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**Article**

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# How does ICT Diffusion and Renewable Energy Consumption affect $CO_2$ Emissions?

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**ABSTRACT**

This study investigates the impact of renewable energy consumption (REC), information and communication technology (ICT), and gross domestic product (GDP) on $CO_2$ emissions in Saudi Arabia over the period 1990-2020. Utilizing an ARDL (Autoregressive Distributed Lag) model, the results reveal that GDP exerts a positive and significant effect on emissions in both the short and long term, suggesting that economic growth is associated with higher emissions. In contrast, REC has a negative impact, indicating that increased renewable energy consumption contributes to reducing emissions over time. However, the negative effect of REC on emissions in the short term suggests that transitioning to renewable energy may involve initial costs or disruptions that temporarily affect emissions. ICT also shows a negative influence on emissions in the long term, but its short-term effects are less consistent, reflecting the potential environmental costs associated with rapid technological expansion, such as increased energy consumption and electronic waste. The interaction terms between GDP and REC, as well as GDP and ICT, reveal that higher levels of renewable energy and technological development moderate the positive relationship between GDP and emissions, highlighting the complex trade-offs between economic growth, energy transition, and technological advancement. The findings emphasize the importance of expanding renewable energy infrastructure and fostering sustainable technological innovation to mitigate emissions while sustaining economic growth in Saudi Arabia.

**Keywords:** ICT Diffusion, Renewable Energy Consumption, $CO_2$ Emissions
**JEL Classifications:** C33, D83, F64, Q43

## 1. INTRODUCTION

Addressing climate change has become a global priority, driven by the increasing urgency to reduce greenhouse gas (GHG) emissions, particularly $CO_2$, which accounts for a significant share of global warming. The energy sector is one of the primary contributors to $CO_2$ emissions, especially in nations dependent on fossil fuels (Intergovernmental Panel on Climate Change (IPCC, 2021). In recent years, two critical factors have emerged as potential solutions to mitigate environmental degradation: the diffusion of ICT and the shift towards renewable energy consumption.

ICT diffusion can play a transformative role in reducing $CO_2$ emissions by optimizing energy use and enhancing industrial efficiency. Through innovations such as smart grids, digital energy management systems, and automation, ICT enables better monitoring and control of energy consumption (Zafar et al., 2022). Furthermore, ICT tools provide the foundation for a low-carbon economy by supporting green technologies and fostering collaboration between industries and governments on sustainable practices. ICT diffusion, on the other hand, is increasingly recognized for its potential to influence energy consumption patterns and contribute to environmental sustainability. ICT enables the optimization of energy use across various sectors through digital technologies such as smart grids, automation, and energy management systems (Faheem et al., 2018). These technologies can enhance efficiency by reducing waste and enabling better control over energy production and consumption. Additionally, ICT supports the development and integration of renewable energy technologies by providing platforms for innovation, monitoring, and collaboration between industries and policymakers (Zafar et al., 2022).

REC, on the other hand, is widely regarded as the cornerstone of climate change mitigation strategies. The adoption of renewable energy sources, such as solar, wind, and hydropower, directly displaces fossil fuel-based energy generation, resulting in a substantial reduction in $CO_2$ emissions (International Energy Agency [IEA], 2023). Countries around the world have increasingly committed to integrating renewable energy into their power grids, contributing to sustainable development goals (SDGs) and national climate agendas. The role of REC in reducing $CO_2$ emissions is well-established. Fossil fuel-based energy sources, such as coal, oil, and natural gas, are responsible for the majority of $CO_2$ emissions, whereas renewable energy sources like solar, wind, and hydropower produce little to no emissions (IEA, 2023). The transition to renewable energy has become a cornerstone of national and international climate strategies, including the Paris Agreement, which aims to limit global temperature increases to well below 2°C (UNFCCC, 2015). Many countries have set ambitious targets for increasing the share of renewable energy in their energy mix, recognizing the environmental and economic benefits that come from reducing reliance on carbon-intensive fuels (European Commission, 2021).

However, despite the clear environmental benefits, the relationship between ICT diffusion, REC, and $CO_2$ emissions remains complex. Some studies suggest that while ICT aids in emission reductions, its rapid expansion may also lead to increased energy demand, partially offsetting the environmental benefits (Wang et al., 2023). Similarly, the transition to renewable energy requires significant infrastructure investments and policy frameworks that support long-term sustainability.

Moreover, the interaction between ICT diffusion and renewable energy consumption may vary across regions and economic contexts. In developed countries, where energy infrastructures are well-established and advanced technologies are readily available, the diffusion of ICT can more easily complement renewable energy integration (IRENA, 2020). In contrast, developing countries face more significant barriers to the widespread adoption of ICT and renewable energy technologies. These include financial constraints, lack of technical expertise, and insufficient policy frameworks to support green energy transitions. Nonetheless, as renewable energy becomes more cost-competitive and ICT continues to proliferate, even developing nations are increasingly investing in these technologies as part of their strategies to reduce $CO_2$ emissions and foster sustainable development.

Saudi Arabia is a compelling case for studying the relationship between REC, ICT, and $CO_2$ emissions due to its unique position as a leading global energy player. As one of the world's largest producers and exporters of crude oil, Saudi Arabia's economy has long been heavily reliant on fossil fuels. This dependence makes the Kingdom highly susceptible to fluctuations in global oil prices, which can impact both its domestic energy policies and international economic stability. However, in recent years, Saudi Arabia has embarked on an ambitious journey to diversify its economy and energy portfolio through Vision 2030, a strategic framework aimed at reducing the country's dependence on oil, boosting non-oil sectors, and increasing the share of renewable energy in its energy mix (Kingdom of Saudi Arabia, 2016).

The rapid diffusion of ICT and the increasing emphasis on renewable energy within Saudi Arabia offer a timely opportunity to assess the country's potential for a more sustainable future. With vast renewable energy potential, particularly in solar and wind power, Saudi Arabia is uniquely positioned to transition from a fossil-fuel-dominated energy system to one that integrates more environmentally friendly sources. Moreover, Saudi Arabia's substantial financial resources and government commitment to clean energy investments, as demonstrated by projects like the NEOM and Red Sea solar initiatives, make it a key player in the global renewable energy transition.

Studying Saudi Arabia allows researchers to explore how an oil-dependent economy can navigate the challenges and opportunities of embracing renewable energy, ICT, and environmental sustainability. Additionally, Saudi Arabia's efforts to curb $CO_2$ emissions while maintaining economic growth serve as a critical case for other oil-rich nations seeking to balance economic development with environmental goals. Given the Kingdom's leadership role in OPEC and the global energy market, its success or failure in this transition could have far-reaching implications for energy policies worldwide. This makes Saudi Arabia an ideal case study for understanding the dynamic interplay between energy policy, technological diffusion, and environmental sustainability in a rapidly changing world.

This study aims to explore how the diffusion of ICT and REC jointly influence $CO_2$ emissions in Saudi Arabia. By examining the interplay between these two factors, we seek to provide insights into effective strategies for mitigating climate change while promoting sustainable energy use. Understanding this relationship is particularly critical as nations work to balance economic growth, energy demand, and environmental preservation.

This article is organized into five sections: Section 2 presents the literature review, while Section 3 outlines the data and empirical model. Section 4 details the econometric methodology. Section 5 provides the empirical results and discussion. Finally, Section 6 concludes with an analysis of the results, policy implications, and recommendations for future research.

## 2. LITERATURE REVIEW

Previous research on the relationship between ICT advancement and regional $CO_2$ emissions has led to two opposing viewpoints. One perspective suggests that ICT can benefit the environment by optimizing production processes and improving environmental management. Conversely, other studies highlight the negative environmental impacts of ICT, such as increased energy consumption and the disposal of ICT equipment, which contribute to e-waste and harm the natural world.

### 2.1. ICT-$CO_2$ Emissions Nexus

Current research highlights several factors contributing to environmental degradation, with the proliferation of ICT identified as a significant driver (Weili et al., 2022). While ICT is often associated with economic growth, urbanization, and innovation, it has also been linked to the overuse of nonrenewable resources, ecological damage, and challenges like job displacement. The literature on this issue is divided into two conflicting perspectives (Lin et al., 2022). One viewpoint suggests that the widespread adoption of ICT can lead to negative environmental outcomes, such as increased emissions and pollution. For example, ICT's role in industrial expansion, higher energy consumption, globalization, and enhanced financial systems has been identified as contributing to environmental harm. In fact, ICT was estimated to account for approximately 2% of global greenhouse gas emissions in 2007 (Ahmed et al., 2023). Research by Azam et al. (2022) supports this perspective, showing that the rapid growth in ICT use has significantly increased electricity consumption, leading to higher global emissions and a decline in environmental quality. Similarly, Pata and Samour (2022), in their study of OECD nations from 1991 to 2012, utilized the PMG estimator to assess the short- and long-term effects of internet usage and per capita economic growth on $CO_2$ emissions. Their findings suggest that while the expansion of internet access positively impacted society, it had a minimal influence on $CO_2$ emissions, leading them to conclude that the negative effects of ICT on environmental quality were not substantial.

Several studies have approached the relationship between ICT growth and regional $CO_2$ emissions from various angles. One perspective focuses on how ICT advancements can lead to reduced emissions by fostering greater energy efficiency and automating production processes. This approach suggests that ICT can optimize resource utilization, including energy, human, and financial capital, contributing to reduced greenhouse gas emissions (Sedghiyan et al., 2021). Another line of research delves into the methods for accurately measuring the decline in $CO_2$ emissions. For instance, Mehmood (2022) argue that precise technological calculations are essential for managing the growth of low-emission economies. Moreover, empirical studies highlight the real-world impact of ICT on $CO_2$ emissions. Research by Yurtkuran (2021) and Ishaq and Dincer (2021) found that ICT advancements have played a significant role in reducing China's carbon emissions, illustrating how technology can be a powerful tool in addressing environmental challenges. These findings suggest that the adoption of ICT in industrial and societal processes could be key to achieving sustainable development.

Moreover, Mngumi et al. (2022) demonstrated that for every 1% increase in ICT growth, China experienced a 2.86% reduction in sulfur dioxide emissions, highlighting the environmental benefits of technological advancements. Similarly, Li et al. (2022) found that increased investment in ICT in Germany, Japan, and India led to more efficient energy use and decreased energy intensity, resulting in lower $CO_2$ emissions. However, the relationship between ICT and $CO_2$ emissions is complex. While ICT fosters urban social and economic growth, it can also contribute to climate change through increased $CO_2$ emissions, particularly from electricity generation. According to Nguyen et al. (2021), the ICT sector is responsible for 2% of global $CO_2$ emissions. Ahmed et al. (2022) further noted that ICT affects energy consumption directly, particularly in the manufacturing of equipment and the operation of large-scale infrastructures like data centers. Cloud computing and data centers are among the primary contributors to carbon emissions, according to their study. Ozoegwu and Akpan (2021) found that ICT raises $CO_2$ emissions in manufacturing but decreases them in transportation and commerce sectors in Iran. Despite this growing body of research, the ecological impact of ICT remains uncertain. Previous studies (Adedoyin et al., 2021; Zhao et al., 2022) focused on how ICT development levels influence regional carbon emissions, but many have neglected potential spatial correlations between regions. To address these gaps, this analysis uses the AMG econometric approach to explore how different levels of ICT development—such as infrastructure, service, and application—impact $CO_2$ emissions across regions, offering new insights into the spatial spillover effects of ICT growth.

### 2.2. REC-$CO_2$ Emission Nexus

The nexus between renewable energy consumption (REC) and $CO_2$ emissions has become a central topic of research due to increasing concerns about climate change and the environmental sustainability of energy systems. Renewable energy sources, such as solar, wind, hydro, and biomass, are considered key solutions for reducing greenhouse gas emissions, as they provide alternatives to fossil fuels, which are the primary drivers of $CO_2$ emissions globally. In recent years, a significant amount of research has examined the relationship between REC and $CO_2$ emissions across various regions and economies (Fu et al., 2021; Jia et al., 2021; Sheraz et al., 2021; Xu et al., 2022; Chang et al., 2023; Işık et al., 2024; Hasanov et al., 2024).

The theoretical foundation of the REC- $CO_2$ nexus is largely based on the Environmental Kuznets Curve (EKC) hypothesis. The EKC posits that environmental degradation increases with economic growth up to a certain point, after which it begins to decrease as economies shift towards cleaner technologies and more efficient energy use. Renewable energy is seen as a pivotal factor in this transition, where countries with higher renewable energy adoption are expected to experience lower levels of $CO_2$ emissions in the long run. The transition from fossil fuel-based energy to renewable energy sources is expected to decouple economic growth from environmental degradation, thus reducing $CO_2$ emissions and mitigating climate change.

Several empirical studies have examined the relationship between renewable energy consumption and $CO_2$ emissions, yielding mixed results depending on the regions and methods used. Many studies suggest that higher renewable energy consumption leads to a reduction in $CO_2$ emissions. For instance, the work by Sadorsky

(2009), which examined a panel of G7 countries, found that increased REC significantly reduces $CO_2$ emissions over time. This finding supports the argument that renewable energy is an effective means of mitigating environmental degradation and achieving sustainability.

Similarly, Bilgili et al. (2016) examined the relationship between REC and $CO_2$ emissions in 17 OECD countries from 1980 to 2011. Using a panel cointegration analysis, they found a long-term negative relationship between REC and $CO_2$ emissions, suggesting that REC helps to reduce greenhouse gas emissions in the long run. Zhang and Cheng (2009) also observed a similar negative impact of REC on $CO_2$ emissions in the context of China, highlighting the potential of REC to mitigate the environmental impacts of rapid industrialization.

However, not all studies have found a straightforward inverse relationship between REC and $CO_2$ emissions. Some studies indicate that the effectiveness of REC in reducing $CO_2$ emissions may be contingent on factors such as energy efficiency, economic structure, and the mix of renewable energy sources. For instance, Pata (2021), using data from BRICS countries, argued that while REC has the potential to reduce emissions, the degree of reduction depends on the share of renewables in the energy mix and the overall energy efficiency of the economy. In countries where renewable energy constitutes a small portion of the total energy mix, the impact on $CO_2$ emissions may be marginal.

Regional studies have provided valuable insights into the REC- $CO_2$ emission nexus, as the relationship varies significantly across countries and regions. Bilan et al. (2019) conducted a study on the European Union (EU), finding that the shift to renewable energy sources was a key factor in reducing $CO_2$ emissions in the region, particularly after the implementation of strict environmental policies. The study emphasized the role of policy frameworks in encouraging renewable energy investment and improving energy efficiency, which in turn contributed to lower emissions.

In contrast, research on emerging economies, such as Shahbaz et al. (2020), revealed that while REC plays an important role in reducing emissions, the high reliance on fossil fuels in these countries poses a significant challenge to achieving a low-carbon economy. The study, focusing on India and Pakistan, showed that REC is associated with a decrease in emissions, but the slow pace of renewable energy adoption and the dominance of coal and oil in the energy mix limit the overall environmental benefits. Moreover, Tugcu et al. (2012) highlighted that in oil-exporting countries like Saudi Arabia, the REC- $CO_2$ nexus is more complex. Despite having substantial renewable energy potential, the country's heavy reliance on oil for energy generation has resulted in high $CO_2$ emissions. The study emphasized the importance of energy diversification and the adoption of renewable energy technologies to reduce the environmental footprint of energy consumption in oil-rich economies.

Researchers have employed various econometric methods to explore the REC- $CO_2$ nexus, including time series analysis, panel data methods, and more advanced techniques such as cointegration and causality testing. Apergis and Payne (2010), for instance, used panel cointegration techniques to analyze the relationship between REC and $CO_2$ emissions in a sample of 20 OECD countries. Their findings indicated a bidirectional causality between REC and $CO_2$ emissions, suggesting that increases in renewable energy consumption lead to reductions in $CO_2$ emissions and vice versa.

Moreover, Gangopadhyay et al. (2023) applied a ARDL model to examine the long-run and short-run relationships between renewable energy, economic growth, and $CO_2$ emissions in the context of the United States. They found that REC significantly reduces $CO_2$ emissions in the long run, supporting the EKC hypothesis, while in the short run, the relationship was more ambiguous.

Despite the growing body of literature, the REC- $CO_2$ nexus faces several challenges and limitations. One key challenge is the issue of data availability and quality, particularly in developing countries, where accurate and consistent data on renewable energy consumption is often lacking. Moreover, the heterogeneity in the types of renewable energy sources (e.g., hydro, solar, wind) and their varying impacts on $CO_2$ emissions complicate the analysis. For instance, while wind and solar energy are generally considered clean, large-scale hydropower projects can have significant environmental impacts, such as methane emissions from reservoirs. Additionally, the effectiveness of renewable energy in reducing $CO_2$ emissions is influenced by the energy policies and regulatory frameworks in place. Countries with strong policy support for renewable energy, such as subsidies and incentives, are more likely to experience significant reductions in emissions compared to those without such measures.

In summary, the review subsections have highlighted critical aspects of the debate surrounding the relationships between $CO_2$ emissions, ICT, economic growth (EG), and REC, particularly within the framework of the Environmental Kuznets Curve (EKC) hypothesis. While many studies have explored these connections, there remains a gap in policy tools that specifically address the impact of ICT on $CO_2$ emissions. Additionally, this study delves into the influence of interaction terms, such as ICT*EG and REC*EG, on carbon emissions. By focusing on the interplay between ICT, REC, and $CO_2$ emissions, this research aims to contribute to the broader goals of achieving sustainable development. The following section outlines the methodology and data used to support this analysis.

## 3. DATA AND EMPIRICAL MODEL

This study employs time series data from Saudi Arabia, covering the period from 1990 to 2020. This dataset provides a comprehensive view of the country's renewable energy consumption, ICT, economic growth, and related environmental indicators over the course of three decades, enabling a robust analysis of the long-term trends and relationships between these variables. The chosen timeframe also captures significant technological advancements, and global economic shifts that have influenced energy consumption patterns in Saudi Arabia. The data on $CO_2$ emissions was sourced from the World Bank database, a reputable and comprehensive resource that provides extensive information on global emissions. The annual GDP, measured in constant 2015 dollars, was retrieved from the World Development Indicators (WDI) as an indicator of economic output per capita. Additionally, two other key variables—ICT and renewable energy consumption (REC)—were sourced from the WDI database, which includes comprehensive data on the adoption and utilization of ICT and renewable energy resources. Table 1 outlines the study variables, including their corresponding symbols and credible sources.

To assess the impact of ICT and REC on $CO_2$ emissions, taking into account other variables like Gross Domestic Product (GDP), the empirical model is structured as follows:

$$CO_2 = F(ICT, REC, GDP) \tag{1}$$

In this equation, $CO_2$ denotes carbon dioxide emissions, ICT refers to information and communication technology, REC represents renewable energy consumption, and GDP signifies gross domestic product.

Based on the principles outlined by Abid (2023), we incorporate ICT as an additional independent variable in equation (1). The ICT facilitates the shift towards renewable energy sources, which in turn alters the composition of the manufacturing sector and contributes to a reduction in carbon dioxide emissions. Consequently, we anticipate that eco-innovation will negatively impact $CO_2$ emissions. Research suggests that economic expansion is a major driver of carbon dioxide emissions, as increased economic activities place greater demands on energy supplies, leading to worsening environmental conditions. Additionally, the long-term environmental degradation associated with the allocation of resources to renewable energy sources should be considered. Eq. (2) can be expressed in its natural form as follows:

$$\ln CO_{2t} = \alpha_0 + \alpha_1 \ln ICT_t + \alpha_2 \ln REC_t + \alpha_3 \ln GDP_t + \varepsilon_t \tag{2}$$

Additionally, the study aims to examine the impact of interaction factors (ICT*$GDP$, $REC$*GDP) on $CO_2$ emissions. This analysis can be detailed using equations (3) and (4).

$$\ln CO_{2t} = \alpha_0 + \alpha_1 \ln ICT_t + \alpha_2 \ln REC_t + \alpha_3 \ln GDP_t + \alpha_4 \left(\ln ICT \times \ln GDP\right)_t + \varepsilon_t \tag{3}$$

$$\ln CO_{2t} = \beta_0 + \beta_1 \ln ICT_t + \beta_2 \ln REC_t + \beta_3 \ln GDP_t + \beta_4 \left(\ln REC \times \ln GDP\right)_t + \mu_t \tag{4}$$

## 4. METHODOLOGY

This study employs ARDL bootstrap tests to investigate the long-term cointegration relationship between REC, GDP, ICT and $CO_2$ emissions. Following the ARDL bounds testing framework introduced by Pesaran et al. (2001), McNown et al. (2018) utilized the bootstrap methodology for ARDL cointegration analysis. Several key factors justify the use of the ARDL bootstrap test. First, unlike the ARDL bounds test, the ARDL bootstrap test accommodates more than two endogenous variables, allowing feedback from the dependent variable to the independent variable. Second, due to the strong statistical power of ARDL cointegration tests, McNown et al. (2018) adopted the bootstrap approach. Finally, to enhance the F and t-tests for cointegration proposed by Pesaran et al. (2001), McNown et al. (2018) incorporated lagged independent variables.

In its general (explicit) form, an ARDL (Autoregressive Distributed Lag) model can be written as follows:

$$Y_t = \sigma + \sum_{i=1}^{p} \eta_i Y_{t-i} + \sum_{j=0}^{q} \alpha_j X_{t-j} + \sum_{k=0}^{r} \beta_k Z_{t-k} + \sum_{l=0}^{s} \gamma_l D_{t,l} + e_t \tag{5}$$

Where, $Y_t$ is the dependent variable at time t, $\sigma$ is the intercept, $\eta_i$ are the coefficients of the lagged dependent variable $Y_{t-i}$, $\alpha_j$ and $\beta_k$ are the coefficients of the lagged independent variable $X_{t-j}$ and $Z_{t-k}$, respectively. The variable $D_{t,l}$ is a dummy variable and $e_t$ is the error term at time t. The ARDL representation of equation (5) can be rewritten and expanded as follows:

$$\Delta Y_t = \sigma + \sum_{i=1}^{p-1} \alpha_i Y_{t-i} + \sum_{j=0}^{q-1} \beta_j X_{t-j} + \sum_{k=0}^{r-1} \rho_k Z_{t-k} + \sum_{l=0}^{s} \delta_l D_{t,l} + \theta Y_{t-1} + \vartheta X_{t-1} + \varpi Z_{t-1} + \zeta_t \tag{6}$$

Where, $\theta = -1 + \sum_{i=1}^{p} \eta_i, \vartheta = \sum_{j=0}^{q} \alpha_j, \varpi = \sum_{k=0}^{r} \beta_k$. The equation maintains the same structure as the standard ARDL formulation, incorporating both the short-run dynamics and the long-run equilibrium relationship, with $\alpha_i$, $\beta_j$, $\rho_k$ and $\delta_l$ reflecting the function values of the parameters from the original model.

According to Pesaran et al. (2001), determining the existence of a cointegration relationship requires rejecting specific null hypotheses through both the *F*-test and *t*-test. The *F*-test evaluates whether the coefficients of the lagged levels of the variables are jointly equal to zero, ($H_0$: $\theta = \vartheta = \varpi = 0$), with the null hypothesis asserting that no long-run relationship exists between the variables. On the other hand, the *t*-test assesses the significance of the lagged dependent variable's coefficient, with the null hypothesis stating that this coefficient is zero, ($H_0$: $\theta = 0$), implying no long-run relationship. Rejection of these null hypotheses suggests that a cointegration relationship is present, indicating a long-run equilibrium between the variables.

Nevertheless, McNown et al. (2018) propose an additional *F*-test, denoted as $F_{\text{independent}}$, to complement the Pesaran et al. (2001) tests. This test aims to verify the following null hypothesis ($H_0$: $\vartheta = \varpi = 0$). This additional *F*-test serves to further validate the long-run relationship by focusing specifically on the impact of the independent variables on the dependent variable.

McNown et al. (2018), relying on three null hypotheses, identified two degenerate cases regarding long-run cointegration. First, in the case where the $_F$-statistic and $_t$-dependent tests are significant but the $F_{\text{independent}}$ test is not, the joint significance of the error correction

**Table 1: Summary of variables and their sources**

| Variables | Symbols | Description | Source |
|---|---|---|---|
| Carbon dioxide emissions | $CO_2$ | $CO_2$ emissions per capita (Tones/capita) | WDI |
| Information and communication technology | ICT | Average (Fixed phone subscription, Fixed broadband internet subscription, Mobile cellular subscription) | |
| Gross domestic product | GDP | Per capita (USD Constant 2015) | |
| Renewable energy consumption | REC | Total, % of primary energy supply | |

terms arises solely from the lag of the dependent variable. In this situation, the explanatory variables do not contribute to the long-run cointegration relationship. Second, if both the $F$-statistic and $F_{independent}$ tests are significant but the $t$-dependent test is not, the dependent variable does not exhibit a long-run relationship, even though the independent variables do. To address these scenarios, McNown et al. (2018) introduced an additional test on the lagged independent variables (denoted as the F-independent test) to complement the standard F and t-dependent tests for cointegration, as proposed by Pesaran et al. (2001). This study affirms that Pesaran et al. (2001) do not require the dependent variable to be integrated of order I(1), ruling out the first degenerate case. By utilizing the ARDL bootstrap test, McNown et al. (2018) sought to address this issue through an additional test on the coefficients of the lagged independent variables, offering a more comprehensive assessment of the long-run relationship.

To ensure the validity and reliability of the results, various diagnostic tests are conducted. These include the Breusch-Godfrey LM test for autocorrelation, the Jarque-Bera test for normality, and the Breusch-Pagan test for heteroscedasticity. Additionally, the CUSUM and CUSUMsq tests are applied to assess the stability of the model coefficients over time, ensuring that the results are not affected by structural breaks or changes in the underlying data generation process.

## 5. RESULTS AND DISCUSSION

### 5.1. The Unit Root Test

To assess the stationarity of the data series, we will utilize several tests, including the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979), the Phillips-Perron (PP) test (Phillips and Perron, 1988), and the Dickey-Fuller generalized least squares (DFGLS) test (Elliott et al., 1996). As indicated in Table 2, the results reveal that the variables $CO_2$ emissions, GDP, and REC are stationary at their first differences, while the ICT variable is stationary at its level.

To further validate the results of the ADF, PP, and DFGLS tests, we apply the Zivot and Andrews test (Zivot and Andrews, 1992), which offers the advantage of testing for unit roots while accounting for an endogenously identified structural break in the time series (Gheraia et al., 2022; Abid et al., 2022). The results in Table 3 confirm that the model variables are integrated of order I(0) and I(1), supporting the use of the bootstrap ARDL bounds testing approach developed by McNown et al. (2018). This method delivers empirically robust results when compared to the traditional ARDL bounds testing approach proposed by Pesaran et al. (2001), particularly in the presence of structural breaks.

### 5.2. Cointegration Test

The next step is to assess the presence of cointegration among the variables. The bootstrapping ARDL approach incorporates the joint F-statistic test and the t-dependent test. The F-statistic test evaluates the lagged values of all level variables, while the t-dependent test focuses on the lagged values of the dependent variable. Additionally, the $F_{independent}$ test examines the lagged levels of the independent variables, confirming the existence of cointegration between them. This demonstrates the advantage of the bootstrapping ARDL approach over the traditional ARDL method for identifying cointegration in our variables (Bertelli et al., 2022).

Table 4 presents the empirical results of the bootstrapping ARDL bounds testing for cointegration. The $F$-test and $t$-test results from the bootstrapping ARDL indicate that the null hypothesis of no cointegration may be rejected, as $CO_2$ emissions, GDP, ICT, and REC were treated as dependent variables. For example, in the $CO_2$ emissions equation, the $F$-statistic is 3.089, exceeding the 5% critical value of 3.07. Both the $F_{independent}$ and $t_{dependent}$ statistics were significant at the 5% level, leading to the conclusion that cointegration exists when $CO_2$ emissions is the dependent variable. Additionally, the joint $F_{statistic}$ test on all error correction terms, along with the $t_{dependent}$ test on the lagged dependent variable and the $F_{independent}$ test on the lagged independent variables, demonstrate the presence of four cointegrating vectors in Saudi Arabia's domestic production function. The analysis concludes that economic growth, $CO_2$ emissions, RECand ICT diffusion maintain a long-run relationship from 1990 to 2020 in Saudi Arabia. Moreover, diagnostic tests show that the model specifications are generally robust. The Jarque-Bera test results indicate that the assumption of normally distributed errors cannot be rejected. Tests for ARCH (Autoregressive Conditional Heteroscedasticity) residuals reveal no heteroscedasticity issues at the 5% level. Therefore, the models successfully pass all diagnostic tests, and the residuals exhibit characteristics of Gaussian white noise.

The long-term results of the ARDL model presented in Table 5 reveal insightful relationships between GDP, REC, and ICT with the $CO_2$ emissions. Across all three models, GDP consistently exhibits a positive and statistically significant long-term effect, suggesting that economic growth is a key driver of the dependent variable. In Model 1, the coefficient of 0.361 indicates that for each unit increase in GDP, the dependent variable increases by 0.361 units, and this effect is significant at the 5% level. The effect of GDP becomes even stronger in Model 2, where the coefficient of 0.514, significant at the 1% level, suggests that GDP has a more pronounced long-term impact in this specification.

Likewise, Model 3 shows a significant coefficient of 0.462 at the 1% level, indicating a consistent and robust positive influence of

**Table 2: Results of unit root tests**

| Variables | Models | ADF test | | PP test | | DFGLS test | | |
|---|---|---|---|---|---|---|---|---|
| | | Level | First difference | Level | First difference | Level | First difference | Results |
| ICT | C | −1.274 (0) | −5.400 (0)* | −1.362 (17) | −6.415 (13)* | −1.351 (0)* | −4.845 (1)* | Unclear |
| | C, T | −4.504 (1) * | −5.332 (0)* | −3.462 (18)** | −7.073 (14)* | −3.784 (0)* | −2.239 (1)* | |
| GDP | C | −1.635 (0) | −6.735 (1)* | −1.740 (1) | −5.918 (3)* | 0.381 (4) | 0.091 (0)* | I (1) |
| | C, T | −2.001 (0) | −6.552 (1)* | −2.102 (1) | −6.468 (5)* | 0.147 (4) | −0.077 (0)* | |
| REC | C | −3.551 (0) | −7.600 (0)* | −2.780 (2) | −9.045 (6)* | 0.346 (0) | −0.395 (0)* | I (1) |
| | C, T | | | | | | | |
| | C | | | | | | | |
| | C, T | | | | | | | |
| | C | | | | | | | |
| | C, T | | | | | | | |
| | C, T | −4.024 (3) | −7.482 (4)* | −4.024 (3) | −8.861 (5)* | 0.124 (0) | 0.434 (0)* | |
| | C | | | | | | | |
| | C, T | | | | | | | |
| | C | | | | | | | |
| | C, T | | | | | | | |
| | C | | | | | | | |
| | C, T | | | | | | | |
| $CO_2$ | C | −2.125 (0) | −8.013 (0)* | −2.394 (2) | −8.069 (1)* | 0.403 (4) | −0.176 (2)* | I (1) |
| | C, T | −2.647 (0) | −7.994 (0)* | −2.656 (3) | −8.408 (3)* | 0.151 (0) | 0.088 (4)* | |

*, and ** indicate significance at the 1% and 5% levels, respectively. The critical values for the t-statistics of the ADF, DFGLS, and PP tests are derived from MacKinnon (1996). The numbers in parentheses denote lag lengths determined using the Schwarz Information Criterion, while the numbers in brackets indicate the automatic Newey-West bandwidth selection with the Bartlett Kernel. "C" denotes the presence of a constant term, and "T" signifies the inclusion of a linear deterministic time trend

**Table 3: Zivot–Andrews unit root test**

| Variables | Level | | 1st difference | | |
|---|---|---|---|---|---|
| | T-statistic | Time break | T-statistic | Time break | Decision |
| ICT | −3.157*** | 2017 | - | - | I (0) |
| GDP | −2.311 | 2001 | −5.099* | 2014 | I (1) |
| REC | −1.241 | 2016 | −4.314*** | 2012 | I (1) |
| $CO_2$ | −1.088 | 2005 | −4.165*** | 2003 | I (1) |

*, and *** represent significance at 1% and 5% levels, respectively

GDP across different model specifications. These results are in line with traditional economic theories, such as those proposed by Solow (1956), which highlight the critical role of GDP growth in driving economic development and sustainability. However, these findings differ somewhat from studies that emphasize the environmental degradation associated with unchecked GDP growth, such as Grossman and Krueger (1995), who point out that GDP growth can lead to increased environmental pressures unless managed carefully with sustainable policies. These results suggest that while GDP remains a significant driver, its positive impact can be tempered by other factors, such as energy consumption patterns and technology use.

However, REC exhibits a negative and statistically significant long-term effect in both Model 1 and Model 2. In Model 1, the coefficient of -0.008 indicates that for every unit increase in REC, the $CO_2$ emissions decreases by 0.008 units, and this relationship is significant at the 1% level. A similar negative relationship is observed in Model 2, with a coefficient of −0.004, also significant at the 1% level. This finding aligns with the transitional cost hypothesis seen in studies like Apergis and Payne (2010), where the initial adoption of renewable energy technologies incurs higher economic costs due to infrastructure upgrades and inefficiencies in energy production compared to conventional energy sources. However, this finding contrasts with studies such as Pao and Fu (2013), which found that renewable energy positively impacts economic growth and environmental sustainability in the long run. The negative effect observed here could be indicative of short-term disruptions and the economic costs of transitioning towards renewables, which may be particularly pronounced in certain sectors or regions heavily reliant on fossil fuels. Thus, this result might highlight the complexities of renewable energy adoption, suggesting that while beneficial in the long term, the initial stages of adoption could pose economic challenges.

Similarly, ICT shows a negative long-term effect in Model 1 and Model 3. In Model 1, the coefficient of −0.075, significant at the 5% level, suggests that an increase in ICT leads to a decrease in the $CO_2$ emissions. Similarly, in Model 3, the coefficient of −0.022, also significant at the 5% level, indicates a negative impact of ICT on the $CO_2$ emissions. This finding diverges from the general consensus found in studies like Brynjolfsson and Hitt (2000) and Jorgenson and Vu (2005), which typically report positive relationships between ICT and economic growth, productivity, and overall development. One possible explanation for this discrepancy could be that the negative impact observed in this study reflects the environmental or energy costs associated with rapid ICT expansion, such as increased electronic waste and energy consumption. Studies like Schreyer (2000) have argued that while ICT boosts economic output, its environmental impact, particularly in terms of carbon emissions and resource depletion, may be a significant downside. Thus, the negative long-term impact of ICT found in this analysis might reflect a growing concern about the sustainability of technological expansion, particularly in contexts where ICT growth is not paired with adequate environmental regulations or energy-efficient practices.

In addition, the interaction terms between REC and GDP, as well as ICT and GDP, provide further insights into the complex relationships between these variables. The interaction term

**Table 4: Bootstrap ARDL cointegration analysis**

| Dependent variable/ independent variable | Bounds testing approach to cointegration | | | | | Diagnostic tests | | | Cointegration Status |
|---|---|---|---|---|---|---|---|---|---|
| | Lag lenght | Break year | $F_{statistic}$ | $t_{dep}$ | $F_{indep}$ | ARCH | LM (2) | JB | |
| $CO_2$ (ICT/REC/GDP) | (1,1,0,2) | 2014 | 3.089** | −5.442* | 3.150* | 0.548 | 1.562 | 0.781 | Cointegration |
| ICT ($CO_2$//REC/GDP) | (2,1,2,2) | 1998 | 5.476* | −4.711** | 3.622* | 0.431 | 2.069 | 0.114 | Cointegration |
| REC ($CO_2$//ICT/GDP) | (1,2,2,2) | 2002 | 4.920** | −6.002* | 9.253* | 0.183 | 2.892 | 1.048 | Cointegration |
| GDP ($CO_2$//REC/ICT) | (1,0,0,2) | 2005 | 6.058** | −4.336* | 4.672** | 0.870 | 2.005 | 0.954 | Cointegration |

*, and ** indicate significance at the 1% and 5% levels, respectively, based on critical values obtained from the bootstrap method recommended by McNown et al. (2018). The Akaike Information Criterion (AIC) is used to determine the optimal lag length. The *F*-statistic refers to the *F*-test for the lagged levels of all variables, while $t_{dependent}$ is the *t*-test for the lagged dependent variable, and $F_{indepdent}$ represents the *F*-test for the lagged independent variables. The LM test is the Lagrange Multiplier test, and JB refers to the Jarque-Bera test for normality

**Table 5: Short-term and long-term ARDL model results**

| Variables | Model1 | Model 2 | Model 3 |
|---|---|---|---|
| | | Long-term | |
| GDP | 0.361** (0.049) | 0.514*** (0.001) | 0.462*** (0.000) |
| REC | −0.008*** (0.001) | −0.004*** (0.000) | - |
| ICT | −0.075** (0.041) | - | −0.022** (0.038) |
| REC*GDP | - | −0.011*** (0.019) | - |
| ICT*GDP | - | - | −0.014*** (0.008) |
| Constant | 0.675** (0.047) | 0.270*** (0.000) | 0.554*** (0.000) |
| CUSUM | Stable | Stable | Stable |
| CUSUMsq | Stable | Stable | Stable |
| Short-term | | | |
| GDP | 0.225* (0.056) | 0.139*** (0.008) | 0.081** (0.013) |
| REC | −0.013*** (0.000) | −0.017*** (0.002) | - |
| ICT | −0.066** (0.021) | - | −0.015 (0.129) |
| REC*GDP | - | −0.101** (0.013) | - |
| ICT*GDP | - | - | −0.023 (0.226) |
| Constant | 1.094** (0.039) | 3.762*** (0.007) | 5.982*** (0.000) |
| ECTt-1 | −0.829*** (0.000) | −0.904*** (0.001) | −0.925*** (0.008) |
| $R^2$ | 0.965 | 0.936 | 0.940 |
| Prob (F-statistic) | 0.000 | 0.001 | 0.000 |
| D.W | 2.689 | 3.045 | 1.876 |
| $\chi^2_{ARCH}$ | 5.037 (0.291) | 6.118 (0.334) | 4.065 (0.153) |
| $\chi^2_{NORMAL}$ | 1.628 (0.551) | 0.872 (0.261) | 2.076 (0.449) |
| $\chi^2_{RAMSET}$ | 0.241 (0.165) | 0.432 (0.510) | 0.381 (0.403) |
| $\chi^2_{SERIAL}$ | 0.135 (0.193) | 0.057 (0.228) | 0.209 (0.571) |

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses represent P-values

REC*GDP in Model 2 has a coefficient of −0.011, significant at the 5% level, indicating that the positive effect of GDP on the $CO_2$ emissions is reduced in the presence of higher REC. This suggests that REC mitigates the positive impact of GDP. This finding mirrors observations in studies like Sadorsky (2009), which argue that while renewable energy can have long-term benefits, it initially moderates the effect of economic growth due to the investment and adaptation period required. In Model 3, the interaction term ICT*GDP has a coefficient of −0.014, significant at the 1% level, implying that the combined effect of GDP and ICT on the $CO_2$ emissions is reduced. This is consistent with findings by Van Ark (2016), who noted that the economic and environmental benefits of ICT might be constrained by infrastructure limitations or inefficiencies in deployment. In these cases, the diminishing returns of ICT could result from factors such as increased energy demands or limited technological absorptive capacity in certain regions, especially where the rapid deployment of technology outpaces the necessary upgrades in renewable energy sources or grid infrastructure.

In the short term, the ARDL model results reveal a somewhat different picture compared to the long-term relationships. The impact of GDP varies across the three models, reflecting the more volatile nature of short-term economic fluctuations. In Model 1, the coefficient of 0.225, significant at the 10% level, suggests that GDP has a positive but relatively weak effect on the $CO_2$ emissions in the short term. This is consistent with findings from studies such as Wang et al. (2023), where the short-term effects of GDP growth are often driven by consumption and investment cycles rather than structural improvements. In Model 2, the coefficient of 0.139, significant at the 1% level, indicates a smaller but still positive short-term impact of GDP, whereas Model 3 shows an even weaker coefficient of 0.081, significant at the 5% level, suggesting that in some cases, short-term increases in GDP might have a diminished effect. This variability echoes findings from studies like DeLong and Summers (1986), which emphasize the cyclical nature of short-term economic growth, often dependent on factors such as government policies, consumer confidence, and short-term fluctuations in demand.

The short-term effects of REC are more consistent across the models, with REC showing a negative and significant impact in Models 1 and 2. In Model 1, the coefficient of -0.013, significant at the 1% level, suggests that an increase in REC leads to a reduction in the $CO_2$ emissions in the short term. Similarly, in Model 2, the coefficient of -0.017, also significant at the 1% level, reinforces this negative relationship. These findings are consistent with studies like Acaravci and Ozturk (2010), which found that RECtends to impose short-term economic costs as industries and consumers adjust to new technologies and energy sources. These transitional costs include higher upfront capital investments, infrastructure development, and disruptions to existing energy markets. However, the negative short-term effect contrasts with more optimistic views in the literature, such as Stern (2004), which suggest that once these costs are absorbed, renewable energy contributes positively to both economic growth and sustainability. The absence effect of REC in Model 3 implies that it does not play a significant role in the short-term dynamics of the $CO_2$ emissions in this model.

The results for ICT are mixed. In Model 1, ICT shows a negative short-term effect, with a coefficient of −0.066, significant at the 5% level. This is consistent with findings from studies like Dedrick et al. (2003), which argue that ICT's environmental costs, such as higher energy consumption and electronic waste, are particularly acute in the short term. However, in Model 3, the short-term effect of ICT is not significant, suggesting that in some contexts, the impact of ICT on the dependent variable may be more neutral or harder to detect. This aligns with the observations in Jorgenson and Stiroh (2017), where the benefits of ICT are seen to accrue more significantly in the long term, while the immediate short-term effects can be muted or even negative due to the need for complementary infrastructure investments and the environmental costs of scaling up technology use.

The interaction terms in the short term also provide interesting insights. In Model 2, the interaction term REC*GDP is significant, with a coefficient of −0.101, suggesting that the short-term impact of GDP on the $CO_2$ emissions is dampened by increasing renewable energy consumption. This indicates that in the short term, the economic gains from GDP growth may be tempered by the costs associated with transitioning to renewable energy. This finding is consistent with the work of Pao and Tsai (2011), who found that renewable energy tends to have a moderating effect on economic performance in the short term due to the initial adaptation costs. In contrast, in Model 3, the interaction term ICT*GDP is not significant, indicating that in the short term, the combined effects of GDP and ICT might not be as influential as they are in the long term.

In the short term, the interaction terms (REC*GDP, ICT*GDP) show varied significance. The interaction term REC*GDP is not significant in Model 2, suggesting that the combined effect of REC and GDP does not significantly influence the $CO_2$ emissions in the short term Conversely, ICT*GDP in Model 3 has a coefficient of −0.023, significant at the 5% level, indicating that the short-term effect of GDP on the $CO_2$ emissions is negatively moderated by ICT. This finding reflects the complex and sometimes counterintuitive effects of ICT on economic variables observed in the literature, such as in studies by Brynjolfsson et al. (2002) and Bertani et al. (2020). Otherwise, the error correction term ($ECT_{t-1}$) is consistently significant and negative across all models (−0.829, −0.904, and −0.925), demonstrating the models' ability to correct deviations from long-term equilibrium. The magnitude of the $ECT_{t-1}$ coefficients suggests a relatively quick adjustment process towards equilibrium, with the highest value indicating the fastest adjustment rate. These results are consistent with findings from various studies that employ ARDL models to explore dynamic adjustments in economic relationships.

The models exhibit high R-squared values (0.965, 0.936, 0.940), reflecting a strong explanatory power in capturing the variance in the dependent variable. The P-values of the F-statistics (0.000-0.001) confirm the overall significance of the models, indicating that the included variables collectively explain the dependent variable effectively. The Durbin-Watson statistics (1.689, 1.981, 1.876) are close to 2, suggesting no major autocorrelation issues in the residuals, which supports the validity of the model results. The stability of the CUSUM and CUSUMsq tests further confirms the reliability and stability of the model parameters over time, aligning with similar results in other ARDL studies.

## 6. CONCLUSIONS AND POLICY IMPLICATIONS

The motivation for studying how ICT diffusion and REC affect $CO_2$ emissions stems from the urgent need to combat climate change and promote sustainable development. ICT can either reduce emissions through energy efficiency and smart technologies or increase them due to higher energy consumption if not powered by clean sources. Renewable energy offers a clean alternative to fossil fuels, but its effectiveness in reducing emissions depends on its scale of adoption and integration. Understanding the combined impact of ICT and renewable energy on emissions is crucial for policymakers aiming to achieve low-carbon growth and environmental sustainability**.** This paper examines the moderating role of ICT diffusion in the relationship between economic growth and $CO_2$ emissions in the Kingdom of Saudi Arabia over the period from 1990 to 2020.

Using an ARDL model, the findings indicate that GDP has a positive and significant effect on $CO_2$ emissions in both the short and long term, suggesting that economic growth leads to higher emissions. In contrast, REC negatively impacts emissions, demonstrating that increased REC helps reduce emissions over time. However, the short-term negative effect of REC implies that the transition to renewable energy may involve initial costs or disruptions. ICT shows a long-term negative influence on emissions, but its short-term effects are inconsistent, reflecting potential environmental costs associated with rapid technological growth, such as higher energy consumption and electronic waste. The interaction between GDP and REC, and GDP and ICT, reveals that renewable energy and technological development moderate the positive relationship between GDP and emissions, illustrating the complex trade-offs between economic growth, energy transition, and technological advancement. The results highlight the need for expanding renewable energy infrastructure and promoting sustainable technological innovation to reduce emissions while supporting economic growth in Saudi Arabia.

To address the findings of the study, several policy suggestions can be implemented. First, promoting sustainable economic growth by incentivizing low-carbon industries and integrating environmental standards into development projects is essential, as GDP growth is associated with higher emissions. Expanding renewable energy infrastructure and offering support for transitioning industries can help mitigate short-term disruptions while maximizing long-term environmental benefits. Additionally, developing energy-efficient ICT infrastructure and managing e-waste is crucial, given the environmental costs linked to ICT diffusion. Policies that combine ICT and renewable energy—such as smart grids and green technologies—can further enhance productivity while reducing emissions. Finally, managing short-term economic costs during the shift to renewable energy and promoting public awareness of sustainability will ensure a balanced approach to economic growth and environmental protection.

The validity of our study is influenced by several limitations. One major constraint is the inclusion of aggregated renewable energy (RE) as a variable, without considering its distinct components such as hydropower, solar, wind, and geothermal. Future research should delve into the effects of these individual RE technologies on $CO_2$ emissions and other pollutants once the data becomes available on a global scale. Additionally, our findings are focused solely on $CO_2$ emissions and do not extend to other pollutants like PM2.5, NOx, and SO2, limiting the scope of generalization. Furthermore, while we examined the impact of ICT on $CO_2$ emissions, future research should control for other relevant factors such as economic complexity indexes, economic freedom indicators, foreign direct investment (FDI), agriculture's role in economic growth, and various pollutants. It is recommended that future studies utilize threshold models, nonparametric models, and spatial empirical models, to capture nonlinearity. Exploring the relationship between $CO_2$ emissions, economic globalisation, renewable energy, and research and development (R&D) is also suggested as data becomes available. Despite these constraints, this research provides valuable insights for policymakers supporting R&D and energy policies aimed at achieving Sustainable Development Goals (SDGs).

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## REFERENCES

Abid, M. (2023), How does renewable energy consumption affect environmental quality in Saudi Arabia? Evidence from quantile regressions. International Journal of Energy Economics and Policy, 13(4), 574-578.

Abid, M., Gheraia, Z., Abdelli, H. (2022), Does renewable energy consumption affect ecological footprints in Saudi Arabia? A bootstrap causality test. Renewable Energy, 189, 813-821.

Acaravci, A., Ozturk, I. (2010), On the relationship between energy consumption, $CO_2$ emissions and economic growth in Europe. Energy, 35(12), 5412-5420.

Adedoyin, F.F., Ozturk, I., Bekun, F.V., Agboola, P.O., Agboola, M.O. (2021), Renewable and non-renewable energy policy simulations for abating emissions in a complex economy: Evidence from the novel dynamic ARDL. Renewable Energy, 177, 1408-1420.

Ahmed, N., Mahboob, F., Hamid, Z., Sheikh, A.A., Ali, M.S.E., Glabiszewski, W., Cyfert, S. (2022), Nexus between nuclear energy consumption and carbon footprint in asia pacific region: Policy Toward Environmental Sustainability. Energies, 15(19), 6956.

Ahmed, R.R., Akbar, W., Aijaz, M., Channar, Z.A., Ahmed, F., Parmar, V. (2023), The role of green innovation on environmental and organizational performance: Moderation of human resource practices and management commitment. Heliyon, 9(1), e12679.

Apergis, N., Payne, J.E. (2010), Renewable energy consumption and growth in Eurasia. Energy Economics, 32(6), 1392-1397.

Azam, A., Rafiq, M., Shafique, M., Yuan, J. (2022), Towards achieving environmental sustainability: The role of nuclear energy, renewable energy, and ICT in the top-five carbon emitting countries. Frontiers in Energy Research, 9, 804706.

Bertani, F., Raberto, M., Teglio, A. (2020), The productivity and unemployment effects of the digital transformation: An empirical and modelling assessment. Review of Evolutionary Political Economy, 1(3), 329-355.

Bertelli, S., Vacca, G., Zoia, M. (2022), Bootstrap cointegration tests in ARDL models. Economic Modelling, 116, 105987.

Bilan, Y., Streimikiene, D., Vasylieva, T., Lyulyov, O., Pimonenko, T., Pavlyk, A. (2019), Linking between renewable energy, $CO_2$ emissions, and economic growth: Challenges for candidates and potential candidates for the EU membership. Sustainability, 11(6), 1528.

Bilgili, F., Koçak, E., Bulut, Ü. (2016), The dynamic impact of renewable energy consumption on $CO_2$ emissions: A revisited Environmental Kuznets Curve approach. Renewable and Sustainable Energy Reviews, 54, 838-845.

Brynjolfsson, E., Hitt, L.M. (2000), Beyond computation: Information technology, organizational transformation and business performance. Journal of Economic perspectives, 14(4), 23-48.

Brynjolfsson, E., Hitt, L.M., Yang, S. (2002), Intangible assets: Computers and organizational capital. Brookings Papers on Economic Activity, 2002(1), 137-181.

Chang, T., Hsu, C.M., Chen, S.T., Wang, M.C., Wu, C.F. (2023), Revisiting economic growth and $CO_2$ emissions nexus in Taiwan using a mixed-frequency VAR model. Economic Analysis and Policy, 79, 319-342.

Dedrick, J., Kraemer, K.L., Shih, E. (2013), Information technology and productivity in developed and developing countries. Journal of Management Information Systems, 30(1), 97-122.

DeLong, J.B., Summers, L.H. (1986), The changing cyclical variability of economic activity in the United States. In: The American Business Cycle: Continuity and Change. Chicago: University of Chicago Press. p79-734.

Dickey, D.A., Fuller, W.A. (1979), Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366a), 427-431.

Elliott, G., Rothenberg, T.J., Stock, J.H. (1996), Efficient tests for an autoregressive unit root. Econometrica, 64, 813-836.

European Commission. (2021), A European Green Deal. Available from: https://ec.europa.eu

Faheem, M., Shah, S.B.H., Butt, R.A., Raza, B., Anwar, M., Ashraf, M.W., Ngadi, M.D., Gungor, V.C. (2018), Smart grid communication and information technologies in the perspective of Industry 4.0: Opportunities and challenges. Computer Science Review, 30, 1-30.

Fu, Q., Álvarez-Otero, S., Sial, M.S., Comite, U., Zheng, P., Samad, S., Oláh, J. (2021), Impact of renewable energy on economic growth and $CO_2$ emissions-evidence from BRICS countries. Processes, 9, 1281.

Gangopadhyay, P., Das, N., Alam, G.M., Khan, U., Haseeb, M., Hossain, M.E. (2023), Revisiting the carbon pollution-inhibiting policies in the USA using the quantile ARDL methodology: What roles can clean energy and globalization play? Renewable Energy, 204, 710-721.

Gheraia, Z., Abid, M., Sekrafi, H., Abdelli, H. (2022), The moderating role of ICT diffusion between financial development and economic growth: A bootstrap ARDL approach in Saudi Arabia. Information Technology for Development, 28(4), 816-836.

Grossman, G.M., Krueger, A.B. (1995), Economic growth and the environment. The Quarterly Journal of Economics, 110(2), 353-377.

Hasanov, F.J., Mukhtarov, S., Suleymanov, E. (2024), The role of renewable energy and total factor productivity in reducing carbon emissions: A case of top-ranked nations in the renewable energy country attractiveness index. Journal of Environmental Management, 361, 121220.

Intergovernmental Panel on Climate Change (IPCC), (2021), Climate Change 2021: The Physical Science Basis. Available from: https://www.ipcc.ch

International Energy Agency (IEA), (2023), Global *Energy Review: Renewables*. Available from: https://www.iea.org

IRENA. (2020), Renewable Energy Statistics 2020. International Renewable Energy Agency. Available from: https://www.irena.org/publications/2020/jul/renewable-energy-statistics-2020

Ishaq, H., Dincer, I. (2021), Comparative assessment of renewable energy-based hydrogen production methods. Renewable and Sustainable Energy Reviews, 135, 110192.

Işık, C., Bulut, U., Ongan, S., Islam, H., Irfan, M. (2024), Exploring how economic growth, renewable energy, internet usage, and mineral rents influence $CO_2$ emissions: A panel quantile regression analysis for 27 OECD countries. Resources Policy, 92, 105025.

Jia, J., Rong, Y., Chen, C., Xie, D., Yang, Y. (2021), Contribution of renewable energy consumption to $CO_2$ emissions mitigation: A comparative analysis from the income levels' perspective in the belt and road initiative (BRI) region. International Journal of Climate Change Strategies and Management, 13(3), 266-285.

Jorgenson, D.W., Stiroh, K.J. (2017), Raising the speed limit: US economic growth in the information age. In: Knowledge Economy, Information Technologies and Growth. England, UK: Routledge. p335-424.

Jorgenson, D.W., Vu, K. (2005), Information technology and the world economy. The Scandinavian Journal of Economics, 107(4), 631-650.

Li, S., Ye, C., Ding, Y., Song, Y., Bao, M. (2022), Reliability assessment of renewable power systems considering thermally-induced incidents of large-scale battery energy storage. IEEE Transactions on Power Systems, 38(4), 3924-3938.

Lin, C.Y., Chau, K.Y., Tran, T.K., Sadiq, M., Van, L., Phan, T.T.H. (2022), Development of renewable energy resources by green finance, volatility and risk: Empirical evidence from China. Renewable Energy, 201, 821-831.

McNown, R., Sam, C.Y., Goh, S.K. (2018), Bootstrapping the autoregressive distributed lag test for cointegration. Applied Economics, 50(13), 1509-1521.

Mehmood, U. (2022), Environmental degradation and financial development: Do institutional quality and human capital make a difference in G11 nations? Environmental Science Pollution Research, 29(25), 38017-38025.

Mngumi, F., Shaorong, S., Shair, F., Waqas, M. (2022), Does green finance mitigate the effects of climate variability: Role of renewable energy investment and infrastructure. Environmental Science and Pollution Research International, 29(39), 59287.

Nguyen, X.P., Le, N.D., Pham, V.V., Huynh, T.T., Dong, V.H., Hoang, A.T. (2021), Mission, challenges, and prospects of renewable energy development in Vietnam. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, Available at: https://doi.org/10.1080/15567036.2021.1965264.

Ozoegwu, C.G., Akpan, P.U. (2021), A review and appraisal of Nigeria's solar energy policy objectives and strategies against the backdrop of the renewable energy policy of the Economic Community of West African States. Renewable and Sustainable Energy Reviews, 143, 110887.

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.

Pao, H.T., Tsai, C.M. (2011), Multivariate Granger causality between $CO_2$ emissions, energy consumption, FDI (foreign direct investment) and GDP (gross domestic product): Evidence from a panel of BRIC (Brazil, Russian Federation, India, and China) countries. Energy, 36(1), 685-693.

Pata, U.K. (2021), Linking renewable energy, globalization, agriculture, $CO_2$ emissions and ecological footprint in BRIC countries: A sustainability perspective. Renewable Energy, 173, 197-208.

Pata, U.K., Samour, A. (2022), Do renewable and nuclear energy enhance environmental quality in France? A new EKC approach with the load capacity factor. Progress in Nuclear Energy, 149, 104249.

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

Phillips, P.C., Perron, P. (1988), Testing for a unit root in time series regression. Biometrika, 75(2), 335-346.

Sadorsky, P. (2009), Renewable energy consumption and income in emerging economies. Energy Policy, 37(10), 4021-4028.

Sadorsky, P. (2009), Renewable energy consumption, $CO_2$ emissions and oil prices in the G7 countries. Energy Economics, 31(3), 456-462.

Schreyer, P. (2000), The contribution of information and communication technology to output growth: A study of the G7 countries. France: OECD.

Sedghiyan, D., Ashouri, A., Maftouni, N., Xiong, Q., Rezaee, E., Sadeghi, S. (2021), RETRACTED: Prioritization of renewable energy resources in five climate zones in Iran using AHP, hybrid AHP-TOPSIS and AHP-SAW methods. Sustainable Energy Technologies and Assessments, 44(7), 101045.

Shahbaz, M., Shafiullah, M., Khalid, U., Song, M. (2020), A nonparametric analysis of energy environmental Kuznets Curve in Chinese Provinces. Energy Economics, 89, 104814.

Sheraz, M., Deyi, X., Mumtaz, M.Z., Ullah, A. (2021), The dynamic nexus between financial development, renewable energy and carbon emission: Role of globalization and institutional quality across BRI Countries. Environmental Science and Pollution Research, 29, 14930–14947.

Solow, R.M. (1956), A contribution to the theory of economic growth. The Quarterly Journal of Economics, 70(1), 65-94.

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

Tugcu, C.T., Ozturk, I., Aslan, A. (2012), Renewable and non-renewable energy consumption and economic growth relationship revisited: Evidence from G7 countries. Energy Economics, 34(6), 1942-1950.

UNFCCC. (2015), INDC Submissions. Available from: https://www4.unfccc.int/submissions/indc/Submission%20Pages/submissions.aspx [Last accessed on 2015 Oct 23].

Van Ark, B. (2016), The productivity paradox of the new digital economy. International Productivity Monitor, 31, 3-18.

Wang, Q., Yang, T., Li, R. (2023), Does income inequality reshape the environmental Kuznets curve (EKC) hypothesis? A nonlinear panel data analysis. Environmental Research, 216, 114575.

Weili, L., Khan, H., Khan, I., Han, L. (2022), The impact of information and communication technology, financial development, and energy consumption on carbon dioxide emission: Evidence from the Belt and Road countries. Environmental Science and Pollution Research, 29, 27703-27718.

Xu, D., Sheraz, M., Hassan, A., Sinha, A., Ullah, S. (2022), Financial development, renewable energy and $CO_2$ emission in G7 countries: New evidence from non-linear and asymmetric analysis. Energy Economics, 109, 105994.

Yurtkuran, S. (2021), The effect of agriculture, renewable energy production, and globalization on $CO_2$ emissions in Turkey: A bootstrap ARDL approach. Renewable Energy, 171, 1236-1245.

Zafar, M.W., Zaidi, S.A.H., Mansoor, S., Sinha, A., Qin, Q. (2022), ICT and education as determinants of environmental quality: The role of financial development in selected Asian countries. Technological Forecasting and Social Change, 177, 121547.

Zhang, X.P., Cheng, X.M. (2009), Energy consumption, carbon emissions, and economic growth in China. Ecological Economics, 68(10), 2706-2712.

Zhao, X., Mahendru, M., Ma, X., Rao, A., Shang, Y. (2022), Impacts of environmental regulations on green economic growth in China: New guidelines regarding renewable energy and energy efficiency. Renewable Energy, 187, 728-742.

Zivot, E., Andrews, D.W.K. (1992), Further evidence on the great crash, the oil price shock, and the unit root hypothesis. Journal of Business and Economic Statistics, 10(3), 251-270.