

REGULATORY QUALITY, DIGITALIZATION, AND ENVIRONMENTAL PRESSURE: EVIDENCE ON GREENHOUSE GAS EMISSIONS FROM DEVELOPING ECONOMIES

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Abstract

This research examines whether the Environmental Kuznets Curve (EKC), represented by an inverted U-shape, applies to developing countries over the period 1995–2022. To account for differences in development levels, the sample is split into upper-middle-income and lower-middle-income groups. An ARDL panel approach is used to explore both short- and long-run relationships. The EKC framework includes per capita income and its squared term to assess the non-linear connection between economic growth and environmental outcomes. Long-run estimates support the inverted U-shaped EKC for the overall sample and for upper-middle-income countries, with per capita income positively related to emissions and the squared term negative and statistically significant. By contrast, for lower-middle-income countries, income growth continues to increase environmental degradation, and the squared term is not significant, indicating that the EKC turning point has not yet been reached. The analysis also considers the effects of ICT penetration and regulatory quality. Results show that higher internet use is associated with lower long-term emissions, while stronger regulatory frameworks further enhance environmental performance. These findings highlight the critical roles of digitalization and regulatory development in promoting sustainable environmental outcomes.

Keywords: Developing Countries, Energy Policy, Panel Data

JEL Kodlar: C23, F41, Q56

1. Introduction

In recent decades, global warming and climate change have emerged as some of the most critical challenges facing humanity, largely driven by the rapid increase in greenhouse gas (GHG) emissions. According to the 2024 EDGAR report, global GHG emissions increased by 62% between 1990 and 2023, with the largest contributions originating from electricity generation (96%), industrial combustion and processes (91%), transportation (78%), waste management (56%), and fuel extraction (48%). As a result, worldwide emissions reached a record high of 53 Gt CO₂-equivalent in 2023, representing a 1.9% increase (994 Mt CO₂-equivalent) compared to 2022 (European Commission, 2024). Growing concerns over the environmental consequences of these emissions have prompted governments and international organizations to develop policy frameworks to support the adoption of renewable energy and sustainable development. In this context, initiatives such as the Millennium Development Goals and the United Nations' Sustainable Development Goals (SDGs) place environmental sustainability at the center of development strategies, emphasizing the need for countries to integrate sustainable development principles into their policies and address the depletion of natural resources (UNDP, 2025; MDG Monitor, 2025).

Investigating the determinants of GHG emissions has become a central topic in research exploring the relationship between economic activity and environmental outcomes. Within this context, the Environmental Kuznets Curve (EKC) hypothesis has attracted considerable attention. First proposed and empirically tested by Grossman and Krueger (1991), the EKC suggests a non-linear relationship

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where environmental quality initially deteriorates during early stages of development but later improves after per capita income exceeds a certain threshold (Acaravci and Ozturk, 2010; Behera and Dash, 2017). Wawrzyniak and Doryn (2020) attribute this inverted-U pattern to structural shifts in the economy and heightened environmental awareness in high-income nations. However, despite an extensive body of research, empirical findings remain inconclusive. While numerous studies provide evidence supporting the EKC hypothesis (e.g., Apargis and Payne, 2009, 2010; Tiwari et al., 2013; Ozturk and Acaravci, 2013; Lau et al., 2014; Farhani et al., 2014; Kasman and Duman, 2015; Apergis and Ozturk, 2015; Öztürk and Öz, 2016; Solarin et al., 2017), a substantial strand of literature reports results that fail to validate it (Saboori et al., 2012; Chandran and Tang, 2013; Ozturk and Al-Mulali, 2015; Begum et al., 2015; Mert and Bölük, 2016; Abid, 2016; Pablo-Romero and De Jesus, 2016; Özokucu and Özdemir, 2017; Arminen and Menegaki, 2019). These mixed outcomes suggest that the income–environment nexus heavily depends on country-specific conditions, model specifications, and sample periods.

While a substantial body of literature has explored the Environmental Kuznets Curve (EKC) hypothesis, the precise mechanisms through which economic growth decouples from environmental degradation remain fiercely debated. Existing studies have frequently examined the roles of information and communication technologies (ICT) or institutional quality, yet often in isolation or broadly across highly heterogeneous global panels. However, the environmental consequences of digital transformation and regulatory capacity are not uniform; they depend heavily on a country's specific stage of structural and economic development. This study contributes to the literature primarily by unpacking these dynamics comparatively across distinct income classifications. Rather than assuming a homogeneous relationship, we evaluate the determinants of greenhouse gas (GHG) emissions across a full sample of developing economies, as well as distinct upper-middle-income and lower-middle-income subgroups. By applying this comparative dimension, the study provides genuinely new insights into whether the environmental benefits of ICT and institutional reforms require a certain threshold of economic maturity to materialize, thereby explaining the structural differences in emission trajectories between poorer and relatively advanced developing nations.

Our second contribution lies in the conceptual integration of internet penetration and regulatory quality within the EKC framework as joint mechanisms of environmental transition. In this context, the 'percentage of individuals using the internet' is employed as a proxy to represent the digitalization process. It is acknowledged that internet usage is a partial indicator that cannot fully capture advanced processes such as digital industrial automation, and it may inherently correlate with a country's broader economic modernization. Nevertheless, the selection of this variable is strategically driven by its capacity to reflect the dual environmental nature of digital transformation. Internet usage serves not merely as a proxy for broad economic modernization, but specifically captures the transition toward digitalized economic activities—such as e-commerce, digital services, and teleworking—that theoretically substitute physical mobility and optimize logistics, thereby lowering overall energy intensity. This activates an emission-reducing channel, a phenomenon known as the substitution effect (Asongu et al., 2018; Islam et al., 2023; Haseeb et al., 2019; Danish et al., 2019). On the other hand, expanding internet access triggers an energy-increasing channel driven by the massive infrastructure demands, hardware production, and electricity requirements of server networks (Islam et al., 2023).

Because digitalization requires such energy-intensive infrastructure, its net environmental impact is ambiguous. By jointly analyzing this digital transition alongside the quality of regulatory institutions, we investigate whether environmental improvement is driven purely by rising income, or if it fundamentally relies on the synergistic effect of digital efficiency gains and robust environmental governance. While our empirical model utilizes internet usage as a single linear variable, its estimated coefficient effectively captures the net effect of these two conflicting forces, the exact direction of which remains an open empirical question strongly tied to a country's developmental context (Khan et al., 2020; Appiah-Otoo et al., 2022). Our income-based sample split precisely addresses this duality without needing multiple variables: in lower-middle-income countries, the lack of statistical significance suggests that the energy-consuming infrastructure demands currently offset any efficiency gains, as their digital networks are not yet mature enough to yield net environmental benefits. Conversely, in upper-middle-income countries, the significant negative coefficient indicates that the efficiency-enhancing 'substitution effect' has successfully overpowered the initial energy-consuming effects of digitalization. Alongside this conceptual framework, the primary empirical rationale behind utilizing internet penetration stems from severe data constraints. While alternative indicators that measure digitalization

more precisely, such as R&D expenditures, the number of R&D personnel, or investments in artificial intelligence, exist, they suffer from chronic data unavailability, particularly within the lower-middle-income cohort. Employing narrower technological variables would risk a dramatic reduction in the sample size, thereby introducing selection bias and undermining the generalizability of the findings across the broader spectrum of developing nations. Consequently, to provide a robust and generalizable comparative analysis across different income groups, the internet usage rate has been incorporated into the model as the optimal proxy, offering the most comprehensive and continuous dataset for testing these structural transitions. Evaluating these mechanisms across different income groups provides a more nuanced structural explanation for the inverted-U-shaped EKC pattern. In this respect, our framework broadens the approach of Wawrzyniak and Doryn (2020), who focus exclusively on institutional factors, by additionally introducing internet usage as a proxy for ICT development.

The study employs a panel Autoregressive Distributed Lag (ARDL) approach to examine these relationships over the period 1995–2022, utilizing both Pooled Mean Group (PMG) and Mean Group (MG) estimators. The panel ARDL methodology is particularly appropriate as it can handle variables of mixed integration orders, allows short-run adjustment dynamics to differ across countries, and provides robust long-run estimates while reducing potential endogeneity issues.

Our empirical findings carry important policy implications. For both income groups, economic growth continues to exert environmental pressure in both the short and long run. However, internet usage and regulatory quality demonstrate negative and statistically significant effects on emissions only in upper-middle-income countries. This suggests that the environmental dividends of digitalization and institutional strengthening become apparent only once a certain level of economic capacity is reached, offering a forward-looking framework for reducing environmental costs at earlier stages of development.

The article is structured as follows. Section 2 provides a review of the relevant literature. Section 3 details the dataset, model specification, variables, and data sources. Section 4 presents and discusses the empirical results. Finally, Section 5 concludes by summarizing the key findings, outlining policy implications, and suggesting directions for future research.

2. Survey of Literature

The empirical literature on the macroeconomic determinants of greenhouse gas (GHG) emissions is extensive, yet it is characterized by conflicting findings that arise from structural, developmental, and institutional differences across countries. Rather than a uniform relationship, recent studies increasingly suggest that the environmental impacts of economic growth, digital transformation, and governance operate through competing theoretical mechanisms. This section reviews the literature by synthesizing these drivers into three primary analytical frameworks: the structural income-environment nexus, the dual mechanisms of digitalization, and the moderating role of regulatory capacity.

2.1. Structural Drivers and the Income-Environment Nexus

The foundational mechanism linking economic activity to environmental degradation is rooted in a country's stage of structural development. While it is widely accepted that economic growth, reliance on fossil fuels, and demographic expansion inherently drive GHG emissions in developing regions (Behera and Dash, 2017; Pala, 2018; Uzair Ali et al., 2022; Hatmanu et al., 2022; Djellouli et al., 2022; Seçilmiş, 2023; Hunjra et al., 2024; Zhou et al., 2025; Gava et al., 2025), the environmental consequences of global integration, such as trade openness and foreign direct investment (FDI), exhibit profound heterogeneity depending on the host country's income level.

Theoretically, trade openness can trigger an "environmental convergence" through green technology spillovers, or conversely, a "pollution haven" effect where developing nations absorb emission-intensive industries. Empirical evidence strongly supports this bifurcation: trade openness generally reduces emissions in high- and upper-middle-income economies but exacerbates them in low-income settings (Shahbaz et al., 2017; Wang and Zhang, 2021). Similarly, country-specific investigations highlight how structural nuances dictate environmental trajectories. For instance, the mitigating roles of renewable energy and innovation have been extensively documented across various contexts, including China (Jalil and Mahmud, 2009), Pakistan (Ahmed and Long, 2012), Malaysia (Lau et al., 2014; Begum et al., 2025), Turkey (Udemba and Keleş, 2022), Bangladesh (Musa et al., 2024; Miah et al., 2025), Mexico (Raihan et al., 2025), and Kenya (Oluwaseun, 2025). Notably, Xuan (2025) and Minh et al. (2023) demonstrate that in fast-growing economies like Vietnam, shifting the FDI composition toward innovation and

renewable infrastructure is a prerequisite for decoupling emissions from growth (see also Ullah et al., 2022). Furthermore, broader structural drivers such as long-term integration of renewable energy (Pal et al., 2025), transportation infrastructure, and agricultural modernization (Wang, 2025) have been identified as critical yet context-dependent determinants of environmental pressure.

2.2. The Dual Mechanisms of Digital Transformation (ICT)

The literature assessing the environmental footprint of Information and Communication Technologies (ICT) is fiercely debated, primarily because digital transformation impacts the environment through two competing theoretical channels.

The first mechanism proposes an *energy-consuming effect*. Expanding internet access and ICT infrastructure inherently demands massive electricity consumption for hardware production, data centers, and server networks. Supporting this hypothesis, numerous studies link ICT expansion to increased carbon emissions, particularly in emerging and developing markets where power grids remain reliant on fossil fuels (Altinoz et al., 2021; Ebaidalla and Abusin, 2022). Even in advanced economies, some empirical models detect marginal, positive, or no causal emission-reducing effects, warning against the assumption that ICT is inherently "green" (Raheem et al., 2020; Kim, 2022; Gür et al., 2025). The opposing mechanism posits an *efficiency-enhancing substitution effect*. In this view, internet penetration dematerializes the economy by substituting physical mobility with teleworking, optimizing logistics, and promoting e-commerce, thereby lowering overall energy intensity. A substantial strand of literature documents this emission-reducing effect across Asian economies and emerging markets (Wen et al., 2022; Islam et al., 2023; Linghu et al., 2023; Murshed, 2025). Furthermore, studies focusing on advanced economies frequently report long-run environmental benefits stemming from digital transition (Salahuddin et al., 2016; Park et al., 2018; Chang et al., 2022).

This stark divergence in the literature suggests that the net environmental outcome of ICT is non-linear and conditional on a threshold of human capital, infrastructural quality, and economic maturity (Al-Mulali, 2015; Khan et al., 2020; Wang and Xu, 2021; Chatti, 2021; Appiah-Otoo et al., 2022).

2.3. The Moderating Role of Environmental Governance

A third analytical framework emphasizes that economic and technological transitions cannot translate into environmental sustainability without the moderating force of robust regulatory institutions. Strong institutional quality facilitates the strict enforcement of environmental regulations, effectively curbing industrial pollution and promoting green investments (Bond and Kim, 2021).

Empirically, cross-country analyses generally confirm a negative association between institutional quality—such as government effectiveness and corruption control—and environmental degradation (Zhang et al., 2016; Wang et al., 2018; Wawrzyniak and Doryn, 2020; Le and Ozturk, 2020; Karim et al., 2022). This mitigating role has been corroborated across diverse regional panels, including Sub-Saharan Africa (Abid, 2017; Karim et al., 2022), the MENA region (Farzanegan and Markwardt, 2018), Asia (Abbas et al., 2021; Wenlong et al., 2023), and other developing blocs (Hunjra et al., 2023; Almulhim et al., 2025). However, highlighting structural heterogeneity, several scholars report that the effect of institutional quality can be weak, insignificant, or highly context-dependent, particularly in countries lacking the administrative depth to enforce environmental standards (Arminen and Menegaki, 2019; Wenlong et al., 2023).

2.4. Synthesis and Literature Gaps

Despite this extensive body of research, a critical gap remains: the literature predominantly examines the mechanisms of digitalization, institutional quality, and economic growth either in isolation or aggregated broadly across highly heterogeneous global panels. By failing to synthesize the competing forces of ICT's "substitution effect" against its "energy demand," and by overlooking the varying capacities of regulatory enforcement at different developmental stages, previous studies often yield contradictory policy recommendations. This study addresses these shortcomings by conceptually integrating internet usage and regulatory quality into a unified Environmental Kuznets Curve (EKC) framework, evaluating their joint mechanisms comparatively across specifically disaggregated upper-middle and lower-middle-income economies.

3. Research Methodology

Identifying the macroeconomic drivers of greenhouse gas (GHG) emissions is critical for designing sustainable development policies, particularly for developing economies prioritizing rapid economic expansion. Accordingly, this study investigates the determinants of GHG emissions across 59

developing countries over the period 1995–2022 using a panel Autoregressive Distributed Lag (ARDL) framework.

To examine whether these determinants exert heterogeneous effects across varying levels of development, the sample is divided into upper-middle-income (31 countries) and lower-middle-income (28 countries) cohorts based on World Bank (2024) classifications. Specifically, economies with a Gross National Income (GNI) per capita ranging from 1,114 USD to 4,515 USD are classified as lower-middle-income, while those between 4,516 USD and 14,505 USD are categorized as upper-middle-income. The primary selection criterion was the availability of continuous data for all variables spanning the 1995–2022 period.

The empirical baseline model is specified as follows:

$$\ln(GHG)_{it} = \beta_0 + \beta_{i1} \ln(GDPPC)_{it} + \beta_{i2} TRD_{it} + \beta_{i3} FDI_{it} + \beta_{i4} INT_{it} + \beta_{i5} REQ_{it} + \beta_{i6} \ln(POP)_{it} + \varepsilon_{it} \quad (1)$$

In this specification, i denotes the cross-sectional dimension (country), t represents the time dimension, and ε_{it} captures idiosyncratic shocks. The dependent variable, $\ln(GHG)$, refers to the natural logarithm of total greenhouse gas emissions. Among the explanatory variables, $\ln(GDPPC)$ denotes the logarithm of GDP per capita, TRD represents trade openness (the ratio of total trade to GDP), and FDI represents net foreign direct investment inflows as a percentage of GDP. INT is used as a proxy for technological diffusion, measured by the percentage of individuals who use the internet. REQ signifies the regulatory quality of country institutions, serving as a specific proxy for environmental governance and policy implementation capacity. While institutional quality is a broad concept encompassing various dimensions, this study specifically employs 'regulatory quality' as its proxy. This choice is deliberate, as environmental governance—such as enforcing emission standards, implementing carbon pricing, and promoting green investments—fundamentally relies on a government's capacity to formulate and implement sound policies and regulations. Therefore, our conclusions are specifically situated within the context of regulatory capacity rather than overarching institutional structures. Finally, $\ln(POP)$ denotes the logarithm of the total population. Table 1 outlines the selected variables, their definitions, and respective data sources.

The variables, their definitions, and data sources are declared in Table 1.

Table 1. Variables

Abbreviations	Definition	Measurement	Source
GHG	Total Greenhouse Gas Emission	Total Greenhouse Gas Emissions per Capita (t CO ₂ e/capita)	WDI
GDPPC	Gross Domestic per Capita	Gross Domestic per Capita (constant 2015 US\$)	WDI
TRD	Trade Openness	The Ratio of Trade Openness to GDP (Annual %)	WDI
FDI	Foreign Direct Investment	Foreign Direct Investment, Net Inflows (% of GDP)	WDI
INT.	Internet	Individuals using the Internet (% of Population)	WDI
REQ	Regularity Quality	Regulatory Quality of Country Institutions	WDI
POP	Population	Total Population	WDI

NOTE: WDI stands for the World Development Indicators. Source: (WDI, 2025)

Prior to estimating the ARDL model, a series of preliminary econometric tests are necessary to ensure the validity of the panel data. The first step is testing for cross-sectional dependence. Given that the cross-sectional dimension (N) exceeds the time dimension (T) for both the full sample and the upper-middle-income group, the Pesaran (2004) Cross-Sectional Dependence (CD) test is highly appropriate. The CD test evaluates the null hypothesis of cross-sectional independence and is computed as follows:

$$CD = \sqrt{\frac{2}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \quad (2)$$

where $\hat{\rho}_{ij}$ is the estimated pairwise correlation coefficient between the residuals of cross-sectional units i and j .

The second preliminary step involves testing whether the slope coefficients are homogeneous across cross-sectional units. We employ the slope homogeneity test developed by Pesaran and Yamagata (2008), which builds upon the Swamy (1970) approach. The foundational Swamy test statistic is defined as:

$$S = \sum_{i=1}^N (\hat{\beta}_i - \hat{\beta}_W)' \hat{V}_i^{-1} (\hat{\beta}_i - \hat{\beta}_W) \quad (3)$$

where $\hat{\beta}_i$ is the estimated coefficient for each cross-section, $\hat{\beta}_W$ is the pooled weighted average coefficient, and $\hat{V}_i^{-1}$ is the inverse of the variance-covariance matrix. Pesaran and Yamagata (2008) adapt this statistic into standardized ($\hat{\Delta}$) and bias-adjusted ($\hat{\Delta}_{adj.}$) versions, where the null hypothesis assumes that slope parameters are identical across all units ($\beta_i = \beta$):

$$\hat{\Delta} = \frac{\sqrt{NN^{-1}(\hat{S}-K)}}{\sqrt{2K}} \quad (4)$$

$\hat{S}$ denotes the Swamy test statistic, while K represents the number of explanatory variables in the model. The test statistic is asymptotically valid for large samples. Pesaran and Yamagata (2008) propose an alternative version of this test that is more suitable for small samples and develop a bias-adjusted statistic to improve its finite-sample properties. This test statistic is for large samples. Pesaran and Yamagata (2008) propose a different version of this test for small samples, and a bias-adjusted version is developed. The bias-adjusted version of this test can be written as follows:

$$\hat{\Delta} = \frac{\sqrt{NN^{-1}(\hat{S}-E(S))}}{\sqrt{Var(S)}} \quad (5)$$

The terms $E(S)$ and $Var(S)$ denote the small-sample adjusted expressions of the expected value and variance, respectively. Under the null hypothesis, the slope parameters are assumed to be identical across cross-sectional units ($\beta_i = \beta$). In contrast, the alternative hypothesis allows the slope parameters to differ, indicating heterogeneity among the units ($\beta_i \neq \beta$).

Following the examination of cross-sectional dependence and slope homogeneity, the next step is to identify the order of integration of the selected variables. To this end, panel unit root tests are conducted for each variable. The choice of unit root test depends on whether cross-sectional dependence is present. When cross-sectional dependence is detected, second-generation panel unit root tests are employed. Among these, the Cross-Sectionally Augmented Im-Pesaran-Shin (CIPS) test, introduced by Pesaran (2007), is one of the most frequently applied methods in empirical studies.

The Cross-Sectional Augmented Dickey-Fuller (CADF) test is a panel-data-based extension of the conventional Augmented Dickey-Fuller (ADF) procedure and constitutes a fundamental building block of the Cross-Sectionally Augmented IPS (CIPS) test introduced by Pesaran (2007). By incorporating cross-sectional averages into the standard ADF framework, the CADF approach adjusts the analysis to account for cross-sectional dependence across units. For this reason, both CADF and CIPS are classified as second-generation panel unit root tests and are widely utilized in empirical research where cross-sectional dependence is a concern.

The CADF test is an adaptation of the classical Augmented Dickey-Fuller (ADF) test for panel data. The main difference is that the cross-sectional average of the panel and its lags are added to the stationarity test for each unit. In this way, the effect of common shocks that may affect all units of the panel is included in the model, and cross-sectional dependence is controlled. The CADF regression equation is expressed as follows:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i \bar{y}_{t-1} + \sum_{p=1}^P \varphi_{ip} \Delta y_{i,t-p} + \sum_{p=0}^P \delta_{ip} \Delta \bar{y}_{t-p} + \varepsilon_{it} \quad (6)$$

In Equation (6), $\bar{y}_{t-1}$ and $\Delta \bar{y}_{t-p}$ represent the lagged cross-sectional mean and the cross-sectional mean of the first-differenced series, respectively. While the t-statistics derived from the CADF regressions provide information at the individual cross-sectional level, panel-wide inference is conducted using the CIPS statistic. After estimating the CADF equation separately for each cross-sectional unit i , the t-statistics corresponding to the lagged level term of the dependent variable are computed. The CIPS statistic is then obtained by taking the arithmetic average of these individual t-values across all units (Baltagi, 2005). Accordingly, the CIPS test is defined as the simple mean of the CADF t-statistics calculated for each cross-section and can be expressed as follows:

$$CIPS = \frac{1}{N} \sum_{i=1}^N t_{CADF,i} \quad (7)$$

Under the CIPS framework, the null hypothesis states that all cross-sectional units contain a unit root, implying that none of the series is stationary. In contrast, the alternative hypothesis allows for stationarity in at least a fraction of the panel units. Accordingly, rejection of the null suggests that stationarity holds for at least some cross-sectional members of the panel.

The empirical model specification is determined based on the results of the unit root tests. When the variables exhibit different integration orders, both short-run and long-run dynamics are analyzed using the Panel Autoregressive Distributed Lag (ARDL) framework proposed by Pesaran et al. (2007). This

methodology is specifically chosen as our primary econometric identification strategy for several reasons. First, it efficiently handles variables with mixed integration orders (I(0) and I(1)). Second, unlike traditional panel estimators, the ARDL framework, particularly through the Mean Group (MG) estimator, effectively controls for unobserved cross-sectional heterogeneity by allowing short-run dynamics, intercepts, and error variances to differ across our highly diverse developing country panels. Finally, by appropriately augmenting the model with sufficient lags, the ARDL specification helps mitigate potential dynamic endogeneity issues and reverse causality, thereby yielding consistent and robust long-run estimates. The long-run panel ARDL specification corresponding to Model 1 is presented in Equation (8).

$$\ln(GHG)_{it} = \alpha_i + \sum_{j=1}^p \beta_{ij} \ln(GHG)_{i,t-j} + \sum_{j=0}^q \theta_{ij} \ln(GDPPC)_{i,t-j} + \sum_{j=0}^k \gamma_{ij} TRD_{i,t-j} + \sum_{j=0}^l \mu_{ij} FDI_{i,t-j} + \sum_{j=0}^m \tau_{ij} INT_{i,t-j} + \sum_{j=0}^n \varphi_{ij} REQ_{i,t-j} + \sum_{j=0}^r \omega_{ij} \ln(POP)_{i,t-j} + \epsilon_{it} \quad (8)$$

Furthermore, Equation (9) outlines the error correction specification of the Panel ARDL framework.

$$\Delta \ln(GHG)_{it} = \alpha_i + \varphi_i \ln(GHG)_{i,t-1} + \theta_{ij} \ln(GDPPC)_{i,t} + \gamma_{ij} TRD_{i,t} + \mu_{ij} FDI_{i,t} + \tau_{ij} INT_{i,t} + \varphi_{ij} REQ_{i,t} + \omega_{it} \ln(POP)_{i,t} + \sum_{j=1}^{p-1} \beta_{ij}^* \Delta \ln(GHG)_{i,t-j} + \sum_{j=0}^q \theta_{ij}^* \Delta \ln(GDPPC)_{i,t-j} + \sum_{j=0}^k \gamma_{ij}^* \Delta TRD_{i,t-j} + \sum_{j=0}^l \mu_{ij}^* \Delta FDI_{i,t-j} + \sum_{j=0}^m \tau_{ij}^* \Delta INT_{i,t-j} + \sum_{j=0}^n \varphi_{ij}^* \Delta REQ_{i,t-j} + \sum_{j=0}^r \omega_{ij}^* \Delta \ln(POP)_{i,t-j} + \vartheta_{it} \quad (9)$$

In Equation (9), the short-run adjustments are reflected in the coefficients ($\beta_{ij}^*, \theta_{ij}^*, \gamma_{ij}^*, \mu_{ij}^*, \tau_{ij}^*, \varphi_{ij}^*, \omega_{ij}^*$), which correspond to the first-differenced terms of the variables. The parameter φ_i , on the other hand, denotes the error-correction coefficient and measures the speed at which the system converges back to its long-run equilibrium following a short-run deviation.

Within the panel ARDL framework, parameter estimation is conducted using two alternative estimators: the Mean Group (MG) and the Pooled Mean Group (PMG). The MG estimator allows for full heterogeneity by running separate regressions for each country and subsequently averaging the country-specific estimates. In contrast, the PMG estimator imposes long-run homogeneity—assuming that the long-run equilibrium relationship is common across all countries—while permitting short-run dynamics, intercepts, and error variances to remain heterogeneous. The Hausman test is formally applied to assess parameter homogeneity and select the most consistent and efficient estimator between the two.

4. Empirical Results

Table 2 presents the descriptive statistics of the variables used in the analysis, disaggregated by country cohorts. On average, the upper-middle-income economies exhibit higher and more volatile greenhouse gas (GHG) emissions (Mean = 1.593, SD = 0.504) compared to the lower-middle-income group (Mean = 0.736, SD = 0.464). A similar structural pattern is observed for per capita GDP, internet usage, and regulatory quality, where upper-middle-income countries consistently display higher average values. Furthermore, the Jarque–Bera test statistics firmly reject the null hypothesis of normal distribution for all variables across all groups ($p < 0.01$), with right-skewed and leptokurtic tendencies indicating the presence of outliers and extreme values, particularly within the lower-middle-income cohort.

Table 2. Descriptive Statistics

Variables	Obs.	Avg.	Med.	Max.	Min.	Std.Dev.	Skew.	Kurt.	J-B.	Prob.
All Developing Countries										
GHG	1652	1.186	1.156	3.013	-0.353	0.647	0.157	2.454	27.234*	0.000
GDPPC	1652	7.690	8.092	9.551	6.169	0.780	-0.174	2.058	69.410*	0.000
TRD	1652	74.136	68.633	220.407	15.636	33.648	0.835	3.703	225.612*	0.000
FDI	1652	3.280	2.373	55.073	-17.292	4.005	4.210	43.734	119093*	0.000
INT	1652	28.843	12.240	97.399	0.000	25.984	0.930	2.598	249.388*	0.000
REQ	1652	-0.302	-0.288	1.197	-2.201	0.544	-0.288	3.143	24.264*	0.000
POP	1652	16.555	16.395	21.078	12.227	1.680	0.259	3.344	26.535*	0.000
Upper-Middle Income Countries										
GHG	868	1.593	1.591	3.013	0.400	0.504	0.189	2.569	11.897*	0.003

GDPPC	868	8.519	8.535	9.551	6.838	0.498	-0.465	3.496	40.243*	0.000
TRD	868	76.300	71.506	220.407	15.636	34.675	0.924	4.200	175.547*	0.000
FDI	868	3.473	2.703	55.073	-7.596	4.249	5.607	58.081	114270.7*	0.000
INT	868	30.259	21.805	97.399	0.000	28.050	0.541	1.905	85.733*	0.000
REQ	868	-0.100	-0.022	1.197	-1.709	0.560	-0.635	3.220	60.133*	0.000
POP	868	16.408	16.350	21.069	12.227	1.853	0.228	2.693	10.892*	0.000
Lower-Middle Income Countries										
GHG	784	0.736	0.697	1.970	-0.353	0.464	0.270	2.503	17.613*	0.000
GDPPC	784	7.342	7.257	9.100	6.169	0.589	0.504	3.105	33.525*	0.000
TRD	784	71.739	64.499	186.676	17.225	32.327	0.688	2.812	63.078*	0.000
FDI	784	3.067	1.949	34.418	-17.292	3.706	1.790	13.086	3741.642*	0.000
INT	784	16.740	6.500	90.500	0.000	21.361	1.459	4.324	335.510*	0.000
REQ	784	-0.525	-0.455	0.339	-2.202	0.427	-0.776	4.008	11.809*	0.000
POP	784	16.717	16.412	21.078	12.944	1.450	0.536	4.559	116.915*	0.000

Note: Authors' own calculation.

Table 3 outlines the pairwise correlation matrix. For both the full sample and the respective income subgroups, GHG emissions consistently show a positive and significant correlation with per capita GDP and internet usage. Notably, regulatory quality exhibits a negative correlation with emissions in upper-middle-income countries but lacks significance in the lower-middle-income group, foreshadowing the structural heterogeneity explored in the subsequent regression analysis.

Table 3. Correlation Matrix								
Variables	GHG	GDPPC	TRD	FDI	INT	REQ	POP	
All Developing Countries								
GHG	1.000	--	--	--	--	--	--	
GDPPC	0.789* (0.000)	1.000	--	--	--	--	--	
TRD	0.235* (0.000)	0.151* (0.000)	1.000	--	--	--	--	
FDI	0.092* (0.000)	0.062** (0.012)	0.307* (0.000)	1.000	--	--	--	
INT	0.384* (0.000)	0.538* (0.000)	0.118* (0.000)	-0.004 (0.878)	1.000	--	--	
REQ	0.194* (0.000)	0.471* (0.000)	0.170* (0.000)	0.111* (0.000)	0.202* (0.000)	1.000	--	
POP	0.081* (0.001)	-0.089* (0.000)	-0.461* (0.000)	-0.223* (0.000)	-0.006 (0.824)	-0.138 (0.000)	1.000	
Upper-Middle Income Countries								
GHG	1.000	--	--	--	--	--	--	
GDPPC	0.424* (0.000)	1.000	--	--	--	--	--	
TRD	0.043 (0.203)	-0.096* (0.005)	1.000	--	--	--	--	
FDI	-0.069** (0.042)	-0.179* (0.000)	0.175* (0.000)	1.000	--	--	--	
INT	0.225* (0.000)	0.522* (0.000)	0.028 (0.417)	-0.066*** (0.051)	1.000	--	--	
REQ	-0.182* (0.000)	0.294* (0.000)	0.160* (0.000)	0.019 (0.568)	0.092* (0.007)	1.000	--	
POP	0.421* (0.000)	0.163* (0.000)	-0.499* (0.000)	-0.190* (0.000)	0.047 (0.166)	-0.167* (0.000)	1.000	
Lower-Middle Income Countries								
GHG	1.000	--	--	--	--	--	--	

GDPPC	0.657* (0.000)	1.000	--	--	--	--	--
TRD	0.525* (0.000)	0.398* (0.000)	1.000	--	--	--	--
FDI	0.280* (0.000)	0.268* (0.000)	0.481* (0.000)	1.000	--	--	--
INT	0.403* (0.000)	0.568* (0.000)	0.225* (0.000)	0.064*** (0.078)	1.000	--	--
REQ	0.044 (0.216)	0.311* (0.000)	0.154* (0.000)	0.233* (0.000)	0.152 (0.000)	1.000	--
POP	-0.166* (0.000)	-0.266* (0.000)	-0.400* (0.000)	-0.270* (0.000)	-0.033 (0.359)	-0.009 (0.809)	1.000

Note: Probability values are in parentheses. *, **, and *** denote the statistically significant at the 1 %, 5 %, and % 10 levels, respectively.

Prior to the primary ARDL estimations, the structural properties of the panel were evaluated. As reported in Table 4, the Pesaran (2004) Cross-Sectional Dependence (CD) test strongly rejects the null hypothesis of cross-sectional independence for nearly all variables, indicating significant interconnectedness across the sampled economies. Furthermore, the Pesaran and Yamagata (2008) slope homogeneity test (Table 5) confirms that the slope coefficients are heterogeneous across all panels ($\hat{\Delta}$ and $\hat{\Delta}_{adj}$. $p < 0.01$).

Table 4. Cross-Dependence Test

Pesaran CD Test		
Variables	Stats.	Prob.
All Developing Countries		
GHG	70.275*	0.000
GDPPC	163.240*	0.000
TRD	29.920*	0.000
FDI	26.860*	0.000
INT	205.950*	0.000
REQ	5.940*	0.000
POP	147.980*	0.000
Upper-Middle Income Countries		
GHG	34.400*	0.000
GDPPC	94.050*	0.000
TRD	16.190*	0.000
FDI	13.760*	0.000
INT	109.310*	0.000
REQ	-0.870	0.382
POP	50.160*	0.000
Lower-Middle Income Countries		
GHG	36.250*	0.000
GDPPC	68.520*	0.000
TRD	14.130*	0.000
FDI	16.210*	0.000
INT	97.010*	0.000
REQ	7.370*	0.000
POP	101.020*	0.000

Note: Probability values are in parentheses. *, **, and *** denotes the statistically significant at the 1 % level, 5 %, and % 10 levels, respectively.

Table 5. Test for the Slope Homogeneity

Variables	Delta		Delta-Adjusted	
	Stats.	Prob.	Stats.	Prob.
Full Sample	31.406*	0.000	37.161*	0.000
Upper Middle Income	21.388 *	0.000	25.306*	0.000

Lower Middle Income	21.447*	0.000	25.376*	0.000
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Note: Probability values are in parentheses. *, **, and *** denote the statistically significant at the 1 %, 5 %, and % 10 levels, respectively.

Given the confirmation of cross-sectional dependence and heterogeneity, the second-generation CIPS panel unit root test was applied (Table 6). The findings reveal a mixed order of integration among the variables, with some series stationary in levels I(0) and others becoming stationary after first differencing I(1). This mixed integration order mathematically justifies the implementation of the Panel ARDL framework.

Table 6. Results of Panel Unit Root Tests

Variable s	Constant		Constant and Trend		Constant		Constant and Trend		Integr- ation Degree
	Stats	Prob.	Stats	Prob.	Stats	Prob.	Stats	Prob.	
	Level		Level		1 st Difference		1 st Difference		
All Developing Countries									
Results of the CIPS Unit Root Test									
GHG	-0.444	0.671	0.444	0.671	-13.653*	0.00 0	-10.854*	0.000	I(1)
GDPPC	-0.766	0.222	1.585	0.944	-8.483*	0.00 0	-7.566*	0.000	I(1)
TRD	1.319	0.906	-1.150	0.125	-13.678*	0.00 0	-10.491*	0.000	I(1)
FDI	-7.670*	0.000	-7.080*	0.000	-21.181*	0.00 0	-17.187*	0.000	I(0)
INT	-0.079	0.468	3.149	0.999	-6.780*	0.00 0	-3.736*	0.000	I(1)
REQ	-0.674	0.250	-1.872**	0.031	-14.165*	0.00 0	-11.862*	0.000	I(1)
POP	-3.075*	0.001	- 1.400***	0.081	-3.334*	0.00 0	-5.871*	0.000	I(0)
Upper-Middle Income Countries									
Results of the CIPS Unit Root Test									
GHG	-2.568*	0.005	-1.034	0.151	-10.791*	0.00 0	-9.034*	0.000	I(1)
GDPPC	-0.742	0.229	0.887	0.813	-6.161*	0.00 0	-6.571*	0.000	I(1)
TRD	-0.389	0.349	-0.469	0.680	-9.976*	0.00 0	-7.864*	0.000	I(1)
FDI	-6.485*	0.000	-6.995*	0.000	-15.336*	0.00 0	-12.196*	0.000	I(0)
INT	-1.756**	0.040	-0.582	0.280	-6.533*	0.00 0	-4.309*	0.000	I(1)
REQ	0.035	0.514	-1.050	0.147	-9.308*	0.00 0	-7.426*	0.000	I(1)
POP	-1.057	0.145	1.185	0.882	- 1.465***	0.07 1	-4.512*	0.000	I(1)
Lower-Middle Income Countries									
Results of the CIPS Unit Root Test									
GHG	-0.406	0.342	2.537	0.994	-9.016*	0.00 0	-7.027*	0.000	I(1)
GDPPC	0.952	0.829	2.355	0.991	-5.097*	0.00 0	-4.838*	0.000	I(1)
TRD	- 1.455***	0.073	-3.762*	0.000	-10.162*	0.00 0	-7.801*	0.000	I(0)
FDI	-4.433*	0.000	-3.549*	0.000	-13.465*	0.00 0	-11.128*	0.000	I(0)
INT	-0.413	0.340	0.175	0.569	-5.502*	0.00 0	-2.367*	0.009	I(1)
REQ	-0.998	0.159	-0.784	0.216	-9.862*	0.00 0	-8.209*	0.000	I(1)
POP	-2.820*	0.002	-0.413	0.340	-1.280*	0.00 0	-3.022*	0.001	I(1)

Notes: Confidence levels of %1, %5, and %10 are expressed as *, **, *** respectively. Lag numbers are determined by the Akaike Information Criteria (AIC).

Table 7 presents the short- and long-run estimates of the panel ARDL models. The lag selection process was guided by the Akaike Information Criterion (AIC), resulting in an ARDL(1,1,1,1,1) specification. Regarding the lag structure, we adopted a maximum lag length of one for all variables across our panels.

This restriction is driven by the limited time dimension of our annual data; in the context of a heterogeneous Mean Group (MG) estimator, higher-order lag specifications would rapidly deplete degrees of freedom, leading to over-parameterization and unreliable estimates. To ensure the robustness of our results, we performed sensitivity analyses by allowing the Akaike Information Criterion (AIC) to select optimal lag lengths up to two. These robustness tests consistently demonstrated that the sign and statistical significance of our long-run coefficients remained invariant, confirming that our core conclusions are not artifacts of the restricted lag structure.

The Hausman statistics for all country groups lead to the rejection of the null hypothesis that the PMG estimator is both consistent and efficient in estimating the long-run coefficients. Consequently, the interpretation focuses on the Panel Mean Group estimates. For the lower middle income group, the Hausman test yields a p-value of 0.093, which represents a borderline case that is only weakly significant at the 10% level. Unlike the rejection observed in the all developing country group and the upper middle income group, this borderline result suggests that lower middle income countries share certain structural similarities in their long-run environmental trajectories, making the restriction of long-run homogeneity (PMG) almost plausible. These countries often face similar early-stage developmental challenges, such as heavily reliance on fossil fuels and parallel struggles in building digital infrastructure, which creates a more homogeneous long-run pattern compared to more developed countries. However, despite this borderline homogeneity, the MG estimator was ultimately preferred for the baseline analysis to maintain methodological consistency across all subgroups and to avoid imposing overly restrictive assumptions on their inherently heterogeneous institutional capacities.

In the short-run dynamics, the error correction terms (ECT (-1)) are negative and statistically significant across all cohorts, confirming the system's convergence to long-run equilibrium. However, the speed of adjustment varies notably: lower-middle-income countries converge most rapidly (eliminating 43.6% of deviations per period), followed by upper-middle-income countries (25.7%) and the full sample (12.7%).

Table 7. Estimation Results of ARDL Models

Models: ARDL(1,1,1,1,1)	Long-Run		Short-Run	
	Coefficient	Prob.	Coefficient	Prob.
All Developing Countries				
GDPPC	0.389*	0.000	0.464*	0.000
GDPPC^2	-0.056**	0.025	0.025*	0.000
TRD	-0.001	0.156	0.0001	0.131
FDI	0.005	0.159	-0.0002	0.876
INT	-0.001*	0.035	-0.0003	0.583
REQ	-0.057**	0.024	-0.003	0.827
POP	0.105*	0.000	-0.494	0.256
ECT(-1)	--	--	-0.127*	0.000
Constant	--	--	0.484*	0.000
Hausman Test	24.467*	0.000	--	--
Upper-Middle Income Countries				
GDPPC	0.607*	0.000	0.433*	0.000
GDPPC^2	-0.159*	0.000	0.959	0.229
TRD	0.001*	0.000	0.001	0.275
FDI	-0.001	0.753	-0.001	0.465
INT	-0.001**	0.015	-0.003*	0.102
REQ	-0.073**	0.012	0.023	0.188
POP	0.180**	0.025	-2.112***	0.073
ECT(-1)	--	--	-0.257	0.000
Constant	--	--	1.010	0.000
Hausman Test	14.791**	0.022	--	--
Lower-Middle Income Countries				
GDPPC	0.317*	0.000	0.272*	0.000
GDPPC^2	0.019	0.466	-1.996	0.197
TRD	0.000	0.808	0.000	0.936

FDI	-0.001	0.552	0.003***	0.071
INT	-0.001	0.725	0.001	0.714
REQ	-0.075	0.250	-0.028	0.200
POP	0.818*	0.000	-0.284	0.873
ECT(-1)	--	--	-0.436*	0.000
Constant	--	--	--	--
Hausman Test	10.857***	0.093	--	--

Notes: Confidence levels of %1, %5, and %10 are expressed as *, **, *** respectively. Lag numbers are determined by the Akaike Information Criteria (AIC).

In the long run, the estimates yield divergent evidence regarding the Environmental Kuznets Curve (EKC) hypothesis across income groups. For the full sample and the upper-middle-income cohort, the coefficient of per capita GDP is positive, while its squared term ($GDPPC^2$) is negative and statistically significant. These signs mathematically satisfy the conditions of the inverted U-shaped EKC. Conversely, in the lower-middle-income group, the squared income term lacks statistical significance. This implies that these economies remain on the upward-sloping segment of the curve, where economic expansion strictly correlates with heightened environmental degradation, and no turning point has yet been reached.

To assess the economic validity of the EKC framework for the significant models, we calculated the implied turning points of per capita income (in natural logarithms) using the standard formulation, $-\frac{\beta_1}{2\beta_2}$, as widely adopted in the literature (Dinda, 2004; Stern, 2004). Based on our long-run MG estimates, the implied turning points for per capita income (logarithmically) are 3.47 for the full sample and 1.90 for the upper-middle-income group. However, referring to the descriptive statistics (Table 2), the observed $\ln(GDPPC)$ values in our sample range from 6.169 to 9.551. Since these calculated turning points fall significantly below the minimum observed income levels of our sample, the empirical evidence suggests that these economies are already operating on the downward-sloping segment of the inverted-U curve in the long run. While the mechanical conditions of the EKC ($-\frac{\beta_1}{2\beta_2} < 0$) are met, the location of the turning point outside the observed data range requires cautious interpretation, as also highlighted by Narayan and Narayan (2010). This finding suggests that the decoupling of emissions from economic growth may structurally differ from traditional EKC trajectories in these specific nations.

Beyond income effects, the long-run estimates highlight the critical structural roles of digitalization and governance. For the full sample and upper-middle-income countries, internet usage (INT) and regulatory quality (REQ) display negative and statistically significant coefficients, indicating that technological diffusion and stronger environmental governance effectively mitigate emissions. In stark contrast, these variables lack statistical significance in the lower-middle-income group. This discrepancy strongly suggests that the environmental dividends of digital transformation and institutional capacity become operational only once an economy reaches a certain level of developmental maturity.

Among other control variables, population growth consistently correlates with higher emissions across all subgroups. Trade openness exacerbates emissions solely in upper-middle-income countries, likely reflecting energy-intensive export production, while FDI exhibits no significant long-run association across the panels.

Finally, the short-run estimates reveal that most explanatory variables lack significant associations with GHG emissions, with the notable exception of per capita GDP, which maintains a positive relationship. This implies that while economic growth immediately drives environmental pressures, structural mitigation efforts—such as internet penetration and regulatory reforms require a long-term horizon to yield environmental benefits.

5. Conclusions

This study investigates the drivers of greenhouse gas (GHG) emissions across 59 developing countries over the 1995–2022 period. Utilizing a panel ARDL framework, we extend the conventional Environmental Kuznets Curve (EKC) specification by integrating internet usage as a proxy for ICT development and regulatory quality as an indicator of environmental governance. Furthermore, by disaggregating our sample into upper-middle-income and lower-middle-income cohorts, we explore

whether the environmental impact of economic growth, trade openness, FDI, and digitalization varies by development level.

Our empirical findings yield several key insights. First, per capita GDP shows a positive and statistically significant association with GHG emissions in both the short and long run across all groups. The long-run estimates confirm the inverted U-shaped EKC hypothesis for the full sample and upper-middle-income countries, though the implied turning points calculated using the exponential formulation fall outside the observed income range. This suggests that while the mechanical conditions for an EKC are met, the decoupling process in these nations may be structurally distinct from traditional hypotheses. Conversely, lower-middle-income economies remain on the upward-sloping segment of the curve, where economic expansion continues to correlate with heightened environmental pressure.

Second, the environmental roles of digitalization and regulatory quality appear contingent on economic maturity. Internet usage and regulatory quality exhibit significant, negative long-run associations with emissions exclusively in upper-middle-income countries. This suggests that the efficiency-enhancing "substitution effect" of digital transformation, facilitated by e-commerce, remote work, and optimized logistics, and the implementation of credible environmental regulations materialize only after a specific threshold of development is achieved. In lower-middle-income economies, however, the energy-consuming infrastructure demands of digital expansion currently offset these potential efficiency gains. Finally, our results indicate that trade openness exerts additional environmental pressure in upper-middle-income countries, whereas population growth remains a consistent driver of emissions across all cohorts.

Our empirical results provide tailored policy implications, acknowledging that the environmental dividends of digitalization and institutional reform are contingent on a country's developmental stage.

For upper-middle-income countries, where ICT and regulatory quality demonstrate significant emission-mitigating effects, policies should focus on consolidating these gains. Expanding 'smart' grid infrastructure and enforcing stringent green-ICT standards will further leverage the existing substitution effect.

For lower-middle-income countries, however, our findings reveal that these drivers are not yet effectively mitigating emissions, likely due to structural bottlenecks. We hypothesize that in these economies, ICT expansion is currently triggering an energy-intensive infrastructure buildup that outpaces efficiency gains. Therefore, for this group, policy should prioritize complementary investments, specifically upgrading basic electricity infrastructure to clean sources, before accelerating digital expansion to ensure that digitalization acts as a catalyst for sustainability rather than a source of increased energy demand. Furthermore, the insignificance of regulatory quality in this cohort suggests that institutions may lack the administrative depth to enforce environmental standards effectively. In these settings, institutional reform should prioritize foundational capacity building and public-sector transparency as prerequisites for more complex environmental governance.

While our study provides robust long-run associations, it remains subject to certain limitations. First, ICT and governance are multidimensional; future research could employ broader institutional indices and alternative technological indicators. Second, although the panel ARDL framework addresses dynamic endogeneity, the complex, jointly determined nature of these processes suggests that future studies could utilize instrumental variable (IV) approaches or GMM estimations to further isolate causal pathways.

Finally, although splitting the sample into income groups provides valuable comparative insights, it is important to acknowledge that this approach relies on indirect inference from differences across subgroups rather than on estimating a direct continuous threshold effect. The observed variations between upper middle and lower middle income countries might also reflect omitted structural heterogeneities across these regions rather than a strictly income-driven developmental threshold. Therefore, the findings regarding developmental thresholds should be interpreted with caution as strong statistical associations rather than as deterministic or structural pathways. Future research could address this limitation by employing advanced non-linear techniques, such as Panel Threshold Regression models or interaction terms, to directly estimate the specific threshold levels.

In conclusion, our results demonstrate that economic growth is not inherently incompatible with environmental quality. Once a sufficient level of development is reached, digital transformation and regulatory strengthening act as key catalysts for decoupling emissions from economic activity.

Sustainable progress thus requires a coordinated strategy that simultaneously advances economic maturity, technological modernization, and governance reform.

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