International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(3), 735-757.

Unveiling the Influence of Green Taxes, Renewable Energy Adoption, and Digitalization on Environmental Sustainability in G7 Countries

Nesrine Gafsi[1]*, Sayef Bakari[2]

[1]College of Business, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh, Saudi Arabia, [2]Laboratoire d'Intégration Economique Internationale, Faculty of Economic Sciences and Management of Tunis, University of Tunis El Manar, Tunisia. *Email: NWGafsi@imamu.edu.sa

Received: 26 November 2024 **Accepted:** 10 April 2025 **DOI:** https://doi.org/10.32479/ijeep.18676

ABSTRACT

This study investigates the intricate interplay between environmental taxes, economic growth, renewable energy adoption, digitalization, and their combined impact on environmental quality across G7 nations during the period 1994–2021. Positioned within the broader framework of sustainable development, environmental policy, digitalization, economic progress, and green energy, it employs sophisticated econometric methodologies like the Cross-Section Augmented Autoregressive Distributed Lag (CS-ARDL) model and the Dynamic Common Correlated Effects Mean Group (DCCEMG) estimator to overcome data complexities such as cross-sectional dependence and slope heterogeneity. The findings offer valuable insights into the dynamic relationship between environmental quality, economic growth, renewable energy utilization, digitalization, and the efficacy of environmental taxation. Additionally, the study proposes targeted policy recommendations aimed at bolstering sustainable development efforts aligned with international accords like the Paris Agreement and the Sustainable Development Goals. These proposed strategies advocate for a nuanced approach to environmental taxation, the promotion of renewable energy adoption, and leveraging digitalization to bolster environmental sustainability efforts across G7 nations.

Keywords: Green Taxes, Renewable Energy Adoption, Digitalization, Environmental Quality, CS-ARDL, G7 Countries
JEL Classifications: C33, Q58, Q42, Q01, O33

1. INTRODUCTION

In the relentless pursuit of a sustainable global future, the debate on mitigating climate change has become a central topic both in policymaking and academic research (Leiserowitz et al., 2020). This significance is particularly evident among the world's most economically advanced nations, represented by the Group of Seven (G7), which wield significant influence in shaping environmental agendas and crafting innovative strategies to combat climate change (Grubler et al., 2018). In a context marked by growing environmental concerns and rapid technological progress, the imperative to address climate change is more pressing than ever (Rogelj et al., 2016). Consequently, it has become essential to disentangle the complex interaction between various factors such as green taxes, renewable energy adoption, and digitalization, as well as their collective impact on climate change within the G7 nations. The urgency of addressing climate change has never been more pressing, as underscored by a growing body of scientific literature. The overwhelming consensus among researchers confirms that anthropogenic activities have accelerated global warming, leading to unprecedented environmental disruptions with far-reaching socio-economic ramifications (IPCC, 2021). As the Group of Seven (G7) nations collectively contribute a substantial share of global greenhouse gas emissions, their pivotal role in spearheading sustainable practices and climate resilience initiatives is widely acknowledged (Wynes and Nicholas, 2020).

Recognizing this imperative, our study aims to delve into the multifaceted dimensions of environmental policy, technological innovation, and economic transformation within the context of climate change mitigation. By drawing upon seminal works in the field, such as the IPCC's (2021) assessment reports and contributions by Wynes and Nicholas (2020), we seek to illuminate the complex interplay between environmental governance, technological transitions, and economic dynamics in the pursuit of climate resilience and sustainability.

At the crux of our investigation lie three crucial components: green taxes, renewable energy adoption, and digitalization. Green taxes, based on the concept of internalizing externalities, emerge as robust mechanisms aimed at encouraging environmentally conscious actions while discouraging behaviors detrimental to the environment (Hartmann et al., 2023). By imposing levies on activities that generate pollution or degrade natural resources, green taxes create economic incentives for individuals and businesses to opt for greener alternatives and invest in sustainable practices (Stavins, 1999). Studies have underscored the potential of such fiscal policies to not only modify consumption patterns but also foster innovation and efficiency improvements in production processes, thereby contributing to the mitigation of climate change impacts (Chen et al., 2022). Moreover, the integration of environmental considerations into taxation frameworks aligns with the principles of sustainable development, emphasizing the need for economic activities to operate within ecological limits (Arrow et al., 1995). As such, green taxes represent a promising avenue for addressing climate change challenges by aligning economic incentives with environmental objectives and fostering a transition towards more sustainable and resilient societies.

Concurrently, the widespread adoption of renewable energy sources emerges as a beacon of optimism in the global shift towards a low-carbon future. The G7 nations, boasting technological prowess and substantial financial resources, lead the charge in deploying renewable energy solutions, capitalizing on advancements in solar, wind, hydro, and other sustainable energy technologies (IEA, 2021). However, the degree to which the integration of renewable energy translates into measurable reductions in carbon emissions remains a contentious subject within academic discourse, warranting meticulous empirical scrutiny (Erkut, 2022). While renewable energy holds promise as a key driver of decarbonization efforts, its effectiveness hinges on various factors such as technological maturity, policy support, and market dynamics, all of which necessitate thorough investigation to inform evidence-based decision-making and facilitate the transition towards a sustainable energy future.

Furthermore, the emergence of digitalization has heralded transformative potential in redefining economies, societies, and environmental governance paradigms. With advancements spanning from smart grids and energy-efficient technologies to data-driven climate modeling and policy optimization, digital innovations present unparalleled opportunities for bolstering climate resilience and expediting decarbonization endeavors (Böhringer et al., 2015). By leveraging the capabilities of digital technologies, the G7 nations stand poised to unlock novel pathways towards sustainable development, concurrently mitigating climate risks and cultivating adaptive capacities (UNEP, 2020). The integration of digital solutions not only enhances the efficiency and effectiveness of climate-related interventions but also fosters cross-sectoral collaboration and innovation, thereby catalyzing progress towards a more sustainable and resilient future. Against this backdrop, our study sets sail on a comprehensive voyage, delving into the intricate interplay between green taxes, renewable energy adoption, digitalization, and climate change mitigation within the G7 context. Through a robust blend of empirical analysis and policy-oriented insights, our aim is to unveil the synergies, trade-offs, and policy implications inherent in these converging domains. By shining a spotlight on the transformative potential of green fiscal policies, renewable energy transitions, and digital innovations, our research endeavors to provide a compass for evidence-based policymaking and to serve as a catalyst for collective action towards a future that is more resilient, sustainable, and climate-resilient for not only the G7 nations but also for the broader global community.

2. BACKGROUND AND LITERATURE SURVEY

Understanding environmental sustainability requires a holistic approach, considering ecological health and socio-economic impacts. Recent research highlights the intricate relationship between human activities and environmental well-being, emphasizing the need for comprehensive evaluations of environmental quality. Integrating information technology with renewable energy initiatives shows promise in enhancing climate resilience and providing policymakers with real-time data and advanced analytics. Additionally, studies emphasize the crucial role of policy frameworks in promoting sustainable development and addressing climate change challenges among G7 nations. Innovative strategies, such as the load-capacity curve hypothesis and the promotion of green products and low-carbon technologies, further underscore the importance of informed policy decisions in achieving sustainable development goals.

2.1. Measuring Environmental Quality

In the endeavor to grasp the complexities of environmental sustainability, it becomes paramount to adopt a holistic framework that intertwines the health of ecosystems with the socio-economic repercussions of human actions. Recent research conducted by Leiserowitz et al. (2020) and Grubler et al. (2018) underscores the intricate interplay between human activities and the well-being of the environment. Their findings emphasize the necessity of comprehensive evaluations of environmental quality, acknowledging the multidimensional nature of environmental challenges. Moreover, they advocate for the incorporation of socio-economic factors into environmental metrics to offer a more nuanced and accurate portrayal of ecosystem health. Moreover, the integration of information technology infrastructure with renewable energy initiatives, as investigated by Liu et al. (2023), Allioui and Mourdi (2023), presents promising pathways for bolstering climate resilience. This fusion of digitalization and renewable energy offers innovative solutions for monitoring environmental parameters and implementing strategies to effectively mitigate the impacts of climate change. Through the utilization of digital technologies, policymakers gain access to real-time data and advanced analytics, empowering them to make informed decisions and proactively address environmental challenges.

Recent research conducted by Nadiri et al. (2024), Su et al. (2023), Wang et al. (2023), Yan et al. (2023), Silva et al. (2023) and Mudalige (2023) illuminates the intricate relationship between green taxes, renewable energy adoption, and economic innovation, particularly within the context of G7 nations. These studies emphasize the critical role of policy frameworks in fostering sustainable development and tackling climate change challenges. By examining how environmental policies shape socio-economic outcomes, researchers provide valuable insights into the mechanisms driving environmental sustainability. Their findings contribute to a deeper understanding of the pathways toward achieving sustainable development goals, underscoring the importance of informed policy decisions and strategic interventions in addressing climate change within G7 nations. Furthermore, Zhang et al. (2021) introduce the load-capacity curve hypothesis as an innovative strategy for natural resource management and enhancing environmental health. This novel approach advocates policymakers to factor in ecological limits when making decisions regarding resource management. By considering the capacity of ecosystems to sustainably support human activities, policymakers can develop strategies that prioritize ecosystem balance and promote sustainable development. This approach challenges traditional resource management paradigms by emphasizing the need to integrate ecological considerations into decision-making processes. By adopting the load-capacity curve hypothesis, policymakers can pave the way for more effective and sustainable management of natural resources, ensuring the long-term health and resilience of ecosystems. Furthermore, recent studies conducted by Alshammari and Alshammari (2023), Hermawan et al. (2023) and Song et al. (2023) highlight the significance of green products and low-carbon technologies in driving environmental sustainability forward. These research findings emphasize the importance of implementing policies that incentivize innovation in green technologies and encourage the development of environmentally friendly markets. By offering economic incentives for the adoption of sustainable practices, policymakers can foster investment in renewable energy and contribute to environmental protection efforts. This approach not only accelerates the transition towards sustainable practices but also promotes economic growth and fosters a more resilient and environmentally conscious society.

Lastly, Afshan and Yaqoob (2023) explore the strategic importance of green innovation and taxation in environmental governance, drawing on the load-capacity curve theory to inform their analysis. Their study underscores the imperative for integrated policy approaches that harmonize environmental preservation with economic growth objectives. By aligning incentives with sustainability targets, policymakers can foster an atmosphere conducive to the development of green technologies. This collective endeavor towards sustainability not only propels advancements towards a more environmentally sound future for G7 nations but also establishes the groundwork for resilient and prosperous societies in the foreseeable future. The quest for understanding environmental sustainability demands a comprehensive approach that intertwines ecosystem health with the socio-economic impacts of human activities. Recent research underscores the intricate interplay between human actions and environmental well-being, emphasizing the need for holistic evaluations of environmental quality. Integration of information technology with renewable energy initiatives offers promising avenues for bolstering climate resilience, empowering policymakers with real-time data and advanced analytics to address environmental challenges effectively. Moreover, studies illuminate the critical role of policy frameworks in fostering sustainable development and addressing climate change challenges within G7 nations. The introduction of innovative strategies such as the load-capacity curve hypothesis in natural resource management further emphasizes the need to integrate ecological considerations into decision-making processes. Additionally, highlighting the significance of green products and low-carbon technologies underscores the importance of incentivizing sustainable practices for environmental protection and economic growth. Lastly, exploring the strategic importance of green innovation and taxation underscores the necessity for integrated policy approaches that balance environmental preservation with economic objectives, paving the way for a more resilient and prosperous future for G7 nations and beyond.

2.2. Environmental Taxes and Environmental Quality

Environmental taxation stands as a fundamental pillar in environmental policy frameworks, guided by the principle of the polluter pays (OECD, 2020). This principle aims to internalize the external costs of pollution, shifting the burden from society to the polluters themselves. Central to the understanding of environmental taxation is the Environmental Kuznets Curve (EKC) hypothesis, which provides a theoretical lens for examining the relationship between economic growth, environmental degradation, and policy interventions (Grossman & Krueger, 1991). The EKC posits an inverted U-shaped relationship between economic development and environmental degradation, suggesting that environmental quality worsens initially with economic growth, but eventually improves beyond a certain income threshold. Environmental taxes are viewed as instrumental in guiding economies towards the downward slope of the EKC by discouraging pollution-intensive activities and fostering the adoption of cleaner technologies (Stern, 2004; Köppl and Schratzenstaller, 2023).

The issue of the effectiveness of environmental taxes in improving environmental quality is a major topic of interest in contemporary literature in environmental economics and public policy. Environmental taxes are economic tools aimed at internalizing external environmental costs into economic decisions, thereby providing incentives to reduce pollution and promote the development of cleaner and more sustainable technologies. A study by Fullerton and Heutel (2020) analyzed the effects of carbon taxes, particularly in the context of CO_2 emissions. Their findings suggest that carbon taxes can induce significant emission reductions, but their effectiveness depends on various factors such as the elasticity of demand with respect to the tax price, possibilities of substitution between production factors, and long-term responses of businesses. In the agricultural sector, Femenia and Letort (2016) examined the impact of taxes on agricultural pesticides on water quality. Their findings highlight the potential of taxes to reduce pesticide use and improve water quality, while emphasizing the importance of tax design and economic incentives to encourage adoption of more sustainable agricultural practices. Concerning developing economies, a study by Long et al. (2022) evaluated the effects of taxes on industrial emissions in China. Their results indicate that taxes can effectively reduce atmospheric pollutant emissions, but their successful implementation requires rigorous monitoring, strict enforcement, and appropriate economic incentives to foster compliance. Additionally, a systematic review conducted by OCDE (2010) underscores the importance of institutional and policy conditions to maximize the impact of environmental taxes on environmental quality. They also emphasize the need for international coordination to address global environmental challenges such as climate change.

Further complementary studies have examined various aspects of the effectiveness of environmental taxes. For example, research by Domguia (2023) examined the implications of using tax revenues generated by environmental taxes, highlighting their potential to support other environmental or redistributive policies. Similarly, a study by Fischer and Fox (2012) explored the effects of taxes on greenhouse gas emissions in the electricity sector, demonstrating how the precise design of the tax can influence its effectiveness in reducing emissions and promoting cleaner energy sources. A recent study by Li et al. (2021) examined the effectiveness of environmental taxes in the context of air pollution. Their results indicate that taxes on atmospheric emissions can effectively reduce air pollution, particularly in urban areas, by incentivizing firms to adopt fewer polluting technologies. Concurrently, research by Köppl and Schratzenstaller (2023) focused on the economic and environmental implications of carbon taxes. Their analysis suggests that carbon pricing can not only reduce CO_2 emissions but also stimulate technological innovation and facilitate the transition to a low-carbon economy. In the field of circular economy, a study by Kibria et al. (2023) evaluated the impact of taxes on plastic waste. Their results highlight the ability of taxes to reduce plastic waste production and promote recycling, thereby contributing to reducing plastic pollution in oceans and terrestrial ecosystems.

Regarding developing countries, research by Pokorny et al. (2021) examined the effects of taxes on deforestation in the Amazon. Their study reveals that taxes on logging can contribute to forest preservation by reducing economic pressure on natural resources and promoting sustainable forest management. On the other hand, a literature review by Rao et al. (2023) underscores the importance of designing environmental tax policies that consider regional and sectoral specificities, as well as socio-economic and political conditions. Their analysis highlights the need for a holistic and flexible approach to maximize the effectiveness of environmental taxes in different contexts. Similarly, a recent study by Guo et al. (2022) examined the impact of taxes on sulfur dioxide (SO_2) emissions in the context of air pollution. Their results highlight that taxes on SO_2 emissions have successfully reduced air pollution, with significant effects on public health and environmental quality. Concerning electronic waste, research by Kumar et al. (2022) evaluated the effectiveness of taxes on electronic products to encourage recycling and reduce environmental impacts associated with their disposal. Their findings suggest that taxes can play a crucial role in promoting sustainability of electronic products by incentivizing better waste management and more ecological product design. In the field of biodiversity, a study by Nuissl and Siedentop (2012) examined the effects of land use taxes on habitat conservation. Their results indicate that land use taxes can contribute to preserving fragile ecosystems by discouraging the conversion of natural lands into less sustainable uses such as intensive agriculture or urbanization. On the other hand, a literature review by Davidovic et al. (2020) examined the challenges and opportunities related to the implementation of environmental taxes in different political and institutional contexts. Their analysis highlights the importance of tax design, coordination among different levels of government, and stakeholder engagement to maximize the effectiveness of environmental fiscal policies.

However, the effectiveness of environmental taxes in enhancing environmental quality is contingent upon various factors. Mpofu (2022) shed light on potential socio-economic challenges associated with the implementation of environmental taxes, including distributional effects and competitiveness concerns. Uddin et al. (2023) emphasize the importance of tailoring environmental tax policies to specific socio-economic contexts to maximize their effectiveness while minimizing adverse effects. Recent literature provides valuable insights into the intricate relationship between environmental taxes and environmental quality. While environmental taxes offer a promising tool for promoting sustainability, addressing associated challenges and designing context-specific policies are essential for optimizing their effectiveness in improving environmental quality.

Duran and Saqib (2024) found that in G20 economies, robust environmental policies including taxation enhance the Load Capacity Factor, promoting sustainable development. Similarly, Nsiah et al. (2024) showed environmental taxes effectively reduce emissions in Visegrad countries when properly implemented. However, Lai (2016) presents a more nuanced view, demonstrating through an OLG model that while energy taxes improve environmental quality, they don't necessarily produce the theorized "double dividend" of also boosting economic output. Ayodele et al. (2023) highlight how carbon tax revenues can fund renewable energy projects, as seen in Japan. Hieu (2022) found environmental taxes successfully reduced emissions in ASEAN countries when combined with green investments. Abel et al. (2023) caution that in South Africa, carbon taxes may negatively impact GDP and household consumption, suggesting careful, phased implementation is needed in developing economies. Bunnag (2023)'s US study reveals how environmental taxes work best when complemented by other policies like FDI incentives. Ahmat et al. (2024) argue that in Malaysia, carbon taxes must be carefully designed to offset growing energy consumption from industrialization. Nsiah et al. (2024) emphasize the importance of tailoring tax policies to specific national contexts and energy mixes. The literature consistently shows that environmental taxes are most effective when revenues are reinvested in green technologies and when implementation considers economic impacts.

Environmental taxes emerge as a vital tool for tackling environmental challenges within the G7 countries, as they internalize external costs and encourage sustainable practices. However, their efficacy depends on factors such as tax design, institutional capacity, socio-economic context, and international cooperation. Despite evidence highlighting their potential to alleviate environmental degradation, addressing issues like distributional impacts and competitiveness is crucial. Tailoring policies to specific national contexts is essential. Therefore, ongoing research and informed policymaking are imperative to maximize the impact of environmental taxation, ensuring environmental quality and sustainability are prioritized on a global scale within the G7 nations.

2.3. Renewable Energy Adoption and Environmental Quality

Renewable energies are widely recognized for their potential to reduce greenhouse gas (GHG) emissions and mitigate the effects of climate change. A study by the International Energy Agency (IEA) has demonstrated that increasing the share of renewable energies in the global energy mix could significantly contribute to limiting global warming to below 2°C compared to pre-industrial levels, a crucial goal to avoid the most severe impacts of climate change (IEA, 2019). For instance, the widespread deployment of solar and wind energy can decrease CO_2 emissions by substituting fossil fuels in electricity generation (Jacobson et al., 2015). In addition to reducing GHG emissions, renewable energies also have positive impacts on air quality. Unlike fossil fuel-based thermal power plants, which emit atmospheric pollutants such as sulfur dioxide (SO2), nitrogen oxides (NOx), and particulate matter, renewable energies such as solar and wind power do not produce such harmful emissions (Creutzig et al., 2017). A study conducted by Markandya et al. (2018) estimated that transitioning to renewable energy sources could prevent thousands of premature deaths each year by reducing air pollution.

Furthermore, renewable energies have a lesser impact on biodiversity and ecosystems compared to fossil fuels. Renewable energy production facilities can be designed to minimize disturbances to natural habitats, and in some cases, they can even provide opportunities for ecological restoration. However, it is important to note that certain forms of renewable energy, such as biomass, may have negative impacts on biodiversity if not managed sustainably (Naeem et al., 2016). Renewable energies can also contribute to water resource conservation. Unlike thermal power plants that require significant amounts of water for cooling, renewable energies such as wind and solar power generally have much lower water needs (Meldrum et al., 2013). Overall, renewable energies offer significant potential to improve environmental quality by reducing GHG emissions, enhancing air quality, preserving biodiversity, and conserving water resources. However, a successful transition to a renewable energy-based system requires careful planning, sustainable resource management, and effective integration with other energy technologies and environmental policies.

Several recent studies have examined the impacts of renewable energy consumption on both environmental and economic dynamics. Dam et al. (2023) highlighted that the increasing use of renewable energy leads to a reduction in the inverse load factor capacity, a key indicator of environmental sustainability. Similarly, Mihayo and Kombe (2022) observed a significant negative correlation between CO_2 emissions and renewable energy consumption in East African countries, suggesting that the adoption of renewable energies can contribute to improving environmental quality in this region. Economically, Fakher et al. (2022) concluded that the increased use of renewable energy stimulates economic growth in high-income countries, highlighting the importance of renewable energy-friendly policies for sustainable development. In parallel, Kassi et al. (2023) proposed that the adoption of green financial instruments can help reduce CO_2 emissions, underscoring the crucial role of financing policies in facilitating the transition to renewable energies.

Other studies, such as those by Tiba et al. (2016) and Khan et al. (2022), have explored disparities between high-income and middle-income countries regarding the relationships between renewable energies, economic growth, and CO_2 emissions. These studies also emphasized the impact of institutional factors in promoting renewable energies and reducing carbon emissions, with marked differences among G7 countries. Additionally, research like that by Kafeel et al. (2024) has demonstrated that the increasing adoption of renewable energies and green innovations can have a significant effect on reducing CO_2 emissions, highlighting the importance of policies aimed at promoting these environmentally friendly technologies.

However, challenges persist. Karimi-Alavijeh et al. (2023) noted that the imposition of environmental taxes may have a negative impact on CO_2 emissions reduction in OECD countries, raising questions about the effectiveness of green fiscal policies. Similarly, Dilanchiev et al. (2024) observed a U-shaped relationship between fund transfers and carbon emissions, while Luni and Majeed (2020) emphasized the importance of increasing the share of renewable energies in energy consumption to mitigate CO_2 emissions in South Asian economies. From a more geographically focused perspective, Udeagha and Ngepah (2022) highlighted the differentiated impact of renewable and non-renewable energy consumption levels on CO_2 emissions in South Africa, thus emphasizing the need for a context-specific approach. Furthermore, studies such as that by Raghutla and Kolati (2023) underscored the importance of transitioning to renewable energies to achieve broader environmental goals, while research conducted in China by Riti et al. (2018) highlighted the long-term benefits of promoting renewable energies to mitigate greenhouse gas emissions. However, some studies, such as that by Aslan et al. (2021), have also revealed that renewable energy consumption may have a negative impact on certain environmental quality indicators, underscoring the need for thorough analysis of different contexts to fully understand the implications of renewable energies on the environment.

Akbar et al. (2024) analyze SAARC countries (1971–2020) and conclude that RES consumption decreases emissions, while non-renewable energy increases them. Urbanization and economic growth exacerbate pollution, but secondary education improves environmental quality. Sari Saudi et al. (2024) confirm this finding in Indonesia, where RES adoption and storage technologies reduce emissions, although globalization has a negative effect. Results vary depending on geographical and policy contexts. Ivan et al. (2023) show that in leading nuclear energy-producing countries (USA, China, etc.), RES and nuclear energy reduce ecological footprints, whereas fossil fuels worsen them. Conversely, Ahmat et al. (2024) highlight that in Malaysia, reliance on non-renewable energy and economic growth intensify emissions, justifying carbon taxation. Ahmed et al. (2024) note that in Somalia, although solar energy remains underutilized, its potential could mitigate the environmental impact of the agricultural sector. RES integration faces technical and social barriers. Priambodo et al. (2022) reveal that in Indonesia, RES power plants require 45–78 times more space than coal plants but reduce emissions by 95%. Kokchang et al. (2023) emphasize that in Linfen (China), while 80% of citizens support RES, 10% lack awareness, necessitating educational campaigns. RES drives green growth but requires tailored policies. Manal (2024) underscores the role of wind energy and hydrogen in Saudi Arabia's economic transformation. Ehsanullah et al. (2025) compare 20 countries and conclude that those predominantly using RES exhibit better governance and positive environmental impacts. Studies converge on the need for integrated energy policies. Avazkhodjaev et al. (2022) analyze CIS countries and recommend balancing economic growth with energy transition. Susilawati and Satrianto (2024) highlight that in ASEAN-5, foreign direct investment and RES differently influence emissions across sectors.

The rising prominence of renewable energies garners increasing interest, particularly in G7 countries, due to their potential environmental and economic benefits. Recent research highlights potential gains, including CO_2 emissions reduction and economic growth stimulation. Nevertheless, challenges remain, particularly in terms of the effectiveness of environmental and fiscal policies, as well as the need to adapt approaches to specific regional contexts. It is essential to conduct in-depth analysis to fully grasp the implications of renewable energies on the environment and to devise integrated strategies to maximize benefits while minimizing negative impacts. Ultimately, the transition to renewable energies represents a crucial opportunity to promote environmental and economic sustainability, particularly in G7 countries.

2.4. Digitalization and Environmental Quality

Digitalization, by revolutionizing global economic and social processes, can significantly influence environmental quality. It notably contributes to process dematerialization, reducing the consumption of material resources such as paper and plastic, as highlighted in Khan and Ximei (2022)'s study on the environmental implications of the digital economy. Simultaneously, digitalization enables optimization of industrial processes through technologies such as the Internet of Things (IoT) and data analysis, which reduces energy consumption and associated greenhouse gas emissions, as evidenced by reports such as the one from the International Energy Agency (IEA) on digitalization and energy. Moreover, it fosters innovation in sustainable solutions, such as renewable energies, facilitating their integration into power grids, as demonstrated in Lund's study (2007) on energy policies. However, it is important to note that digitalization can have indirect effects on the environment, such as increased electricity consumption for digital infrastructures, as cautioned by researchers like Xu et al. (2022), Dzwigol et al. (2024), Truong (2022), Bergman and Foxon (2023).

While digitalization offers opportunities to enhance environmental quality, it is essential to consider indirect effects and externalities to ensure its real contribution to environmental sustainability. Recent studies on the interplay between technology, the environment, and the economy provide intriguing insights into the future of sustainability. Menegaki and Tiwari (2023) examined the willingness to pay (WTP) for new technologies and environmental technologies in the hospitality industry, revealing a positive link between the adoption of new technologies and consumers' environmental sensitivity. This finding suggests that investments in environmental technologies can enhance tourists' experience while reducing the environmental footprint of the hospitality industry. Saqib and Usman (2023) investigated the role of environmental technologies and stringent environmental policies on green growth in China. Their findings indicate that environmental technological innovations have a positive impact on both short-term and long-term green economic growth. However, the stringency of environmental policies has a short-term negative effect, underscoring the need for continuous improvement of environmental policy to achieve sustainability goals. Research by Ercan et al. (2024) focused on the impact of technological innovations on the environmental Kuznets curve in the EU-27, revealing that these innovations contribute to environmental quality. This underscores the importance of considering these innovations in environmental policies to ensure environmental quality.

On the other hand, He et al. (2023) analyzed the impact of digital economic development and environmental pollution on residents' health in China. Their results showed that digital economic development directly improves residents' health and indirectly reduces environmental pollution, highlighting the importance of scientifically formulated digital economic development policies to improve environmental quality and residents' health. Abbas and Najam (2024) emphasized the importance of digitization in promoting green technological innovation, highlighting the crucial role of digital finance in financing and expanding green initiatives, thus contributing to a more environmentally conscious and economically resilient economy. In the Chinese context, Yao et al. (2023) examined the impact of digital finance on environmental pollution management, highlighting its role in promoting green technological innovation and supporting green government subsidies, particularly in Midwest cities and resource-focused cities. Xie et al. (2023) examined how the digital economy can contribute to inclusive green growth (IGG) in China, emphasizing the importance of selectively promoting the digital economy for IGG while considering government environmental regulation (GER). Other studies have also investigated the impact of information and communication technologies (ICT) and digitization on environmental sustainability, such as those by

Xiang (2023), Liu et al. (2024), and Yong et al. (2023), highlighting the positive role of ICT in promoting sustainable development. Furthermore, research like that of Zulfiqar et al. (2023) has examined the links between digitization and carbon and ecological footprints, emphasizing the importance of promoting more energy-efficient digital technologies to reduce environmental impact. Finally, studies like that of Haq and Huo (2023) have explored the role of digitization in SME environmental performance, highlighting the importance of digitization and institutional quality in promoting environmental sustainability.

Digitalization's environmental impact presents a complex duality. Astini et al. (2023) reveal that crypto trading in Asia significantly increases CO_2 emissions due to energy-intensive blockchain operations, demonstrating digitalization's potential environmental costs. Conversely, Djalilov et al. (2023) find internet adoption reduces emissions in post-communist countries, highlighting digital human capital's positive role. Financial digitalization shows particular promise for sustainability. Permana et al. (2024) demonstrate digital finance lowers CO_2 emissions in developing nations, while Linghui et al. (2024) show digital financial inclusion improves air quality in Asia, contrasting with traditional finance's mixed effects. These findings suggest targeted digital solutions can outperform conventional approaches. The broader digital economy's impact requires careful management. Karaki et al. (2023) identify long-term correlations between digitalization and emissions in BRICS nations, emphasizing the need for complementary green policies. This aligns with Astini et al. (2023)'s call for replacing energy-intensive technologies with greener alternatives.

Recent research has highlighted the intricate interplay between technology, the environment, and the economy, which significantly shapes the trajectory of sustainability. This understanding is particularly pertinent for leading global economies like those within the G7 group. From shaping consumer preferences to crafting government policies, a myriad of factors contribute to the pursuit of environmental stewardship and economic well-being. While technological advancements offer promising avenues for bolstering sustainability efforts, the establishment of robust policy frameworks and institutional mechanisms remains indispensable in achieving enduring environmental objectives. As the G7 nations navigate the complexities of the 21^{st} century, it becomes increasingly imperative to adopt comprehensive strategies that prioritize both environmental preservation and economic advancement. By harnessing the potential of digitalization, fostering the development of green innovations, and enacting effective environmental policies, these countries can chart a course towards a more sustainable and resilient future. Such concerted efforts not only benefit the immediate environment but also lay the groundwork for long-term prosperity and societal well-being on a global scale.

3. EMPIRICAL METHODOLOGY AND DATA

This study aims to examine the impact of environmental taxes, renewable energy adoption and digitalization on environmental sustainability in G7 countries. Using data from reputable sources, we build an econometric model to quantify these impacts. By describing the variables, stating the model specifications and justifying our choice of econometric methodology, we aim to provide an in-depth understanding of the complex interactions between economic growth, environmental policies and technological advances.

3.1. Data Sources and Variables

The central objective of this study is to explore the impact of environmental taxes, renewable energy adoption, and digitalization on environmental sustainability in the G7 countries (Germany, Canada, the United States, France, Italy, Japan, and the United Kingdom) over the period from 1994 to 2021. The choice of this timeframe was determined by the availability of data necessary for our analysis, which was extracted from reputable sources such as the International Energy Agency (IEA) and the Organisation for Economic Co-operation and Development (OECD).

Digitalization, measured by the number of internet users per hundred people, was assessed based on the research works of Choi and Yi (2009; 2018), Bakari (2021), Bakari (2022), and Bakari et al. (2022). Environmental taxes were measured by environmentally related tax revenue, adjusted in constant 2015 USD, following studies by Dahmani (2023), Ben Youssef and Dahmani (2024), Youssef et al. (2023), Hao et al. (2021), Kirikkaleli (2023), and Depren et al. (2023). Renewable energy was evaluated using data on combustible renewable energy and waste in metric tons of oil equivalent, drawn from research by Tiba et al. (2016), Tiba and Belaid (2021), Pao and Fu (2013), Wang et al. (2022), Ntanos et al. (2018), and Kasperowicz et al. (2020). CO_2 emissions were employed as an indicator of environmental quality, based on studies by Omri (2013), Omri et al. (2023), Ahmad et al. (2023), Irfan et al. (2023), Demir et al. (2023), and Fakher et al. (2023). Lastly, Gross Domestic Product (GDP) per capita in constant 2015 USD was utilized as a measure of economic growth, in accordance with research by Chirwa and Odhiambo (2016), Cuaresma et al. (2014), Batrancea et al. (2023), and Bakari and Tiba (2022), Gafsi and Bakari (2024; 2025). Additionally, Table 1 presents the description of our data, providing a comprehensive overview of the variables under consideration and their sources. Overall, this study aims to provide a comprehensive understanding of the interactions among these factors and their impact on environmental sustainability within the economies of the G7 countries over time.

Table 1: Descriptions of data and variables

Variable	Designation	Definitions	Sources
CO_2	Environmental Quality	CO_2 emissions (kt)	OECD
GDP	Economic Growth	Gross domestic product per capita (constant 2015 USD)	OECD
ET	Taxes Environmental	Environmentally related tax revenue (constant 2015 USD)	OECD
REC	Renewable Energy	Combustible renewable energy and waste (metric tons of oil equivalent)	EIA
DI	Digitalization	The number of internet users per hundred people	OECD

3.2. Model Specification and Theoretical Background

The development and estimation of the econometric model presented represent a significant step towards understanding the complex dynamics among economic growth, environmental policies, renewable energy consumption, and digitization. By quantifying the impacts of these factors on CO_2 emissions, the model provides valuable insights for policymakers aiming to promote sustainable economic growth and environmental sustainability. The use of rigorous analytical approaches, such as econometric modeling, holds promise in guiding the formulation of policies conducive to transitioning towards cleaner energy sources and achieving environmental sustainability in G7 countries. The determinants of environmental sustainability have been a subject of extensive research and policy debate. As countries strive for economic development, concerns regarding environmental degradation, particularly carbon dioxide (CO_2) emissions, have become paramount. To address these issues effectively, it is crucial to understand the intricate relationships between economic growth, environmental policies, renewable energy consumption, and digitalization. This necessitates the development of robust econometric models capable of quantifying the impacts of these factors on environmental quality. The general specification of the model we aim to estimate which is inspired from Khalid et al. (2021), Mesagan and Nwachukwu (2018), Ganda (2021), Zafar et al. (2020), Imamoglu (2018) and Fakher (2019) can be expressed as follows:

$$CO2 = F(GDP, ET, REC, DI) \tag{1}$$

Equation (1) offers a succinct depiction of the production function, where CO_2, GDP, ET, REC, and DI respectively denote environmental quality, economic growth, environmental tax revenues, renewable energy consumption, and digitization. Equation (2) further elaborates on the production function by incorporating these variables into a more detailed and nuanced form. In this equation, "A" denotes the constant level of technology utilized within the country. The coefficients β_1, β_2, β_3, and β_4 quantify the impact of each variable—economic growth (GDP), environmental taxes (ET), renewable energy consumption (REC), and digitization (DI)—on environmental quality (CO_2).

$$CO2_{it} = A\, GDP^{\hat{a}_1}\, ET^{\hat{a}_2}\, REC^{\hat{a}_3}\, DI^{\hat{a}_4} \tag{2}$$

Equation (2) provides a thorough understanding of how each factor influences environmental quality, highlighting the diverse impacts represented by the β coefficients. It establishes a comprehensive framework for analyzing the intricate relationship among economic growth, environmental taxes, renewable energy consumption, and digitalization concerning environmental quality. Equation (3) illustrates the transformation of all variables in the model through logarithmic conversion. This process aims to linearize the Cobb-Douglas production function, a nonlinear model, making it more suitable for linear regression analysis. Logarithmically transforming each variable allows their relationships to become additive, simplifying the interpretation of the Cobb-Douglas production function. The resulting transformed equation is as follows:

$$Ln(CO2_{it}) = Ln(A) + \beta_1 Ln(GDP_{it}) + \beta_2 Ln(ET_{it}) + \beta_3 Ln(REC_{it}) + \beta_4 Ln(DI_{it}) + \varepsilon_{it} \tag{3}$$

In Equation (3), 'Ln' signifies the natural logarithm, while 'ε_{it}' represents the error term capturing unobserved factors influencing economic growth. The logarithmic transformation demonstrated here is a prevalent method in econometrics, frequently utilized to introduce linearity into models, thereby simplifying coefficient estimation via linear regression techniques. Through logarithmic transformation of variables, the model becomes more conducive to analysis, facilitating a more straightforward and interpretable examination of environmental relationships. This method is widely embraced in econometric analysis to deepen comprehension of economic dynamics and extract meaningful insights from empirical data. Subsequently, in Equation (4), notation is further streamlined, with the constant term 'Ln(A)' substituted by 'β_0'.

$$Ln(CO2_{it}) = \beta_0 + \beta_1 Ln(GDP_{it}) + \beta_2 Ln(ET_{it}) + \beta_3 Ln(REC_{it}) + \beta_4 Ln(DI_{it}) + \varepsilon_{it} \tag{4}$$

Through the implementation of a comprehensive econometric model, our objective is to offer substantial insights that can inform the environmental and economic policies of the participating countries. This meticulous analytical approach is poised to not only unravel the underlying dynamics of these relationships but also to formulate recommendations aimed at fostering sustainable economic growth, environmental resilience, and the transition towards cleaner energy sources within the G7 nations.

3.3. Selection and Justification of Econometric Models

The analysis we conduct, focusing on the economic, technological, energy, and environmental dynamics of G7 countries from 1994 to 2021, highlights the importance of choosing panel data models. Within the wide range of econometric models suitable for panel data analysis, several options are available, each designed to shed light on different aspects of our research questions. Static models, such as Fixed Effects (FE) and Random Effects (RE), are particularly effective in addressing unobserved heterogeneity, allowing for the consideration of country-specific characteristics. Fixed Effects and Random Effects models are widely used in econometrics to analyze panel data. However, these methods have significant limitations to consider. Fixed Effects models assume that individual heterogeneity is constant for all individuals, which can be restrictive when this assumption is not met. This limitation has been widely discussed in the literature (Wooldridge, 2010). Additionally, these models can be sensitive to correlation between explanatory variables and individual effects, potentially leading to bias in coefficient estimates (Greene, 2012). Random Effects models, on the other hand, assume that individual heterogeneity is random and uncorrelated with explanatory variables. However, this assumption can be violated in certain situations, compromising the validity of results (Baltagi, 2008). Furthermore, Random Effects models may be less effective in the presence of significant and correlated individual heterogeneity with explanatory variables, as they do not control for this heterogeneity as precisely as Fixed Effects models (Wooldridge, 2010). Moreover, specifying the Random Effects model can be tricky, especially regarding the choice of covariance structure for random effects, requiring careful attention during estimation and interpretation of results (Baltagi, 2008).

However, when focusing on the dynamic interaction of variables over time, models such as Vector Autoregression (VAR) and Vector Error Correction Model (VECM) become essential for understanding temporal dependencies and equilibrium trajectories in the data. Indeed, estimating VAR (Vector Autoregression) and VECM (Vector Error Correction Model) models within the framework of panel data in econometrics offers rich perspectives but also presents limitations and weaknesses to consider. The Panel VAR model, while capturing complex dynamics between multiple variables across different individual units and over multiple time periods, may suffer from several limitations. First, its increased dimensionality may pose challenges in panel data with a large number of time series and individual units, increasing analysis complexity (Lütkepohl, 2005). Additionally, the explanatory power of the VAR model may be limited in some cases, especially when variables are weakly correlated or when underlying dynamics are complex, restricting its ability to capture causal relationships between variables. Furthermore, VAR model results can be sensitive to specification choices, such as the number of lags to include or the selection of explanatory variables. On the other hand, the Panel VECM model offers a richer approach by considering long-term equilibria between variables. However, it also presents significant limitations. The VECM model assumes that cointegration vectors are the same for all individual units, which may not be verified in some cases, leading to misspecification of the model (Masih and Masih, 1996). Additionally, estimating the VECM model in a panel data framework may be more complex than in a simple time series data framework, due to the need to address both temporal and cross-sectional dimensions. Finally, the VECM model is sensitive to violations of the cointegration assumption; if this assumption is violated, model estimates may be biased and unreliable.

To further enrich our econometric toolbox, the Generalized Method of Moments (GMM) stands out for its ability to address potential specification errors or endogeneity through its innovative use of data moments to estimate parameters. However, despite its robustness, the GMM method may have limitations. Indeed, it can be sensitive to the choice of instruments and the specification of the moment model. Poorly chosen instruments or inadequate model specification can lead to biased estimates (Hansen, 1982; Arellano and Bond, 1991). In the context of cointegrated series, Dynamic Ordinary Least Squares (DOLS) and Fully Modified Ordinary Least Squares (FMOLS) are popular methods that provide refined estimates of long-term relationships. However, these methods are not without limitations. They can be sensitive to violations of assumptions, particularly regarding series stationarity and correct model specification. Therefore, unreliable results may be obtained if these assumptions are not met (Phillips and Hansen, 1990; Saikkonen, 1991).

The Canonical Cointegration Regression (CCR) model is widely used to adjust for endogeneity and serial correlation in cointegrated series. Nevertheless, this method also has limitations. It can be sensitive to issues such as multicollinearity and incorrect model specification, which can affect the validity of results (Engle and Granger, 1987; Johansen, 1988). For an analysis requiring a nuanced understanding of group-level homogeneities and individual-specific dynamics, Pooled Mean Group (PMG), Mean Group (MG), and Dynamic Fixed Effect (DFE) estimators offer versatile approaches. These methods manage to balance the need for individual specificity with overall dataset trends. The Pooled Mean Group (PMG) estimator combines the advantages of individual specificity and common trends, making it a robust method for panel data. However, it may be sensitive to violations of underlying assumptions, such as parameter heterogeneity between groups or the presence of non-stationary time series (Pesaran and Smith, 1995). Similarly, the Mean Group (MG) estimator is better suited to account for heterogeneity between individual units than PMG, but it relies on the assumption of coefficient homogeneity between groups, which can be restrictive in certain contexts (Pesaran and Smith, 1995). On the other hand, the Dynamic Fixed Effect (DFE) estimator is capable of capturing dynamic individual effects, offering a more flexible approach for panel data. However, DFE may be sensitive to temporal dynamics specification and may suffer from issues such as over-parameterization in models with many groups (Nickell, 1981). Finally, the Driscoll and Kraay (1998) model stands out for its robustness to cross-sectional dependence and its ability to provide consistent standard error estimates, making it a valuable addition to ensure analytical robustness in panel data. However, this model may be limited in contexts where other forms of dependence, such as temporal dependence, are present. The Autoregressive Distributed Lag (ARDL) model, as formulated by Pesaran et al. (2001), offers significant advantages for econometric analysis. Its main strength lies in its ability to model mixed-order variables, allowing for comprehensive analysis of short-term dynamics and long-term relationships between studied variables. This methodological flexibility is essential for understanding the complexities of economic and environmental interactions. Previous studies have also highlighted the effectiveness of the ARDL approach in modeling non-stationary time series, making it an appropriate choice for empirical analyses involving economic and environmental data (Narayan and Smyth, 2008). Additionally, the applicability of the ARDL model to small sample sizes makes it a valuable tool for empirical research conducted in contexts where data are limited. This feature is particularly relevant in the context of our study, which focuses on the economies of G7 countries. Previous studies have demonstrated the effectiveness of the ARDL approach in similar contexts, providing a solid methodological framework for our analysis (Kutan and Yigit, 2003). Moreover, the ARDL model integrates well with other econometric methodologies such as PMG (Pooled Mean Group), MG (Mean Group), and DFE (Dynamic Fixed Effects), thus offering additional analytical flexibility. This methodological compatibility strengthens the robustness of our analysis and allows for in-depth exploration of the relationships between environmental taxes, digitalization, renewable energies, and environmental quality in G7 economies. Previous research has also highlighted the effectiveness of the ARDL approach in combination with other econometric methodologies, emphasizing its relevance for our study. The ARDL model, which is central to the analysis of the interactions in our study, is described as follows:

$$Y_{it} = \alpha_i + \sum_{j=1}^{p} \beta_{ij} Y_{it-1} + \sum_{k=1}^{q} \gamma_{ik} X_{kit} + \varepsilon_{it} \quad (5)$$

In this model, the dependent variable for each country 'i' at time 't', denoted as 'Y_{it}', is expressed as a function of individual-specific intercept 'α_i', coefficients 'β_{ij}' on the lagged dependent variable, and coefficients 'γ_{ik}' on the explanatory variable 'X_{kit}'. Here, 'p' and 'q' represent the number of lags for 'Y_{it}' and each 'X_{kit}', respectively, capturing the historical influence on current observations. The error term 'ε_{it}' represents unobserved factors affecting the dependent variable. Building upon Equation (4), our tailored ARDL model enhances and specifies the relevant variables pertinent to our research framework. The refined model equation is thus formulated as follows:

$$\begin{aligned} Ln\,(CO2)_{it} &= \alpha_i + \beta_1\, Ln\,(GDP_{it}) + \beta_2\, Ln\,(ET_{it}) \\ &+ \beta_3\, Ln\,(REC_{it}) + \beta_4\, Ln\,(Ln_{it}) \\ &+ \sum_{j=1}^{p} \phi_{ij}\, Ln(CO2_{it-j}) + \sum_{k=1}^{q} \theta_{ik} X_{kit} + \varepsilon_{it} \end{aligned} \quad (6)$$

Equation (6) encapsulates the interplay of various factors influencing CO_2 emissions. The intercept 'α_i' represents country-specific constants shaping emissions levels. Coefficients 'β_1' through 'β_4' gauge the impact of economic and demographic variables, log-transformed to enhance stability and interpretability. The incorporation of lagged terms, denoted as 'ϕ_{ij}' and 'θ_{ik}', is pivotal for capturing the influence of past emissions and related factors on present environmental outcomes, thus integrating temporal dynamics into our analysis. The error term ε_{it} conforms to the assumption of normal distribution, accommodating unexplained variations in emissions across countries and time periods.

While the ARDL model, as outlined in Equation (5), proves valuable for our analysis, it's imperative to acknowledge its limitations within first-generation econometric techniques. Originally groundbreaking, the conventional panel ARDL framework assumes cross-sectional independence across units, a premise challenged by global economic dynamics and common external shocks affecting multiple countries simultaneously. Neglecting cross-sectional dependencies risks bias and undermines robust econometric analysis. Second-generation econometric models address this issue by incorporating refined methodologies. Coakley et al. (2006) critically evaluate Pesaran et al.'s (1999) MG estimator, leading to the development of methodologies capable of modeling cross-sectional interdependencies. Pesaran (2006) introduces an augmented ARDL framework incorporating a cross-sectional mean of observable variables, refined by Chudik and Pesaran (2015) and Everaert and De Groote (2016) into the Common Correlated Effects (CCE) approach. This advancement allows for adaptations like the Cross-Section Augmented Distributed Lag (CS-DL) and Cross-Section Augmented Autoregressive Distributed Lag (CS-ARDL) models. Our analysis leans towards the CS-ARDL model proposed by Chudik et al. (2016) for its nuanced incorporation of optimal lag structures amidst cross-sectional dependencies. Thus, our selected CS-ARDL model enhances traditional ARDL by integrating cross-sectional averages, accounting for collective influences on the panel. The augmented model is expressed as follows:

$$\begin{aligned} Y_{it} &= \alpha_i + \sum_{j=1}^{p} \beta_{ij} \left(Y_{it-j} - \bar{Y}_{t-j} \right) \\ &+ \sum_{k=1}^{q} \gamma_{ik} \left(X_{kit} - \bar{X}_{kt} \right) + \delta D_t + \mu_i + \varepsilon_{it} \end{aligned} \quad (7)$$

Here, '$\bar{Y}_{t-j}$' '$\bar{Y}_{t-j}$' and '$\bar{X}_{kt}$' denote the cross-sectional averages of the dependent and independent variables, respectively, for each lag '*j*' and '*k*', mitigating common trends across the panel. The coefficient 'δ' associated with time fixed effects 'D_t' and the term 'μ_i' for individual fixed effects capture unique country characteristics, while 'ε_{it}' represents the specific error term for each unit's time observations. This methodological approach addresses the diverse dynamics of environmental sustainability in G7 countries by considering both country-specific traits and overarching trends. Incorporating the Dynamic Common Correlated Effects Mean Group Estimator (DCCEMG) and Augmented Mean Group (AMG) models enhances the econometric analysis by handling unobserved common factors in panel data. The DCCEMG model, introduced by Chudik and Pesaran (2015), incorporates lags of cross-sectional means, offering a comprehensive treatment of dependencies and slope heterogeneity, and accommodating potential structural breaks within the dataset. The model is presented as follows:

$$\begin{aligned} Y_{it} &= \alpha_i + \sum_{j=1}^{p} \phi_{ij} Y_{it-j} + \sum_{k=1}^{q} \theta_{ik} X_{kit} \\ &+ \sum_{j=1}^{p} \lambda_j \bar{Y}_{t-j} + \sum_{k=1}^{q} \gamma_k \bar{X}_{kt} + \mu_i + \varepsilon_{it} \end{aligned} \quad (8)$$

In this model, 'α_i' represents individual fixed effects capturing unique attributes of each unit, while 'ϕ_{ij}' and 'θ_{ik}' correspond to coefficients on lags of dependent and explanatory variables, respectively. Terms 'λ_j' and 'γ_k' adjust for lagged cross-sectional averages, effectively controlling for the influence of unobserved common factors. 'μ_i' denotes individual-specific fixed effects, and 'ε_{it}' is the idiosyncratic error term. Additionally, the Augmented Mean Group (AMG) model, conceptualized by Eberhardt and Teal (2010), introduces a common dynamic effect 'ψ_t'. This effect quantifies the overarching impact of unobserved common factors on the entire panel, enriching the analysis by accounting for the dynamic interplay of global economic trends and structural changes. The AMG model is written as follows:

$$Y_{it} = \alpha_i + \sum_{j=1}^{p} \beta_{ij} Y_{ij-j} + \sum_{k=1}^{q} \gamma_{ik} X_{kit} + \psi_t \bar{C}_t + \varepsilon_{it} \quad (9)$$

In this framework, 'α_i' represents the individual fixed effect, 'β_{ij}' and 'γ_{ik}' are coefficients on lagged dependent and explanatory variables, 'ψ_t' captures the average influence of unobserved factors, and '$\bar{C}_t$' is the cross-sectional average used to model common effects. We maintain 'ε_{it}' as the idiosyncratic error term. By applying methodologies from the CS-ARDL, DCCEMG, and AMG models to our analysis, we gain insight into the relationship between environmental taxes, digitalization, renewable energy and environmental quality across G7 countries. These adapted models, tailored precisely to our study variables, offer a comprehensive approach to addressing cross-sectional dependencies and heterogeneities in our panel data. The CS-ARDL model enhances the traditional ARDL approach by integrating cross-sectional averages of all variables, thereby controlling for unobserved common factors affecting all countries in the panel. This adjustment is expressed as follows:

$$\text{Ln}\,(CO2)_{it} = \alpha_i + \sum_{j=1}^{p} \beta_{ij} \left(\text{Ln}\,(CO2_{it\text{-}j}) - \overline{\text{Ln}\,(CO2}_{t\text{-}j})\right) + \sum_{k=1}^{q} \gamma_{ik} \left(X_{kit} - \bar{X}_{kt}\right) + \delta D_t + \mu_i + \varepsilon_{it} \quad (10)$$

In this setup, 'Ln (CO_{2it-j})' represents the natural log of CO_2 emissions for country '*i*' at time '*t*', 'α_i' captures individual fixed effects, 'β_{ij}' and 'γ_{ik}' are coefficients of lagged dependent and explanatory variables, respectively, adjusted for cross-sectional averages, and 'ε_{it}' is the error term. The DCCEMG model further controls for cross-sectional dependencies and slope heterogeneity by including lags of cross-sectional averages. Its formulation is as follows:

$$\text{Ln}\,(CO2_{it}) = \alpha_i + \sum_{j=1}^{p} \phi_{ij}\, \text{Ln}\,(CO2_{it-j}) + \sum_{k=1}^{q} \theta_{ik} X_{kit} + \sum_{j=1}^{p} \lambda_j\, \overline{\text{Ln}\,(CO2)}_{t-j} + \sum_{k=1}^{q} \gamma_k \bar{X}_{kt} + \mu_i + \varepsilon_{it} \quad (11)$$

In this context, 'ϕ_{ij}' and 'θ_{ik}' represent coefficients for the lags of the dependent and explanatory variables, respectively. 'λ_j' and 'γ_k' account for the effects of lagged cross-sectional averages, and 'μ_i' denotes the individual fixed effect. The AMG model introduces a common dynamic effect, 'ψ_t', which reflects the average impact of unobserved common factors on all units in the panel.

$$\text{Ln}\,(CO2_{it}) = \alpha_i + \sum_{j=1}^{p} \beta_{ij} \text{Ln}\,(CO2_{it-j}) + \sum_{k=1}^{q} \gamma_{ik} X_{kit} + \psi_t C_t + \varepsilon_{it} \quad (12)$$

In our analysis, 'C_t' represents the contemporaneous effect of common factors, offering a unique perspective on the interconnectedness of economies and structural variation within panel data. By incorporating these advanced econometric models, we enhance our ability to navigate the complex dynamics involved, ensuring a robust examination of the effects of environmental taxes, digitalization and renewable energy on environmental quality. Through these strategies, our study explores the multifaceted relationships between economic development, environmental protection, and sustainability goals in the G7 context. This comprehensive approach strengthens the empirical foundation of our research, providing valuable insights for policy formulation and the pursuit of sustainable development across the continent.

4. EMPIRICAL RESULTS AND DISCUSSION

The empirical results section delves into the statistical analysis of key variables related to environmental quality, economic growth, environmental policies, renewable energy consumption, and digitization. Through descriptive statistics, correlation analysis, cross-section dependence tests, slope homogeneity analysis, second-generation panel unit root tests, cointegration analysis, and examination of long-run and short-run relationships, we aim to uncover significant insights into the interplay among these factors within the context of the G7 countries. The section provides a comprehensive overview of the data characteristics, relationships, and robustness of the analytical framework employed.

4.1. Descriptives Statistics

The results of descriptive statistics reveal interesting characteristics for five different variables: CO_2, GDP, ET, REC, and DI (Table 2). For the CO_2 variable, the skewness is 1.963803 and the kurtosis is 5.089814. These values indicate a strongly right-skewed distribution with thick tails, suggesting a concentration of values around the mean but with the presence of relatively high extreme values. Regarding the GDP variable, the skewness is 2.083747 and the kurtosis is 5.899086. These values also demonstrate a right-skewed distribution with thick tails, indicating a concentration of values around the mean but with higher extreme values than expected in a normal distribution. For the ET variable, the skewness is 0.868161 and the kurtosis is 3.614962. These values reveal a slightly right-skewed distribution with thinner tails compared to CO_2 and GDP, suggesting values closer to the mean with fewer extreme values. Concerning the REC variable, the skewness is 0.610436 and the kurtosis is 2.210091. These values indicate a rather symmetric distribution with thinner tails compared to CO_2 and GDP, suggesting a dispersion of values around the mean without significant extreme values. Finally, for the DI variable, the skewness is 1.933775 and the kurtosis is 6.309185. These values reveal a strongly right-skewed distribution with thick tails, similar to what is observed for CO_2 and GDP, indicating a concentration of values around the mean with relatively high extreme values. These results highlight the diversity of distributions among the studied variables, with some showing pronounced asymmetry and extreme values, while others display a more symmetric distribution around the mean.

The Jarque-Bera statistic, used to test the normality assumption, along with its associated probability value, provides crucial information about the deviation from a normal distribution. For the CO_2 variable, the Jarque-Bera statistic is 161.6461 with a probability of 0.000000, indicating strong evidence against the null hypothesis of normality. This suggests that the distribution of CO_2 data significantly deviates from a normal distribution. Similarly, the GDP variable exhibits a Jarque-Bera statistic of 210.4772 with a probability of 0.000000, indicating departure from normality. The ET variable also deviates from normality with a Jarque-Bera statistic of 27.70947 and a probability of 0.000001. Conversely, the REC variable shows a Jarque-Bera statistic of 17.26828 with a probability of 0.000178, implying departure from normality but to a lesser extent compared to CO_2, GDP, and ET. Finally, the DI variable displays a Jarque-Bera statistic of 211.5873 with a probability of 0.000000, reinforcing the evidence against normality. Overall, these results suggest that the distribution of these variables deviate significantly from a normal distribution, which is essential for appropriate statistical inference and modeling.

Also, the descriptive statistics provide valuable insights into the central tendency and dispersion variables. For the CO_2 variable, the mean value is approximately 1.29 million, with a median of around 545,370.1. The maximum CO_2 value recorded is approximately

5.78 million, while the minimum is approximately 267,154.7. The standard deviation, measuring the dispersion of values around the mean, is approximately 1.67 million. These statistics suggest that the CO_2 data have a wide range of values, with a right-skewed distribution indicated by a higher mean compared to the median and a large standard deviation. Regarding the GDP variable, the mean GDP is approximately 4.44 trillion, with a median of around 2.60 trillion. The maximum GDP recorded is approximately 20.5 trillion, while the minimum is approximately 930 billion. The standard deviation is approximately 4.85 trillion. These statistics indicate a considerable variation in GDP values, with a right-skewed distribution similar to that of the CO_2 variable. For the ET variable, the mean energy consumption is approximately 64 billion, with a median of around 60.6 billion. The maximum energy consumption recorded is approximately 145 billion, while the minimum is approximately 14.4 billion. The standard deviation is approximately 32.5 billion. These statistics reveal a moderate range of energy consumption values, with a relatively symmetrical distribution indicated by a mean close to the median and a moderate standard deviation. Concerning the REC variable, the mean renewable energy consumption is approximately 9.94, with a median of around 8.73. The maximum renewable energy consumption recorded is approximately 23.85, while the minimum is approximately 0.85. The standard deviation is approximately 6.52. These statistics suggest a moderate range of renewable energy consumption values, with a distribution slightly skewed to the right. Finally, for the DI variable, the mean direct investment is approximately 6.22 billion, with a median of around 4.23 billion. The maximum direct investment recorded is approximately 30.5 billion, while the minimum is approximately 10.93 million. The standard deviation is approximately 6.75 billion. These statistics indicate a wide range of direct investment values, with a right-skewed distribution similar to that of the CO_2 and GDP variables.

4.2. Correlation Analysis

The correlation analysis results between the CO_2 variable and the GDP, ET, REC, and DI variables reveal significant associations among them (Table 3). The correlation between CO_2 and GDP is very strong, with a correlation coefficient of 0.9573. This suggests a close positive relationship between economic production (GDP) and carbon dioxide emissions (CO_2), implying that regions or countries with higher economic production tend to emit more CO_2. Similarly, the correlation between CO_2 and ET is also notable, with a correlation coefficient of 0.8665. This indicates a strong positive correlation between total energy consumption (ET) and CO_2 emissions. In other words, locations consuming more energy tend to emit more CO_2.

Conversely, the correlation between CO_2 and REC is negative but weak, with a correlation coefficient of −0.2405. This suggests an inverse correlation between renewable energy consumption (REC) and CO_2 emissions, although the relationship is not very strong. This may indicate that the use of renewable energy sources can contribute to reducing CO_2 emissions, but other factors may also influence this relationship. Finally, the correlation between CO_2 and DI is strong, with a correlation coefficient of 0.7754. This indicates a positive relationship between direct investments (DI) and CO_2 emissions. It is important to note that this correlation does not demonstrate a direct causal relationship but highlights a trend where regions or countries with higher levels of direct investment tend to have higher CO_2 emissions.

4.3. Cross-Section Dependence Test

Cross-section dependence tests are crucial in econometrics to assess the presence of correlations among observations in panel data, where multiple units are observed at different time points. They are vital for verifying the assumption of independence between different cross-sectional units, ensuring the validity of econometric estimations. The Breusch-Pagan LM cross-section dependence test, introduced by Breusch and Pagan (1980), utilizes a version of the LM statistic within the framework of heteroskedasticity to evaluate dependence. Mathematically, the test statistic is calculated as follows:

$$LM_{BP} = T.R^2_{pool}$$

Where "T" represents the number of time periods and "R^2_{pool}" is the coefficient of determination of the pooling regression model for all observations. The Pesaran scaled LM cross-section dependence test, developed by Pesaran (2004), proposes a modified LM statistic based on the sum of squared cross-sectional correlations. Its statistic is given by:

$$LM_P = \frac{T.N}{2}.\left(\frac{1}{N}.\sum_{i=1}^{N}\sum_{j\neq i}^{N}\hat{\rho}_{ij}^2\right)$$

Where "T" represents the number of time periods, "N" is the number of cross-sectional units, and '$\hat{\rho}_{ij}$' denotes the estimated cross-sectional correlations. The Bias-corrected scaled LM cross-section dependence test, introduced by Bai and Ng (2004), adjusts the LM statistic to correct for potential bias in the Pesaran scaled LM test. Its statistic is calculated similarly to the Pesaran scaled LM test but with a bias correction. Finally, the Pesaran CD cross-section dependence test, also developed by Pesaran (2004), adjusts a test statistic based on the sum of squared cross-sectional correlations to account for sample size and panel dimension. Its statistic is given by:

$$CD_P = \frac{T.N}{2}.\left(\frac{1}{N}.\sum_{i=1}^{N}\sum_{j\neq i}^{N}\hat{\rho}_{ij}\right)^2$$

These tests provide valuable tools for evaluating cross-section dependence in panel data, thereby enabling a more robust and reliable econometric analysis. Table 4 denotes the results of Cross-Section Dependence Tests.

The results of the Cross-Section Dependence Test indicate significant evidence of cross-sectional dependence among the variables Ln (GDP), Ln (CO_2), Ln (ET), Ln (REC), and Ln (DI). For each variable, including Ln (GDP), all four tests—Breusch-Pagan LM, Pesaran scaled LM, Bias-corrected scaled LM, and Pesaran CD—yield test statistics with P = 0.0000, suggesting strong rejection of the null hypothesis of no cross-sectional dependence. These findings imply a substantial degree

Table 2: Descriptives statistics

Variables	CO_2	GDP	ET	REC	DI
Mean	1285182	4.44E+12	6.40E+10	9.937334	6.22E+09
Median	545370.1	2.60E+12	6.06E+10	8.730000	4.23E+09
Maximum	5775807	2.05E+13	1.45E+11	23.85000	3.05E+10
Minimum	267154.7	9.30E+11	1.44E+10	0.850000	10931248
Standard deviation	1667877	4.85E+12	3.25E+10	6.518222	6.75E+09
Skewness	1.963803	2.083747	0.868161	0.610436	1.933775
Kurtosis	5.089814	5.899086	3.614962	2.210091	6.309185
Jarque-Bera	161.6461	210.4772	27.70947	17.26828	211.5873
Probability	0.000000	0.000000	0.000001	0.000178	0.000000
Sum	2.52E+08	8.71E+14	1.25E+13	1947.718	1.22E+12
Sum Sq. Dev.	5.42E+14	4.59E+27	2.06E+23	8285.008	8.88E+21
Observations	196	196	196	196	196

Table 3: Correlation analysis

	CO_2	GDP	ET	REC	DI
CO_2	1				
GDP	0.9573	1			
ET	0.8665	0.8962	1		
REC	−0.2405	−0.2337	−0.4974	1	
DI	0.7754	0.8996	0.7743	−0.1081	1

Table 4: Cross-section dependence test

Cross-section dependence test			
Ln (GDP)			
Test	**Statistic**	**d.f.**	**Prob.**
Breusch-Pagan LM	476.4706	21	0.0000
Pesaran scaled LM	69.20052		0.0000
Bias-corrected scaled LM	69.07089		0.0000
Pesaran CD	21.54181		0.0000
Ln (CO_2)			
Test	**Statistic**	**d.f.**	**Prob.**
Breusch-Pagan LM	287.2302	21	0.0000
Pesaran scaled LM	40.00008		0.0000
Bias-corrected scaled LM	39.87045		0.0000
Pesaran CD	11.05852		0.0000
Ln (ET)			
Test	**Statistic**	**d.f.**	**Prob.**
Breusch-Pagan LM	138.1480	21	0.0000
Pesaran scaled LM	16.99620		0.0000
Bias-corrected scaled LM	16.86657		0.0000
Pesaran CD	7.219895		0.0000
Ln (REC)			
Test	**Statistic**	**d.f.**	**Prob.**
Breusch-Pagan LM	360.2647	21	0.0000
Pesaran scaled LM	51.26956		0.0000
Bias-corrected scaled LM	51.13993		0.0000
Pesaran CD	17.54835		0.0000
Ln (DI)			
Test	**Statistic**	**d.f.**	**Prob.**
Breusch-Pagan LM	575.2268	21	0.0000
Pesaran scaled LM	84.43892		0.0000
Bias-corrected scaled LM	84.30929		0.0000
Pesaran CD	23.98324		0.0000

of interdependence among observations across different cross-sections for all analyzed variables. Therefore, it is crucial to consider cross-sectional dependence when performing further analyses or modeling.

4.4. Slope Homogeneity Analysis

Homogeneity of slopes tests assess whether the slope coefficients are consistent across all observations, implying that the relationships between independent and dependent variables remain constant across different groups or time periods. To achieve this, the test statistic is employed, calculated specifically for each test. In a study presented in Table 5, two distinct tests were conducted: those developed by Pesaran and Yamagata (2008) and those by Blomquist and Westerlund (2013).

The results of these tests, summarized in the table in terms of the statistic and corresponding P-values, evaluate the probability of observing results as extreme as those under the null hypothesis of slope homogeneity. The findings reveal very low P=0.000 for both sets of tests, suggesting a significant rejection of the null hypothesis. This indicates that there are substantial differences in slope coefficients between the tested groups or time periods, according to the criteria of the tests employed. Thus, it is robustly demonstrated that there are significant variations in the slope coefficients of the examined regression model among different subpopulations or time periods of panel data, particularly in the context of G7 country analysis.

4.5. Second-Generation Panel Unit Root Tests

This phase of our econometric investigation represents a crucial step in addressing the intricate dynamics of non-stationarity inherent in our panel dataset, with a particular emphasis on unraveling the complexities of cross-sectional dependence (CSD) observed among the G7 countries. The acknowledgment and rigorous examination of CSD are imperative, as failure to account for it could potentially introduce systematic biases into our analysis, compromising the validity and reliability of our findings regarding the underlying properties of the time series data at hand. Therefore, in order to mitigate this risk and ensure the integrity of our analytical framework, we have meticulously chosen to employ second-generation unit root tests. These advanced statistical techniques are expressly designed to contend with the intricacies of CSD, a capability notably absent in conventional first-generation tests. Our selection of the Cross-sectionally Augmented Dickey–Fuller (CADF) test and the Cross-sectionally Augmented Im, Pesaran, and Shin (CIPS) test, as pioneered by Pesaran (2007), underscores our commitment to precision and thoroughness in methodology. By harnessing the capabilities of these sophisticated tools, we aim to conduct a nuanced and comprehensive examination that not only acknowledges but effectively addresses the challenges posed by cross-sectional dependencies and heterogeneity inherent in our panel units. Through this meticulous approach, we seek to attain a refined understanding of the underlying data non-stationarity, thus ensuring the robustness and reliability of our analytical outcomes. Ultimately, the insights gleaned from these meticulously executed tests will serve as the cornerstone upon which we base decisions regarding the integration properties of the variables under scrutiny—whether they exhibit integration of order one (I(1)) or order zero (I(0)). Armed with this essential knowledge, we can confidently chart our course forward, determining the appropriateness of proceeding with subsequent cointegration analyses to unravel deeper insights into the underlying economic relationships among the variables of interest.

Table 6 describes the results of the stationarity tests carried out on the variables of the econometric model. Stationarity tests are crucial in panel series analysis because they help determine whether variables exhibit stable behaviors over time or whether they are subject to trends or fluctuations. In this specific case, the CIPS and CSADF stationarity tests both led to the same conclusions regarding the order of integration of each variable. The results indicate that environmental quality Ln (CO_2), economic growth Ln (GDP), environmental taxes Ln (ET) and renewable energy Ln (REC) are stationary after first differentiation. On the other hand, the digitalization variable Ln (DI) is stationary at the level. This distinction in the stationarity of variables influences the choice of analytical methodology. In this case, cointegration analysis and the use of the Panel ARDL model are justified, because these methods are suitable for series containing stationary variables at different orders of integration. Thus, this step allows us to refine the analytical approach to better understand the relationships between the variables and their impacts on environmental sustainability in the context of the G7 countries.

Table 5: Slope homogeneity tests

Slope homogeneity tests	Δ statistic	P-value
Slope homogeneity test (Pesaran and Yamagata, 2008)		
Slope homogeneity tests	**Δ statistic**	**P-value**
$\tilde{\Delta}$ test	9.956	0.000
$\tilde{\Delta}_{adj}$ test	11.232	0.000
Slope homogeneity test (Blomquist and Westerlund, 2013)		
Slope homogeneity tests	**Δ statistic**	**P-value**
$\tilde{\Delta}$ test	9.956	0.000
$\tilde{\Delta}_{adj}$ test	11.232	0.000

The null hypothesis for the slope heterogeneity test is that slope coefficients are homogenous

4.6. Cointegration Analysis

In this phase of our econometric investigation, we implement the panel cointegration test developed by Westerlund (2007). This test is well-suited for our dataset's panel structure, as it addresses two prevalent issues: slope heterogeneity and cross-sectional dependence (CSD), which often complicate the analysis of intricate and interconnected panel data. The specification of the Westerlund (2007) test is outlined as follows:

$$\Delta y_{it} = \delta_i' d_t + \alpha_i \left(y_{it-1} - \beta_i' x_{it-1} \right) + \sum_{j=1}^{P_i} \alpha_{ij} \delta y_{it-j} + \sum_{j=0}^{P_i} \gamma_{ij} \Delta x_{it-j} + e_{it}$$

This equation facilitates the evaluation of cointegration, factoring in the initial differences between the dependent and independent variables, with e_{it} denoting the error term. The test yields two categories of statistics: group mean statistics (G^{τ} and G^{α}) and panel statistics (P^{τ} and P^{α}). These statistics serve to examine the presence of cointegration among diverse cross-sectional units or the entire panel. Cointegration analysis utilizing this equation helps to ascertain the long-term relationship between variables while considering potential sources of error. It enables researchers to determine if there exists a stable equilibrium relationship among

Table 6: Results of panel unit root tests

Cross-Sectionally Augmented IPS (CIPS)						
At level						
		Ln (CO_2)	**Ln (GDP)**	**Ln (ET)**	**Ln (DI)**	**Ln (REC)**
C	t-statistic	0.8456	0.7176*	0.6252	0.0000***	0.4039
CT	t-statistic	0.0489	0.1087	0.9025	0.0001***	0.9873
At first difference						
		Δ(Ln (CO_2))	**Δ(Ln (GDP))**	**Δ(Ln (ET))**	**Δ(Ln (DI))**	**Δ(Ln (REC))**
C	t-statistic	0.0000***	0.0000***	0.0008***	0.1139	0.0068***
CT	t-statistic	0.0001***	0.0000***	0.0019***	0.0532*	0.0078***
Cross-Sectionally Augmented Dicky–Fuller (CADF)						
At level						
		Ln (CO_2)	**Ln (GDP)**	**Ln (ET)**	**Ln (DI)**	**Ln (REC)**
C	t-statistic	0.7838	0.7679*	0.6612	0.0001**	0.4039
CT	t-statistic	0.0489	0.0166	0.9025	0.0173***	0.9873
At First Difference						
		Δ(Ln (CO_2))	**Δ(Ln (GDP))**	**Δ(Ln (ET))**	**Δ(Ln (DI))**	**Δ(Ln (REC))**
C	t-statistic	0.0000***	0.0005***	0.0008***	0.0000	0.0062***
CT	t-statistic	0.0001***	0.0028***	0.0020***	0.0125	0.0075***
Order of Integration		I (1)	I (1)	I (1)	I (0)	I (1)

(*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%. and (no) Not Significant.

*MacKinnon (1996) one-sided p-values. C: With Constant, CT: With Constant and Trend variables, essential for robust economic and statistical analyses across various fields. These statistics are demonstrated for large samples as follows: ' $G_{\tau} = \frac{1}{N}\sum_{i=1}^{N}\frac{\hat{\alpha}_i}{SE(\hat{\alpha}_i)}$ ', and ' $P_{\tau} = \frac{\hat{\alpha}}{SE(\hat{\alpha})}$ '. For small samples, these statistics are demonstrated as follows: ' $G_{\alpha} = \frac{1}{N}\sum_{i=1}^{N}\frac{T\hat{\alpha}_i}{\hat{\alpha}_i(1)}$ ' and ' $P_{\alpha} = T\hat{\alpha}$ '. These tests play a crucial role in validating the presence of long-term associations among the variables under scrutiny, even when individual non-stationarity is present. Upon establishing cointegration, our analysis progresses to examining both short- and long-term relationships. We employ second-generation models tailored to accommodate the unique characteristics of time series data, accounting for common shocks and potential structural shifts evident within our sample of G7 nations. By employing these sophisticated models, we aim to capture the intricate dynamics of the data while ensuring robustness in our analysis, particularly in the face of changing economic conditions and policy interventions across the G7 countries.

Table 7 displays the outcomes of the cointegration tests conducted using the Westerlund (2007) methodology. The findings unequivocally demonstrate the presence of at least one cointegration equation within our model. Notably, the statistically significant values of the four test statistics (G_{τ}, G_{α}, P_{τ}, and P_{α}) surpassing the 1% threshold decisively reject the null hypothesis of no cointegration relationship among the variables. These results provide compelling evidence supporting the existence of a long-term connection between environmental quality and key determinants such as economic growth, environmental tax revenues, renewable energy consumption, and digitalization across the G7 countries included in our panel dataset. With the confirmation of cointegration, we are now poised to delve into the analysis of long-run elasticities utilizing advanced econometric models such as the CS-ARDL, AMG, and DCCEMG. These models will enable us to explore the nuanced relationships between environmental quality and its determinants, offering insights into the long-term dynamics shaping environmental sustainability within the G7 economies.

4.7. Analysis of Long-Run and Short-Run Relationships: CS-ARDL Model

The CS-ARDL model utilized in our analysis sheds light on the intricate dynamics among environmental quality, economic growth, renewable energy, environmental taxes, and digitalization within the framework of G7 nations, as illustrated in Table 8. Notably, the model's error correction term (ECT) exhibits a coefficient of −1.135205, indicating the rapid adjustment of these economies towards equilibrium following disturbances. This underscores their remarkable adaptability in navigating economic and environmental fluctuations. Furthermore, the CD statistic of 0.91 indicates minimal cross-sectional dependence, bolstering the suitability of the model for our analytical purposes. This statistic suggests that the observations across different cross-sectional units exhibit relatively weak interdependencies, thus validating the reliability of the CS-ARDL model in capturing the nuanced relationships among the variables under investigation.

Table 7: The results from the Westerlund (2007) cointegration analysis

Statistic	Value	Z-value	P-value
G_{τ}	2,372	8,749	0.005
G_{α}	12,421	3,157	0.003
P_{τ}	14,589	6,008	0.000
P_{α}	9,354	3,325	0.001

The G_{τ} and G_{α} statistics assess cointegration for each individual cross-section, while the P_{τ} and P_{α} statistics evaluate panel cointegration when the null hypothesis of no cointegration is assumed.

Table 8: CS-ARDL panel data estimation results.

Variable	Coefficient	Standard error	t-statistic	Prob.*
Long run equation				
Ln (GDP)	0.710618	0.117039	6.071615	0.0000
Ln (ET)	−0.133727	0.061325	−2.180619	0.0308
Ln (REC)	−0.113881	0.035450	−3.212444	0.0016
Ln (DI)	−0.011330	0.003777	−3.000120	0.0032
Short run equation				
ECT (−1)	−1.135205	0.089455	−12.69019	0.0000
Ln (GDP)	0.381031	0.081133	4.696361	0.0000
Ln (ET)	−0.225738	0.077947	2.896060	0.0044
Ln (REC)	−0.010321	0.040621	0.254075	0.0198
Ln (DI)	−0.031776	0.007281	-4.364140	0.0000
C	0.277125	0.020709	13.38189	0.0000
CD statistic	0.91			0.452

The CD test serves as a diagnostic tool to assess the presence and severity of cross-sectional dependence, guiding researchers in the appropriate specification and interpretation of econometric models for panel data analysis

Overall, these findings enhance our understanding of the complex interactions shaping environmental sustainability and economic development within the G7 countries.

The analysis of Table 8 reveals several significant findings regarding the impact of various variables on carbon dioxide (CO_2) emissions both in the short and long term. Firstly, the coefficient of the logarithmic function of Gross Domestic Product (GDP) stands at 0.710618 with a probability of 0.0000, indicating a significant positive effect of GDP on CO_2 emissions in the long term. Specifically, a 1% increase in GDP is associated with a 0.710618% increase in CO_2 emissions in the long term. Similarly, the coefficient of the logarithmic function of GDP in the short term is 0.381031 with a probability of 0.0000, also suggesting a significant positive effect of GDP on CO_2 emissions in the short term, where a 1% increase in GDP is associated with a 0.381031% increase in CO_2 emissions in the short term. When the economy grows, the demand for energy typically increases. Much of this energy is generated from fossil fuels such as coal, oil, and natural gas, which are major sources of CO_2 emissions when burned for electricity production, transportation, and industry. Therefore, economic growth often leads to increased combustion of these fuels, resulting in higher CO_2 emissions (IEA, 2022, Jeon, 2022). Economic growth is often accompanied by increased industrial development and urbanization. These processes generally require intensive energy use and infrastructure, leading to additional CO_2 emissions from industry, construction, transportation, and related activities (Raihan et al., 2022; Khoshnevis Yazdi and Golestani Dariani, 2019; Khan and Majeed, 2023). Although G7 economies have made significant progress in adopting cleaner technologies and improving energy efficiency, these gains may be offset by the rebound effect or the backfire effect. The rebound effect occurs when improvements in energy efficiency led to a relative decrease in energy costs, which encourages an increase in energy consumption and CO_2 emissions (Mumuni and Hamadjoda-Lefe, 2023; Coscieme et al., 2019). In many G7 countries, fossil fuels remain a significant component of the energy mix. Even with policies aimed at promoting renewable energies and reducing emissions, the transition to a low-carbon economy may be slow due to existing infrastructure and established economic interests in the fossil fuel sector (Chen et al., 2023; Suzuki et al., 2023; Talan et al., 2023).

Regarding environmental taxes, the coefficient of the logarithmic function is −0.133727 with a probability of 0.0308 for long-term CO_2 emissions, and −0.225738 with a probability of 0.0044 for short-term CO_2 emissions. These results reveal a significantly negative effect of environmental taxes on CO_2 emissions, where a 1% increase in environmental taxes is associated with a decrease of 0.133727% in the long term and 0.225738% in the short term. Environmental taxes act as a deterrent mechanism by increasing the cost of pollution-generating activities, such as fossil fuel usage. By imposing taxes on CO_2 emissions, governments aim to internalize the external costs of pollution and encourage businesses and individuals to adopt more environmentally friendly behaviors (Sarpong et al., 2023; Sackitey, 2023; He et al., 2019; Doğan et al., 2022). Additionally, environmental taxes send price signals to consumers and producers, incentivizing them to seek fewer polluting alternatives and stimulating innovation in clean energy and energy efficiency sectors, potentially leading to long-term reductions in CO_2 emissions. Businesses and consumers may react to environmental taxes by substituting less polluting energy sources for traditional fossil fuels, thereby contributing to emissions reductions (Koval et al., 2022; Ghazouani et al., 2020). Moreover, the rational economic behavior of agents, driven by cost minimization considerations, leads to adjustments in behavior to reduce CO_2 emissions in response to higher pollution costs imposed by environmental taxes, resulting in observed reductions in both short- and long-term emissions (Aminzadegan et al., 2022; Baranzini et al., 2017; Mehmood et al., 2024).

Regarding renewable energies, the coefficient of the logarithmic function is −0.113881 with a probability of 0.0016 for long-term CO_2 emissions, and −0.010321 with a probability of 0.0198 for short-term CO_2 emissions. These results indicate a significantly negative effect of renewable energies on CO_2 emissions, where a 1% increase in the share of renewable energies is associated with a reduction of 0.113881% in the long term and 0.010321% in the short term. Renewable energy sources, including solar, wind, and hydroelectric power, exhibit lower carbon intensity compared to fossil fuels, leading to decreased emissions during energy generation. As the proportion of renewable energies in the energy mix increases, there is a notable reduction in CO_2 emissions over both short and long terms. This outcome can be elucidated by several mechanisms: the substitution effect, wherein the shift towards renewables diminishes reliance on carbon-intensive fuels; technological advancements and economies of scale driving down costs and enhancing competitiveness of renewable energy; government policies and market incentives favoring renewable energy deployment, fostering investment and capacity expansion; and heightened awareness of environmental impacts prompting support for renewable energy development, in alignment with sustainability goals and climate change mitigation (Paraschiv and Paraschiv, 2023; Rahman et al., 2022; Farghali et al., 2023; Osman et al., 2023).

Finally, concerning digitalization (DI), the coefficient of the logarithmic function is −0.011330 with a probability of 0.0032 for long-term CO_2 emissions, and −0.031776 with a probability of 0.0000 for short-term CO_2 emissions. These results highlight a significantly negative effect of digitalization on CO_2 emissions, where a 1% increase in digitalization is associated with a decrease of 0.011330% in the long term and 0.031776% in the short term. These findings highlight the potentially beneficial role of digitization in reducing CO_2 emissions and transitioning towards a more sustainable economy in G7 countries, aligning with trends observed in economic literature and academic research on the subject. Firstly, digitization leads to process optimization and increased efficiency across various economic sectors, potentially reducing energy demand and hence CO_2 emissions associated with energy production and use (Lyu et al., 2023; Shen et al., 2023; Li et al., 2023). Secondly, digitization fosters the adoption of cleaner and more efficient technologies, such as energy management solutions and smart monitoring systems, resulting in reduced energy consumption and CO_2 emissions (Shi et al., 2024). Thirdly, digitization can facilitate the transition to more sustainable business models and remote working practices, reducing the need for travel and physical infrastructure and consequently contributing to lower CO_2 emissions from transportation and buildings (Charfeddine and Umlai, 2023; Ben Youssef and Zeqiri, 2022). Lastly, digitization enables better resource planning and management, optimization of supply chains, and reduction of waste, leading to more efficient resource utilization and less carbon-intensive industrial processes (Li et al., 2023; Akbari and Hopkins, 2022).

4.8. Results Robustness: DCCEMG and AMG Estimators

We conduct robustness checks using the DCCEMG and AMG estimators to validate the long-run relationships between economic growth, environmental taxes, renewable energy, digitalization, and environmental quality across G7 countries, reaffirming the initial findings from the CS-ARDL model. Table 9, supported by the CD statistic indicating low cross-sectional dependence from the DCCEMG model, strengthens the reliability of the results by demonstrating consistency across different methodologies and ensuring that the observed relationships are not significantly influenced by shared factors among the G7 countries, thereby enhancing the credibility of the research findings.

In the AMG model, the coefficients of the explanatory variables indicate that an increase in GDP is associated with an increase in CO_2 levels, as evidenced by the positive coefficient of 0.566. This suggests that economic growth generally leads to an increase in CO_2 emissions. Conversely, other explanatory variables such as environmental taxes (ET), renewable energy consumption (REC),

Table 9: DCCEMG and AMG panel data long-run estimation results

Variable	AMG		DCCEMG	
	Coefficient	Standard error	Coefficient	Standard error
Ln (GDP)	0.566***	0.137	0.479***	0.119
Ln (ET)	−0.092***	0.555	−0.019***	0.0411
Ln (REC)	−0.106***	0.298	−0.064***	0.0222
Ln (DI)	−0.011***	0.019	−0.014***	0.0127
CD Statistic	1.16 (0.371)			

The CD statistic test follows a standard normal distribution under the null hypothesis of weak cross-sectional dependence. The value in parentheses accompanying the CD statistic represents the *P* value. Significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively

and digitalization (DI) are associated with a decrease in CO_2 emissions, as indicated by their respective negative coefficients (−0.0928, −0.1061, and −0.0116). This indicates that policies such as the use of environmental taxes, adoption of renewable energy sources, and promotion of digitalization can contribute to reducing CO_2 emissions. Regarding the DCCEMG model, the coefficients show similar trends. An increase in GDP is still associated with an increase in CO_2 emissions, as evidenced by the positive coefficient of 0.4790. However, other explanatory variables such as environmental taxes (ET), renewable energy consumption (REC), and digitalization (DI) also exhibit negative coefficients (−0.0195, −0.0642, and −0.0140 respectively), indicating that these factors are associated with a reduction in CO_2 emissions. It is important to note that all coefficients in both models are significant, reinforcing the reliability of the results. These findings suggest that economic growth (GDP) is often associated with an increase in CO_2 emissions, but policies such as environmental taxes, promotion of renewable energies, and digitalization can help mitigate these emissions, thereby offering prospects for more sustainable and environmentally friendly growth.

5. CONCLUSIONS AND POLICY RECOMMENDATIONS

This study sheds light on the crucial impact of measures such as environmental taxes, the adoption of renewable energies, and digitalization on environmental sustainability in G7 countries over the period 1994-2021. This analysis relies on estimations derived from the CS-ARDL, AMG, and DCCEMG models. While economic growth is typically associated with an increase in CO_2 emissions, the results indicate that policies such as environmental taxes, the promotion of renewable energies, and digitalization are effective means of reducing these emissions. These findings underscore the importance of integrated and targeted policies to support sustainable development goals, thus paving the way for environmentally respectful economic growth within the world's most advanced economies.

5.1. Policy Implications and Strategic Recommendations

The policy implications of this study are significant and call for decisive action from the governments of G7 countries. Firstly, the results underscore the crucial importance of adopting effective environmental policies, particularly concerning environmental taxes. Governments should consider expanding and strengthening these taxes to encourage the transition towards more environmentally friendly practices. Additionally, actively promoting the adoption of renewable energies is imperative, necessitating investment in research, development, and infrastructure to facilitate this transition. Lastly, digitalization presents promising opportunities for reducing CO_2 emissions, and policies should encourage its widespread adoption while ensuring equitable distribution of benefits.

Regarding strategic recommendations, an integrated approach is necessary to maximize the impact of environmental policies. Governments should adopt a holistic approach that combines the use of environmental taxes, promotion of renewable energies, and digitalization to achieve ambitious environmental objectives. This requires close coordination among various government departments, as well as collaboration with the private sector and civil society. Furthermore, it is crucial for environmental policies to align with international goals, such as the Paris Agreement and the Sustainable Development Goals, to ensure coherent and harmonized action globally. G7 governments should take a leadership role in promoting international cooperation to address global environmental challenges. To achieve this, it is essential to adopt a progressive and balanced approach in implementing these policies, taking into account the economic and social realities of each country. Transition measures should be designed to minimize negative impacts on the most vulnerable populations and promote inclusive and sustainable economic growth.

5.2. Limitations

Despite its valuable contributions, this study has several limitations. Firstly, its focus on G7 countries may restrict the generalizability of findings to other regions with different socio-economic contexts. Secondly, while sophisticated econometric methodologies were utilized, such as the CS-ARDL model and DCCEMG estimator, inherent assumptions and limitations in these models, such as linearity assumptions and reliance on secondary data sources, may introduce biases or inaccuracies. Additionally, the study primarily quantifies relationships between environmental taxes, renewable energy adoption, digitalization, and CO_2 emissions, neglecting potential mediating or moderating factors like institutional frameworks and socio-cultural dynamics. Moreover, its temporal scope may overlook long-term trends or structural changes in environmental policy and economic development. Addressing these limitations is crucial for enhancing our understanding of environmental systems and informing evidence-based policy decisions on a global scale.

5.3. Future Recommendations

Moving forward, several recommendations can enhance the scope and depth of future research in this domain. Firstly, expanding the geographical scope beyond G7 countries to include emerging economies and developing nations can provide a more comprehensive understanding of the global dynamics of environmental sustainability and policy interventions. This broader perspective would facilitate the identification of common trends, differences, and best practices across diverse socio-economic contexts. Additionally, future studies could benefit from employing more advanced econometric methodologies that address the limitations of linear models, such as incorporating non-linear dynamics and accounting for structural breaks in the data. Furthermore, efforts to improve data quality and reliability through primary data collection or more rigorous validation of secondary sources would enhance the robustness of analyses and reduce potential biases. Moreover, integrating qualitative research methods alongside quantitative analyses can capture nuanced socio-cultural, institutional, and political factors that influence the effectiveness of environmental policies. This interdisciplinary approach would offer a more holistic understanding of the complex interactions shaping environmental sustainability. Additionally, extending the temporal scope of studies to include longitudinal analyses would enable researchers to track changes over time and assess the long-term effectiveness of policy interventions. Finally, fostering collaboration between academia, policymakers, industry stakeholders, and civil society organizations can facilitate the translation of research findings into actionable policy recommendations and promote the implementation of evidence-based strategies to address environmental challenges on a global scale.

6. FUNDING STATEMENT

This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (grant number IMSIU-DDRSP2502).

REFERENCES

Abbas, J., & Najam, H. (2024), Role of environmental decentralization, green human capital, and digital finance in firm green technological innovation for a sustainable society. Environment, Development and Sustainability, 1-15.

Abel, S., Mukarati, J., Jeke, L., Roux, P.L. (2023), Carbon tax and environmental quality in South Africa. International Journal of Energy Economics and Policy, 13(2), 484-488.

Afshan, S., Yaqoob, S. (2023), Green innovation and taxation: A policy framework for environmental governance in G7 nations. Environmental Science and Pollution Research, 31(1), 189-197.

Aguir Bargaoui, S. (2022), The impact of energy efficiency and renewable energies on environmental quality in OECD countries. Journal of the Knowledge Economy, 13(4), 3424-3444.

Ahmad, M., Dai, J., Mehmood, U., Abou Houran, M. (2023), Renewable energy transition, resource richness, economic growth, and environmental quality: Assessing the role of financial globalization. Renewable Energy, 216, 119000.

Ahmat, N., Christopher, S., Saputra, J., Sukemi, M.N., Nawawi, M.N. (2024), The Impact of energy consumption, economic growth, and non-renewable energy on carbon dioxide emission in Malaysia. International Journal of Energy Economics and Policy, 15(1), 143-152.

Ahmed, S., Abdi, A.H., Sodal, M., Yusuf, O.A., Mohamud, M.H. (2024), Assessing the energy-economy-environment nexus in Somalia: The impact of agricultural value added on CO_2 emissions. International Journal of Energy Economics and Policy, 15(1), 221-232.

Akbar, A., Gul, A., Sohail, M., Hedvicakova, M., Haider, S.A., Ahmad, S., Iqbal, S. (2024), Impact of renewable and non-renewable energy resources on CO_2 emission: Empirical evidence from SAARC. International Journal of Energy Economics and Policy, 14(1), 141-149.

Akbari, M., Hopkins, J.L. (2022), Digital technologies as enablers of supply chain sustainability in an emerging economy. Operations Management Research, 15(3), 689-710.

Akpanke, T. A., Deka, A., Ozdeser, H., & Seraj, M. (2023), The role forest resources, energy efficiency, and renewable energy in promoting environmental quality. Environmental Monitoring and Assessment, 195(9), 1071.

Allioui, H., Mourdi, Y. (2023), Exploring the full potentials of IoT for better financial growth and stability: A comprehensive survey. Sensors (Basel), 23(19), 8015.

Alshammari, K.H., Alshammari, A.F. (2023), Green innovation and its effects on innovation climate and environmental sustainability: The moderating influence of green abilities and strategies. Sustainability, 15(22), 15898.

Aminzadegan, S., Shahriari, M., Mehranfar, F., Abramović, B. (2022), Factors affecting the emission of pollutants in different types of transportation: A literature review. Energy Reports, 8, 2508-2529.

Arellano, M., Bond, S. (1991), Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. The Review of Economic Studies, 58(2), 277-297.

Arrow, K., Bolin, B., Costanza, R., Dasgupta, P., Folke, C., Holling, C.S., Jansson, B.O., Levin, S., Mäler, KG., Perrings, C., Pimentel, D. (1995), Economic growth, carrying capacity, and the environment. Ecological Economics, 15(2), 91-95.

Aslan, A., Ozsolak, B., & Doğanalp, N. (2021), Environmental quality and renewable energy consumption with different quality indicators: evidence from robust result with panel quantile approach. Environmental Science and Pollution Research, 28, 62398-62406.

Asongu, S. A., Iheonu, C. O., & Odo, K. O. (2019), The conditional relationship between renewable energy and environmental quality in sub-Saharan Africa. Environmental Science and Pollution Research, 26(36), 36993-37000.

Astini, R., Ishrat, K., Ramli, Y., Tafiprios, T., Chong, K.W., Keong, O.C. (2023), Nexus among crypto trading, environmental degradation, economic growth and energy usage: Analysis of top 10 crypto friendly Asian economies. International Journal of Energy Economics and Policy, 13(5), 339-347.

Avazkhodjaev, S., Usmonov, J., Bohdalová, M., Lau, W.Y. (2022), The causal nexus between renewable energy, CO_2 emissions, and economic growth: New evidence from CIS countries. International Journal of Energy Economics and Policy, 12(6), 248-260.

Ayodele, F.O., Mustapa, S.I., Ayodele, B.V. (2023), The potential of renewable energy green financing through carbon taxation to achieve net-zero emissions target. International Journal of Energy Economics and Policy, 13(6), 388-396.

Bai, J., Ng, S. (2004), A panic attack on unit roots and cointegration. Econometrica, 72(4), 1127-1177.

Bakari, S. (2021), The nexus between domestic investment and economic growth in G7 countries. Does internet matter? Journal of Applied Economic Sciences, 16(72), 238-243.

Bakari, S. (2022), The impact of digitalization and patent on economic growth in Romania. Journal of Research, Innovation and Technologies, 1(1), 49-61.

Bakari, S., El Weriemmi, M., Mabrouki, M. (2022), The Impact of digitalization and trade openness on economic growth: New evidence from richest Asian countries. Journal of Research, Innovation and Technologies, 1(2), 7.

Bakari, S., Tiba, S. (2022), Determinants of economic growth: The case of the United States of America. Journal of Developing Economies, 7(1), 29-44.

Baltagi, B.H. (2008), Econometric Analysis of Panel Data. Vol. 4. Chichester: Wiley. p135-145.

Baranzini, A., Van den Bergh, J.C., Carattini, S., Howarth, R.B., Padilla, E., Roca, J. (2017), Carbon pricing in climate policy: Seven reasons, complementary instruments, and political economy considerations. Wiley Interdisciplinary Reviews: Climate Change, 8(4), e462.

Batrancea, L.M., Rathnaswamy, M.M., Rus, M.I., Tulai, H. (2023), Determinants of economic growth for the last half of century: A panel data analysis on 50 countries. Journal of the Knowledge Economy, 14(3), 2578-2602.

Ben Youssef, A., Dahmani, M. (2024), Evaluating environmental sustainability in Africa: The role of environmental taxes, productive capacities, and urbanization dynamics. Economies, 12(4), 80.

Ben Youssef, A., Zeqiri, A. (2022), Hospitality industry 4.0 and climate change. Circular Economy and Sustainability, 2(3), 1043-1063.

Bergman, N., Foxon, T.J. (2023), Drivers and effects of digitalization on energy demand in low-carbon scenarios. Climate Policy, 23(3), 329-342.

Blomquist, J., & Westerlund, J. (2013). Testing slope homogeneity in large panels with serial correlation. Economics Letters, 121(3), 374-378.

Böhringer, C., Rivers, N., Rutherford, T., Wigle, R. (2015), Sharing the burden for climate change mitigation in the Canadian federation. Canadian Journal of Economics/Revue Canadienne d'économique, 48(4), 1350-1380.

Breusch, T.S., Pagan, A.R. (1980), The Lagrange multiplier test and its applications to model specification in econometrics. The Review of Economic Studies, 47(1), 239-253.

Bunnag, T. (2023), Environmental Kuznets curve model for the United States: A consideration of foreign direct investment variable. International Journal of Energy Economics and Policy, 13(4), 130-138.

Charfeddine, L., Umlai, M. (2023), ICT sector, digitization and environmental sustainability: A systematic review of the literature from 2000 to 2022. Renewable and Sustainable Energy Reviews, 184, 113482.

Chen, Q., Zha, D., Salman, M. (2022), The influence of carbon tax on CO_2 rebound effect and welfare in Chinese households. Energy Policy, 168, 113103.

Chen, S., Zhang, C., Lu, X. (2023), Energy conversion from fossil fuel to renewable energy. In: Handbook of Air Quality and Climate Change. Singapore: Springer Nature Singapore. p1-44.

Chirwa, T.G., Odhiambo, N.M. (2016), Macroeconomic determinants of economic growth: A review of international literature. South East European Journal of Economics and Business, 11(2), 33-47.

Choi, C., Yi, M.H. (2009), The effect of the Internet on economic growth: Evidence from cross-country panel data. Economics Letters, 105(1), 39-41.

Choi, C., Yi, M.H. (2018), The Internet, R&D expenditure and economic growth. Applied Economics Letters, 25(4), 264-267.

Chudik, A., & Pesaran, M. H. (2015), Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. Journal of Econometrics, 188(2), 393-420.

Chudik, A., Mohaddes, K., Pesaran, M. H., & Raissi, M. (2016), Long-run effects in large heterogeneous panel data models with cross-sectionally correlated errors. Essays in Honor of Aman Ullah (Advances in Econometrics, Vol. 36), 85-135.

Coakley, J., Fuertes, A. M., & Smith, R. P. (2006), Unobserved heterogeneity in panel time series models. Computational Statistics & Data Analysis, 50(9), 2361-2380.

Coscieme, L., Sutton, P., Mortensen, L.F., Kubiszewski, I., Costanza, R., Trebeck, K., Pulselli, F.M., Giannetti, B.F., Fioramonti, L. (2019), Overcoming the myths of mainstream economics to enable a new wellbeing economy. Sustainability, 11(16), 4374.

Creutzig, F., Agoston, P., Goldschmidt, J.C., Luderer, G., Nemet, G., Pietzcker, R.C. (2017), The underestimated potential of solar energy to mitigate climate change. Nature Energy, 2(9), 17140.

Cuaresma, J.C., Doppelhofer, G., Feldkircher, M. (2014), The determinants of economic growth in European regions. Regional Studies, 48(1), 44-67.

Dahmani, M. (2023), Environmental quality and sustainability: Exploring the role of environmental taxes, environment-related technologies, and R&D expenditure. Environmental Economics and Policy Studies, 26, 449-477.

Dam, M. M., Işık, C., & Ongan, S. (2023), The impacts of renewable energy and institutional quality in environmental sustainability in the context of the sustainable development goals: A novel approach with the inverted load capacity factor. Environmental Science and Pollution Research, 30(42), 95394-95409.

Davidovic, D., Harring, N., Jagers, S.C. (2020), The contingent effects of environmental concern and ideology: Institutional context and people's willingness to pay environmental taxes. Environmental Politics, 29(4), 674-696.

Demir, S., Demir, H., Karaduman, C., Cetin, M. (2023), Environmental quality and health expenditures efficiency in Türkiye: The role of natural resources. Environmental Science and Pollution Research, 30(6), 15170-15185.

Depren, Ö., Kartal, M.T., Ayhan, F., Depren, S.K. (2023), Heterogeneous impact of environmental taxes on environmental quality: Tax domain-based evidence from the nordic countries by nonparametric quantile approaches. Journal of Environmental Management, 329, 117031.

Dilanchiev, A., Sharif, A., Ayad, H., & Nuta, A. C. (2024), The interaction between remittance, FDI, renewable energy, and environmental quality: a panel data analysis for the top remittance-receiving countries. Environmental Science and Pollution Research, 1-15.

Djalilov, B., Kobiljonov, I., Salahodjaev, R. (2023), Can digital human capital mitigate CO_2 emissions? Empirical test for post-communist countries. International Journal of Energy Economics and Policy, 13(4), 383-388.

Doğan, B., Chu, L.K., Ghosh, S., Truong, H.H.D., Balsalobre-Lorente, D. (2022), How environmental taxes and carbon emissions are related in the G7 economies? Renewable Energy, 187, 645-656.

Domguia, E.N. (2023), Taxing for a better life? The impact of environmental taxes on income distribution and inclusive education. Heliyon, 9, e21443.

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.

Dudin, M.N., Zasko, V.N., Dontsova, O.I., Osokina, I.V., Berman, A.M. (2018), Renewable energy sources as an instrument to support the competitiveness of agro-industrial enterprises and reduce their costs. International Journal of Energy Economics and Policy, 8(2), 162-167.

Duran, I.A., Saqib, N. (2024), Load capacity factor and environmental quality: Unveiling the role of economic growth, green innovations, and environmental policies in G20 economies. International Journal of Energy Economics and Policy, 14(6), 287-294.

Duran, I.A., Saqib, N., Mahmood, H. (2023), Assessing the connection between nuclear and renewable energy on ecological footprint within the EKC framework: Implications for sustainable policy in leading nuclear energy-producing countries. International Journal of Energy Economics and Policy, 13(2), 256-264.

Dzwigol, H., Kwilinski, A., Lyulyov, O., Pimonenko, T. (2024), Digitalization and energy in attaining sustainable development: Impact on energy consumption, energy structure, and energy intensity. Energies, 17(5), 1213.

Eberhardt, M., & Teal, F. (2010). Productivity analysis in global manufacturing production. Economics Series Working Papers, 515, UK: University of Oxford.

Ehsanullah, E., Al Mamun, T.G.M., Abdur, R.M. (2025), Environmental effects of renewable and non-renewable energy: Data from a few selected group States. International Journal of Energy Economics and Policy, 15(2), 521-528.

Engle, R.F., Granger, C.W. (1987), Co-integration and error correction:

Representation, estimation, and testing. Econometrica: Journal of the Econometric Society, 55, 251-276.

Ercan, H., Savranlar, B., Polat, M. A., Yıgıt, Y., & Aslan, A. (2024), The impact of technological innovations on the environmental Kuznets curve: evidence from EU-27. Environmental Science and Pollution Research, 1-18.

Erkut, B. (2022), Renewable energy and carbon emissions: New empirical evidence from the Union for the Mediterranean. Sustainability, 14(11), 6921.

Everaert, G., & De Groote, T. (2016), Common correlated effects estimation of dynamic panels with cross-sectional dependence. Econometric Reviews, 35(4), 684-704.

Fakher, H.A. (2019), Investigating the determinant factors of environmental quality (based on ecological carbon footprint index). Environmental Science and Pollution Research, 26(10), 10276-10291.

Fakher, H.A., Ahmed, Z., Acheampong, A.O., Nathaniel, S.P. (2023), Renewable energy, nonrenewable energy, and environmental quality nexus: An investigation of the N-shaped Environmental Kuznets Curve based on six environmental indicators. Energy, 263, 125660.

Fakher, H. A., Ahmed, Z., Alvarado, R., & Murshed, M. (2022), Exploring renewable energy, financial development, environmental quality, and economic growth nexus: new evidence from composite indices for environmental quality and financial development. Environmental Science and Pollution Research, 29(46), 70305-70322.

Farghali, M., Osman, A.I., Chen, Z., Abdelhaleem, A., Ihara, I., Mohamed, I.M., Yap, P.S., Rooney, D.W. (2023), Social, environmental, and economic consequences of integrating renewable energies in the electricity sector: A review. Environmental Chemistry Letters, 21(3), 1381-1418.

Femenia, F., Letort, E. (2016), How to significantly reduce pesticide use: An empirical evaluation of the impacts of pesticide taxation associated with a change in cropping practice. Ecological Economics, 125, 27-37.

Fischer, C., Fox, A.K. (2012), Comparing policies to combat emissions leakage: Border carbon adjustments versus rebates. Journal of Environmental Economics and Management, 64(2), 199-216.

Fullerton, D., Heutel, G. (2017), The general equilibrium incidence of environmental taxes. In: Distributional Effects of Environmental and Energy Policy. United Kingdom: Routledge. p161-181.

Gafsi, N., Bakari, S. (2024), Impacts of agricultural CO_2 emissions, agricultural exports and financial development on economic growth: Insights from East Asia and Pacific countries. International Journal of Energy Economics and Policy, 14(6), 136-153.

Gafsi, N., Bakari, S. (2025), Analyzing the influence of agricultural raw material imports on agricultural growth in 48 Sub-Saharan African countries. International Journal of Innovative Research and Scientific Studies, 8(1), 2876-2885.

Gafsi, N., Bakari, S. (2025), Unlocking the green growth puzzle: Exploring the nexus of renewable energy, CO_2 emissions, and economic prosperity in G7 countries. International Journal of Energy Economics and Policy, 15(2), 236-247.

Ganda, F. (2021), The influence of growth determinants on environmental quality in Sub-Saharan Africa states. Environment, Development and Sustainability, 23(5), 7117-7139.

Ghazouani, A., Xia, W., Ben Jebli, M., Shahzad, U. (2020), Exploring the role of carbon taxation policies on CO_2 emissions: Contextual evidence from tax implementation and non-implementation European Countries. Sustainability, 12(20), 8680.

Greene, W.H. (2012), Econometric Analysis. London, United Kingdom: Pearson Education.

Grossman, G.M., Krueger, A.B. (1991), Environmental Impacts of a North American Free Trade Agreement. United States: National Bureau of Economic Research.

Grubler, A., Wilson, C., Bento, N., Boza-Kiss, B., Krey, V., McCollum, D.L., Rao, N.D., Riahi, K., Rogelj, J., De Stercke, S., Cullen, J. (2018), A low energy demand scenario for meeting the 1.5°C target and sustainable development goals without negative emission technologies. Nature Energy, 3(6), 515-527.

Guo, B., Wang, Y., Feng, Y., Liang, C., Tang, L., Yao, X., Hu, F. (2022), The effects of environmental tax reform on urban air pollution: A quasi-natural experiment based on the environmental protection tax law. Frontiers in Public Health, 10, 967524.

Hansen, L.P. (1982), Large sample properties of generalized method of moments estimators. Econometrica: Journal of the Econometric Society, 50, 1029-1054.

Hao, L.N., Umar, M., Khan, Z., Ali, W. (2021), Green growth and low carbon emission in G7 countries: How critical the network of environmental taxes, renewable energy and human capital is? Science of the Total Environment, 752, 141853.

Haq, I. U., & Huo, C. (2023), Digital strategy and environmental performance: the mediating role of digitalization in SMEs. Digital Economy and Sustainable Development, 1(1), 9.

Hartmann, P., Marcos, A., Barrutia, J.M. (2023), Carbon tax salience counteracts price effects through moral licensing. Global Environmental Change, 78, 102635.

He, P., Ning, J., Yu, Z., Xiong, H., Shen, H., Jin, H. (2019), Can environmental tax policy really help to reduce pollutant emissions? An empirical study of a panel ARDL model based on OECD countries and China. Sustainability, 11(16), 4384.

He, Y. T., Zhang, Y. C., Huang, W., Wang, R. N., He, L. X., Li, B., & Zhang, Y. L. (2023), Impact of digital economic development and environmental pollution on residents' health: an empirical analysis based on 279 prefecture-level cities in China. BMC Public Health, 23(1), 959.

Hermawan, A.N., Masudin, I., Zulfikarijah, F., Restuputri, D.P., Shariff, S.S.R. (2023), The effect of sustainable manufacturing on environmental performance through government regulation and eco-innovation. International Journal of Industrial Engineering and Operations Management, 6, 299-325.

Hieu, V.M. (2022), Influence of green investment, environmental tax and sustainable environment: Evidence from ASEAN countries. International Journal of Energy Economics and Policy, 12(3), 227-235.

IEA. (2019), World Energy Outlook 2019. Paris: IEA.

IEA. (2021), Renewables 2021. Paris: International Energy Agency.

IEA. (2022), Global Energy Review: CO_2 Emissions in 2021. Paris: IEA.

Imamoglu, H. (2018), Is the informal economic activity a determinant of environmental quality? Environmental Science and Pollution Research, 25, 29078-29088.

IPCC. (2018), Global Warming of 1.5°C: An IPCC Special Report. Geneva, Switzerland: Intergovernmental Panel on Climate Change.

IPCC. (2021), IPCC Sixth Assessment Report. Geneva, Switzerland: Intergovernmental Panel on Climate Change.

Irfan, M., Ullah, S., Razzaq, A., Cai, J., Adebayo, T.S. (2023), Unleashing the dynamic impact of tourism industry on energy consumption, economic output, and environmental quality in China: A way forward towards environmental sustainability. Journal of Cleaner Production, 387, 135778.

Jacobson, M.Z., Delucchi, M.A., Bazouin, G., Bauer, Z.A., Heavey, C.C., Fisher, E., Morris, S.B., Piekutowski, D.Y.J., Vencilla, T.A., Yeskoo, T.W. (2015), 100% clean and renewable wind, water, and sunlight (WWS) all-sector energy roadmaps for the 50 United States. Energy and Environmental Science, 8(7), 2093-2117.

Jeon, H. (2022), CO_2 emissions, renewable energy and economic growth in the US. The Electricity Journal, 35(7), 107170.

Johansen, S. (1988), Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control, 12(2-3), 231-254.

Kafeel, K., Zhou, J., Phetkhammai, M., Heyan, L., & Khan, S. (2024), Green innovation and environmental quality in OECD countries: the mediating role of renewable energy and carbon taxes. Environmental Science and Pollution Research, 31(2), 2214-2227.

Karaki, B.A., Al_Kasasbeh, O., Alassuli, A., Alzghoul, A. (2023), The Impact of the digital economy on carbon emissions using the STIRPAT model. International Journal of Energy Economics and Policy, 13(5), 139-143.

Karimi Alavijeh, N., Ahmadi Shadmehri, M. T., Nazeer, N., Zangoei, S., & Dehdar, F. (2023), The role of renewable energy consumption on environmental degradation in EU countries: do institutional quality, technological innovation, and GDP matter?. Environmental Science and Pollution Research, 30(15), 44607-44624.

Kasperowicz, R., Bilan, Y., Štreimikienė, D. (2020), The renewable energy and economic growth nexus in European countries. Sustainable Development, 28(5), 1086-1093.

Kassi, D. F., Li, Y., Gnangoin, T. Y., Tuo, S. J., Gnahe, F. E., Shaikh, R., & Yongjie, D. (2023), Green credits, green securities, renewable energy, and environmental quality: a comparative analysis of sustainable development across Chinese provinces. Environment, Development and Sustainability, 1-37.

Khalid, K., Usman, M., Mehdi, M.A. (2021), The determinants of environmental quality in the SAARC region: A spatial heterogeneous panel data approach. Environmental Science and Pollution Research, 28, 6422-6436.

Khan, A. A., Khan, S. U., Ali, M. A. S., Safi, A., Gao, Y., & Luo, J. (2022), Identifying impact of international trade and renewable energy consumption on environmental quality improvement and their role in global warming. Environmental Science and Pollution Research, 29(23), 33935-33944.

Khan, A., Ximei, W. (2022), Digital economy and environmental sustainability: Do Information Communication and Technology (ICT) and economic complexity matter? International Journal of Environmental Research and Public Health, 19(19), 12301.

Khan, S., Majeed, M.T. (2023), Toward economic growth without emissions growth: The role of urbanization & industrialization in Pakistan. Journal of Environmental Studies and Sciences, 13(1), 43-58.

Khoshnevis Yazdi, S., Golestani Dariani, A. (2019), CO_2 emissions, urbanisation and economic growth: Evidence from Asian countries. Economic Research-Ekonomska Istraživanja, 32(1), 510-530.

Kibria, M.G., Masuk, N.I., Safayet, R., Nguyen, H.Q., Mourshed, M. (2023), Plastic waste: Challenges and opportunities to mitigate pollution and effective management. International Journal of Environmental Research, 17(1), 20.

Kirikkaleli, D. (2023), Environmental taxes and environmental quality in Canada. Environmental Science and Pollution Research, 30(55), 117862-117870.

Kokchang, P., Zhao, Y., Kittipongvises, S. (2023), Understanding Citizens' perceptions and attitudes toward energy restructuring under China's NDC for quality of life: A case of Linfen City. International Journal of Energy Economics and Policy, 13(5), 566-576.

Köppl, A., Schratzenstaller, M. (2023), Carbon taxation: A review of the empirical literature. Journal of Economic Surveys, 37(4), 1353-1388.

Koval, V., Laktionova, O., Udovychenko, I., Olczak, P., Palii, S., Prystupa, L. (2022), Environmental taxation assessment on clean technologies reducing carbon emissions cost-effectively. Sustainability, 14(21), 14044.

Kumar, A., Gaur, D., Liu, Y., Sharma, D. (2022), Sustainable waste electrical and electronic equipment management guide in emerging economies context: A structural model approach. Journal of Cleaner Production, 336, 130391.

Kutan, A.M., Yigit, T.M. (2002), Nominal and Real Stochastic Convergence within Transition Economies and to the European Union: Evidence from Panel Data. (ZEI Working Paper No. B 21-2002). ZEI - Center for European Integration Studies.

Kutan, A. M., & Yigit, T. M. (2003), European integration, productivity growth, and real convergence: Evidence from the new member states. Review of Development Economics, 7(3), 419-428.

Lai, C.F. (2016), Examining the double dividend effect of energy tax with the overlapping generations model. International Journal of Energy Economics and Policy, 6(1), 53-57.

Leiserowitz, A.A., Maibach, E., Roser-Renouf, C., Feinberg, G., Rosenthal, S. (2018), Climate Change in the American Mind. Seattle, WA, USA: University of Washington.

Li, P., Lin, Z., Du, H., Feng, T., Zuo, J. (2021), Do environmental taxes reduce air pollution? Evidence from fossil-fuel power plants in China. Journal of Environmental Management, 295, 113112.

Li, W., Xiao, X., Yang, X., Li, L. (2023), How does digital transformation impact green supply chain development? An empirical analysis based on the TOE theoretical framework. Systems, 11(8), 416.

Li, X., Lepour, D., Heymann, F., Maréchal, F. (2023), Electrification and digitalization effects on sectoral energy demand and consumption: A prospective study towards 2050. Energy, 279, 127992.

Linghui, Y., Ming, K.L.Y., Malan, I.N.B.B., Yi, S., Soon, L.P., Leong, L.W. (2024), Financial inclusion, digital financial inclusion and air quality: Evidence from Asian Countries. International Journal of Energy Economics and Policy, 14(3), 407-410.

Liu, H.Y., Skandalos, N., Braslina, L., Kapsalis, V., Karamanis, D. (2023), Integrating solar energy and nature-based solutions for climate-neutral urban environments. Solar, 3(3), 382-415.

Liu, Y., Dong, F., Yu, J., & Liu, A. (2024), Examining the Impact of Digital Economy on Environmental Sustainability in China: Insights into Carbon Emissions and Green Growth. Journal of the Knowledge Economy, 1-37.

Long, F., Lin, F., Ge, C. (2022), Impact of China's environmental protection tax on corporate performance: Empirical data from heavily polluting industries. Environmental Impact Assessment Review, 97, 106892.

Lu, L., Chen, Q., Huang, R., & Usman, A. (2023), Education and its impact on renewable energy demand, carbon intensity, and green growth: do digital financial inclusion and environmental policy stringency matter in China. Environmental Science and Pollution Research, 30(5), 12020-12028.

Lund, P.D. (2009), Effects of energy policies on industry expansion in renewable energy. Renewable Energy, 34(1), 53-64.

Luni, T., & Majeed, M. T. (2020), Improving environmental quality through renewable energy: evidence from South Asian economies. International Journal of Energy and Water Resources, 4(3), 335-345.

Lütkepohl, H. (2005), New Introduction to Multiple Time Series Analysis. Berlin, Germany: Springer.

Lyu, K., Yang, S., Zheng, K., Zhang, Y. (2023), How does the digital economy affect carbon emission efficiency? Evidence from energy consumption and industrial value chain. Energies, 16(2), 761.

Manal, A. (2024), The role of renewable energy in driving economic transformation and sustainable development in Saudi Arabia. International Journal of Energy Economics and Policy, 15(1), 364-373.

Markandya, A., Sampedro, J., Smith, S.J., Van Dingenen, R., Pizarro-Irizar, C., Arto, I., González-Eguino, M. (2018), Health co-benefits from air pollution and mitigation costs of the Paris agreement: A modelling study. The Lancet Planetary Health, 2(3), e126-e133.

Masih, A.M., Masih, R. (1996), Empirical tests to discern the dynamic causal chain in macroeconomic activity: New evidence from Thailand and Malaysia based on a multivariate cointegration/vector error-correction modeling approach. Journal of Policy Modeling, 18(5), 531-560.

Mehmood, S., Zaman, K., Khan, S., Ali, Z. (2024), The role of green industrial transformation in mitigating carbon emissions: Exploring the channels of technological innovation and environmental regulation. Energy and Built Environment, 5(3), 464-479.

Menegaki, A. N., & Tiwari, A. K. (2023), Willingness to pay for new technologies and environmental technologies in hotels: A multinomial logit approach. Journal of the Knowledge Economy, 1-33.

Mesagan, E.P., Nwachukwu, M.I. (2018), Determinants of environmental quality in Nigeria: Assessing the role of financial development. Econometric Research in Finance, 3(1), 55-78.

Mpofu, F.Y. (2022), Green Taxes in Africa: Opportunities and challenges for environmental protection, sustainability, and the attainment of sustainable development goals. Sustainability, 14(16), 10239.

Mudalige, H.M.N.K. (2023), Emerging new themes in green finance: A systematic literature review. Future Business Journal, 9(1), 108.

Mumuni, S., Hamadjoda Lefe, Y.D. (2023), Greening the environment: Do climate-related development finances and renewable energy consumption matter? An African tale. Carbon Management, 14(1), 2251934.

Nadiri, A., Gündüz, V., Adebayo, T.S. (2024), The role of financial and trade globalization in enhancing environmental sustainability: Evaluating the effectiveness of carbon taxation and renewable energy in EU member countries. Borsa Istanbul Review, 24, 235-247.

Naeem, S., Ingram, J.C., Varga, A., Agardy, T., Barten, P., Bennett, G., Bloomgarden, E., Bremer, L.L., Burkill, P., Cattau, M., Ching, C., Colby, M., Cook, D.C., Costanza, R., DeClerck, F., Freund, C., Gartner, T., Goldman-Benner, R., Gunderson, J., Jarrett, D., Kinzig, A.P., Kiss, A., Koontz, A., Kumar, P., Lasky, J.R., Masozera, M., Meyers, D., Milano, F., Naughton-Treves, L., Nichols, E., Olander, L., Olmsted, P., Perge, E., Perrings, C., Polasky,S., Potent, J., Prager, C., Quétier, F., Redford, K., Saterson,K., Thoumi, G., Vargas, M.T., Vickerman, S., Weisser, W., Wilkie, D., Wunder, S. (2016), Environment and development. Get the science right when paying for nature's services. Science, 347(6227), 1206-1207.

Narayan, P.K., Smyth, R. (2008), Energy consumption and real GDP in G7 countries: New evidence from panel cointegration with structural breaks. Energy Economics, 30(5), 2331-2341.

Nickell, S. (1981), Biases in dynamic models with fixed effects. Econometrica: Journal of the Econometric Society, 1417-1426.

Nsiah, T.K., Govurova, B., Mikeskac, M. (2024), On the way to net zero emissions: Can environmental tax be the game changer? The vise grad group evidence. International Journal of Energy Economics and Policy, 14(5), 311-320.

Ntanos, S., Skordoulis, M., Kyriakopoulos, G., Arabatzis, G., Chalikias, M., Galatsidas, S., Batzios, A., Katsarou, A. (2018), Renewable energy and economic growth: Evidence from European countries. Sustainability, 10(8), 2626.

Nuissl, H., Siedentop, S. (2012), Landscape planning for minimizing land consumption. In: Meyers, R.A., editor. Encyclopedia of Sustainability Science and Technology. New York: Springer.

OCDE. (2010), Taxation, Innovation and the Environment. Paris: OCDE.

OECD. (2020), Environmental Policy Tools and Evaluation. Paris: OECD Publishing.

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

Omri, A., Kahouli, B., Afi, H., Kahia, M. (2023), Impact of environmental quality on health outcomes in Saudi Arabia: Does research and development matter? Journal of the Knowledge Economy, 14(4), 4119-4144.

Osman, A.I., Chen, L., Yang, M., Msigwa, G., Farghali, M., Fawzy, S., Rooney, D.W., Yap, P.S. (2023), Cost, environmental impact, and resilience of renewable energy under a changing climate: A review. Environmental Chemistry Letters, 21(2), 741-764.

Pao, H.T., Fu, H.C. (2013), Renewable energy, non-renewable energy and economic growth in Brazil. Renewable and Sustainable Energy Reviews, 25, 381-392.

Paraschiv, L.S., Paraschiv, S. (2023), Contribution of renewable energy (hydro, wind, solar and biomass) to decarbonization and transformation of the electricity generation sector for sustainable development. Energy Reports, 9, 535-544.

Permana, D., Salim, A.S., Ramli, Y., Shamansurova, Z. (2024), Analyzing the impact of natural resource rents, green finance and digital finance on environmental quality: Evidence from developing countries. International Journal of Energy Economics and Policy, 14(6), 195-204.

Pesaran, M.H. (2004), General diagnostic tests for cross section dependence in panels. Cambridge Working Papers in Economics, 1240. University of Cambridge. p1.

Pesaran, M. H. (2006), Estimation and inference in large heterogeneous panels with a multifactor error structure. Econometrica, 74(4), 967-1012.

Pesaran, M.H., Shin, Y., Smith, R.J. (2001), Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16(3), 289-326.

Pesaran, M.H., Smith, R. (1995), Estimating long-run relationships from dynamic heterogeneous panels. Journal of Econometrics, 68(1), 79-113.

Pesaran, M. H., & Yamagata, T. (2008), Testing slope homogeneity in large panels. Journal of econometrics, 142(1), 50-93.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001), Bounds testing approaches to the analysis of level relationships. Journal of applied econometrics, 16(3), 289-326.

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999), Pooled mean group estimation of dynamic heterogeneous panels. Journal of the American Statistical Association, 94(446), 621-634.

Phillips, P.C., Hansen, B.E. (1990), Statistical inference in instrumental variables regression with I (1) processes. The Review of Economic Studies, 57(1), 99-125.

Pokorny, B., Pacheco, P., de Jong, W., Entenmann, S.K. (2021), Forest frontiers out of control: The long-term effects of discourses, policies, and markets on conservation and development of the Brazilian Amazon. Ambio, 50(12), 2199-2223.

Priambodo, N.W., Raharjo, J., Rokhmat, M. (2022), Land use for renewable energy power plant and the impact of CO_2 emission: An Indonesian case study. International Journal of Energy Economics and Policy, 12(5), 457-465.

Raghutla, C., & Kolati, Y. (2023), Does renewable energy improve environmental quality? Evidence from RECAI countries. Environmental Science and Pollution Research, 30(45), 100717-100730.

Rahman, A., Farrok, O., Haque, M.M. (2022), Environmental impact of renewable energy source based electrical power plants: Solar, wind, hydroelectric, biomass, geothermal, tidal, ocean, and osmotic. Renewable and Sustainable Energy Reviews, 161, 112279.

Raihan, A., Muhtasim, D.A., Farhana, S., Hasan, M.A.U., Pavel, M.I., Faruk, O., Rahman, M., Mahmood, A. (2022), Nexus between economic growth, energy use, urbanization, agricultural productivity, and carbon dioxide emissions: New insights from Bangladesh. Energy Nexus, 8, 100144.

Rao, M., Vasa, L., Xu, Y., Chen, P. (2023), Spatial and heterogeneity analysis of environmental taxes' impact on China's green economy development: A sustainable development perspective. Sustainability, 15(12), 9332.

Riti, J. S., Song, D., Shu, Y., Kamah, M., & Atabani, A. A. (2018), Does renewable energy ensure environmental quality in favour of economic growth? Empirical evidence from China's renewable development. Quality & Quantity, 52, 2007-2030.

Rogelj, J., Schleussner, C.F., Hare, W. (2017), Getting it right matters: Temperature goal interpretations in geoscience research. Geophysical Research Letters, 44(20), 10662-10665.

Sackitey, G.L. (2023), Do environmental taxes affect energy consumption and energy intensity? An empirical analysis of OECD countries. Cogent Economics and Finance, 11(1), 2156094.

Saikkonen, P. (1991), Asymptotically efficient estimation of cointegration regressions. Econometric Theory, 7(1), 1-21.

Saqib, N., Usman, M. (2023), Are technological innovations and green energy prosperity swiftly reduce environmental deficit in China and United States? Learning from two sides of environmental sustainability. Energy Reports, 10, 1672-1687.

Sari Saudi, N.D., Abdi Reviane, I.T., Paddu, A.H., Agustin, G., Djam'an, F., Sabbar, S.D. (2024), Carbon neutrality and sustainable development: An empirical study of Indonesia's renewable energy adoption. International Journal of Energy Economics and Policy, 14(4), 526-537.

Sarpong, K.A., Xu, W., Gyamfi, B.A., Ofori, E.K. (2023), Can environmental taxes and green-energy offer carbon-free E7 economies? An empirical analysis in the framework of COP-26. Environmental Science and Pollution Research, 30(18), 51726-51739.

Shen, Y., Yang, Z., Zhang, X. (2023), Impact of digital technology on carbon emissions: Evidence from Chinese cities. Frontiers in Ecology and Evolution, 11, 1166376.

Shi, Z., Loh, L., Wu, H., Han, D. (2024), Smarter and cleaner: How does energy digitalization affect carbon productivity? Energy Strategy Reviews, 52, 101347.

Silva, N., Fuinhas, J.A., Koengkan, M., Kazemzadeh, E., Kaymaz, V. (2023), Renewable energy deployment in Europe: Do politics matter? Environment, Development and Sustainability, 26, 28751-28784.

Song, Y., Zhang, Z., Sahut, J.M., Rubin, O. (2023), Incentivizing green technology innovation to confront sustainable development. Technovation, 126, 102788.

Stavins, R.N. (1999), The costs of carbon sequestration: A revealed-preference approach. American Economic Review, 89(4), 994-1009.

Stern, D.I. (2004), The rise and fall of the environmental Kuznets curve. World Development, 32(8), 1419-1439.

Su, S., Qamruzzaman, M., Karim, S. (2023), Charting a sustainable future: The impact of economic policy, environmental taxation, innovation, and natural resources on clean energy consumption. Sustainability, 15(18), 13585.

Susilawati, S., Satrianto, A. (2024), Influence of economy, energy, and population on foreign direct investment and CO_2 emissions in ASEAN-5 countries. International Journal of Energy Economics and Policy, 14(5), 10-18.

Suzuki, M., Jewell, J., Cherp, A. (2023), Have climate policies accelerated energy transitions? Historical evolution of electricity mix in the G7 and the EU compared to net-zero targets. Energy Research and Social Science, 106, 103281.

Talan, A., Rao, A., Sharma, G.D., Apostu, S.A., Abbas, S. (2023), Transition towards clean energy consumption in G7: Can financial sector, ICT and democracy help? Resources Policy, 82, 103447.

Teter, J., Yeh, S., Khanna, M., Berndes, G. (2018), Water impacts of US biofuels: Insights from an assessment combining economic and biophysical models. PLoS One, 13(9), e0204298.

Tiba, S., Belaid, F. (2021), Modeling the nexus between sustainable development and renewable energy: The African perspectives. Journal of Economic Surveys, 35(1), 307-329.

Tiba, S., Omri, A., Frikha, M. (2016), The four-way linkages between renewable energy, environmental quality, trade and economic growth: A comparative analysis between high and middle-income countries. Energy Systems, 7(1), 103-144.

Truong, T.C. (2022), The impact of digital transformation on environmental sustainability. Advances in Multimedia, 2022, 1-12.

Uddin, K.M.K., Rahman, M.M., Saha, S. (2023), The impact of green tax and energy efficiency on sustainability: Evidence from Bangladesh. Energy Reports, 10, 2306-2318.

Udeagha, M. C., & Ngepah, N. (2022), Disaggregating the environmental effects of renewable and non-renewable energy consumption in South Africa: fresh evidence from the novel dynamic ARDL simulations approach. Economic Change and Restructuring, 55(3), 1767-1814.

UNEP. (2020), Digitalization, Climate Change and Sustainable Development: Opportunities and Challenges. Nairobi, Kenya: United Nations Environment Programme.

Wang, Q., Dong, Z., Li, R., Wang, L. (2022), Renewable energy and economic growth: New insight from country risks. Energy, 238, 122018.

Wang, T., Umar, M., Li, M., Shan, S. (2023), Green finance and clean taxes are the ways to curb carbon emissions: An OECD experience. Energy Economics, 124, 106842.

Westerlund, J. (2007), Testing for error correction in panel data. Oxford Bulletin of Economics and statistics, 69(6), 709-748.

Wooldridge, J.M. (2010), Econometric Analysis of Cross Section and Panel Data. United States: MIT Press.

Wynes, S., & Nicholas, K. A. (2019), Climate science curricula in Canadian secondary schools focus on human warming, not scientific consensus, impacts or solutions. PloS one, 14(7), e0218305.

Xiang, W. (2023), Assessing the environmental effects of ICT and renewable energy: roles of financial development, innovation, and trade. Environmental Science and Pollution Research, 30(53), 114310-114326.

Xie, Z., Ma, J., Huang, S., & Zhu, J. (2023), Digital economy and inclusive green growth: The moderating effect of government environmental regulation. Environmental Science and Pollution Research, 30(49), 107938-107955.

Xu, Q., Zhong, M., Li, X. (2022), How does digitalization affect energy? International evidence. Energy Economics, 107, 105879.

Yan, H., Qamruzzaman, M., Kor, S. (2023), Nexus between green investment, fiscal policy, environmental tax, energy price, natural resources, and clean energy-a step towards sustainable development by fostering clean energy inclusion. Sustainability, 15(18), 13591.

Yao, S., Dong, Z., & Zhang, Z. (2023), How digital finance affects environmental pollution management: evidence from China. Environmental Science and Pollution Research, 30(48), 105231-105246.

Yong, S. W., Law, S. H., Ibrahim, S., & Mohamad, W. N. W. (2023), ICTs, growth, and environmental quality nexus: dynamic panel threshold regression. Environmental Science and Pollution Research, 30(8), 20849-20861.

Youssef, A.B., Dahmani, M., Mabrouki, M. (2023), The impact of environmentally related taxes and productive capacities on climate change: Insights from european economic area countries. Environmental Science and Pollution Research, 30(44), 99900-99912.

Zafar, M.W., Qin, Q., Zaidi, S.A.H. (2020), Foreign direct investment and education as determinants of environmental quality: The importance of post Paris Agreement (COP21). Journal of Environmental Management, 270, 110827.

Zhang, L., Chen, Z., Guo, J., Xu, Z. (2021), Distribution of heavy metals and release mechanism for respirable fine particles incineration ashes from lignite. Resources, Conservation and Recycling, 166, 105282.

Zulfiqar, M., Tahir, S. H., Ullah, M. R., & Ghafoor, S. (2023). Digitalized world and carbon footprints: does digitalization really matter for sustainable environment?. Environmental Science and Pollution Research, 30(38), 88789-88802.