3110

Ang JB (2007) CO2 emissions, energy consumption, and output in France. Energy Policy 35:4772–4778

Anser, M. K., Khan, M. A., Khan, M. A., Huizhen, W., & Haider, A. (2024). The effectiveness of emerging markets’ legal structure in explaining financial development. Plos one, 19(4), e0299831. https://doi.org/10.1371/journal.pone.0299831

Arif, M., Hasan, M., Al Shiam, S. A., Ahmed, M. P., Tusher, M. I., Hossan, M. Z., … Imam, T. (2024). Predicting Customer Sentiment in Social Media Interactions: Analyzing Amazon Help Twitter Conversations Using Machine Learning. International Journal of Advanced Science Computing and Engineering, 6(2), 52–56. https://doi.org/10.62527/ijasce.6.2.211

Arouri MEH, Youssef AB, M'henni H, Rault C (2012) Energy consumption, economic growth and CO 2 emissions in the Middle East and north African countries. Energy Policy 45:342–349

Attiaoui, I., & Boufateh, T. (2019). Impacts of climate change on cereal farming in Tunisia: a panel ARDL–PMG approach. Environmental Science and Pollution Research, 26, 13334-13345. https://doi.org/10.1007/s11356-019-04867-y

Awosusi AA, Kutlay K, Altuntaş M, Khodjiev B, Agyekum EB, Shouran M, Kamel S (2022) A roadmap toward achieving sustainable environment: evaluating the impact of technological innovation and globalization on load capacity factor. Int J Environ Res Public Health 19(6):3288

Aye, G. C., Edoja, P. E., & Charfeddine, L. (2017). Effect of economic growth on CO2 emission in developing countries: Evidence from a dynamic panel threshold model. Cogent Economics & Finance, 5, 1379239. https://doi.org/10.1080/23322039.2017.1379239

Bhattacharyya PS (2018) Sustainability of coal as a source of energy in India. In: Green Energy and Technology, pp 255–264

Boussaidi, R., & Hakimi, A. (2024, January). Financial inclusion, economic growth, and environmental quality in the MENA region: What role does institution quality play?. In Natural Resources Forum. Oxford, UK: Blackwell Publishing Ltd. https://doi.org/10.1111/1477-8947.12406

Carfora, A., Ronghi, M., & Scandurra, G. (2017). The effect of climate finance on greenhouse gas emission: A quantile regression approach. International Journal of Energy Economics and Policy, 7(1), 185-199.
Chen F, Wang L, Gu Q, Wang M, Ding X (2022) Nexus between natural resources, financial development, green innovation and environmental sustainability in China: Fresh insight from novel quantile ARDL. Resour Policy 79:102955. https://doi.org/10.1016/j.resourpol.2022.102955
Cyman D, Gromova E, Juchnevicius E (2021) Regulation of artificial intelligence in BRICS and the European Union. Brics Law J 8(1):86–115
Dai, J., Ahmed, Z., Alvarado, R., & Ahmad, M. (2024). Assessing the nexus between human capital, green energy, and load capacity factor: policymaking for achieving sustainable development goals. Gondwana Research, 129, 452-464. https://doi.org/10.1016/j.gr.2023.04.009
Danish R, Ulucak, Ud-Din Khan S (2020) Determinants of the ecological footprint: role of renewable energy, natural resources, and urbanization. Sustain Cities Soc 54:101996
Danish Z, Wang Z (2019) Does biomass energy consumption help to control environmental pollution? Evidence from BRICS countries. Sci Total Environ 670:1075–1083. https://doi.org/10.1016/j.scitotenv.2019.03.268
Danish, Ulucak R, Khan SU (2020) Determinants of the ecological footprint: role of renewable energy, natural resources, and urbanization. Sustain Cities Soc 101996
Das A, Sethi N (2023) Modelling the environmental pollution-institutional quality nexus in low-and middle-income countries: exploring the role of financial development and educational level. Environ Dev Sustain 25(2):1492–1518. https://doi.org/10.1007/s10668-021-02105-5
Dastgeer, A., Shabir, M., Usman, M. et al. Environmental cost of natural resources, globalization, and economic policy uncertainty in the G-7 bloc: do human capital and renewable energy matter?. Environ Sci Pollut Res 30, 115081–115097 (2023). https://doi.org/10.1007/s11356-023-30485-w
De Hoyos, R. E., & Sarafidis, V. (2006). Testing for cross-sectional dependence in panel-data models. The stata journal, 6(4), 482-496.
Dogan, A., & Pata, U. K. (2022). The role of ICT, R&D spending and renewable energy consumption on environmental quality: Testing the LCC hypothesis for G7 countries. Journal of Cleaner Production, 380, 135038. https://doi.org/10.1016/j.jclepro.2022.135038
Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. Review of economics and statistics, 80(4), 549-560.
Du, J., Yang, X., Long, D., & Xin, Y. (2024). Modelling the influence of natural resources and social globalization on load capacity factor: New insights from the ASEAN countries. Resources Policy, 91, 104816. https://doi.org/10.1016/j.resourpol.2024.104816
Dukhi N, Sewpaul R, Sekgala MD, Awe OO (2021) Artificial intelligence approach for analyzing anaemia prevalence in children and adolescents in BRICS countries: a review. Curr Res Nutr Food Sci J 9(1):01–10
Dumitrescu, E. I., Hué, S., & Hurlin, C. (2021). Machine Learning or Econometrics for Credit Scoring: Let's Get the Best of Both Worlds.
Einar H. Dyvik, Oct 19, 2023 Gross domestic product of G7 countries 2000-2023
El Anshasy, A. A., & Katsaiti, M. S. (2014). Energy intensity and the energy mix: What works for the environment?. Journal of environmental management, 136, 85-93. https://doi.org/10.1016/j.jenvman.2014.02.001
Engle, R. F., & Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. Econometrica: journal of the Econometric Society, 251-276.
Fang, Z., Wang, T., & Yang, C. (2024). Nexus among natural resources, environmental sustainability, and political risk: Testing the load capacity factor curve hypothesis. Resources Policy, 90, 104791. https://doi.org/10.1016/j.resourpol.2024.104791

Faruk, O., Hasan, S. E., Jubayer, A., Akter, K., Shiam, S. A. A., Rahman, K., Ali, M. Y., & Tufael. (2023). Microbial Isolates from Urinary Tract Infection and their Antibiotic Resistance Pattern in Dhaka city of Bangladesh. Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online), 2(3), 76-87. https://doi.org/10.60087/jklst.vol2.n3.p87

Ferdous, J., Sunny, A. R., Khan, R. S., Rahman, K., Chowdhury, R., Mia, M. T., Shiam, A. A., & Mithun, M. H. (2023). Impact of Varying Synthetic Hormone on Mystus cavasius (Hamilton): : Fertilization, Hatching, and Survival Rates. Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online), 2(3), 88-105. https://doi.org/10.60087/jklst.vol2.n3.p103

Gao, S., Zhu, Y., Umar, M., Kchouri, B., & Safi, A. (2024). Financial inclusion empowering sustainable technologies: Insights into the E-7 economies from COP28 perspectives. Technological Forecasting and Social Change, 201, 123177. https://doi.org/10.1016/j.techfore.2023.123177

Global footprint network. (2019). https://data.footprintnetwork.org/?_ga=2.12382004.1846558294.1655222840 2120200587.1654990805#/countryTrends?cn=5001&type=BCtot,EFCtot

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. Econometrica: journal of the Econometric Society, 424-438. https://doi.org/10.2307/1912791

Graver, B., & Rutherford, D. (2018, September). Transatlantic airline fuel efficiency ranking, 2017. ICCT.

Haseeb, A., Xia, E., Danish et al. Financial development, globalization, and CO2 emission in the presence of EKC: evidence from BRICS countries. Environ Sci Pollut Res 25, 31283–31296 (2018). https://doi.org/10.1007/s11356-018-3034-7

Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. The stata journal, 7(3), 281-312. https://doi.org/10.1177/1536867X0700700301

Hossain, M. S., Mohammad Ridwan, Akhter, A., Nayeem, M. B., M Tazwar Hossain Choudhury, Asrafuzzaman, M., Shoha, S., Abir, S. I., & Sumaira. (2024). Exploring the LCC Hypothesis in the Nordic Region: The Role of AI Innovation, Environmental Taxes, and Financial Accessibility via Panel ARDL. Global Sustainability Research, 3(3), 54–80. https://doi.org/10.56556/gssr.v3i3.972

Hossain, M., Kuddus, M. A., Foysal, A. M., Sahriar Khan, R., Moniruzzaman, Mia, M. T., Rahman, K., Chowdhury, R., & Shiam, S. A. A. (2023). Climate Change and Current Adaptation Strategies in the Haor Areas. Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online), 2(3), 230-241. https://doi.org/10.60087/jklst.vol2.n3.p241

Huilan, W., Akadiri, S. S., Haouas, I., Awosusi, A. A., & Odu, A. T. (2024). Impact of trade liberalization and renewable energy on load capacity factor: Evidence from novel dual adjustment approach. Energy & Environment, 35(2), 795-814. https://doi.org/10.1177/0958305X221137559

Hurtado, S. R. B., Tenesaca-Martínez, K., Torres-Diaz, V., Quito, B., Ojeda, C., & Ochoa-Moreno, S. (2024). Assessing the influence of GDP, globalization, civil liberties, and foreign direct investment on researchers in R&D per country: Dynamic Panel Cointegration Analysis for Latin American countries. Social Sciences & Humanities Open, 10, 100929. https://doi.org/10.1016/j.ssaho.2024.100929

Ibrahim, R.L., Ajide, K.B. Nonrenewable and renewable energy consumption, trade openness, and environmental quality in G-7 countries: the conditional role of technological progress. Environ Sci Pollut Res 28, 45212–45229 (2021). https://doi.org/10.1007/s11356-021-13926-2

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. Journal of econometrics, 115(1), 53-74. https://doi.org/10.1016/S0304-4076(03)00092-7

Islam, M.S. Does financial development cause environmental pollution? Empirical evidence from South Asia. Environ Sci Pollut Res 29, 4350–4362 (2022). https://doi.org/10.1007/s11356-021-16005-8

Islam, S., Raihan, A., Paul, A., Ridwan, M., Rahman, M. S., Rahman, J., ... & Al Jubayed, A. (2024). Dynamic Impacts of Sustainable Energies, Technological Innovation, Economic Growth, and Financial Globalization on Load Capacity Factor in the Top Nuclear Energy-Consuming Countries. Journal of Environmental and Energy Economics, 1-14. https://doi.org/10.56946/jeee.v3i1.448

Jahanger A, Usman M, Murshed M, Mahmood H, Balsalobre-Lorente D (2022) The linkages between natural resources, human capital, globalization, economic growth, financial development, and ecological footprint: the moderating role of technological innovations. Res Policy 76:102569. https://doi.org/10.1016/j.resourpol.2022.102569

Jahanger, A., Ogwu, S. O., Onwe, J. C., & Awan, A. (2023). The prominence of technological innovation and renewable energy for the ecological sustainability in top SDGs nations: Insights from the load capacity factor. Gondwana Research, 129, 381-397. https://doi.org/10.1016/j.gr.2023.05.021

Jahanger, A., Usman, M., & Balsalobre-Lorente, D. (2022). Autocracy, democracy, globalization, and environmental pollution in developing world: fresh evidence from STIRPAT model. Journal of Public Affairs, 22(4), e2753. https://doi.org/10.1002/pa.2753

Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. Journal of econometrics, 90(1), 1-44. https://doi.org/10.1016/S0304-4076(98)00023-2

Karimi Alavijeh, N., Ahmadi Shadmehri, M., Nazeer, N. et al. The role of renewable energy consumption on environmental degradation in EU countries: do institutional quality, technological innovation, and GDP matter?. Environ Sci Pollut Res 30, 44607–44624 (2023). https://doi.org/10.1007/s11356-023-25428-4

Khan MK, Teng JZ, Khan MI, Khan MO (2019) Impact of globalization, economic factors and energy consumption on CO2 emissions in Pakistan. Sci Total Environ 688:424–436. https://doi.org/10.1016/j.scitotenv.2019.06.065

Khan, U., Khan, A.M., Khan, M.S. et al. Are the impacts of renewable energy use on load capacity factors homogeneous for developed and developing nations? Evidence from the G7 and E7 nations. Environ Sci Pollut Res 30, 24629–24640 (2023). https://doi.org/10.1007/s11356-022-24002-8

Khan, Z., Ali, S., Umar, M., Kirikkaleli, D., & Jiao, Z. (2020). Consumption-based carbon emissions and international trade in G7 countries: the role of environmental innovation and renewable energy. Science of The Total Environment, 138945.

Khurshid, N., Fiaz, A., Ali, K. et al. Unleashing the effect of energy efficiency, knowledge spillover, and globalization on environmental sustainability: an VECM analysis for policy empirics. Environ Dev Sustain 26, 6027–6049 (2024). https://doi.org/10.1007/s10668-023-02949-z

Kilinc-Ata, N., Barut, A., & Citil, M. (2024). Do military expenditures have an impact on the adoption of renewable energy in OECD nations? Evidence from a panel cointegration test approach. International Journal of Energy Sector Management.

Kirikkaleli, D., Abbasi, K.R. & Oyebanji, M.O. The asymmetric and long-run effect of environmental innovation and CO2 intensity of GDP on consumption-based CO2 emissions in Denmark. Environ Sci Pollut Res 30, 50110–50124 (2023). https://doi.org/10.1007/s11356-023-25811-1

Kirton J (2012). The G7/8 system and evolution. G8 Information Centre, University of Toronto. 2004a. Available at http://www. g8. utoronto. ca/g8online/2004/english/lectures/lecture01. html Accessed November.

Koenker, R. and Bassett, G. Jr, (1978), "Regression quantiles", Econometrica, Vol. 46 No. 1, pp. 33-50.

Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. Journal of econometrics, 108(1), 1-24. https://doi.org/10.1016/S0304-4076(01)00098-7

Li, Q., Zhao, M., Hei, P., Li, F., & Zhang, K. (2024). Driving sustainable development: Exploring the Nexus of financial inclusion, green mobility, and CO2 emissions in China's natural resource landscape. Resources Policy, 89, 104656. https://doi.org/10.1016/j.resourpol.2024.104656

Lin, B., & Ullah, S. (2024). Evaluating forest depletion and structural change effects on environmental sustainability in Pakistan: Through the lens of the load capacity factor. Journal of Environmental Management, 353, 120174. https://doi.org/10.1016/j.jenvman.2024.120174

Liu, X., Latif, K., Latif, Z., & Li, N. (2020). Relationship between economic growth and CO2 emissions: Does governance matter? Environmental Science and Pollution Research, 27, 17221–17228. https://doi.org/10.1007/s11356-020-08142-3

Liu, Y., Yan, B., & Zhou, Y. (2016). Urbanization, economic growth, and carbon dioxide emissions in China: A panel cointegration and causality analysis. Journal of Geographical Sciences, 26, 131–152. https://doi.org/10.1007/s11442-016-1259-2

Masiero, L., Nicolau, J. L., & Law, R. (2015). A demand-driven analysis of tourist accommodation price: A quantile regression of room bookings. International Journal of Hospitality Management, 50, 1-8.

Md Nasir Uddin Rana, Sarder Abdulla Al Shiam, Sarmin Akter Shochona, Md Rasibul Islam, Md Asrafuzzaman, Proshanta Kumar Bhowmik, Refat Naznin, Sandip Kumar Ghosh, Md Ariful Islam Sarkar, & Md Asaduzzaman. (2024). Revolutionizing Banking Decision-Making: A Deep Learning Approach to Predicting Customer Behavior. Journal of Business and Management Studies, 6(3), 21–27. https://doi.org/10.32996/jbms.2024.6.3.3

Mithun, M. H., kar, A., Sunny, A. R., Billah, M., Sazzad, S. A., Salehin, S., Foysal, A. M., Jahan, N., Rahman, K., Shiam, A. A., Chowdhury, R., Arafat, J., & Baten, A. (2023). Assessing Impact of Microplastics on Aquatic Food System and Human Health. Preprints. https://doi.org/10.20944/preprints202311.1092.v1

Nathaniel, S. P., & Iheonu, C. O. (2019). Carbon dioxide abatement in Africa: The role of renewable and non-renewable energy consumption. Science of the Total Environment, 679, 337–345. https://doi.org/10.1016/j.scitotenv.2019.05.011

Nathaniel, S., Nwodo, O., Sharma, G. et al. Renewable energy, urbanization, and ecological footprint linkage in CIVETS. Environ Sci Pollut Res 27, 19616–19629 (2020). https://doi.org/10.1007/s11356-020-08466-0

Olsen, M. A., Tian, F., Wallace, A. E., Nickel, K. B., Warren, D. K., Fraser, V. J., ... & Hamilton, B. H. (2017). Use of quantile regression to determine the impact on total health care costs of surgical site infections following common ambulatory procedures. Annals of surgery, 265(2), 331-339. https://doi.org/10.1097/SLA.0000000000001590

Onwe, J. C., Ridzuan, A. R., Uche, E., Ray, S., Ridwan, M., & Razi, U. (2024). Greening Japan: Harnessing Energy Efficiency and Waste Reduction for Environmental Progress. Sustainable Futures, 100302. https://doi.org/10.1016/j.sftr.2024.100302

Ozcan B, Ozturk I (2019) Renewable energy consumption-economic growth nexus in emerging countries: a bootstrap panel causality test. Renew Sust Energ Rev 104:30–37

Özkan, O., Saleem, F. & Sharif, A. Evaluating the impact of technological innovation and energy efficiency on load capacity factor: empirical analysis of India. Environ Sci Pollut Res 31, 5610–5624 (2024). https://doi.org/10.1007/s11356-023-31233-w

Ozturk I, Ullah S (2022) Does digital financial inclusion matter for economic growth and environmental sustainability in OBRI economies? An empirical analysis. Resour Conserv Recycl 185:106489. https://doi.org/10.1016/j.resconrec.2022.106489

Pata, U. K., & Kartal, M. T. (2023). Impact of nuclear and renewable energy sources on environment quality: Testing the EKC and LCC hypotheses for South Korea. Nuclear Engineering and Technology, 55(2), 587-594. https://doi.org/10.1016/j.net.2022.10.027

Pata, U. K., Kartal, M. T., Erdogan, S., & Sarkodie, S. A. (2023). The role of renewable and nuclear energy R&D expenditures and income on environmental quality in Germany: Scrutinizing the EKC and LCC hypotheses with smooth structural changes. Applied Energy, 342, 121138. https://doi.org/10.1016/j.apenergy.2023.121138

Pata, U.K. Do renewable energy and health expenditures improve load capacity factor in the USA and Japan? A new approach to environmental issues. Eur J Health Econ 22, 1427–1439 (2021). https://doi.org/10.1007/s10198-021-01321-0

Pattak, D. C., Tahrim, F., Salehi, M., Voumik, L. C., Akter, S., Ridwan, M., ... & Zimon, G. (2023). The driving factors of Italy's CO2 emissions based on the STIRPAT model: ARDL, FMOLS, DOLS, and CCR approaches. Energies, 16(15), 5845. https://doi.org/10.3390/en16155845

Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxford Bulletin of Economics and statistics, 61(S1), 653-670. https://doi.org/10.1111/1468-0084.0610s1653

Pedroni, P. (2004). Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. Econometric theory, 20(3), 597-625. https://doi.org/10.1017/S0266466604203073

Pesaran MH, Shin Y, Smith RJ (1999) Pooled mean group estimation of dynamic heterogeneous panels. J Am Stat Assoc 94(446):621–634

Pesaran MH, Shin Y, Smith RJ (2001) Bounds testing approaches to the analysis of level relationships. J Appl Econ 16(3):289–326

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. Econometrica, 74(4), 967–1012. https://doi.org/10.1111/j.1468-0262.2006.00692.x

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. Journal of applied econometrics, 22(2), 265-312. https://doi.org/10.1002/jae.951

Pesaran, M. H. (2015). Testing weak cross-sectional dependence in large panels. Econometric reviews, 34(6-10), 1089-1117. https://doi.org/10.1080/07474938.2014.956623

Polcyn, J., Voumik, L. C., Ridwan, M., Ray, S., & Vovk, V. (2023). Evaluating the influences of health expenditure, energy consumption, and environmental pollution on life expectancy in Asia. International Journal of Environmental Research and Public Health, 20(5), 4000. https://doi.org/10.3390/ijerph20054000

Qin, Y., Xu, Z., Wang, X. et al. Artificial Intelligence and Economic Development: An Evolutionary Investigation and Systematic Review. J Knowl Econ (2023). https://doi.org/10.1007/s13132-023-01183-2

Raggad B (2018) Carbon dioxide emissions, economic growth, energy use, and urbanization in Saudi Arabia: evidence from the ARDL approach and impulse saturation break tests. Environ Sci Pollut Res 25(15):14882–14898

Rahman, J., Raihan, A., Tanchangya, T., & Ridwan, M. (2024). Optimizing the Digital Marketing Landscape: A Comprehensive Exploration of Artificial Intelligence (AI) Technologies, Applications, Advantages, and Challenges. Frontiers of Finance, 2(2). https://doi.org/10.59429/ff.v2i2.6549

Raihan, A., Atasoy, F. G., Atasoy, M., Ridwan, M., & Paul, A. (2022b). The role of green energy, globalization, urbanization, and economic growth toward environmental sustainability in the United States. Journal of Environmental and Energy Economics, 1(2), 8-17. https://doi.org/10.56946/jeee.v1i2.377

Raihan, A., Bala, S., Akther, A., Ridwan, M., Eleais, M., & Chakma, P. (2024b). Advancing environmental sustainability in the G-7: The impact of the digital economy, technological innovation, and financial accessibility using panel ARDL approach. Journal of Economy and Technology. https://doi.org/10.1016/j.ject.2024.06.001

Raihan, A., Hasan, M. A., Voumik, L. C., Pattak, D. C., Akter, S., & Ridwan, M. (2024c). Sustainability in Vietnam: Examining Economic Growth, Energy, Innovation, Agriculture, and Forests' Impact on CO2 Emissions. World Development Sustainability, 100164. https://doi.org/10.1016/j.wds.2024.100164

Raihan, A., Rahman, J., Tanchangya, T., Ridwan, M., Rahman, M. S., & Islam, S. (2024e). A review of the current situation and challenges facing Egyptian renewable energy technology. Journal of Technology Innovations and Energy, 3(3), 29-52. https://doi.org/10.56556/jtie.v3i3.965

Raihan, A., Rashid, M., Voumik, L. C., Akter, S., & Esquivias, M. A. (2023b). The dynamic impacts of economic growth, financial globalization, fossil fuel, renewable energy, and urbanization on load capacity factor in Mexico. Sustainability, 15(18), 13462. https://doi.org/10.3390/su151813462

Raihan, A., Ridwan, M., Tanchangya, T., Rahman, J., & Ahmad, S. (2023a). Environmental Effects of China's Nuclear Energy within the Framework of Environmental Kuznets Curve and Pollution Haven

Hypothesis. Journal of Environmental and Energy Economics, 2(1), 1-12. https://doi.org/10.56946/jeee.v2i1.346
Raihan, A., Tanchangya, T., Rahman, J., & Ridwan, M. (2024a). The Influence of Agriculture, Renewable Energy, International Trade, and Economic Growth on India's Environmental Sustainability. Journal of Environmental and Energy Economics, 37-53. https://doi.org/10.56946/jeee.v3i1.324
Raihan, A., Tanchangya, T., Rahman, J., Ridwan, M., & Ahmad, S. (2022a). The influence of Information and Communication Technologies, Renewable Energies and Urbanization toward Environmental Sustainability in China. Journal of Environmental and Energy Economics, 1(1), 11-23. https://doi.org/10.56946/jeee.v1i1.351
Raihan, A., Voumik, L. C., Ridwan, M., Akter, S., Ridzuan, A. R., Wahjoedi, ... & Ismail, N. A. (2024d). Indonesia's Path to Sustainability: Exploring the Intersections of Ecological Footprint, Technology, Global Trade, Financial Development and Renewable Energy. In Opportunities and Risks in AI for Business Development: Volume 1 (pp. 1-13). Cham: Springer Nature Switzerland.
Raihan, A., Voumik, L. C., Ridwan, M., Ridzuan, A. R., Jaaffar, A. H., & Yusoff, N. Y. M. (2023c). From growth to green: navigating the complexities of economic development, energy sources, health spending, and carbon emissions in Malaysia. Energy Reports, 10, 4318-4331. https://doi.org/10.1016/j.egyr.2023.10.084
Richards, G., Yeoh, W., Chong, A.Y.L. and Popovic, A. (2019), "Business intelligence effectiveness and corporate performance management: an empirical analysis", Journal of Computer Information Systems, Vol. 59 No. 2, pp. 188-196.
Ridwan, M. (2023). Unveiling the powerhouse: Exploring the dynamic relationship between globalization, urbanization, and economic growth in Bangladesh through an innovative ARDL approach.
Ridwan, M., Bala, S., Al Shiam, S. A., Akhter, A., Asrafuzzaman, M., Shochona, S. A., ... & Shoha, S. Leveraging AI for a Greener Future: Exploring the Economic and Financial Impacts on Sustainable Environment in the United States. https://doi.org/10.56556/jescae.v3i3.970 (2024b)
Ridwan, M., Bala, S., Al Shiam, S. A., Akhter, A., Hasan, M. M., Asrafuzzaman, M., ... & Bibi, R. Leveraging AI for Promoting Sustainable Environments in G-7: The Impact of Financial Development and Digital Economy via MMQR Approach. https://doi.org/10.56556/gssr.v3i3.971 (2024c)
Ridwan, M., Raihan, A., Ahmad, S., Karmakar, S., & Paul, P. (2023). Environmental sustainability in France: The role of alternative and nuclear energy, natural resources, and government spending. Journal of Environmental and Energy Economics, 2(2), 1-16. https://doi.org/10.56946/jeee.v2i2.343
Ridwan, M., Urbee, A. J., Voumik, L. C., Das, M. K., Rashid, M., & Esquivias, M. A. (2024a). Investigating the environmental Kuznets curve hypothesis with urbanization, industrialization, and service sector for six South Asian Countries: Fresh evidence from Driscoll Kraay standard error. Research in Globalization, 8, 100223.
Ruel, M. T., Garrett, J. L., & Haddad, L. (2008). Rapid urbanization and the challenges of obtaining food and nutrition security. Nutrition and health in developing countries, 639-656.
Saba, C.S., Monkam, N. Leveraging the potential of artificial intelligence (AI) in exploring the interplay among tax revenue, institutional quality, and economic growth in the G-7 countries. AI & Soc (2024). https://doi.org/10.1007/s00146-024-01885-4
Sadiq, M., Wen, F., 2022. Environmental footprint impacts of nuclear energy consumption: The role of environmental technology and globalization in ten largest ecological footprint countries. Nucl. Eng. Technol. https://doi.org/10.1016/j.net.2022.05.016
Sadorsky P (2010) The impact of financial development on energy consumption in emerging economies. Energy Policy 38(5):2528–2535
Saidi K, Mbarek MB (2017) The impact of income, trade, urbanization, and financial development on CO 2 emissions in 19 emerging economies. Environ Sci Pollut Res 24(14):12748–12757

Sarder Abdulla Al Shiam, Md Mahdi Hasan, Md Boktiar Nayeem, M. Tazwar Hossian Choudhury, Proshanta Kumar Bhowmik, Sarmin Akter Shochona, Ahmed Ali Linkon, Md Murshid Reja Sweet, & Md Rasibul Islam. (2024b). Deep Learning for Enterprise Decision-Making: A Comprehensive Study in Stock Market Analytics. Journal of Business and Management Studies, 6(2), 153–160. https://doi.org/10.32996/jbms.2024.6.2.15

Sarder Abdulla Al Shiam, Md Mahdi Hasan, Md Jubair Pantho, Sarmin Akter Shochona, Md Boktiar Nayeem, M Tazwar Hossain Choudhury, & Tuan Ngoc Nguyen. (2024a). Credit Risk Prediction Using Explainable AI. Journal of Business and Management Studies, 6(2), 61–66. https://doi.org/10.32996/jbms.2024.6.2.6

Schröder E, Storm S (2020) Economic Growth and Carbon Emissions: The Road to “Hothouse Earth” is Paved with Good Intentions. Int J Polit Econ 49(2):153–173

Shah SAA, Zhou P, Walasai GD, Mohsin M (2019) Energy security and environmental sustainability index of south Asian countries: a composite index approach. Ecol Indic 106:105507. https://doi.org/10.1016/j.ecolind.2019.105507

Shahbaz M, Shahzad SJH, Mahalik MK (2018) Is globalization detrimental to CO 2 emissions in Japan? New threshold analysis. Environ Model Assess 23:557–568

Shahbaz, M., Khan, S., Ali, A., & Bhattacharya, M. (2017). The impact of globalization on CO2 emissions in China. The Singapore Economic Review, 62(04), 929-957. https://doi.org/10.1142/S0217590817400331

Shahzad, S. J. H., Shahbaz, M., Ferrer, R., & Kumar, R. R. (2017). Tourism-led growth hypothesis in the top ten tourist destinations: New evidence using the quantile-on-quantile approach. Tourism Management, 60, 223-232. https://doi.org/10.1016/j.tourman.2016.12.006

Shahzadi, H. N., Sheikh, S. M., Sadiq, A., & Rahman, S. U. (2023). Effect of Financial Development, Economic Growth on Environment Pollution: Evidence from G-7 based ARDL Cointegration Approach. Pakistan Journal of Humanities and Social Sciences, 11(1), 68-79. https://doi.org/10.52131/pjhss.2023.1101.0330

Sharif A, Saqib N, Dong K, Khan SAR (2022) Nexus between green technology innovation, green financing, and CO2 emissions in the G7 countries: the moderating role of social globalisation. Sustain Dev 30(6):1934–1946

Sharif, A., Mehmood, U., Tariq, S. et al. The role of financial inclusion and globalization toward a sustainable economy in ASEAN countries: evidence from advance panel estimations. Environ Dev Sustain 26, 10243–10260 (2024). https://doi.org/10.1007/s10668-023-03145-9

Sheraz, M., Deyi, X., Mumtaz, M.Z., Ullah, A., 2022. Exploring the dynamic relationship between financial development, renewable energy, and carbon emissions: A new evidence from belt and road countries. Environ. Sci. Pollut. Res. 29 (10), 14930–14947. https://doi.org/10.1007/s11356-021-16641-0

Siche, R., Pereira, L., Agostinho, F., & Ortega, E. (2010). Convergence of ecological footprint and emergy analysis as a sustainability indicator of countries: Peru as case study. Communications in Nonlinear Science and Numerical Simulation, 15(10), 3182-3192. https://doi.org/10.1016/j.cnsns.2009.10.027

Siche, R., Pereira, L., Agostinho, F., & Ortega, E. (2010). Convergence of ecological footprint and emergy analysis as a sustainability indicator of countries: Peru as case study. Communications in Nonlinear Science and Numerical Simulation, 15(10), 3182-3192.

Sohail, M. N., Jiadong, R., Irshad, M., Uba, M. M., and Abir, S. I, “Data mining techniques for Medical Growth: A Contribution of Researcher reviews,” Int. J. Comput. Sci. Netw. Secur, 18, 5-10, 2018b.

Sohail, M. N., Ren, J. D., Uba, M. M., Irshad, M. I., Musavir, B., Abir, S. I., and Anthony, J. V, “Why only data mining? a pilot study on inadequacy and domination of data mining technology,” Int. J. Recent Sci. Res, 9(10), 29066-29073, 2018a.

Sohail, M. N., Ren, J., Muhammad, M. U., Rizwan, T., Iqbal, W., Abir, S. I., and Bilal, M, “Group covariates assessment on real-life diabetes patients by fractional polynomials: a study based on logistic regression modeling,” Journal of Biotech Research, 10, 116-125, 2019.

Solarin, S.A., Nathaniel, S.P., Bekun, F.V. et al. Towards achieving environmental sustainability: environmental quality versus economic growth in a developing economy on ecological footprint via dynamic simulations of ARDL. Environ Sci Pollut Res 28, 17942–17959 (2021). https://doi.org/10.1007/s11356-020-11637-8

Sun, Y., Usman, M., Radulescu, M., Pata, U. K., & Balsalobre-Lorente, D. (2024). New insights from the STIPART model on how environmental-related technologies, natural resources and the use of the renewable energy influence load capacity factor. Gondwana Research, 129, 398-411. https://doi.org/10.1016/j.gr.2023.05.018

Tamazian A, Chousa JP, Vadlamannati KC (2009) Does higher economic and financial development lead to environmental degradation: evidence from BRIC countries. Energy Policy 37(1):246–253

Tamazian A, Rao BB (2010) Do economic, financial and institutional developments matter for environmental degradation? Evid Transitional Econ Energy Econ 32(1):137–145

Teal, F., & Eberhardt, M. (2010). Productivity analysis in global manufacturing production. Department of economics, Discussion paper series. https://ora.ox.ac.uk/objects/uuid:f9d91b40-d8b7-402d-95eb-75a9cbdcd000

Tufail, M., Song, L., Umut, A., Ismailova, N., & Kuldasheva, Z. (2022). Does financial inclusion promote a green economic system? Evaluating the role of energy efficiency. Economic research-Ekonomska istraživanja, 35(1), 6780-6800. https://doi.org/10.1080/1331677X.2022.2053363

Ulucak R, Khan SUD (2020) Determinants of the ecological footprint: role of renewable energy, natural resources, and urbanization. Sustain Cities Soc 54:101996. https://doi.org/10.1016/j.scs.2019.101996

Ulucak, R., Erdogan, S., 2022. The effect of nuclear energy on the environment in the context of globalization: Consumption vs production-based CO2 emissions. Nucl. Eng. Technol. 54 (4), 1312–1320. https://doi.org/10.1016/j. net.2021.10.030

United Nations Environment Programme (2019) Emissions gap report 2019. UNEP, Nairobi

Usman, O., Olanipekun, I.O., Iorember, P.T. et al. Modelling environmental degradation in South Africa: the effects of energy consumption, democracy, and globalization using innovation accounting tests. Environ Sci Pollut Res 27, 8334–8349 (2020). https://doi.org/10.1007/s11356-019-06687-6

Van Song, N., Phuong, N.T.M., Oanh, T.T.K. et al. Does tradeoff between financial and social indicators matters in environmental consideration: evidence from G7 region. Environ Sci Pollut Res 28, 19911–19925 (2021). https://doi.org/10.1007/s11356-020-12041-y

Voumik, L. C., & Ridwan, M. (2023). Impact of FDI, industrialization, and education on the environment in Argentina: ARDL approach. Heliyon, 9(1). https://doi.org/10.1016/j.heliyon.2023.e12872

Voumik, L. C., & Sultana, T. (2022). Impact of urbanization, industrialization, electrification and renewable energy on the environment in BRICS: fresh evidence from novel CS-ARDL model. Heliyon, 8(11).

Voumik, L. C., Akter, S., Ridwan, M., Ridzuan, A. R., Pujiati, A., Handayani, B. D., ... & Razak, M. I. M. (2023b). Exploring the factors behind renewable energy consumption in Indonesia: Analyzing the impact of corruption and innovation using ARDL model. International Journal of Energy Economics and Policy, 13(5), 115-125. https://doi.org/10.32479/ijeep.14530

Voumik, L. C., Rahman, M. H., Rahman, M. M., Ridwan, M., Akter, S., & Raihan, A. (2023c). Toward a sustainable future: Examining the interconnectedness among Foreign Direct Investment (FDI), urbanization, trade openness, economic growth, and energy usage in Australia. Regional Sustainability, 4(4), 405-415.https://doi.org/10.1016/j.regsus.2023.11.003

Voumik, L. C., Ridwan, M., Rahman, M. H., & Raihan, A. (2023a). An investigation into the primary causes of carbon dioxide releases in Kenya: Does renewable energy matter to reduce carbon emission?. Renewable Energy Focus, 47, 100491.https://doi.org/10.1016/j.ref.2023.100491

Wang, J., Yang, L. & Yang, J. How sustainable environment is influenced by the foreign direct investment, financial development, economic growth, globalization, innovation, and urbanization in China. Environ Sci Pollut Res 30, 49889–49904 (2023). https://doi.org/10.1007/s11356-023-25634-0

Wang, J., Zhang, S., & Zhang, Q. (2021). The relationship of renewable energy consumption to financial development and economic growth in China. Renewable Energy, 170, 897-904. https://doi.org/10.1016/j.renene.2021.02.038

WB (2022) GDP (current US$). https://data.worldbank.org, August 5, 2022

Wen, J., Mughal, N., Zhao, J., Shabbir, M. S., Niedbała, G., Jain, V., & Anwar, A. (2021). Does globalization matter for environmental degradation? Nexus among energy consumption, economic growth, and carbon dioxide emission. Energy policy, 153, 112230.

World Bank. (2017). World Bank development indicators. Retrieved from: https://data.worldbank.org/indicator/. Accessed 12 Jan 2021

Wu W, Qi Z, Zhou L (2020) Environmentally responsible closed-loop supply chain models for joint environmental responsibility investment, recycling and pricing decisions. J Clean Prod 259:120776

Xu J, Ji KX, Liu XT, Xia Y et al (2022) Robot applications, gender wage gap, and common prosperity. J Quant Techn Econ 39(09):134–156. https://doi.org/10.13653/j.cnki.jqte.2022.09.007

Xu, D., Salem, S., Awosusi, A. A., Abdurakhmanova, G., Altuntaş, M., Oluwajana, D., ... & Ojekemi, O. (2022). Load capacity factor and financial globalization in Brazil: the role of renewable energy and urbanization. Frontiers in Environmental Science, 9, 823185. https://doi.org/10.3389/fenvs.2021.823185

Yuan Y, Xi QM, Sun TS et al (2016) The impact of the industrial structure on regional carbon emissions: empirical evidence across countries. Geogr Res 35(1):82–94. https://doi.org/10.11821/dlyj201601008

Zhu H, Xia H, Guo Y, Peng C (2018) The heterogeneous effects of urbanization and income inequality on CO 2 emissions in BRICS economies: evidence from panel quantile regression. Environ Sci Pollut Res 25:17176–17193 1-18