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Assessing the Impact of ICT and the Transition from 2G to 5G on CO₂ Emissions

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Assessing the Impact of ICT and the Transition from 2G to 5G on CO₂ Emissions

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The opinions and analysis in this paper are solely those of the authors and do not represent the official stance or policies of the NBTC.

Abstract

This study examines the environmental impact of global ICT expansion, focusing on CO₂ emissions across 173 countries from 2000 to 2021 using a one-step difference GMM. The findings reveal a two-phase relationship: Early-stage ICT deployment tends to increase emissions; however, as adoption expands, emissions are significantly reduced. The environmental impact of upgrading to 4G/5G networks is not uniform. For nations primarily reliant on 2G/3G infrastructure, the transition yields immediate environmental benefits. Conversely, in advanced ICT nations, the rollout may initially increase emissions, an effect that is later offset by substantial long-term reductions. The study concludes that ICT development does not automatically guarantee environmental benefits. Strategic policies—such as managing the full life cycle of ICT infrastructure from production to disposal, promoting renewable power in the ICT sector, and phasing out legacy networks—are essential to align ICT growth with decarbonization goals.

Keywords: ICT, Mobile Cellular Network, CO₂ Emissions

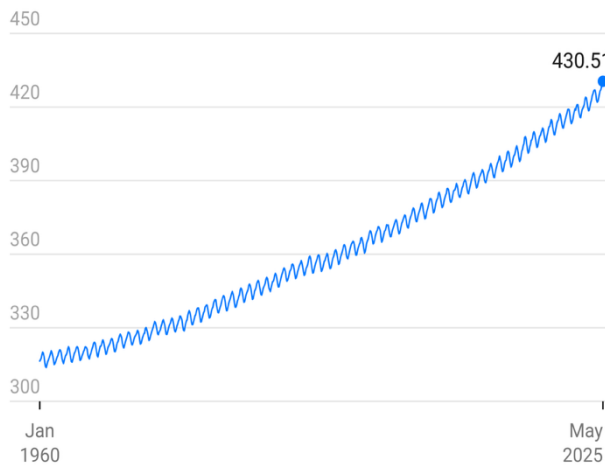
1. Introduction

The global climate crisis has reached a critical juncture. In 2024, the average global surface temperature from January to September rose to $1.54 \pm 0.13^{\circ}\text{C}$ above pre-industrial levels (World Meteorological Organization [WMO], 2024), surpassing the 1.5°C threshold. A 1.5°C increase represents the target limit reaffirmed at COP27 to avoid the most severe impacts of climate change, while a 2°C rise is widely regarded as the critical threshold beyond which the risk of catastrophic and irreversible consequences significantly escalates (United Nations Framework Convention on Climate Change [UNFCCC], 2023). This temperature rise poses serious challenges to the goals outlined in the Paris Agreement. It is primarily driven by anthropogenic greenhouse gas emissions. Carbon dioxide (CO₂) is the dominant greenhouse gas, accounting for approximately 74% of total global emissions when including all sources like land use. The vast majority of this comes from fossil fuels and industry, which alone contribute about 64% of total greenhouse gases (Intergovernmental Panel on Climate Change [IPCC], 2022). Since the beginning of the industrial period in the 18th century, human activities have increased atmospheric CO₂ concentrations by roughly 50% (NASA, 2025a). This ongoing warming is intensifying the frequency and severity of climate-related disruptions, from extreme weather events to ecosystem degradation. These developments lacking underscore the mounting difficulty of achieving the global target of net-zero emissions by 2050. As temperatures continue to rise, societies face increasingly interconnected environmental, economic, and social risks that threaten sustainable development and human well-being

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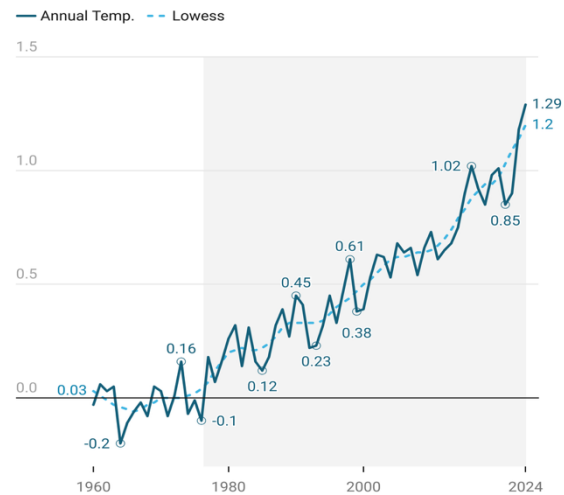
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Fig 1. Average Atmospheric CO₂ Levels (ppm), 1960 – 2025



Source: climate.nasa.gov

Fig 2. Average Global Surface Temperature (°C), 1960 - 2024



Amid accelerating climate concerns, the rapid expansion of digital technologies presents both significant opportunities and environmental challenges. The widespread integration of information and communication technologies (ICTs)—including digital services, artificial intelligence, cloud computing, and the Internet of Things—has reshaped economies and lifestyles. However, this digital transformation comes with a rising environmental cost, as the rapid growth in digital services drives substantial increases in data consumption and computing workloads. To illustrate, global internet traffic surged by over 600% between 2015 and 2022, while data center workloads rose by 340%. Although significant advances in energy efficiency helped moderate the impact of a 78% increase in internet users during this period, absolute energy use continues to climb. Data centers and data transmission networks each currently account for approximately 1–1.5% of global electricity use. Moreover, their consumption is growing rapidly; between 2015 and 2022, electricity use grew by 20–70% for data centers (excluding cryptocurrency) and by 18–64% for data networks (International Energy Agency [IEA], 2023).

Beyond operational energy use, ICT also contributes to environmental degradation through electronic waste (e-waste). According to Forti et al. (2020), global e-waste generation reached 53.6 Mt in 2019 and is projected to nearly double by 2030. With less than one-fifth properly recycled, the remaining waste contributes to hazardous pollution and significant resource inefficiencies, particularly in regions that lack formal recycling infrastructure.

Despite its growing energy demands and the environmental burden associated with electronic waste, the ICT sector holds significant potential as an enabler of decarbonization. When strategically implemented, digital technologies can reduce emissions across multiple sectors through practical applications such as smart grids that balance electricity supply and demand, intelligent transport systems that optimize traffic flow and reduce fuel use, real-time industrial monitoring to enhance process efficiency, remote work platforms that lower commuting-related emissions, and automation tools that streamline operations. According to the GeSI SMARTer2030 report, these enabling effects could contribute to a 20% reduction in global CO₂ emissions by 2030, representing an abatement potential ten times greater than the ICT sector's own footprint (Global e-Sustainability Initiative [GeSI], 2015).

The dual role illustrates the value of assessing the environmental implications of ICT. While often regarded as a source of emissions, ICT also offers essential tools for climate change mitigation. The central challenge lies in balancing its increasing energy consumption with its capacity to drive systemic emissions reductions—particularly when supported by robust climate governance and a coordinated transition to low-carbon energy sources.

This study examines the relationship between CO₂ emissions and ICT development, providing critical insights for researchers, policymakers, and industry stakeholders who are striving to align the growth of the ICT sector and broader digital transformation with long-term environmental sustainability objectives.

2. Review of literature

2.1 ICT and CO₂ emissions (CO₂E)

Empirical studies on the ICT–CO₂E nexus reveal mixed findings, generally categorized into three main relationships: a positive relationship, where ICT contributes to increased emissions primarily through heightened electricity consumption, the deployment of energy-intensive infrastructure (e.g., data centers, mobile base stations, and server farms), and the rebound effect—where efficiency gains lower the cost of ICT services, thereby encouraging greater usage and overall energy demand; a negative relationship, where ICT helps reduce emissions via energy efficiency improvements, technological innovation, and shifts toward less carbon-intensive economic structures; and a neutral relationship, where ICT has little to no statistically significant impact on CO₂E. These divergent outcomes often reflect two dominant theoretical frameworks: one aligns with the Environmental Kuznets Curve (EKC) hypothesis, while the other emphasizes linear or context-specific relationships.

The first group of studies adopts the Environmental Kuznets Curve (EKC) hypothesis, proposing an inverted U-shaped relationship between ICT and CO₂E. Añón Higón et al. (2017) were among the first to integrate ICT into the EKC framework. Examining 142 countries from 1995 to 2010, they identified a nonlinear ICT–CO₂E relationship: ICT initially raises emissions via the scale effect—where increased economic activity driven by ICT expansion leads to higher energy consumption and CO₂E—but later reduces them through efficiency gains and sectoral shifts toward low-emission services. The turning point for this reduction lies beyond current ICT levels in developing countries, implying continued emission growth, whereas developed countries have already surpassed this threshold and are experiencing declines. Similarly, Haini (2021), using panel data from 1996 to 2019, confirmed this pattern in ASEAN countries. His findings indicate that ICT initially increases but later reduces emissions—consistently lowering them across sectors. In contrast, human capital generally raises emissions, particularly in manufacturing. This study underscores the importance of ICT infrastructure for targeted emission reduction strategies.

In comparison, Arshad et al. (2020) analyzed 14 South and Southeast Asian countries from 1990 to 2014 and found that ICT and financial development increase emissions in both advanced- and developing-status countries, with stronger effects observed in less-developed areas due to energy inefficiencies. Their findings highlight ICT's energy burden and the critical need for efficiency-focused regulation.

Country-level heterogeneity is further illustrated by several studies. For instance, Jin and Yu (2022) focused on China using cross-regional and cross-industry data. Their study found that ICT increases emissions due to rebound effects in energy-intensive sectors, such as non-metal manufacturing. Peng et al. (2023) analyzed 31 Chinese provinces from 2000 to 2018 and reported that the relationship between internet use and emissions in the logistics sector follows an inverted U-shaped curve. However, this pattern varies regionally—nonlinear in the eastern and western provinces but linear in central areas. In North Africa, Ben Lahouel et al. (2021) examined Tunisia from 1970 to 2018 and concluded that ICT improves carbon efficiency by moderating the influence of total factor productivity on emissions. However, Amri et al. (2019), also studying Tunisia from 1975 to 2014, rejected the EKC hypothesis and found ICT's effect on emissions statistically insignificant—despite productivity's strong long-run impact on CO₂E. These divergent findings underscore the complexity of the relationship and highlight the critical role of country-specific factors in determining the net environmental outcome of ICT development.

The second group of studies departs from the EKC hypothesis, presenting a more nuanced perspective in which ICT's environmental impact is highly context-dependent. Edquist and Bergmark (2022) analyzed data from 181 countries between 2002 and 2020, finding that mobile broadband initially increases emissions due to infrastructure investments but ultimately reduces per capita CO₂E by 7% for every 10-percentage-point increase in penetration. Similarly, Appiah-Otoo et al. (2022), examining 110 countries from 2000 to 2018, found that ICT reduces CO₂E only in high-quality ICT environments, while it increases emissions in others. Their causality analysis revealed bi-directional relationships in countries with high- and moderate-quality ICT infrastructure and a one-way relationship from CO₂E to ICT in low-quality contexts.

Further region-specific evidence reinforces this variation across contexts. Andlib and Khan (2021) analyzed data from four South Asian countries covering the period 1995–2019 and found that

both ICT development and governance effectiveness contribute to reducing emissions, whereas financial development tends to exacerbate them. In South Africa, Atsu et al. (2021), using data from 1970 to 2019, reported that ICT and fossil fuel consumption are positively associated with emissions, while renewable energy and financial development play a mitigating role. Similarly, Khanal (2021), using Australian data from 1990 to 2019, observed that ICT increases emissions in the short term but contributes to emission reductions over the long term.

In the national context, Pan et al. (2023), using data from 283 Chinese cities between 2003 and 2019, demonstrated that internet development promotes low-carbon transformation through industrial upgrading and green innovation. Similarly, in Saudi Arabia, Kahouli et al. (2022), using data from 1980 to 2020, found that ICT has a short-term negative relationship with the ecological footprint—suggesting early-stage environmental benefits from digital growth.

Overall, these findings challenge the notion of a uniform ICT–emissions trajectory. Instead, the outcomes are highly dependent on national circumstances, including institutional capacity, energy infrastructure, ICT quality, and the stage of economic development.

2.1 Mobile Cellular Network

The transition of mobile networks from 2G to 5G is reshaping energy consumption patterns, with significant implications for carbon dioxide emissions (CO₂E). This shift requires a careful balance. On one hand, mobile technologies serve as tools for reducing emissions across various sectors. They enhance operational efficiency and enable smarter, more sustainable solutions—often compensating for their own environmental footprint (GSMA, 2024).

This challenge is most evident with 5G. Although the technology offers substantial energy efficiency gains per unit of data—dramatically outperforming 2G and 3G—its initial deployment has paradoxically led to an increase in overall energy consumption. This imbalance is primarily due to the densification of network infrastructure needed for higher frequency bands and the inefficient, simultaneous operation of multiple network generations. This rollout has also coincided with an exponential surge in data traffic from high-bandwidth applications like video streaming and the Internet of Things (IoT).

However, the long-term decarbonization potential of 5G is substantial when paired with targeted interventions. Strategies such as reallocating radio spectrum from legacy networks, optimizing operations with artificial intelligence, and powering infrastructure with renewable energy can unlock these gains. Such measures not only reduce direct emissions but also address indirect Scope 3 emissions by extending efficiency across the entire mobile ecosystem. According to industry climate reports, this makes 5G a foundational element in the global transition to low-carbon digital infrastructure (GSMA, 2023).

The inefficiency of legacy systems is particularly stark. A study by France's ARCEP (2023) concludes that a swift migration from 2G/3G to 4G/5G is environmentally beneficial, as the continuous energy savings from modern networks far outweigh the one-time environmental cost of replacing incompatible devices. Similarly, Ayers et al. (2023) advocate reallocating radio spectrum from these outdated technologies to more energy-efficient systems.

In summary, while upgrading mobile networks introduces short-term environmental costs, the long-term benefits in energy efficiency and emissions mitigation are significant. These gains can be maximized through forward-looking policies, the integration of renewable energy, and sustained technological innovation.

Table 1: Literature on ICT and Environmental

Study	Area / Period	Methodology	Variable	ICT indicator	Relationships
Añón Higón et al. (2017)	142 countries (1995 – 2010)	POLS, DFFE, IVFE	CO ₂ E, ICT, GDPPC, IND, EDU, POP, REG, GOV, EN, CAR	ICT index	ICTs reduce CO ₂ E under the EKC
Amri et al. (2019)	Tunisia (1975 – 2014)	ARDL-SB	CO ₂ E, ICT, TFP	The sum of mobile and fixed telephone subscription	ICT insignificant to CO ₂ E under EKC

Study	Area / Period	Methodology	Variable	ICT indicator	Relationships
Arshad et al. (2020)	14 South and Southeast Asia Countries (1990 – 2014)	PMG, FMOLS, DOLS	CO ₂ E, ICT, GDPPC, EN, FIN	The sum of mobile and fixed telephone subscription	ICTs increase CO ₂ E under the EKC
Atsu et al. (2021)	South Africa (1972-2019)	ARDL, DOLS, FMOLS	CO ₂ E, ICT, REC, EN, TTO, FIN, GDPPC	Fixed telephone subscription	ICT reduce CO ₂ E ICT increase CO ₂ E in the short-run reduce CO ₂ E in the long-run
Andlib and Khan (2021)	South Asia (1996 – 2019)	FOLS, DOLS, FEOLS	CO ₂ E, ICT, real GDP, FIN, GOV	The sum of internet users and mobile cellular subscriptions	ICT reduce CO ₂ E
Ben Lahouel et al. (2021)	Tunisia (1970 - 2018)	LSTR	CO ₂ E, ICT, TFP	The sum of mobile and fixed telephone subscription	ICT reduce CO ₂ E
Haini (2021)	ASEAN (1996 - 2019)	FEOLS	CO ₂ E, ICT, GDPPC, REC, TO, REG, HC	1. Internet users 2. Mobile cellular subscriptions	ICTs reduce CO ₂ E and sectoral CO ₂ E under the EKC
Khanal (2021)	Australia (1990 – 2019)	ARDL	CO ₂ E, ICT, EN, GDPPC, POP	Internet users	ICT reduce CO ₂ E ICT increase CO ₂ E in the short-run but reduce CO ₂ E in the long-run
Appiah-Otoo et al. (2022)	110 countries (2000 – 2018)	IV-GMM	CO ₂ E, ICT, GDPPC, TO	1. Mobile cellular subscriptions 2. Internet users 3. Fixed broadband subscriptions 4. Fixed telephone subscriptions 5. ICT index	ICT reduce CO ₂ E in countries with high ICT quality but increase in countries with moderate and low ICT quality.
Edquist and Bergmark (2022)	181 countries (1970 – 2018)	DID-IV	CO ₂ E, ICT, real GDPPC, share EPC from fuel, POP, IND, REG	Mobile broadband penetration	ICT reduce CO ₂ E
Kahouli et al. (2022)	Saudi Arabia (1990-2018)	VECM	EFP, ICT, TFP, EPC, REC, TO	ICT index	ICT improve EFP in the short run
Jin and Yu (2022)	Chinese regions	2FE	CO ₂ EPC, ICT, POP, URBAN, 2IND, FDI, ROAD, EN	1. Internet users 2. Mobile cellular subscriptions	ICT increase CO ₂ E under the EKC “Rebound effect”
Pan et al. (2023)	283 Chinese cities (2003 – 2019)	2FE, MP-DID	CO ₂ E, ICT, 2nd industrial CO ₂ E, regional GDP, IS, GI, POP, TECH, FDI, HC, REG	ICT internet index	ICT reduce CO ₂ E
Peng et al. (2023)	Chinese regions (2000 – 2018)	FEOLS, 2SLS, SYS-GMM	CO ₂ E, ICT, PE, IND, FIN, LOG, TO, CON, COA, GOI, POP	Internet users	ICT reduce CO ₂ E in logistics sector Eastern and Western region but increase in Central region under the EKC

Note: A glossary of all abbreviations is provided in Tables A1 and A2.

3. Methodology

3.1 Data and variables

This study employs annual panel data from 2000–2021 for 173 countries, which are listed in Table A6. The data are sourced from the World Development Indicators (World Bank, 2025) and GSMA Intelligence (GSMA, 2025). Tables 2 and 3 present the variable definitions, units of measurement, and descriptive statistics used in the empirical analysis.

Table 2: Variable definition

Variable	Code	Definition	Unit	Source
CO ₂ emissions	lnCO ₂	Annual CO ₂ emissions from agriculture, energy, waste, and industry (excluding LULUCF), standardized to CO ₂ -equivalent	Mt CO ₂ eq	WDI
Internet use	lnnet	Individuals who have accessed the Internet in the past three months using any device (computer, mobile phone, digital TV, etc.).	(%) of population	
Economic activity	lngdppc	GDP divided by midyear population, based on total value added, taxes minus subsidies, without depreciation or resource adjustments.	constant 2015 U.S. dollars	
Energy	lnenergy	Energy use refers to the consumption of primary energy before conversion, calculated as domestic production plus imports and stock changes, minus exports and international fuel supplies.	kg of oil equivalent per capita	
Renewable energy	lnrenewable	The share of renewables energy in total final energy consumption.	(%) of total final energy consumption	
2G connection	2G	Mobile network connections that use traditional cellular technologies (2G, 3G, 4G, or 5G) for non-IoT or general mobile use, excluding connections specifically designated for licensed cellular IoT (such as NB-IoT and LTE-M).	(%) of total connection	GSMA
3G connection	3G			
4G connection	4G			
5G connection	5G			

Table 3: Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
lnCO ₂	3,806	2.4431	2.5132	-3.180	9.443
lnnet	3,732	2.7571	1.7522	-2.563	4.605
lngdppc	3,787	8.5863	1.4936	6.060	11.630
lnenergy	3,798	1.4997	0.5545	-5.655	-1.332
lnrenweable	3,649	-1.8365	1.5935	-6.908	-0.910
2G	3,806	0.7170	0.3286	0	1.0000
3G	3,806	0.1728	0.2096	0	0.9999
4G	3,806	0.0871	0.1910	0	0.9640
5G	3,806	0.0010	0.0108	0	0.3320

3.2 Empirical Model

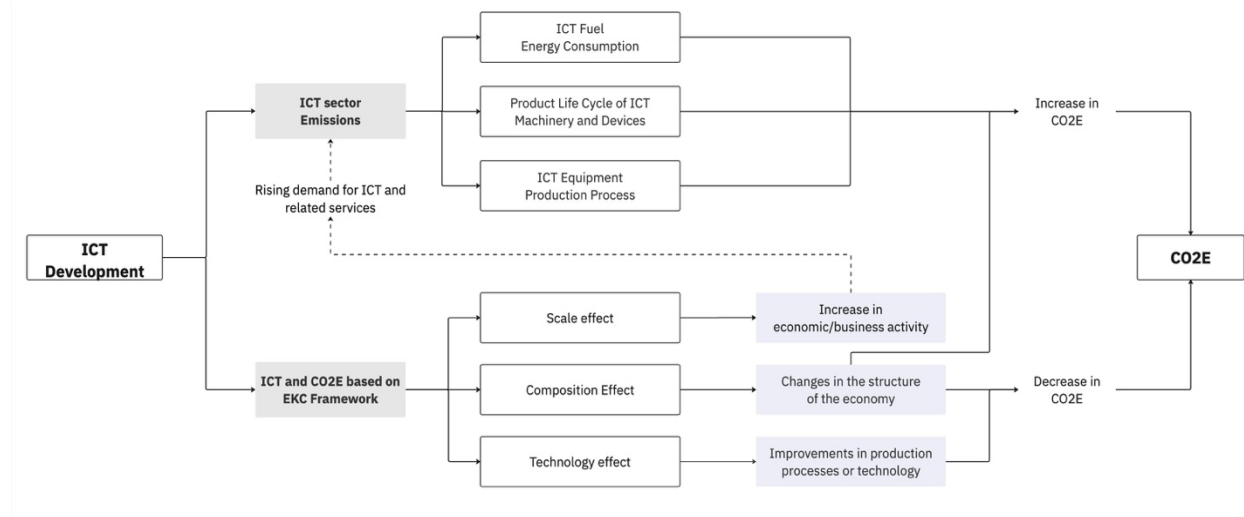
3.2.1 Theoretical background

This study employs the broadened Environmental Kuznets Curve (EKC) framework to examine the impact of ICT on CO₂ emissions across the panel. Prior research indicates that ICT's environmental effects—positive, negative, or neutral—are shaped by contextual factors such as economic development, government policy, and technological maturity. EKC-based studies frequently report an inverted U-shaped relationship, where emissions initially rise due to scale effects but decline as ICT

drives efficiency gains. Many context-specific analyses support this trend, finding that ICT's impact often corresponds to a short-term increase in emissions followed by a long-term reduction.

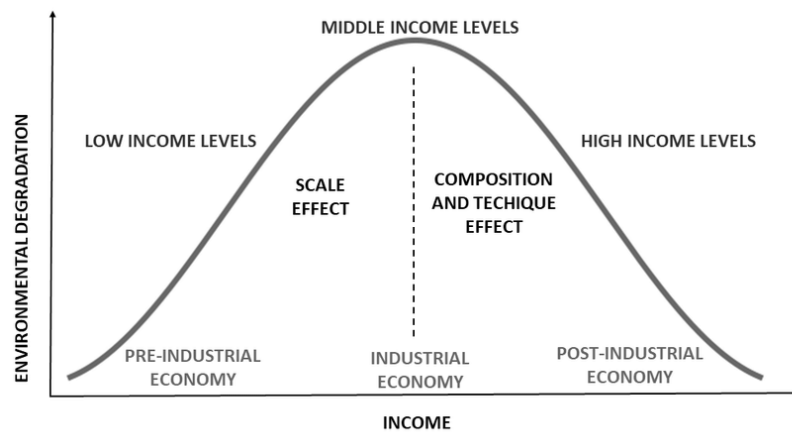
Aligned with these insights, we do not seek to test the EKC hypothesis directly. Instead, it adopts the EKC's underlying mechanisms—scale, composition, and technique effects—to evaluate ICT's environmental impact. In early stages, ICT may amplify the scale effect by increasing energy demand from infrastructure expansion. At more advanced phases, however, ICT is expected to mitigate emissions through productivity gains, structural upgrading, and technological innovation.

Fig 3. Conceptual Framework Linking ICT Sector Development and CO₂ Emissions



Note: This framework is based on the work of Añón Higón et al. (2017) and Ayers et al. (2023). It addresses the linkage carbon dioxide (CO₂ E) emissions associated with the Information and Communication Technology (ICT) sector.

Fig 4. The Environmental Kuznets Curve (EKC) (Grossman & Krueger, 1995)



3.2.2 The model

To empirically assess these relationships, we employ a fixed-effects panel regression model to control for unobserved, time-invariant heterogeneity across countries. Its appropriateness is validated by the Hausman test, which determines whether fixed effects are preferred over random effects by testing the null hypothesis that the random effects estimator is both consistent and efficient (Hausman, 1978). Additionally, a pooled OLS model is estimated to provide a basis for comparison.

The empirical model, adopting a log-log transformation of the panel data, is specified below to examine the relationship between ICT development and CO₂ emissions.

$$\ln CO_{2i,t} = \alpha + b_1 \ln net * 2G3G_{i,t} + b_2 \ln net * 4G5G_{i,t} + b_3 (\ln CO_2 * \ln net * 2G3G)_{i,t-1} \\ + b_4 (\ln CO_2 * \ln net * 4G5G)_{i,t-1} + b_5 \ln gdp pc_{i,t} + b_6 \ln energy_{i,t} + b_7 \ln renewable_{i,t} + \varepsilon_{i,t}$$

To capture ICT development, we use two proxy variables. The first, representing ICT access and usage, is the number of internet users. This measure is chosen because previous research (Appiah-Otoo et al., 2022; Haini, 2021; Khanal, 2021; Peng et al., 2023) has shown that internet penetration is a key indicator of progress in the sector. For the second variable, we measure technological advancement within the ICT sector by aggregating cellular network connections into two groups: 2G/3G and 4G/5G. This distinction captures the impact of legacy mobile technologies and more advanced network infrastructure, enabling an analysis of both the environmental burden of older connections and the potential efficiency gains from newer generations. A composite interaction term is then constructed to assess the combined effect of ICT penetration and technological progress on CO₂ emissions. To account for the persistent nature of CO₂ emissions, we incorporate past emissions levels as a predictor for current emissions. Furthermore, we interact this lagged emissions variable with the ICT variables to test whether the environmental impact of ICT infrastructure is immediate or develops over time.

The analysis includes GDP per capita ($\ln gdp pc$), energy use ($\ln energy$), and the share of renewable energy ($\ln renewable$) as control variables, all of which are widely acknowledged as key determinants of CO₂ emissions. GDP per capita serves as a proxy for economic activity, where growth often leads to increased energy consumption in emission-intensive sectors, thereby elevating emission levels. This positive relationship between economic development and environmental degradation is extensively documented in the literature (Añón Higón et al., 2017; Andlib & Khan, 2021; Appiah-Otoo et al., 2022; Arshad et al., 2020; Atsu et al., 2021; Edquist & Bergmark, 2022; Haini, 2021; Khanal, 2021).

The energy sector is the dominant source of climate pollution, accounting for approximately three-quarters of global greenhouse gas (GHG) emissions. Within this sector, electricity and heat generation were responsible for nearly 44% of global CO₂ emissions from fuel combustion in 2022 (IEA, 2022). Several studies, including Arshad et al. (2020), Peng et al. (2023), and Atsu et al. (2021), highlight the continued reliance on fossil fuels as a major barrier to decarbonization.

In contrast, a higher share of renewables helps mitigate emissions. Sources such as solar, wind, and bioenergy emit minimal greenhouse gases and significantly reduce carbon intensity. Renewable energy plays a crucial role in advancing both environmental protection and long-term climate goals. These findings are supported by Atsu et al. (2021) and Kahouli et al. (2022), who emphasize the environmental benefits of transitioning to renewable energy sources.

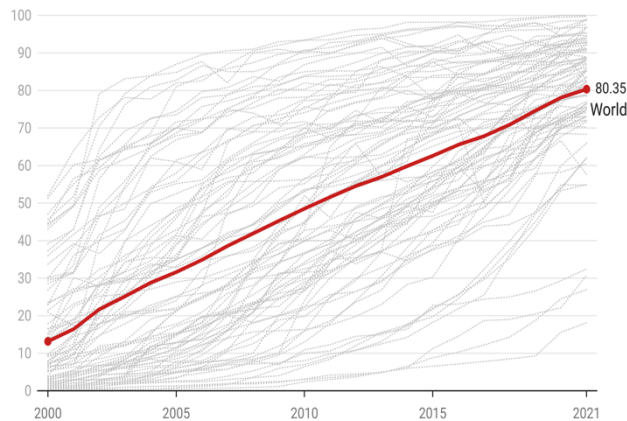
To address endogeneity, this analysis employs the instrumental variable Generalized Method of Moments (IV-GMM) estimator, which uses the forward orthogonal deviations (FOD) transformation to remove fixed effects by subtracting the average of future observations from each period, thereby preserving sample size and mitigating issues associated with serial correlation and unbalanced panels (Arellano & Bover, 1995).

Internal instruments are used to obtain consistent estimates in dynamic panel settings (Arellano & Bond, 1991). Instrument validity is assessed using the Hansen J-statistic, which is robust to heteroskedasticity and tests the exogeneity of instruments (Hansen, 1982). The Sargan test is also reported; however, it assumes homoskedasticity and tend to overreject the null hypothesis under heteroskedastic conditions, potentially leading to biased inferences (Sargan, 1958)

$$\Delta^{FOD} \ln CO_{2i,t} = \Delta^{FOD} b_1 \ln CO_{2i,t-1} + \Delta^{FOD} b_2 \ln net * 2G3G_{i,t} + \Delta^{FOD} b_3 \ln net * 4G5G_{i,t} \\ + \Delta^{FOD} b_4 (\ln CO_2 * \ln net * 2G3G)_{i,t-1} + \Delta^{FOD} b_5 (\ln CO_2 * \ln net * 4G5G)_{i,t-1} \\ + \Delta^{FOD} b_6 \ln gdp pc_{i,t} + \Delta^{FOD} b_7 \ln energy_{i,t} + \Delta^{FOD} b_8 \ln renewable_{i,t} + \Delta \varepsilon_{i,t}$$

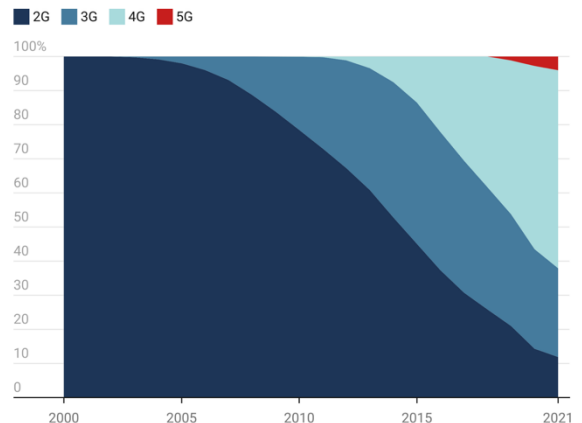
The model aims to estimate the coefficients b_1 to b_5 and test their statistical significance. This evaluation will determine whether ICT sector development has a significant impact on CO₂ emissions.

Fig 5. Internet Usage as a Share of Population in Selected Countries, 2000–2021



Source: World Development Indicators

Fig 6. Distribution of Cellular Network Connection Shares (2G–5G) in Selected Countries, 2000 – 2021



Source: GSMA Intelligence

4. Results and Discussion

For our static panel estimations, we compared three models: pooled Ordinary Least Squares (OLS), random effects (RE), and fixed effects (FE). While pooled OLS provides a useful baseline, its primary limitation is its failure to account for unobserved heterogeneity, a shortcoming that can introduce biased estimates. This limitation led us to evaluate the RE and FE models. The critical difference between them lies in the RE model's assumption that individual-specific effects are not correlated with the regressors. When we put this assumption to the test using the Hausman test, the evidence pointed strongly against it, revealing a significant divergence between the RE and FE outputs (see Table A3). Consequently, the FE model was selected as the most appropriate choice, as its strength is providing consistent estimates in the presence of such correlation. This is crucial for addressing bias arising from time-invariant omitted factors. To ensure reliable inference, cluster-robust standard errors are used to correct for potential bias in the presence of heteroskedasticity and intra-cluster correlation.

A test for serial correlation in the residuals of the fixed-effect model (Table A5) indicates that the error terms are not independent across time. This finding confirms that the process is dynamic—meaning past levels influence current ones—which renders a static model unsuitable. To address the resulting endogeneity and control for unobserved heterogeneity, we employed the instrumental variable Generalized Method of Moments (IV-GMM) estimator. This is a standard approach for dynamic panels (Arellano & Bond, 1991) and aligns with recent literature, such as Appiah-Otoo et al. (2022) and Pan et al. (2023). Additionally, we utilized robust standard errors to ensure valid statistical inference in the presence of potential heteroskedasticity. The full results of this estimation are presented in Table 4

The results of our one-step difference GMM estimation, presented in Table 4, illustrate the impact of ICT development on CO₂ emissions. The significance of the lagged dependent variable's coefficient indicates a persistence in emission levels, where past emissions significantly affect current levels. An examination of the interaction effects indicates that increased internet usage significantly raises short-term CO₂ emissions when supported by either legacy (2G/3G) or modern (4G/5G) mobile networks. This finding suggests that the early stages of ICT adoption come with an environmental cost; however, the reasons for this effect vary by technology generation. The emissions increase associated with 2G and 3G is likely attributable to the inherent energy inefficiency of their infrastructure. Conversely, the impact of 4G and 5G is more likely a consequence of the modern digital ecosystem, characterized by massive data consumption, the widespread deployment of devices, and the growing energy demands of digital services.

An important finding is that the long-term effects for both technology groups are negative and statistically significant. The result suggests that while digital expansion may initially increase emissions, its delayed effects can contribute to their reduction. This conclusion aligns with a broad

stream of research demonstrating the potential for ICT development to lower emissions. The mechanisms for these reductions often include improved energy efficiency, improved production processes, and the broader adoption of ICT across industries (Añón Higón et al., 2017; Appiah-Otoo et al., 2022; Atsu et al., 2021; Edquist and Bergmark, 2022; Jin and Yu, 2022; Khanal, 2021).

Table 4: Estimation Results for ICT and CO₂ Emissions (one-step difference GMM)

Variable	Coefficient	Robust Std. Err.
$\ln\text{CO}_{2,t-1}$	0.5713***	0.1159
$\ln\text{net} * 2\text{G}3\text{G}$	0.0641***	0.0174
$\ln\text{net} * 4\text{G}5\text{G}$	0.0671***	0.0161
$(\ln\text{CO}_2 * \ln\text{net} * 2\text{G}3\text{G})_{t-1}$	-0.0076**	0.0027
$(\ln\text{CO}_2 * \ln\text{net} * 4\text{G}5\text{G})_{t-1}$	-0.0126***	0.0032
$\ln\text{gdppc}$	0.3844***	0.1148
$\ln\text{energy}$	0.2747***	0.1147
$\ln\text{renewable}$	-0.0432*	0.0177
Time dummy	Y	
Observations	3,220	
F-statistics	96.17	
AR (1)	0.000	
AR (2)	0.405	
Sargan test χ^2	37.35	
prob. > χ^2	0.276	
Hansen test χ^2	41.25	
prob. > χ^2	0.153	

Note: Coefficients that are statistically significant at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

The environmental impact of transitioning mobile networks depends on a country's current technology. We calculated the change in CO₂ emissions that would result from a 1% shift in network users from 2G/3G to 4G/5G in 2020. In countries still reliant on 2G and 3G, switching to 4G and 5G provides clear environmental gains by replacing obsolete and energy-inefficient infrastructure. However, in more digitally advanced nations where 4G and 5G are already widespread, further expansion may initially lead to higher emissions, as illustrated in Figure 7. This increase appears to stem from the substantial energy requirements of modern digital ecosystems, including massive data consumption, cloud platforms, data centers, and extensive networks of connected devices.

Interestingly, the trend toward emission reductions becomes more pronounced as countries increase their adoption of 4G/5G technologies. These benefits do not emerge immediately or uniformly across contexts. Rather, the reduction in emissions tends to strengthen when digital infrastructure reaches higher levels of development and integration. The relationship is nonlinear—initial gains are modest, but more substantial improvements occur at advanced stages of 4G/5G penetration (Figure 8)

Moreover, the persistence of emissions may undermine the effectiveness of ICT-driven reductions. In such cases, the initial surge in emissions from digital infrastructure deployment may outweigh the delayed environmental benefits. This situation highlights a fundamental trade-off: while ICT can support long-term decarbonization, its short-term effects may impose greater environmental burdens than benefits.

Fig 7. Estimated change in CO₂E in 2020 resulting from a 1% shift in network share from 2G/3G to 4G/5G

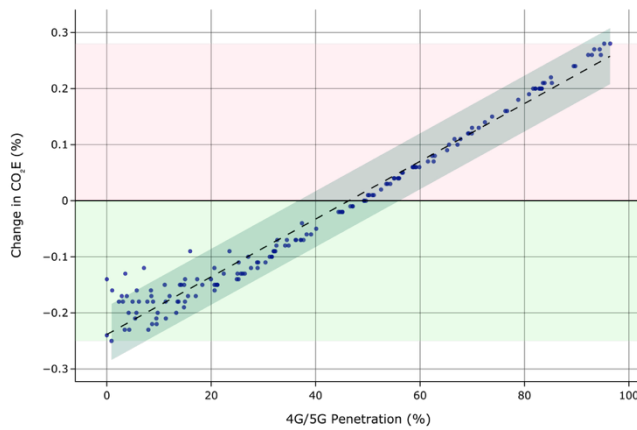
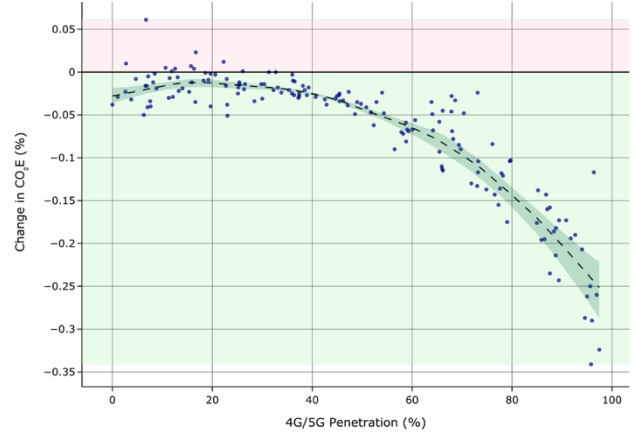


Fig 8. Estimated change in CO₂E in 2021 resulting from a 1% shift in network share from 2G/3G to 4G/5G in 2020



Source: Author's calculations based on model estimations using data from 2020 and 2021.

In addition to our primary variables of interest, the control factors—GDP per capita, energy consumption, and the share of renewable energy—are significant drivers of CO₂ emission patterns. The results confirm that higher GDP per capita and increased energy consumption are both positively correlated with emissions, underscoring the environmental pressures tied to economic growth. On the other hand, a greater share of renewable energy is clearly linked to lower emissions. This confirms its crucial role in mitigating environmental impact and supporting efforts to decarbonize the economy. This finding is consistent with the research of Arshad et al. (2020), Haini (2021), Atsu et al. (2021), and Peng et al. (2023).

Model diagnostics further support the robustness of these estimates. The AR (1) test indicates expected first-order serial correlation in the differenced errors, while the AR (2) confirms the absence of second-order correlation in the differenced errors, which supports the model's dynamic specification. The Hansen test fails to reject the null hypothesis of instrument validity (p-value = 0.153), indicating that the instruments are not collectively correlated with the error term. Similarly, the Sargan test (p-value = 0.276) fails to reject the null at the 5% significance level, supporting the validity of the overidentifying restrictions and the exogeneity of the instruments.

5. Conclusion

This study examines the relationship between the information and communication technology (ICT) sector and carbon dioxide (CO₂) emissions within an extended EKC framework. Drawing on panel data from 173 countries over the period 2000–2021, the analysis applies a one-step difference Generalized Method of Moments (IV-GMM) estimator to address country-specific differences, emission persistence, and potential endogeneity concerns.

The findings highlight a nonlinear and time-dependent relationship between ICT development and CO₂ emissions. In the early stages, ICT growth tends to raise emissions, largely due to infrastructure expansion and increased energy demand. Over time, however, this trend begins to reverse. A gradual decline in emissions is driven by delayed effects such as technological improvements and efficiency gains. The environmental impact of ICT varies with the stage of technological maturity. In countries still reliant on 2G/3G, the transition to 4G/5G reduces emissions by replacing outdated and inefficient systems. Conversely, in nations with widespread 4G/5G adoption, emissions may initially increase due to the energy demands of data-intensive ICT services, exemplifying a rebound effect whereby efficiency gains are offset by heightened usage and infrastructure expansion. Although long-term environmental benefits from ICT development are observed across various contexts, their magnitude differs considerably. These benefits tend to be more substantial in countries with higher levels of digital advancement and deeper integration of technologies such as 4G and 5G.

Critically, the findings highlight a trade-off: the short-term rise in emissions from ICT expansion can outpace subsequent environmental benefits. This, combined with the persistent nature of CO₂ emissions, suggests that the positive environmental outcomes of digitalization are not guaranteed. Realizing ICT's full decarbonization potential requires coordinated policy action, particularly expanding renewable energy adoption and enhancing energy efficiency throughout the digital ecosystem. Without strategic governance, digital advancement may exacerbate environmental challenges rather than mitigate them.

These findings underscore an urgent need for national regulators to embed sustainability goals directly into ICT policy frameworks. Policymakers should mandate environmental performance benchmarks for high-speed networks such as 4G and 5G, especially regarding energy-intensive infrastructure like data centers, artificial intelligence systems, and cloud platforms. Key policy measures should also prioritize accelerating legacy network decommissioning, promote renewable integration, and establish robust sector-specific emissions monitoring systems. As digitalization deepens, regulatory approaches must evolve to address the full life cycle of ICT systems—from infrastructure deployment to end-of-life management—to mitigate their environmental footprint.

While we offer a broad empirical overview of the ICT–emissions relationship, several limitations highlight promising directions for future research. Firstly, the use of a large panel is beneficial in identifying general patterns; however, it may obscure critical country-specific factors—including policy environments, industrial structures, and societal digital behaviors—that influence the impact of ICT on emissions. To better capture these contextual nuances, future research could focus on more homogeneous regional groups or conduct in-depth case studies.

Second, while the results show a nonlinear relationship, the actual dynamics may be more intricate than standard models can capture. Future studies would benefit from adopting more flexible and sophisticated techniques or even machine learning approaches. These methods can help reveal complex interactions that conventional models might overlook, offering a deeper understanding of ICT's varied environmental impacts.

Lastly, we use commonly accepted proxies for ICT development, which, while effective, may not fully reflect the environmental footprint of newer technologies such as artificial intelligence, cloud computing, and large-scale data centers. As more granular data on the energy consumption of these specific technologies becomes available, incorporating it into future analyses will be crucial for developing a more precise understanding of the digital sector's environmental effects and for informing targeted policy decisions.

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Appendix

Table A1: Abbreviations of Methods Employed in the Literature

Abbreviation	Full Method Name	Abbreviation	Full Method Name
POLS	Pooled Ordinary Least Squares	LSTR	Logistic Smooth Transition Regression
DFFE	Dynamic Fixed Effects	MP-DID	Multiperiod Difference-in-Differences
IVFE	Instrumental Variable Fixed Effects	FOLS	First-difference Ordinary Least Squares
PMG	Pooled Mean Group Estimator	SYS-GMM	System Generalized Method of Moments
FMOLS	Fully Modified Ordinary Least Squares	IV-GMM	Instrumental Variable GMM
DOLS	Dynamic Ordinary Least Squares	2SLS	Two-Stage Least Squares
FEOLS	Fixed Effects Ordinary Least Squares	VECM	Vector Error Correction Model
2FE	Two-way Fixed Effects	ARDL	Autoregressive Distributed Lag Model

DID-IV	Difference-in-Differences with Instrumental Variables	ARDL-SB	Autoregressive Distributed Lag Model with Structural Break
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Table A2: Abbreviations of Variables Employed in the Literature

Abbreviation	Full Variable Name	Abbreviation	Full Variable Name
2IND	Secondary sector output to GDP	GOV	Government indicator
BU	Business activity	HC	Human capital indicator
CAR	Number of car passengers	ICT	ICT indicator
CO₂E	Carbon dioxide emissions	IND	Industry share of GDP
CO₂E 2nd industrial	Carbon dioxide emissions from secondary industry	IS	Industrial structure upgrading
CO₂EPC	Carbon dioxide emissions per capita	LOG	logistics industry
COA	Coal consumption to total energy consumption	PE	Growth rate of private enterprise
CON	Retail sales of social consumer goods to GDP	POP	Population
EDU	Education indicator	real GDP/GDP/ regional GDP	
EFP	Ecological footprint	real GDPPC/ GDPPC	Real GDP per capita/ GDP per capita
EN	Fossil fuel energy consumption Energy consumption	REC	Renewable energy consumption
EPC	Electric power consumption	REG	Regulation indicator
EPC share from fuel	Electricity consumption from fossil fuel	ROAD	Road area per capita
FDI	Foreign direct investment	TECH	Technological Level
FIN	Financial indicator	TFP	Total factor productivity
GI	Green innovation	TO	Trade openness
GOI	Government investment in environmental governance to GDP	URBAN	Urban population to total population

Table A3: Results of the Hausman test

Variable	Coefficient		(b-B) Difference	sqrt (diag (Vibe – B_B)) S.E.
	(b) few	(B) re		
lnnet * 2G3G	0.1492	0.0161	0.0078	0.0012
lnnet * 4G5G	0.1496	0.0203	0.0079	0.0014
(lnCO ₂ * lnnet* 2G3G) _{t-1}	-0.0072	0.0021	-0.0077	0.0003
(lnCO ₂ * lnnet* 4G5G) _{t-1}	-0.0107	0.0030	-0.0074	0.0003
lngdppc	0.7222	0.1049	0.6477	0.0190
lnenergy	0.5708	0.1163	0.5791	0.0093
lnrenewable	-0.0929	0.0151	-0.0918	0.0030

Test: Ho difference in coefficients not systematic

$$\chi^2 = 985.14$$

$$\text{prob.} > \chi^2 = 0.0000$$

Table A4: Estimation Results for ICT and CO₂ Emissions (Pooled OLS, Fixed Effects, and Random Effects)

Variable	Pooled OLS	Random effect	Fixed effect
lnnet * 2G3G	-0.0651 (0.1297)	0.1415*** (0.0185)	0.1492*** (0.0187)
lnnet * 4G5G	-0.7750*** (0.0909)	0.1418*** (0.0210)	0.1497*** (0.0217)

Variable	Pooled OLS	Random effect	Fixed effect
$(\ln\text{CO}_2 * \ln\text{net} * 2\text{G3G})_{t-1}$	0.3194*** (0.1207)	0.0005 (0.0038)	-0.0072* (0.0037)
$(\ln\text{CO}_2 * \ln\text{net} * 4\text{G5G})_{t-1}$	0.3488*** (0.0184)	-0.0033 (0.0042)	-0.0107** (0.0043)
lngdppc	0.4391*** (0.0408)	0.6476*** (0.1062)	0.7222*** (0.1347)
lnenergy	0.9539*** (0.0727)	0.5791*** (0.1564)	0.5708*** (0.1642)
lnrenewable	-0.1337*** (0.0273)	-0.0918*** (0.0307)	-0.9290*** (0.0302)
Constant	-3.6342*** (0.3392)	-4.5088*** (1.0612)	-5.0566*** (1.3410)
Observation	3,390	3,390	3,390
F-statistics/Wald – χ^2	206.92	348.87	47.14
Within – R^2		0.6158	0.6204
Between – R^2		0.1916	0.1554
Overall – R^2	0.2999	0.1972	0.1613

Note: Coefficients that are statistically significant at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Table A5: Diagnostic Test for Correlation Between Fixed Effects Residuals and Lagged Dependent Variable

	$\ln\text{CO}_2 \text{ }_{t-1}$	residuals
$\ln\text{CO}_2 \text{ }_{t-1}$	1.0000	
residuals	0.4070* (0.0000)	1.0000

The analysis began by estimating three static panel data models: pooled OLS (serving as a baseline), Random effects (RE), and Fixed effects (FE). The results of these initial estimations are presented in Table A4. To choose between the fixed and random effects specifications, a Hausman test was performed. The results of the test (Table A3) were statistically significant ($\chi^2 = 985.14$, $p < 0.001$), indicating a preference for the fixed effects model over the random effects model. However, further diagnostic testing based on the results in Table A5 revealed a significant correlation between the error term and the lagged dependent variable. The presence of this dynamic endogeneity suggests that static models, including the fixed effects model, may not be appropriate in this situation. Consequently, we prefer a dynamic panel data model over the static approaches.

Table A6: Countries Included in the Study

Afghanistan, Aruba, Ethiopia, Finland, Argentina, Fiji, Australia, Austria, Azerbaijan, France, Gabon, United Kingdom, Bangladesh, Barbados, Grenada, Belgium, Georgia, Ghana, Gambia, The, Bosnia and Herzegovina, Guinea, Equatorial Guinea, Greece, Burkina Faso, Cambodia, Guinea-Bissau, Cayman Islands, Guyana, Hong Kong SAR, China, Chad, Honduras, Croatia, Haiti, Comoros, Hungary, Indonesia, Ireland, Israel, India, Iraq, Iran, Islamic Rep., Iceland, Italy, Jamaica, Jordan, Japan, Eswatini, Kenya, Kyrgyz Republic, Kiribati, French Polynesia, St. Kitts and Nevis, Korea, Rep., Kuwait, Lao PDR, United Arab Emirates, Lebanon, St. Lucia, Liberia, Lesotho, Lithuania, Luxembourg, Latvia, Libya, Morocco, Moldova, Madagascar, North Macedonia, Mali, Myanmar, Mongolia, Macao SAR, China, Mauritania, Malta, Mauritius, Maldives, Malawi, Malaysia, Mexico, Mozambique, Namibia, Niger, Nigeria, Nepal, Nicaragua, Netherlands, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Philippines, Poland, Portugal, Qatar, Romania, Russian Federation, Rwanda, Saudi Arabia, Senegal, Seychelles, Sierra Leone, Singapore, Slovak Republic, Slovenia, Solomon Islands, Somalia, Suriname, Sweden, Tajikistan, Thailand, Togo, Timor-Leste, Turkmenistan, Tunisia, Tonga, Türkiye, Trinidad and Tobago, Tanzania, Ukraine, Uganda, United States, Uruguay, Bulgaria, Uzbekistan, St. Vincent and the Grenadines, Bahrain, Vanuatu, Samoa, Yemen, Rep., South Africa, Zambia, Zimbabwe, Burundi, Benin, Bermuda, Brunei Darussalam, Bolivia, Brazil, Antigua and Barbuda, Albania, Bahamas, The, Bhutan, Botswana, Belarus, Belize, Canada, Congo, Dem. Rep., Central African Republic, Congo, Rep., Switzerland, Chile, Cameroon, China, Colombia, Costa Rica, Cuba, Cabo Verde, Cyprus, Czechia, Germany, Djibouti, Denmark, Dominica, Dominican Republic, Armenia, Algeria, Ecuador, Estonia, Egypt, Arab Rep., Angola, Spain
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