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The Nexus of CO₂ Emissions, Economic Growth, and ICT Adoption in Saudi Arabia Assessed via an ARDL Framework

Naif Alajlan 

Computer Engineering Department, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia; najlan@ksu.edu.sa

Abstract

The rapid expansion of information and communication technology (ICT) alongside sustained economic growth poses a critical policy challenge for hydrocarbon-based economies seeking to reconcile digital development with environmental sustainability. This study examines both the short- and long-term relationships between per capita CO₂ emissions, GDP per capita, and the adoption of ICT in Saudi Arabia, using annual time-series data for 1995–2024. Methodologically, we employ the ARDL bounds test, an error correction model (ECM), and Granger causality analysis to test the EKC hypothesis. Additionally, we use the Zivot–Andrews test to detect structural breaks, accounting for these through dummy variables. Long-run cointegration among the three variables is validated by the bounds test results. GDP is the dominant long-run driver of internet-based ICT adoption, while CO₂ emissions and GDP are strongly cointegrated through the 2010 structural break and the EKC mechanism. No direct causal link is found between ICT and CO₂ emissions in either direction. The long-run validity of the EKC hypothesis is confirmed, with an estimated income turning point of approximately USD 26,021 per capita, a level reached during the latter part of the sample period. These findings suggest that Saudi Arabia’s internet adoption has yet to generate an independent decarbonization dividend, underscoring the need for policies that couple ICT investment with clean energy deployment under Vision 2030.

Keywords: ICT adoption; CO₂ emissions; economic growth; ARDL; Granger causality; environmental Kuznets curve; Saudi Arabia

1. Introduction

The rapid diffusion of information and communication technology (ICT) is one of the most consequential structural changes reshaping modern economies. As countries deepen their digital infrastructure, including expanding broadband networks, e-government platforms, cloud computing, and mobile connectivity, the macroeconomic and environmental implications of this transformation have attracted growing scholarly attention. Simultaneously, the dual pressures of economic development and environmental preservation have pushed carbon emissions to the forefront of global policy, as seen in national commitments to the Paris Agreement and net-zero targets. Understanding how ICT adoption interacts with economic growth and CO₂ emissions is therefore not merely an academic exercise; it is a prerequisite for designing policies that can reconcile digital development with environmental responsibility.

The empirical literature on this nexus has expanded substantially over the past decade, yet its findings remain deeply heterogeneous. In high-income economies with clean energy systems, ICT tends to reduce emissions through efficiency gains, digital substitution



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for physical activities, and dematerialization effects. By contrast, in fossil-fuel-intensive economies, the energy demands of expanding digital infrastructure may outweigh these efficiency benefits, resulting in a net increase in CO₂ emissions. This structural ambiguity is most acute in hydrocarbon-based economies, where the energy mix driving digitalization is still heavily reliant on fossil fuels, making the net environmental sign of ICT adoption an empirical question that cannot be resolved by theory alone.

Saudi Arabia provides an exceptionally important and underexplored case study for this inquiry. As a leading G20 economy and the global leader in oil exports, the Kingdom has simultaneously committed to ambitious decarbonization targets under the Saudi Green Initiative, including a 278 million ton annual CO₂ reduction by 2030 and net-zero emissions by 2060, and to a sweeping digital transformation agenda under Vision 2030 [1]. Yet, to date, no published study has applied a comprehensive autoregressive distributed lag (ARDL) time-series framework to simultaneously examine the short-run dynamics, long-run equilibrium, and Granger causality among all three variables in the case of Saudi Arabia.

This paper addresses this gap by employing the ARDL framework to assess the annual data for Saudi Arabia from 1995 to 2024. The econometric analysis considers (i) whether a long-run cointegrating relationship exists between CO₂ emissions per capita, GDP per capita, and internet usage; (ii) the direction and magnitude of short-run and long-run causal effects among these variables; and (iii) whether the environmental Kuznets curve (EKC) hypothesis is validated for Saudi Arabia in this sample. This paper offers four main contributions to the literature. First, it provides the first standalone country-level ARDL analysis of the CO₂–GDP–ICT nexus for Saudi Arabia, covering the most up-to-date data until 2024. Second, it establishes a rigorous causal architecture, distinguishing short-run from long-run effects, to provide a context that previous panel studies have obscured by pooling Saudi Arabia with heterogeneous country groups. Third, it explicitly tests the EKC hypothesis within the Saudi context, where a turning point has not previously been confirmed. Fourth, the findings are contextualized directly within the frameworks of Saudi Arabia's Vision 2030 and the Saudi Green Initiative, generating actionable policy insights for the digital–environmental transition.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature, while Section 3 details the data and econometric methodology. Section 4 presents and discusses the empirical findings, and Section 5 concludes with key policy implications.

2. Literature Review

An increasing volume of literature examines the triangular nexus among ICT adoption, economic growth, and CO₂ emissions, yielding a large body of methodologically diverse insights. The reviewed studies are classified according to their core variable combinations: (i) ICT and CO₂ emissions; (ii) economic growth and CO₂ emissions via the EKC hypothesis; (iii) ICT, economic growth, and CO₂ emissions jointly; and (iv) extended models that incorporate renewable energy and financial development.

2.1. ICT and CO₂ Emissions

Studies examining the bilateral link between ICT adoption and carbon emissions constitute the most populated strand of the literature and yield heterogeneous results that depend on each country's income level, energy structure, and the choice of ICT proxy. Ozcan and Apergis applied panel FMOLS and Granger causality to data for 20 emerging economies from 1990 to 2015 [2]. Their results indicate that expanded internet access mitigates long-run CO₂ emissions. This relationship is driven by a unidirectional causal flow from internet usage to emissions, implying that digital connectivity serves as an

environmental asset by replacing carbon-heavy practices. Añón Higón et al. introduced non-linearity into this relationship using a global panel of data from 142 economies from 1995 to 2010 [3]. An inverted-U ICT–Kuznets curve was confirmed, with emissions rising initially as ICT penetration increased and declining beyond a turning point already reached by most developed countries. Shehzad et al. reinforced the asymmetric dimension through a non-linear ARDL (NARDL) model for Pakistan during 1990 to 2019 [4]. They demonstrated that positive ICT shocks decreased CO₂ emissions while negative shocks increased them, with a long-run inverted-U relationship confirmed.

At the developing country level, Ke et al. showed that ICT directly reduced CO₂ emissions in 77 developing countries for 1990–2016, using pooled regression and GMM [5]. However, the interaction between ICT and financial development reversed this benefit. Li et al. adopted a country-heterogeneity framework [6]. Their findings indicate that while ICT effectively lowers carbon emissions in nations with advanced renewable energy frameworks, its environmental impact becomes detrimental in fossil-fuel-dependent economies. Appiah-Otoo et al. applied panel ARDL to 58 developing countries and documented an inverted-U pattern for BRICS, a negative ICT coefficient for low-income developing countries, and statistical insignificance for the high-income developing group [7]. For the GCC region specifically, Ebaidalla and Abusin employed mean group (MG) and augmented mean group (AMG) estimators for six GCC countries for 1995 to 2018 [8]. They concluded that ICT exerts a positive and significant long-run effect on CO₂ emissions—a result diametrically opposite to the global consensus and attributed to the region’s fossil-fuel-intensive digital infrastructure. Salahodjaev et al. studied the relationship among internet users and CO₂ emissions in OIC countries for 1990–2019, using a two-step system GMM estimator [9]. Their findings indicate that a 10% expansion in internet penetration resulted in a 4.2% reduction in CO₂ emissions. Internet diffusion has a causal negative impact on carbon emissions even after controlling for other economic factors.

2.2. Economic Growth and CO₂ Emissions: The EKC Hypothesis

The EKC hypothesis, which outlines an inverted U-shaped relationship between GDP per capita and carbon emissions, provides the macroeconomic backbone for understanding the growth–environment nexus examined in the present paper. Kim, using FE-2SLS and GMM for OECD countries for the period 1991 to 2018, confirmed the inverted-U EKC while simultaneously showing that ICT reduces emissions and trade openness is emission-reducing in the long run [10]. Batool et al., employing the PMG estimator for East and South Asian developing countries for 1985 to 2020, validated the EKC through a GDP-squared specification, although ICT and financial development were found to increase emissions in the long run [11]. Daghbagi et al. applied the ARDL-PMG model to MENA for the period 2000 to 2021 [12]. Their findings indicate that economic expansion consistently drives higher CO₂ emissions, supported by a unidirectional causal flow running from both GDP and natural capital to emissions; ICT and institutional quality reduce emissions individually, but their interaction with natural capital raises emissions due to oil-revenue dependence.

Tekbaş and İslamoğlu used FMOLS and Dumitrescu–Hurlin causality for 15 representative countries and found positive impacts of both economic growth and internet usage on CO₂ emissions [13]. The EKC turning point was not confirmed, while mobile subscriptions and capital accumulation reduced the emissions. In another study, Lu and Lu applied system GMM to data from 30 Chinese provinces for 2011 to 2019 [14]. They documented a U-shaped GDP–CO₂ path, indicating that most provinces remained on the rising limb of the growth–emissions curve.

2.3. ICT, Economic Growth, and CO₂ Emissions

The most relevant category for this study is research that simultaneously analyses ICT, GDP, and CO₂ within a single empirical framework. Lee and Brahmastreene employed panel cointegration for nine ASEAN economies for 1991 to 2009 [15]. They found that ICT significantly increased both GDP and CO₂ emissions, with inverse bidirectional causality between economic growth and CO₂.

Salahuddin and Alam used ARDL and VECM on data from Australia for 1985 to 2012 [16]. They concluded that internet usage and economic growth increased electricity consumption and emissions in the long run, with unidirectional causality from internet use and GDP to energy demand. Salahuddin et al. extended this to a panel of 28 OECD countries from 1991 to 2012, using FMOLS and ECM [17]. They found only a marginal positive effect of internet usage on CO₂ and no significant causality between internet use and emissions, consistent with decoupling at high income levels. Khanal replicated the ARDL methodology for Australia for 1985 to 2017, and confirmed that ICT increased electricity consumption and, via that channel, CO₂ emissions [18]. Huang et al. used FMOLS, DOLS, and Granger causality for E7 and G7 country groups for 1990 to 2018 [19]. That study revealed that ICT reduced the ecological footprint in G-7 economies but increased it in E-7 countries, while the results confirmed a bidirectional causal relationship between ICT and the ecological footprint across both groups.

2.4. Extended Models: Renewable Energy and Financial Development

Several studies add renewable energy (RE) and/or financial development (FD) to the core model, testing whether these variables moderate the ICT–emissions and growth–emissions relationships. Raheem et al. employed the PMG estimator for G7 countries for 1990 to 2014 [20]. They found that ICT alone positively affects CO₂ in the long run, but the ICT and FD interaction is negative, indicating that financial deepening moderates the carbon-intensive impact of ICT. Bennaceur et al., in the most directly relevant study for Saudi Arabia using ARDL (for 1990–2020), found that GDP increases emissions in both the short and long run, ICT exerts a negative long-run effect on emissions, and RE reduces them [21]. The interaction between GDP and ICT suggests that technological development moderates the carbon intensity of growth. Rahman and Ferdaous used panel ARDL, FMOLS, DOLS, and Dumitrescu–Hurlin (D–H) causality for SAARC, MENA, and OECD countries for 1998 to 2019 [22]. They confirmed a positive ICT–CO₂ linkage in MENA and OECD but negative in SAARC, with bidirectional ICT–emissions causality for MENA. Kahouli et al. applied FMOLS, DOLS, PCSE, and MGP to 38 OECD countries (2000–2021) and found that ICT reduced CO₂ in the long run while growth increased emissions and RE reduced them [23].

Kurt et al. used Fourier panel cointegration and causality for 28 OECD countries (for 1994 to 2019) and found that internet use significantly reduced CO₂ emissions while GDP increased them, with bidirectional Fourier–Granger causality between internet use and emissions [24]. Zhang and Rong investigated the digital economy’s carbon-reducing effect across 30 Chinese provinces for the period 2011–2023, using mediation and threshold models [25]. The digital economy inhibits carbon emissions, exhibiting a pronounced threshold effect that underscores a non-linear relationship. Green finance mediates the digital economy–carbon emissions link. Zhang et al. applied CS-ARDL and NARDL to MENA (2001–2022) and documented that ICT and technological innovation reduced environmental degradation, with bidirectional causality between ICT and emissions [26].

2.5. Synthesis and Research Gaps

This review reveals important patterns alongside significant gaps. Across the global literature, the impact of ICT on CO₂ emissions is predominantly negative in high-income economies with clean energy systems, but turns positive or ambiguous in resource-intensive, fossil-fuel-dependent contexts, which is precisely the structural profile of Saudi Arabia. The only GCC-specific study [8] confirms a positive long-run ICT–CO₂ relationship, stemming from the high energy consumption inherent in the region’s digital infrastructure. Comparative MENA evidence [10,20] equally documents a positive ICT–CO₂ linkage, while bidirectional causality between ICT and emissions is consistently reported for this region. Regarding the EKC hypothesis, its confirmation in OECD and several emerging economies contrasts with the absence or non-confirmation of an income-based turning point in MENA and GCC economies, where hydrocarbon-driven growth trajectories maintain a rising growth–emissions path.

From a Saudi Arabian perspective, the sole country-specific study [21] found a negative long-run ICT effect on CO₂ and a positive GDP effect, but it incorporated renewable energy consumption as an additional covariate rather than examining the pure trivariate ICT–GDP–CO₂ nexus, and it did not include a comprehensive short-run causality framework. No study to date has investigated this nexus for Saudi Arabia through a standalone ARDL model with full unit root diagnostics, bounds cointegration, and Granger causality analysis. This gap is particularly consequential given Saudi Arabia’s Vision 2030 commitments, which simultaneously target rapid ICT-led transformation and a substantial reduction in carbon emissions through energy diversification. Whether internet-based ICT adoption in the Kingdom operates as an environmental asset by reducing emissions through efficiency and substitution effects, or as a liability by expanding energy demand and thereby CO₂ output, remains an open empirical question. The present study directly addresses this gap.

3. Materials and Methods

Using econometric modeling on annual time-series data for Saudi Arabia, this study investigates the tripartite relationship among carbon emissions, economic growth, and internet-based ICT adoption. The empirical approach proceeds through four sequential steps: (i) unit root testing to decide the order of integration of each series; (ii) ARDL bounds test for cointegration and estimation of long-run equilibrium relations; (iii) ECM-based Granger-causality analysis to identify short-run and long-run causal directions; and (iv) EKC hypothesis testing. Lastly, stability checks are conducted to confirm the reliability of the empirical results.

3.1. Variable Description

The empirical analysis utilizes annual data for Saudi Arabia spanning 1995 to 2024, tracking CO₂ emissions per capita (measured in metric tons), GDP per capita (in USD), and internet-based ICT adoption (individuals using the internet as percentage of population), as detailed in Table 1.

Table 2 presents the descriptive statistics for the variables under consideration. The skewness and kurtosis metrics are derived from the third-order and fourth-order central moments, capturing the asymmetry and peakness of the distributions, respectively. For all three variables, the Jarque–Bera test [27] statistics fail to reject the null hypothesis of normality, confirming that the data series are normally distributed. Additionally, Figure 1 illustrates the trajectories of the variables, revealing a consistently positive upward trend across the entire sample period.

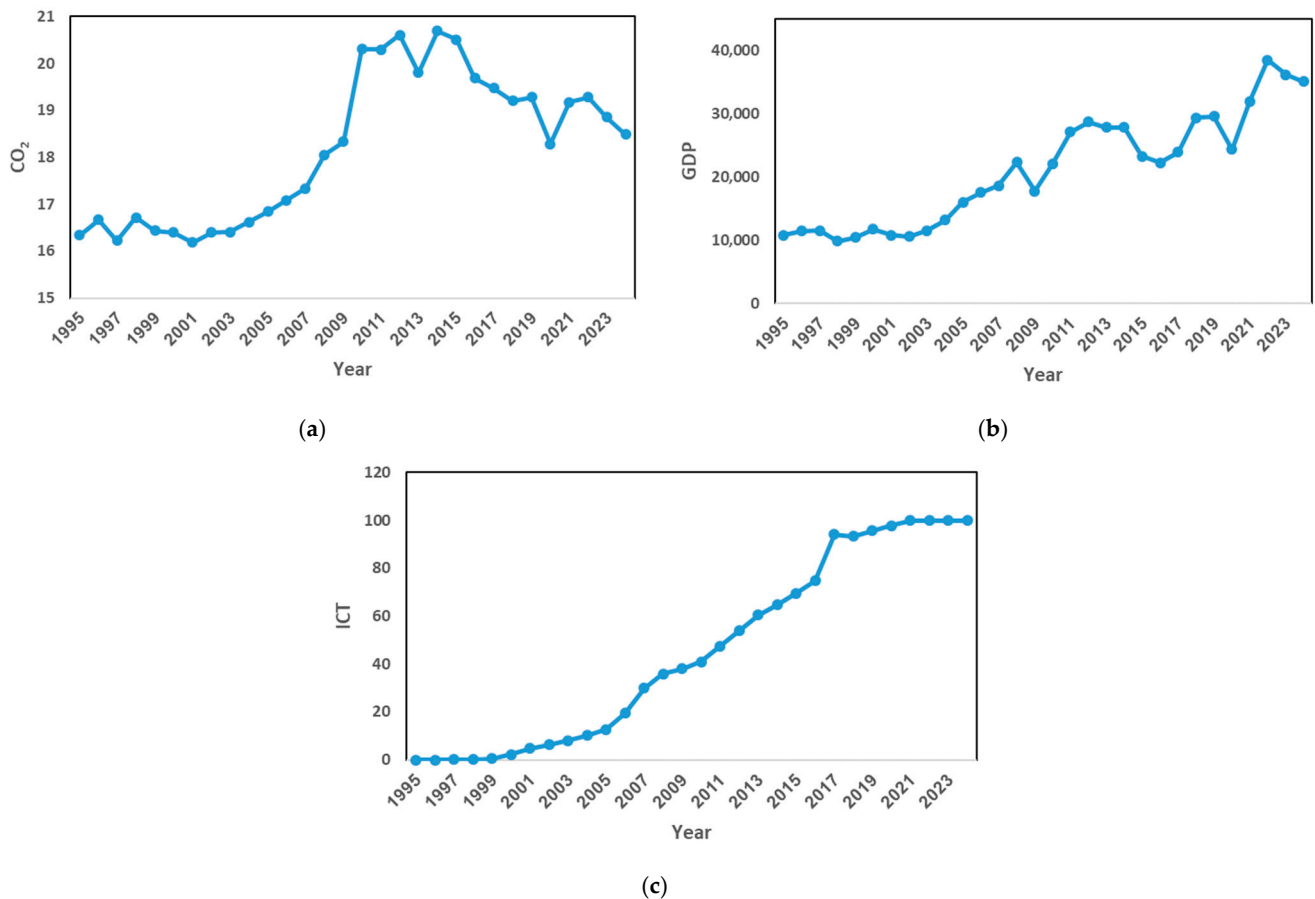


Figure 1. Plots of (a) CO₂ emissions per capita, (b) GDP per capita, and (c) ICT in Saudi Arabia for 1995 to 2024.

Table 1. Variable descriptions and data sources.

Variable	Description	Unit	Years	Data Source
CO ₂	CO ₂ emissions per capita including sources from fossil fuel use and industrial processes	ton CO ₂ /capita	1995–2024	[28]
GDP	GDP per capita expressed in current USD converted by PPP conversion factor	USD/capita	1995–2024	[29]
ICT	Individuals who have used the internet in the past 3 months (% of population)	Percentage	1995–2024	[29]

3.2. Unit Root Test

Before any regression modelling, each time series was tested for stationarity to prevent spurious regressions. Two complementary tests were employed: the augmented Dickey–Fuller (ADF) test [30] and the Phillips–Perron (PP) test [31]. Both tests impose the null hypothesis of a unit root (non-stationarity); rejection of the null implies stationarity. The ADF procedure modifies the standard Dickey–Fuller specification by adding lagged first differences of the dependent variable, thereby mitigating the issue of serially correlated errors, while the PP test uses a non-parametric correction of the Newey–West type to handle serial correlation and heteroskedasticity without adding lagged differences. Both unit root tests were estimated under two separate specifications: one with a constant and another with both a constant and a linear trend, to ensure robustness. The order of integration of a series, denoted $I(k)$, indicates the number of differencing operations to achieve stationarity.

However, a well-known limitation of the standard ADF and PP tests is their low statistical power when applied to data series containing structural breaks, and they can

incorrectly classify a stationary series with a break as non-stationary. Therefore, we supplemented the ADF/PP results with the Zivot–Andrews (ZA) test [32], which endogenously identifies a single structural break in either the intercept, the trend, or both, under the alternative hypothesis of stationarity with a break.

Table 2. Descriptive statistics for Saudi Arabian time-series data (1995–2024).

Variable	CO ₂	GDP	ICT
Mean	18.20	21,067	45.39
Median	18.31	22,148	39.50
Maximum	20.69	38,510	100
Minimum	16.18	9836	0.011
Std. dev.	1.5817	8794	38.99
Skewness	0.1233	0.2709	0.2233
Kurtosis	1.5133	1.8911	1.4890
Jarque–Bera	2.84 (0.2419)	1.90 (0.3859)	3.10 (0.2119)
Observations	30	30	30

3.3. ARDL Bounds Test for Cointegration

By allowing nonstationary variables to share a stable, long-run equilibrium, cointegration offers a rigorous framework for mitigating unit root issues and enhancing the reliability of econometric specifications. Fundamentally, cointegration detects the long-run equilibrium relations toward which time-series variables converge over time. However, traditional cointegration frameworks require rigid preconditions concerning the uniform integration order of the variables being analyzed. To address these limitations, this paper utilizes the ARDL bounds testing method for cointegration [33], which offers distinct advantages over classical methodologies such as the Johansen and Juselius test [34]. First, the ARDL framework accommodates variables integrated of different orders, specifically $I(0)$ and $I(1)$, though it remains inapplicable to $I(2)$ series. Second, the ARDL model demonstrates superior performance and statistical power when applied to small sample sizes. To account for the limitation that ARDL models do not inherently accommodate structural breaks, a dummy variable, constructed based on the ZA unit root test, was introduced to incorporate the identified breakpoint into the estimation framework. Therefore, for time-series Y_t , the ARDL model is defined as follows:

$$Y_t = c_0 + \sum_{i=1}^p \delta_i Y_{t-i} + \sum_{j=1}^r \sum_{i=0}^{q_j} \beta_{j,i} X_{j,t-i} + \rho D_\tau + \varepsilon_t \quad (1)$$

where c_0 is a constant, δ_i are coefficients of the lagged terms Y_{t-i} , p is the number of lagged terms of the dependent variable, $\beta_{j,i}$ are coefficients of the exogenous variables $X_{j,t}$ and their lagged terms $X_{j,t-i}$ for $i > 0$, r is the number of exogenous variables, q_j is the number of lagged terms of the exogenous variable X_j , D_τ is dummy variable that represents the structural break, where $D_\tau = 1$, for $t \geq \tau$, and $D_\tau = 0$, for $t < \tau$, ρ is the coefficient of the dummy variable, and ε_t is zero-mean white noise term. The ARDL framework is employed to estimate both the long-run equilibrium relationship and the corresponding

short-run dynamics. To explicitly isolate these short-run adjustments, Equation (1) can be reformulated in error-correction (differential) form as follows:

$$\Delta Y_t = \gamma_0 + \alpha_0 Y_{t-1} + \sum_{i=1}^r \alpha_i X_{i,t-1} + \sum_{i=1}^p \omega_{0,i} \Delta Y_{t-i} + \sum_{j=1}^r \sum_{i=0}^{q_j} \omega_{j,i} \Delta X_{j,t-i} + \rho \Delta D_\tau + \varepsilon_t \quad (2)$$

where $\Delta Y_t = Y_t - Y_{t-1}$ is a difference operator and γ_0 is a constant. The coefficients $\alpha_i, 0 \leq i \leq r$, represent the long-run part of the ARDL model and the coefficients $\omega_j, 0 \leq j \leq r$ represent the short-run dynamics of the model. The bounds test for cointegration proposed by Pesaran et al. [33] assumes the null hypothesis H_0 as $\alpha_0 = \alpha_1 = \dots = \alpha_r = 0$, which reflects the absence of cointegration, while the alternative hypothesis H_1 supports the presence of cointegration. The ARDL bounds testing procedure compares the computed F-statistic against two critical value thresholds: the lower bound, $F(0)$, and the upper bound, $F(1)$. Given the finite dataset in this paper, the critical values compiled by Narayan [35] are adopted, which are specifically optimized for small-sample sizes. The null hypothesis of no cointegration is rejected if the calculated F-statistic exceeds the upper bound $F(1)$ threshold, whereas it cannot be rejected if the statistic falls below the lower bound $F(0)$. Any value falling between these two limits yields an inconclusive result. Should the bounds test fail to reject the null hypothesis, it implies the absence of a long-run cointegrating relationship, restricting the analysis solely to the short-run specification, expressed as follows:

$$\Delta Y_t = \gamma_0 + \sum_{i=1}^p \omega_{0,i} \Delta Y_{t-i} + \sum_{j=1}^r \sum_{i=0}^{q_j} \omega_{j,i} \Delta X_{j,t-i} + \rho \Delta D_\tau + \varepsilon_t \quad (3)$$

However, if the null hypothesis is rejected, then cointegration is confirmed and the ARDL model is reparameterized into the error correction model (ECM) of Engle and Granger [36]. ECM represents both the short-run dynamics and the long-run equilibrium adjustment and can be expressed as follows:

$$\Delta Y_t = \gamma_0 + \sum_{i=1}^p \omega_{0,i} \Delta Y_{t-i} + \sum_{j=1}^r \sum_{i=0}^{q_j} \omega_{j,i} \Delta X_{j,t-i} + \rho \Delta D_\tau + \phi Z_{t-1} + \varepsilon_t \quad (4)$$

where Z_{t-1} is called the error correction term (ECT) and is given as follows:

$$Z_{t-1} = Y_{t-1} - \beta_0 - \sum_{j=1}^r \beta_j X_{j,t-1} \quad (5)$$

The ECT captures the deviation of Y_t from its long-run equilibrium path in the previous period. The coefficient ϕ , the speed of adjustment, measures the fraction of this disequilibrium that is corrected each period. For the model to be stable and convergent, ϕ must be negative and statistically significant; the magnitude of this coefficient reflects the speed of adjustment, indicating how rapidly the system dissipates short-run shocks to return to its long-run equilibrium path.

3.4. Granger Causality Analysis

Given confirmed cointegration, Granger causality is examined within the ECM framework. Cointegration guarantees Granger causality in at least one direction, but leaves the precise directions and magnitudes to be empirically determined [36]. Three ECM systems are estimated as follows:

$$\Delta \ln CO_{2t} = \gamma_1 + \sum_{i=1}^{p_1} \omega_{10,i} \Delta \ln CO_{2t-i} + \sum_{i=0}^{q_{11}} \omega_{11,i} \Delta \ln GDP_{t-i} + \sum_{i=0}^{q_{12}} \omega_{12,i} \Delta \ln ICT_{t-i} + \rho_1 \Delta D_{\tau_1} + \phi_1 Z_{1,t-1} + \varepsilon_{1t} \quad (6)$$

$$\Delta \ln GDP_t = \gamma_2 + \sum_{i=1}^{p_2} \omega_{20,i} \Delta \ln GDP_{t-i} + \sum_{i=0}^{q_{21}} \omega_{21,i} \Delta \ln CO_{2t-i} + \sum_{i=0}^{q_{22}} \omega_{22,i} \Delta \ln ICT_{t-i} + \rho_2 \Delta D_{\tau_2} + \phi_2 Z_{2,t-1} + \varepsilon_{2t} \quad (7)$$

$$\Delta \ln ICT_t = \gamma_3 + \sum_{i=1}^{p_3} \omega_{30,i} \Delta \ln ICT_{t-i} + \sum_{i=0}^{q_{31}} \omega_{31,i} \Delta \ln GDP_{t-i} + \sum_{i=0}^{q_{32}} \omega_{32,i} \Delta \ln CO_{2t-i} + \rho_3 \Delta D_{\tau_3} + \phi_3 Z_{3,t-1} + \varepsilon_{3t} \quad (8)$$

where $\ln CO_2$, $\ln GDP$, and $\ln ICT$ are natural logarithms of CO_2 emissions, GDP, and ICT, and p_i, q_{ij} are the lag lengths of the dependent and independent variables, respectively. The natural logarithm of the data is used to achieve constant variance and enable description of the relations between the variables. Short-run Granger causality is inferred from the joint significance of the ω coefficients with regard to the lagged differences of the independent variables. Long-run Granger causality is inferred from the significance of the ECT coefficient ϕ ; a negative and statistically significant ϕ implies that the dependent variable adjusts toward the long-run equilibrium, confirming that the independent variables collectively Granger-cause the dependent variable in the long run. The long-run elasticities are recovered from the static long-run Equations [37], as follows:

$$\ln CO_{2t} = \alpha_{10} + \alpha_{11} \ln GDP_{t-1} + \alpha_{12} \ln ICT_{t-1} + \rho_1 D_{\tau_1} \quad (9)$$

$$\ln GDP_t = \alpha_{20} + \alpha_{21} \ln CO_{2t-1} + \alpha_{22} \ln ICT_{t-1} + \rho_2 D_{\tau_2} \quad (10)$$

$$\ln ICT_t = \alpha_{30} + \alpha_{31} \ln CO_{2t-1} + \alpha_{32} \ln GDP_{t-1} + \rho_3 D_{\tau_3} \quad (11)$$

The parameters specified in Equations (6) through (11) are estimated using the ordinary least squares (OLS) method. To test the EKC hypothesis, which predicts an inverted-U relationship between GDP and CO_2 emissions, the quadratic term $\ln GDP^2$ (representing the square of $\ln GDP$) is added to Equations (6) and (9). The augmented short-run ECM for the EKC test becomes:

$$\Delta \ln CO_{2t} = \gamma_1 + \sum_{i=1}^{p_1} \omega_{1,i} \Delta \ln CO_{2t-i} + \sum_{i=0}^{q_{11}} \omega_{2,i} \Delta \ln GDP_{t-i} + \sum_{i=0}^{q_{12}} \omega_{3,i} \Delta \ln ICT_{t-i} + \sum_{i=0}^{q_{13}} \omega_{4,i} \Delta \ln GDP_{t-i}^2 + \rho_1 \Delta D_{\tau_1} + \phi_1 Z_{EKC,t-1} + \varepsilon_{1t} \quad (12)$$

The augmented long-run EKC equation is:

$$\ln CO_{2t} = \alpha_1 + \alpha_2 \ln GDP_{t-1} + \alpha_3 \ln ICT_{t-1} + \alpha_4 \ln GDP_{t-1}^2 + \rho_1 D_{\tau_1} \quad (13)$$

In Equation (13), α_4 denotes the coefficient of the quadratic term of $\ln GDP^2$. The long-run EKC hypothesis is empirically validated if and only if α_2 is positive and α_4 is negative, confirming the inverted U-shaped relationship between economic growth and environmental degradation. An analogous interpretation applies to the short-run parameters $\omega_{2,i}$ and $\omega_{4,i}$ in Equation (12) to evaluate the short-run validity of the EKC. The implied income turning point, i.e., the value of GDP per capita where emissions peak, is given by [38]:

$$GDP^* = \exp\left(-\frac{\alpha_2}{2\alpha_4}\right) \quad (14)$$

A turning point within the observed range of Saudi GDP per capita would provide evidence that the Kingdom has already passed (or is approaching) the emissions peak predicted by the EKC.

4. Results and Discussion

4.1. Unit Root Test Results

Table 3 presents the empirical outcomes of the ADF and PP unit root tests. For the variables $\ln CO_2$, $\ln GDP$ and $\ln GDP^2$, both testing procedures fail to reject the null hypothesis of a unit root in their levels, but they reject it at the 1% significance level in their first differences. This pattern establishes that these series are integrated of order one, or $I(1)$. Conversely, the test results for $\ln ICT$ conclusively reject the null hypothesis in its level form, demonstrating that the series is stationary at levels and integrated of order zero, or $I(0)$.

Table 3. Stationarity diagnostics: ADF and PP Results.

	Variable	At Level		At First Difference		Decision
		Intercept	Intercept and Trend	Intercept	Intercept and Trend	
ADF Test	$\ln CO_2$	−1.3221 (0.6056)	−0.9502 (0.9358)	−5.7147 *** (0.0001)	−5.7495 *** (0.0003)	$I(1)$
	$\ln GDP$	−0.7533 (0.8173)	−2.5295 (0.3127)	−5.2681 *** (0.0002)	−4.9157 *** (0.0027)	$I(1)$
	$\ln ICT$	−5.0191 *** (0.0005)	−4.4716 *** (0.0085)	−5.3310 *** (0.0003)	−4.9665 *** (0.0034)	$I(0)$
	$\ln GDP^2$	−0.7338 (0.8225)	−2.6066 (0.2802)	−5.2697 *** (0.0002)	−4.9779 *** (0.0023)	$I(1)$
PP Test	$\ln CO_2$	−1.3374 (0.5983)	−1.0343 (0.9231)	−5.7001 *** (0.0001)	−5.7286 *** (0.0004)	$I(1)$
	$\ln GDP$	−0.5801 (0.8603)	−2.6187 (0.2753)	−5.5188 *** (0.0001)	−5.3673 *** (0.0009)	$I(1)$
	$\ln ICT$	−13.2651 *** (0.0000)	−5.9878 *** (0.0002)	−1.5537 (0.4923)	−2.0991 (0.5241)	$I(0)$
	$\ln GDP^2$	−0.5256 (0.8721)	−2.6961 (0.2452)	−5.5913 *** (0.0001)	−5.4261 *** (0.0007)	$I(1)$

Note: *** indicate statistical significance at 1%.

However, to address the limitation of the ADF and PP tests in the presence of structural breaks, the ZA unit root test was applied to all three variables at level under the intercept-and-trend specification, which accommodates breaks in both the intercept and the trend simultaneously and is the most general and appropriate model for trending macroeconomic series. The maximum lag length was set to 4, with optimal lag selection based on the Akaike information criterion. The results are reported in Table 4. For $\ln GDP$ and $\ln GDP^2$, the ZA test fails to reject the null hypothesis of a unit root even after allowing for an endogenous structural break, with the most likely break date identified as 2015. This confirms that $\ln GDP$ and $\ln GDP^2$ are $I(1)$ regardless of the structural break and consistent with the ADF and PP results. For $\ln ICT$, the ZA test rejects the null hypothesis at the 5% significance level, with the break identified as 2017, confirming $I(0)$ status under all three tests. Most importantly, for $\ln CO_2$, the ZA test rejects the null hypothesis of a unit root at the 5% significance level, with an endogenously identified structural break at 2010. This reclassifies $\ln CO_2$ as $I(0)$ once the structural break is accommodated, coinciding with the aftermath of the 2008–2009 global financial crisis that triggered a sharp contraction in global oil demand, and the post-crisis recovery established a structurally different emissions trajectory from 2010 onward. Once this break is accommodated, $\ln CO_2$ is reclassified from $I(1)$ under the conventional ADF and PP tests to $I(0)$ under the ZA test, indicating that the apparent unit root was driven by the unaccounted structural shift rather than a genuine stochastic trend.

Table 4. Zivot–Andrews test results. The model used is intercept and trend, with maximum lag length = 4.

Variable	Break Year (τ)	t-Stat	Critical Value (5%)	Decision
$\ln GDP$	2015	−3.61	−5.08	I(1)
$\ln ICT$	2017	−5.13		I(0)
$\ln CO_2$	2010	−5.99		I(0)
$\ln GDP^2$	2015	−3.66		I(1)

In summary, the variables of interest exhibit a mixed order of integration, specifically $I(0)$ and $I(1)$, with no series integrated of order $I(2)$. These stationarity properties strictly satisfy the fundamental assumptions required for the ARDL framework, thereby justifying its application for the subsequent cointegration and long-run estimation analyses.

4.2. Cointegration Analysis Results

Following the confirmation of a mixed order of integration among the time series, the test for cointegration was conducted to identify potential long-run equilibrium relationships. Table 5 presents the ARDL bounds testing outcomes across three distinct specifications, sequentially alternating $\ln GDP$, $\ln ICT$, and $\ln CO_2$ as the dependent variable in Equation (1).

Table 5. Empirical results of the cointegration bounds test.

Dependent Variable	Independent Variables	Lag Lengths	F-Stat	Cointegration Exists?	Decision	Significance Level	F(0)	F(1)
$\ln GDP$	$\ln ICT, \ln CO_2, D_{2015}$	(4, 4, 0)	15.35 ***	Yes	Estimate ECM	1%	7.98	9.41
$\ln ICT$	$\ln GDP, \ln CO_2, D_{2017}$	(4, 3, 0)	40.72 ***	Yes	Estimate ECM	5%	5.55	6.75
$\ln CO_2$	$\ln GDP, \ln ICT, D_{2010}$	(1, 4, 3)	49.70 ***	Yes	Estimate ECM	10%	4.58	5.60

Note: *** indicates statistical significance at 1%.

All parameters were estimated via ordinary least squares (OLS). The empirical F-statistics for the models featuring $\ln GDP$, $\ln ICT$ and $\ln CO_2$ as dependent variables were 15.35, 40.72, and 49.70, respectively. Because each calculated value systematically exceeds the 1% critical upper bound threshold tabulated by Narayan [35], the null hypothesis of no cointegration is decisively rejected across all three models. These baseline regressions incorporate an unrestricted constant without a linear trend, with optimal lag structures selected automatically using the Akaike information criterion (AIC) [39]. This outcome establishes that CO_2 emissions, GDP, and ICT share a common stochastic trend and are pulled toward a long-run equilibrium despite short-run deviations. This outcome confirms the presence of a long-run cointegrating relationship among CO_2 emissions, economic growth, and internet-based ICT adoption in Saudi Arabia over the investigated period. Consequently, the ECM was estimated for each dependent variable to examine both short- and long-run Granger-causal dynamics.

4.3. Granger Causality Results

Given that the variables are cointegrated, a Granger-causal relationship exists in at least one direction. To determine the optimal lag lengths for the ECM in Equations (6)–(8), Table 6 presents the lag selections based on four distinct criteria. The subsequent Granger causality results for these three models are summarized in Table 7, which details the coefficients and p -values for both short- and long-run Granger causality.

Table 6. Optimal lag selection for ECM.

Dependent Variable	Independent Variables	Lag Length Selected by Criteria				Lag Order
		FPE *	AIC *	SC *	HQ *	
<i>lnGDP</i>	<i>lnICT, lnCO₂, D₂₀₁₅</i>	1	1	1	1	1
<i>lnICT</i>	<i>lnGDP, lnCO₂, D₂₀₁₇</i>	3	3	3	3	3
<i>lnCO₂</i>	<i>lnGDP, lnICT, D₂₀₁₀</i>	1	1	1	1	1

* Note: FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan–Quinn information criterion.

Table 7. Empirical coefficients and *p*-values for short-run Granger causality.

Model Independent Variables	Model Dependent Variable		
	$\Delta \ln GDP_t$	$\Delta \ln ICT_t$	$\Delta \ln CO_{2t}$
<i>Constant</i>	−0.0023 (0.9542)	−0.0282 (0.4719)	0.0031 (0.6491)
$\Delta \ln GDP_{t-1}$	1.0185 ** (0.0419)	−0.1732 (0.3822)	−0.0071 (0.8683)
$\Delta \ln GDP_{t-2}$	-	0.5966 *** (0.0055)	-
$\Delta \ln GDP_{t-3}$	-	−0.0864 (0.6853)	-
$\Delta \ln ICT_{t-1}$	−0.0164 (0.7844)	1.8697 *** (0.0000)	−0.0115 (0.3527)
$\Delta \ln ICT_{t-2}$	-	−1.5449 *** (0.0000)	-
$\Delta \ln ICT_{t-3}$	-	0.6651 *** (0.0000)	-
$\Delta \ln CO_{2t-1}$	0.5654 (0.5302)	0.1418 (0.8655)	1.1457 *** (0.0067)
$\Delta \ln CO_{2t-2}$	-	−2.7533 *** (0.0049)	-
$\Delta \ln CO_{2t-3}$	-	1.1518 (0.1501)	-
<i>D_τ</i>	−0.0932 (0.5092)	−0.0841 (0.5287)	−0.0085 (0.8050)
<i>Z_{t-1}</i>	−1.3693 ** (0.0130)	−1.7789 *** (0.0000)	−1.5719 *** (0.0007)

Note: ***, and **, indicate statistical significance at 1%, and 5%, respectively.

In the short run (Table 7), neither ICT nor CO₂ emissions exerted a statistically significant effect on GDP growth (Table 6, $\Delta \ln GDP$ column), and neither GDP nor ICT significantly affected CO₂ emissions ($\Delta \ln CO_2$ column). These findings indicate that in Saudi Arabia, short-run fluctuations in digital adoption or carbon output do not feed back into the business cycle in a statistically detectable way. This result is economically plausible. The Kingdom's short-run GDP dynamics are dominated by oil price cycles, factors external to both ICT diffusion and domestic emissions levels, which obscure any short-run ICT–growth or emissions–growth feedback. In contrast, both GDP and CO₂ emissions significantly influenced internet-based ICT adoption in the short run ($\Delta \ln ICT$ column). A 1% increase in GDP induced a 0.6% increase in ICT at two lags (significant at 1%), while a 1% increase in CO₂ emissions decreased internet-based ICT adoption by 2.75% at two lags (significant at 1%). The negative short-run effect of CO₂ on ICT is particularly informative. It suggests that periods of rapid emissions growth, associated with energy-intensive industrial expansion, construction booms, or oil production surges, coincided with a relative deceleration in internet penetration, possibly because resource allocation during commodity booms shifted away from digital infrastructure toward extractive and industrial sectors.

For the long-run relationships, the ECT coefficients are negative and statistically significant in all three models, confirming long-run Granger causality among all three variables and validating the trivariate cointegrating relationship (Table 7). The speed of adjustment coefficients is economically meaningful. GDP, ICT, and CO₂ emissions returned to their long-run equilibrium paths within approximately 0.78, 0.55, and 0.77 years, respectively, following a short-run shock. The adjustment speeds exceeding unity, i.e., $|ECT| > 1$, for GDP and ICT indicate over-shooting correction; the system initially overshoot the long-run equilibrium before converging, which is consistent with the highly dynamic nature of Saudi

Arabia's ICT sector and GDP, where sudden adjustments to oil revenue shocks or digital policy announcements can temporarily overshoot long-run trends.

The long-run causal relationships, recovered from the static long-run Equations (9)–(11) and reported in Table 8, reveal a nuanced structural hierarchy among the three variables. Several findings merit detailed interpretation. Regarding $GDP \rightarrow ICT$, GDP is the dominant long-run driver of internet-based ICT adoption in Saudi Arabia. A 1% increase in GDP per capita Granger-causes a 3.85% increase in internet penetration (significant at 5%), an elasticity that reflects the strong income dependence of digital adoption in the Kingdom. With reference to $CO_2 \rightarrow GDP$, CO_2 emissions Granger-cause GDP in the long run, reflecting the deep interdependence between fossil fuel combustion, industrial energy use, and economic output that is characteristic of a hydrocarbon economy. A 1% increase in CO_2 per capita is associated with a 2.13% increase in GDP per capita in the long run (significant at 1%). Considering $ICT \rightarrow GDP$, internet-based ICT adoption positively and significantly Granger-causes GDP in the long run, confirming a modest but statistically robust productivity dividend from digital investment. A 1% increase in internet penetration raises GDP per capita by approximately 0.07% in the long run. In addition, neither GDP nor ICT exerts a statistically significant direct long-run effect on CO_2 emissions. The structural break dummy itself is highly significant, indicating that the 2010 structural shift, associated with the implications of the 2008–2009 global financial crisis and the post-crisis reconfiguration of Saudi Arabia's energy-intensive production, permanently elevated the CO_2 emissions trajectory by approximately 11.7%.

Table 8. Empirical coefficients and p -values for long-run Granger causality.

Model Dependent Variable	Independent Variables				
	Constant	$\ln GDP_{t-1}$	$\ln ICT_{t-1}$	$\ln CO_{2t-1}$	D_τ
$\ln GDP_t$	3.4999 * (0.0606)	- -	0.0698 *** (0.0018)	2.1268 *** (0.0023)	0.1490 (0.1288)
$\ln ICT_t$	-42.7373 *** (0.0004)	3.8517 ** (0.0351)	- -	2.6173 (0.7221)	0.0130 (0.9883)
$\ln CO_{2t}$	2.6065 *** (0.0000)	0.0226 (0.5619)	0.0048 (0.2905)	- -	0.1167 *** (0.0002)

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

To validate the EKC hypothesis, the parameters of Equations (12) and (13) were estimated using OLS regression to obtain Equations (15) and (16), respectively, as follows:

$$\Delta \ln CO_{2t} = 0.0013 + 0.91^{***} \Delta \ln CO_{2t-1} - 0.002 \Delta \ln GDP_{t-1} - 0.005 \Delta \ln ICT_{t-1} - 0.001 \Delta \ln GDP_{t-1}^2 + 0.02 \Delta D_{2010} - 1.5^{***} Z_{EKC,t-1} \quad (15)$$

$$\ln CO_{2t} = -15.4^{***} + 3.66^{***} \ln GDP_{t-1} - 0.002 \ln ICT_{t-1} - 0.18^{***} \ln GDP_{t-1}^2 - 0.12^{***} D_{2010} \quad (16)$$

The estimated long-run EKC equation (Equation (16)) yields coefficients of +3.66 on $\ln GDP$ (significant at 1%) and -0.18 on $\ln GDP^2$ (significant at 1%), satisfying the theoretical conditions $\alpha_2 > 0$ and $\alpha_4 < 0$ and confirming that the EKC hypothesis is validated in the long run for Saudi Arabia. Applying Equation (14), the EKC turning point in GDP per capita is as follows:

$$GDP^* = \exp\left(-\frac{3.66}{2 \times (-0.18)}\right) = \exp(10.03) \approx \$26,021$$

This implied turning point of approximately USD 26,021 per capita falls within the observed sample range (mean GDP = USD 21,067; maximum = USD 38,510), suggesting that Saudi Arabia is likely to have passed its emissions peak as measured per capita during

the latter part of the sample period. The estimated turning point should be interpreted with caution for several reasons. First, it is derived from a quadratic specification of PPP-adjusted current GDP, and different GDP deflators or income measures may yield a somewhat different turning point. Second, the turning point estimate is sensitive to the sample period; adding or removing a few years at either end of the time series can shift the implied peak. Nonetheless, it should be treated as an indicative estimate rather than a precise threshold.

This interpretation aligns with the observation that Saudi Arabia's CO₂ per capita has been broadly stable or slightly declining since the mid-2010s despite continued GDP growth, as the Kingdom has made some progress in reducing energy subsidies, diversifying toward services, and initiating renewable energy projects. In the short run, however, neither the $\ln GDP$ nor the $\ln GDP^2$ coefficients in Equation (15) are statistically significant, indicating that the EKC pattern is a long-run phenomenon that does not manifest in annual fluctuations.

Figure 2 captures the full causal architecture. GDP occupies the central position in the long-run causal structure. It is the dominant driver of internet-based ICT adoption, while CO₂ emissions Granger-cause GDP in the long run, reflecting the deep interdependence between fossil fuel combustion and economic output that is characteristic of Saudi Arabia's hydrocarbon-based economy. Internet-based ICT adoption also contributes positively to GDP growth in the long run, confirming a modest but robust productivity dividend from digital investment. Critically, neither GDP nor ICT exerts a statistically significant direct long-run effect on CO₂ emissions once the 2010 structural break is controlled for; instead, the CO₂ equilibrium is governed by the permanent shift captured by the structural break dummy and by the non-linear income–emissions relationship confirmed by the EKC test. In the short run, the only significant causal flows pass through internet-based ICT adoption, which is positively influenced by GDP growth and negatively by CO₂ emission surges.

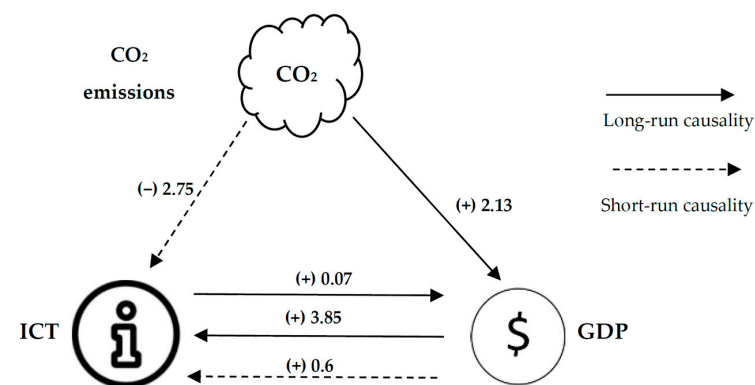


Figure 2. Illustration of the short-run and long-run Granger-causality relationships. Note that (+) and (−) signs mean positive and negative effects, respectively.

4.4. Robustness and Diagnostics Tests

The outcomes of the diagnostic tests validate the reliability of the empirical findings. The Breusch–Godfrey LM test [40] failed to reject the null of no serial correlation in all three models (Table 9), indicating that the residuals are serially uncorrelated and that the chosen lag structures adequately capture the dynamic structure of the data. The Breusch–Pagan–Godfrey test [41] similarly failed to reject homoskedasticity in all three models (Table 10). The Ramsey RESET test [42] was applied to assess functional form misspecification by testing whether the squared and cubic fitted values had significant explanatory power beyond the original regressors. The null hypothesis of no misspecification was not rejected for any of the three ECM models at the 5% significance level (Table 11). The CUSUM

and CUSUMSQ plots [43] for all three models remain within the 5% significance bands throughout the full sample period (Figure 3), confirming that the estimated coefficients are structurally stable and that no evidence of parameter instability is present. Taken together, these diagnostic results validate the ARDL/ECM framework as well specified and statistically reliable for the Saudi time-series data.

Table 9. Breusch–Godfrey Serial Correlation LM test results.

Model Dependent Variable	Null Hypothesis: No Serial Correlation at up to 1 Lag		
	N * $\times$ R-Squared	p-Value	Decision
$\Delta \ln GDP_t$	1.5178	0.4041	Fail to reject the null
$\Delta \ln ICT_t$	0.9390	0.4975	Fail to reject the null
$\Delta \ln CO_{2t}$	1.6423	0.2655	Fail to reject the null

Note: * N is the number of observations.

Table 10. Breusch–Pagan–Godfrey Heteroskedasticity test results.

Model Dependent Variable	Null Hypothesis: Absence of Heteroskedasticity		
	N * $\times$ R-Squared	p-Value	Decision
$\Delta \ln GDP_t$	2.5324	0.8175	Fail to reject the null
$\Delta \ln ICT_t$	6.9137	0.8987	Fail to reject the null
$\Delta \ln CO_{2t}$	9.1637	0.1983	Fail to reject the null

Note: * N is the number of observations.

Table 11. Results of the Ramsey RESET Test with two fitted terms.

Model Dependent Variable	Null Hypothesis: No Functional Form Misspecification ($p > 0.05$)		
	F-Statistic	p-Value	Decision
$\Delta \ln GDP_t$	0.9343	0.4093	Fail to reject the null
$\Delta \ln ICT_t$	1.4560	0.3331	Fail to reject the null
$\Delta \ln CO_{2t}$	3.1997	0.0881	Fail to reject the null

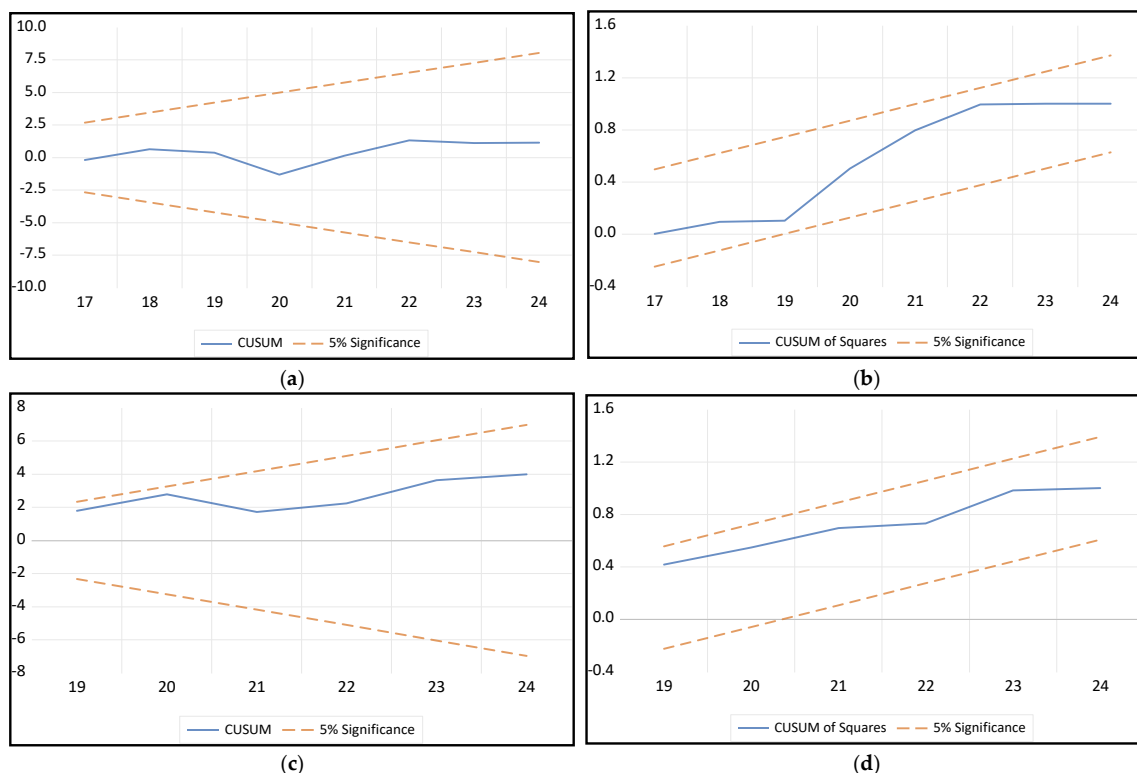


Figure 3. Cont.

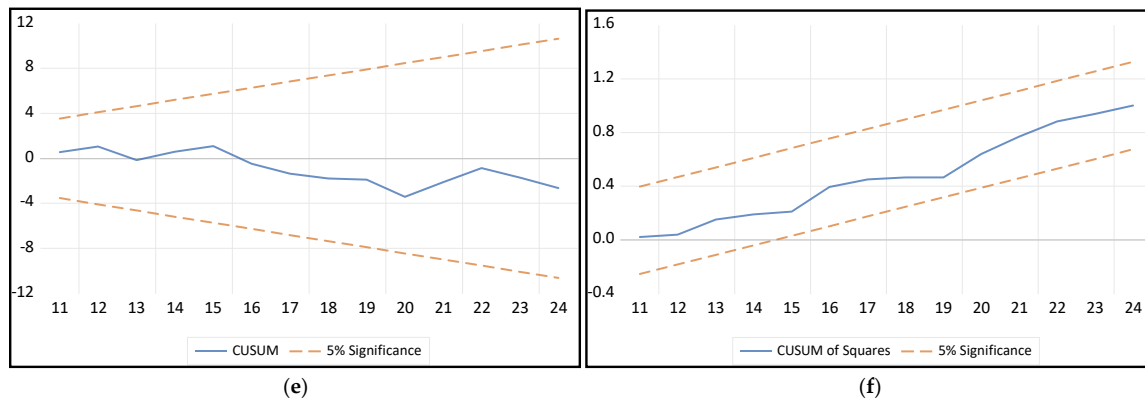


Figure 3. Plots of CUSUM and CUSUM square tests for the models of the dependent variables: $\Delta \ln \text{GDP}$ (a,b), $\Delta \ln \text{ICT}$ (c,d), and $\Delta \ln \text{CO}_2$ (e,f).

The choice of the linear ARDL modeling adopted in this study is justified over the non-linear ARDL (NARDL) specification [44]. The NARDL framework decomposes each independent variable into its positive and negative partial sum components to capture potential asymmetric responses of the dependent variable to positive versus negative shocks. The Ramsey RESET test (Table 11) failed to reject the null hypothesis of correct functional form specification for all three ECM models, providing direct statistical evidence that the log-linear symmetric specification is not misspecified and that adding non-linear terms does not improve the model fit. In addition, the study's core objective is about causal direction and long-run equilibrium, which is more naturally addressed in a symmetric ECM framework than in the asymmetric multiplier framework of NARDL.

4.5. Discussion

The empirical findings carry direct and consequential implications for Saudi Arabia's simultaneous pursuit of connectivity expansion and environmental sustainability under Vision 2030. The confirmed long-run EKC result, with a turning point of approximately USD 26,021 GDP per capita, is an encouraging finding. It suggests that the structural relationship between income growth and emissions has already begun to bend downward in Saudi Arabia, at least in per-capita terms. This is broadly consistent with the Kingdom's energy subsidy reforms initiated in 2016, its investments in renewable energy under the National Renewable Energy Program (which targets 50% of electricity from renewables by 2030), and the gradual diversification of GDP toward non-oil services and ICT sectors under Vision 2030.

However, the finding that GDP remains the primary long-run driver of ICT, with the CO_2 equilibrium governed by the 2010 structural break and the non-linear EKC mechanism, with no independent direct causal link from ICT to CO_2 , highlights a fundamental challenge. Vision 2030 assumes that increased connectivity will yield environmental co-benefits by enabling smart energy systems, precision industry, e-government, and digital logistics, thereby reducing the carbon intensity of growth. The present empirical analysis suggests that as of 2024, this digitally mediated decarbonization dividend has not yet materialized as an independent causal channel. Internet-based ICT adoption in Saudi Arabia has, to date, primarily functioned as a product of income growth rather than as an autonomous environmental lever. This finding does not imply that ICT cannot become an environmental asset; rather, it suggests that the conditions enabling direct ICT-to-emissions efficiency transmission (clean electricity powering ICT infrastructure, green ICT applications in industry and buildings, digital dematerialization) have not yet been sufficiently developed [45].

The short-run finding that CO_2 emission surges reduce internet-based ICT adoption underlines a subtler structural tension. When Saudi Arabia's economy shifts into high-

emissions modes (such as hydrocarbon production booms, heavy industrialization), the relative momentum of digital sector investment slows. This inverse relationship may reflect budgetary or sectoral resource competition; oil-revenue booms historically concentrate investment in traditional industries, while digital sector momentum tends to build in diversification phases. Vision 2030's non-oil revenue target, raising non-oil GDP contribution from approximately 16% to 50% by 2030, would, if achieved, systematically break this tension by making ICT investment relatively more prominent in the economic growth process and less dependent on the carbon-intensive production cycle.

The GDP $\rightarrow$ ICT elasticity of 3.85 in the long run is also directly relevant to policy. It implies that the Kingdom's income growth trajectory is a powerful predictor of digital adoption. As Saudi Arabia diversifies its income sources, the continued growth of per-capita income will drive further digital adoption, supporting the Saudi Green Initiative's vision of a data-driven, digitally optimized economy. However, this also means that slowing economic growth would directly constrain ICT diffusion, potentially undermining Vision 2030's digital ambitions. This sensitivity highlights the importance of policies that decouple ICT investment from the oil revenue cycle, for example, through sustained public investment in digital public goods and broadband infrastructure regardless of commodity price conditions.

While this study provides valuable empirical insights, it is accompanied by certain limitations that offer fruitful avenues for future research. First, internet-based ICT adoption is proxied solely by internet penetration, which, while the most widely used and consistently available ICT indicator for Saudi Arabia across the sample period, captures only one dimension of a multifaceted construct. Other dimensions of ICT may produce different coefficient magnitudes or even alter the causal direction, as evidenced by the mixed results across ICT proxies reported by Belloumi and Alharethi [46]. Data availability constraints precluded the inclusion of these alternative proxies for the full sample period. Second, the results may be sensitive to model specification choices (including lag selection criteria, the number and timing of structural break dummies, and the set of conditioning variables) and the relatively small sample of 30 annual observations limits statistical power and the number of parameters that can be reliably estimated. Third, the trivariate framework employed here deliberately isolates the pure ICT–GDP–CO₂ nexus but omits potentially important mediating variables, including energy consumption, electricity use, oil rents, and renewable energy deployment, which are known to influence the emissions trajectory in hydrocarbon economies and have been identified as significant determinants of CO₂ emissions in related Saudi and GCC studies [21]. The exclusion of these variables means that the structural break dummy at 2010 may have captured some of the variance attributable to energy-side dynamics rather than purely to the post-GFC macroeconomic regime shift. Future research should extend the model to incorporate energy and resource variables within a penalized or factor-augmented ARDL framework that can accommodate a larger variable set without sacrificing degrees of freedom, and studies should consider panel extensions across GCC economies to improve the generalizability of these findings.

5. Conclusions and Policy Implications

This paper employs annual time-series data from Saudi Arabia for the period 1995–2024 and an ARDL/ECM Granger-causality framework to analyze the short-run and long-run nexus among CO₂ emissions per capita, GDP per capita, and internet-based ICT adoption measured as internet penetration. The Granger-causality analysis yields four principal findings. First, in the long-run, GDP exerts a statistically significant positive long-run effect on internet-based ICT adoption, while its direct linear effect on CO₂ emissions is not statistically significant once the 2010 structural break is controlled for,

identifying economic growth as the central nexus connecting the digital economy to the carbon economy in Saudi Arabia. Second, internet-based ICT adoption positively and significantly Granger-causes GDP in the long run (elasticity = 0.07), confirming a modest but statistically robust productivity return to digital investment. Third, CO₂ emissions Granger-cause GDP in the long run (elasticity = 2.13 at 1% significance), reflecting the deep linkage between fossil-fuel-powered industrial activity and economic output that is characteristic of a hydrocarbon economy. Fourth, no direct causal link exists between internet-based ICT adoption and CO₂ emissions in either direction, in either the short or long run.

The EKC hypothesis is validated in the long run, confirming an inverted-U GDP–CO₂ relationship. A turning point is estimated at approximately USD 26,021 per capita, a level already reached during the study period. In the short run, neither GDP-level effects nor EKC effects are statistically significant for the CO₂ model, affirming that the EKC is a structural long-run phenomenon.

The model's omission of energy consumption and renewable energy reflects a deliberate parsimony in the face of a small sample, but it also leaves an important policy dimension unexplored. Saudi Arabia's Vision 2030 explicitly targets a 50% renewable energy share by 2030, and emerging evidence from other energy-dependent economies suggests that transitioning toward renewables need not come at the expense of economic growth. Oliveira et al. [47], studying South American economies, found positive contributions to GDP from both traditional and renewable energy consumption, with renewable energy exhibiting a stronger growth effect. This evidence, while from a different regional context, suggests that a renewable energy transition in Saudi Arabia could simultaneously support economic growth and reduce CO₂ emissions, a pathway that ICT-enabled smart grid technologies and digital energy management systems could help facilitate.

The results generate several concrete and actionable policy insights, organized around Saudi Arabia's Vision 2030 and Saudi Green Initiative framework, which can be stated as follows:

1. Break the ICT–Growth dependence loop. The finding that internet-based ICT adoption is driven almost entirely by income growth, with an elasticity of 3.85, means that if economic growth slows, digital diffusion could decelerate significantly. Policymakers should institutionalize ICT investment as a non-cyclical budget commitment, shielded from oil revenue volatility.
2. Activate the direct ICT–environment channel. The absence of a direct causal link from ICT to CO₂ emissions implies that Saudi Arabia has not yet exploited the full environmental potential of digital technologies. Targeted policy interventions should aim to create this channel, for example, by mandating smart meters and AI-driven energy management in residential, commercial, and industrial buildings, scaling up digital twin technology in the oil and gas and petrochemical sectors to optimize energy efficiency, and promoting digital platforms for shared mobility, remote work, and e-commerce logistics to reduce transportation emissions.
3. Power digital infrastructure with renewable energy. The finding that ICT does not reduce CO₂ emissions is likely to be connected to the fact that Saudi Arabia's digital infrastructure is predominantly powered by fossil fuels. The Saudi Green Initiative's target of 50% renewable electricity by 2030 is therefore not only an energy sector commitment, but also a prerequisite for ICT adoption to transition from an environmentally neutral to an environmentally beneficial force. Policymakers should prioritize dedicated renewable energy supply agreements for data centers, telecommunications networks, and AI computation facilities.

4. Leverage the confirmed EKC turning point. The empirical confirmation of the EKC with a turning point of approximately USD 26,021 per capita provides an evidence-based foundation for optimism about Saudi Arabia's long-run environmental trajectory. As the economy diversifies and per capita income rises beyond the turning point, the structural tendency toward lower emissions per unit of income growth should strengthen. However, this inherent improvement is a slow-moving structural process. The Saudi Green Initiative's binding 2030 CO₂ reduction targets require accelerated action beyond the pace implied by EKC dynamics alone. Policies that simultaneously raise income and reduce the carbon intensity of production, through renewable energy deployment, energy efficiency mandates, carbon pricing, and industrial diversification, will compress the timeline of the EKC adjustment.
5. Exploit the ICT–GDP productivity dividend. The long-run elasticity of GDP with respect to internet-based ICT confirms that digital adoption generates a measurable economic return in Saudi Arabia. Scaling digital infrastructure, through 5G coverage, fiber-to-home penetration, cloud computing adoption in SMEs, and digital skills programs, will not only advance Vision 2030's non-oil GDP targets but will also create positive feedback into long-run income growth, which in turn drives further digital adoption. Policies that break down barriers to ICT adoption among small firms, women entrepreneurs, and non-urban populations will therefore yield multiplier effects across both growth and digital economy dimensions of Vision 2030.

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