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The Effect of Digital Communications on Carbon Emission: A Panel Data Model

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Abstract

The main objective of this paper is to explore the impact of Digital Communications on carbon emissions of the selected countries of the world. Very few studies have investigated the relationship between digital communications and carbon emissions from different perspectives. To the best of our knowledge, no previous studies have compared this effect between low- and high-income countries. This study will contribute to addressing this untapped area. More specifically, the following research questions need to be addressed: What kind of impact does digital communication have on carbon emissions, and are the effects different for low-income and high-income countries? This study selects 98 countries and divides them into different groups according to their income status from 2007 to 2021. The study used panel data techniques and reported the results obtained from Fixed Effects estimations. Data is collected from the World Bank, ITU (International Telecommunication Union). The empirical results showed that digital communication negatively and significantly affects CO_2 emissions, which means more digital communication advancement will reduce carbon emissions. The findings demonstrate that the index of digital communications has a negative but insignificant influence on CO_2 emissions for regions with lower income.

Keywords: Digital Communication, Carbon Emissions, Panel Data Analysis, Fixed effect model
JEL Classification: Q53, O44, Q55

1 Introduction

Given the significance of lowering carbon emissions in addressing the climate change problem, it is necessary to find significant factors responsible for inducing carbon emissions. Developing countries focus on digitization and high-quality products for economic growth, and the goals for reducing carbon emissions are inextricably linked to social and economic advancement (Wang et al., 2022). While there is little literature on how digital communication (DC) may affect CO_2 emissions directly or indirectly, this study will provide a new approach to contribute to this field. Since DC spreads in different regions differently, we expect they might have different effects across regions.

The development of digital communication technology can reduce local carbon emissions (Nguyen et al., 2020). According to Karacay (2018), places with high levels of digital technology development tend to attract capital, skilled labour, and other production-related resources. These areas could be more capable of cutting carbon emissions if they kept their upgraded manufacturing capability. Most analyses of existing studies on digital technology and carbon emissions are based on technical models incorporating information, communication technology, and the Internet

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(Moyer and Hughes, 2012). Existing studies have examined the impacts of traditional economic variables on carbon emissions. To the best of our knowledge, no studies deal with how different the effects are for low-income and high-income countries.

Empirical evidence suggests a non-linear relationship between digitalisation and carbon emissions. Studies across 190 countries reported an inverted U-shaped link, where digitalisation initially increased emissions but reduced them beyond a threshold (Zhang et al., 2021). Recent cross-country studies further confirm that digital economy development can influence carbon emission intensity through both technological efficiency and structural changes, with evidence from 72 countries highlighting significant variations across income levels (Akter et al., 2024). Similar patterns were observed in Mediterranean countries, with digitalisation fostering dematerialization and emission reductions (Li et al., 2024), and in a cross-country study of 72 nations, confirming the inverted U-shaped effect on carbon intensity (Akter et al., 2024). These results indicate that the digitalisation-emissions nexus depends on development level, energy mix, and institutional capacity (Rehman and Gill, 2023).

Country income levels further influence this relationship. In higher-income and technologically advanced economies, digitalisation produces stronger decarbonisation effects through industrial restructuring and green innovation (Li et al., 2024; Akter et al., 2024). By contrast, in lower-income countries, where digital investment coincides with rising consumption, inefficient energy systems, and weaker regulation, emissions-reducing effects are weaker or absent (Zhang et al., 2021; Rehman and Gill, 2023). Infrastructure quality and urbanization also modulate outcomes, with better-equipped regions experiencing amplified benefits (Rehman and Gill, 2023).

Building on this literature, this study selects 98 countries and divides them into different groups according to their income and developing status from 2007-2021. The study will use panel data Fixed Effects models to examine the causation between carbon emissions and digital communications. The causality analysis confirms that a 1-index increase in the digital communication index is associated with a 0.0185 metric ton per capita decrease in carbon emissions, holding other factors constant. GDP per capita shows a significant positive correlation with emissions, suggesting that countries with higher GDP per capita have achieved substantial energy efficiency gains, allowing pro-growth policies without exacerbating emissions (Salahuddin et al., 2016). Consumption expenditure exhibits a significant negative correlation with emissions, and renewable energy usage is also negatively associated with CO_2, indicating the potential for emission reductions. No significant relationship is found between net trade and emissions.

Income-level heterogeneity is evident: in low-income countries, the digital communication index has a negative but insignificant effect on emissions (a 1-index increase reduces CO_2 by 0.0166 metric tons per capita), whereas in upper-middle-income countries, digital communications have a positive and significant impact (a 1-index increase raises CO_2 by 0.042 metric tons per capita).

This study contributes by: (i) focusing specifically on digital communication technologies rather than the broader digital economy, (ii) providing cross-country evidence on income-level heterogeneity, and (iii) offering policy insights on aligning digital expansion with low-carbon pathways, particularly in emerging economies. The results suggest that governments should implement support measures to promote digital communication infrastructure while balancing environmental impacts.

The article is organized as follows: Section 2 summarizes the literature review, Section 3 outlines methodology, Section 4 discusses the data sources. The regression results are presented in Section 5, while Section 6 concludes and suggests recommendations for policymakers.

2 Literature Review

Scholars have focused a lot of attention on the global rise in carbon emissions and the quick growth of digital communication. This study discusses the existing literature to cover the key aspects of our research theme: the impact of DC development on carbon emissions; and the selected control variables' effect on carbon emissions.

The Paris Agreement was signed in 2015, and since then, global warming has put significant burdens on social and economic development and has become a major global concern. Researchers in this sector are trying to open a new dimension to finding the nexus between finance and emissions and found that trade openness, capital market expansion, and economic growth are the main carbon emissions factors (Zheng et al., 2019; Nguyen et al., 2021).

Lee and Brahmasrene (2014) analyzed data from nine ASEAN countries between 1991 and 2009, while Salahuddin et al. (2016) focused on OECD countries over the period 1991–2012, both finding that increased Internet usage correlates with higher carbon emissions. Numerous studies (Lee and Brahmasrene, 2014; Moyer and Hughes, 2012; Sims et al., 2003) have examined the impact of digital technology development on carbon emissions in a global context with both advantages and disadvantages as arguments.

Previous studies have confirmed that environmental regulations can effectively reduce carbon emissions in the long run (Ouyang et al., 2019; Leiter et al., 2011). Some scholars pay attention to the environmental effects of trade openness and have done some research which implies a positive and statistically significant association between them (Frankel and Rose, 2005; Zhu and Shan, 2020; Jorgenson, 2007).

Government intervention plays a significant role in reducing carbon emissions (Lin and Huang, 2022). Government consumption expenditure as a share of GDP is used to measure the level of government intervention (Dong et al., 2022). The more government consumption expenditure on environment protection, the less will be carbon emissions.

Most of the literature found a unidirectional causal relationship between GDP growth and carbon emission (Ameyaw and Yao, 2018; Odhiambo, 2011; Khan et al., 2022). The GDP per capita square positively affects Carbon emission (Aslam et al., 2021).

Renewable energy consumption has been investigated since it contributes significantly to carbon emissions. Renewable energy consumption harms carbon emissions, whereas financial development has a growing impact (Khan et al., 2020). OECD countries' carbon emissions are shown to decrease as renewable energy consumption rises (Shafiei and Salim, 2014).

There are still certain gaps in the existing literature that apply to this investigation. First, there hasn't been much research on how digital finance services affect CO_2 emissions, especially when looking at developed and developing nations in a single model. Although there is research on these countries and digital communication is increasingly common there, we are unsure how they will affect carbon emissions in developed countries. Second, no other research before this one had employed the control variable set used in this study.

2.1 Theoretical Justification of the Relationship Between Digital Communication and Carbon Emissions

Digital communication and carbon emissions are connected through multiple theoretical channels. On one hand, digitalization can reduce emissions by improving energy efficiency, optimizing production processes, and reducing transaction costs through the use of information and communication technologies (ICT) (Lee and Brahmasrene, 2014; Salahuddin et al., 2016). The diffusion of digital platforms promotes smart logistics, online transactions, and cloud-based coordination, which minimize unnecessary travel and resource use (Liu et al., 2022). Moreover, digital transformation supports the transition toward renewable energy integration by enabling smart grids and real-time energy management systems (Wang and Zhou, 2023). These mechanisms suggest that increased digital communication can lead to structural improvements in the economy that lower overall carbon intensity.

Conversely, digitalization can also increase emissions through the rebound effect, as higher internet usage, data centers, and digital infrastructure raise electricity consumption and promote greater production and consumption (Zhang et al., 2021; Chen et al., 2023). In upper-middle-income countries, where industrial activities expand alongside digital infrastructure growth, these energy-intensive processes can initially outweigh efficiency gains, leading to a temporary increase in emissions (Liu et al., 2022).

Therefore, the relationship between digital communication and carbon emissions may be nonlinear and income-dependent. Low-income economies may benefit more from the efficiency and substitution effects of digital communication, while middle- and upper-middle-income countries may experience transitional increases in emissions as their digital infrastructure expands (Wang and Zhou, 2023). This theoretical framework is consistent with the findings of this study, where the digital communication index shows a negative but insignificant association in low-income economies and a positive, significant one in upper-middle-income regions.

3 Methodology

3.1 Mechanism and Hypothesis

Hypothesis: The development of digital communications can significantly reduce carbon emissions. The expected sign of the coefficient is negative.

Figure 1: Mechanism of DC and carbon emissions

3.2 Empirical Models

3.2.1 Benchmark Model

This paper uses the following benchmark model to test the fundamental relationship between carbon emissions and the development of digital communications:

$$\mathrm{CO_2pc}_{it} = \beta_0 + \beta_1 \mathrm{Digital}_{it} + \sum_{k=1}^{6} \beta_k \mathrm{control}_{it} + \alpha_i + \gamma_t + \mu_{it} \tag{1}$$

Here, the dependent variable ($\mathrm{CO_2pc}$)$isCO_2$ emissions (metric tons per capita), the explanatory variable of interest (Digital) indicates digital communication technology index. Four (4) selected indicators (mentioned in Appendix 1) are used to construct the index.

In addition, the model uses the control variables, like; GDP Per Capita (gdppc), Net trade in goods (trade), Renewable Energy Consumption as percentage of total final energy consumption (energy), and Consumption Expenditure as percentage of GDP (Cons_Exp).

Here, i denotes country ($i = 1, 2, 3, \ldots, 98$), t denotes year. Here, α_i represents the country fixed effect; γ_t represents the time fixed effect; μ_{it} represents the random error term, and β_0 is the constant term, where β_k ($k = 1, 2, 3, \ldots, 5$) are the estimated coefficients.

3.2.2 Interaction Model

The interaction term is taken as the interaction between Digital and incomegroup. Here, the variable 'income group' is a categorical variable (dummy) representing country income classifications: low-income, lower-middle-income, upper-middle-income, and high-income, based on World Bank country classifications. The interaction term (Digital × income group) captures the heterogeneous effects of digital communication on carbon emissions across different income levels.

$$\mathrm{CO_2pc}_{it} = \beta_0 + \beta_1 \mathrm{Digital}_{it} + \sum_{k=1}^{6} \beta_k \mathrm{control}_{it} + \mathrm{Digital} \times \mathrm{incomegroup} + \alpha_i + \gamma_t + \mu_{it} \quad (2)$$

While GDP per capita is included as a control to account for the level of economic activity, the income group dummies reflect broader structural differences—such as stage of development, infrastructure quality, and institutional capacity—that may moderate the impact of digitalization on emissions.

3.3 Identification Problem

We choose the fixed effect model over the naive OLS regression as the unobserved heterogeneity is correlated with one or more explanatory variables, OLS parameter estimates are biased and inconsistent. The OLS estimator is not efficient (although it's still unbiased) if the residual errors of the OLS model are heteroskedastic.

In the regression model, α_i is an unobserved country fixed effect. It represents all factors affecting country's carbon emission that do not change over time. Such as the country's geographical location is included in α_i. To estimate pooled OLS, we must assume that the unobserved effect is uncorrelated with explanatory variables (X_{it}). In the model, $\alpha_i + \mu_{it} = v_{it}$, is called as composite error, which is assumed to be uncorrelated with X_{it}. So, even if μ_{it} uncorrelated with X_{it}, if α_i is correlated with v_{it}, the pooled OLS or cross-section OLS will be biased. It is true for any kind of naïve OLS estimation, which is called heterogeneity bias. Using panel data, we want to measure the causal relationship between the CO_2 Emissions and digital communication technology index. Carbon Tax (unavailable for low-income countries) and Research and Development investment data were two crucial variables omitted from the model. So, the model omitted variable biased. Since the model used panel data and α_i, such as geographical location is affecting the explanatory variables in the model (such as a more developed country has better infrastructure to develop better digital communication technology), we choose the fixed effect model over the naïve OLS estimation. Because naïve OLS cannot solve the omitted bias problem or heterogeneity bias problem (Wooldridge, 2018).

Since fixed effects (FE) model can deal with unobserved heterogeneity across units, it always has advantages over OLS when it is panel data. Fixed effect model controls for all variables that vary over the cross-sectional units but are constant over time. Moreover, the FE model can include interactions between time-constant and time-varying variables, which a naïve model cannot do.

4 Data Sources

This study uses annual data from 2007 to 2021 for 98 countries of the world. The main criterion for picking the data was its availability for the highest amount of period. The dependent variable, CO_2 emissions (metric tons per capita), is collected from the World Bank website (World Bank, 2021). The computation of the core explanatory variable, digital communication technology index was challenging because no official standardized procedure for determining the amount of development of the digital economy has been established. To construct the digital technology development index we follow Liu et al. (2022). A total of

4 variables have been chosen to fully assess the situation of the country's digital communication technology development in terms of its usage and geographic reach, which is displayed in Appendix 1. The simple mean was chosen to calculate the index.

The sources and units of control variables, explanatory and dependent variables are given in Appendix 2. The Digital Communication Technology (DCT) index is the core explanatory variable. Constructing this index was challenging because no official standardized procedure exists to measure the development of the digital economy. Following the methodology of Liu et al. (2022) and other studies on ICT/digital indices (International Telecommunication Union (ITU), 2022; World Bank, 2021; Van Dijk, 2020), a composite index was created using four indicators capturing different dimensions of digital communication technology: internet usage, fixed-telephone subscriptions, fixed broadband subscriptions, and mobile cellular subscriptions (Table 1).

While these indicators are correlated, this is expected because they reflect complementary aspects of digital connectivity. Correlation analysis confirmed that each component contributes meaningful information to the composite index without redundancy. The simple mean of the four indicators was used to calculate the index. This approach aligns with established practices in the literature for measuring digital communication and ICT adoption.

5 Findings

Following earlier empirical works examining the relationship between digitalization and carbon emissions (Lee and Brahmasrene, 2014; Salahuddin et al., 2016; Liu et al., 2022), the Benchmark model estimates the direct effect of digital communication on carbon emissions, controlling for GDP per capita, consumption expenditure, renewable energy, and trade. To capture cross-country heterogeneity, particularly by income level, we extend the baseline specification into an Interaction model by including interaction terms between income-group dummies and the digital communication index (Chen et al., 2023; Wang and Zhou, 2023). These two models allow us to identify both the average global effect and the differential effects across income groups.

Table 1 and Table 2 display the estimation result of our benchmark model and interaction model accordingly.

The causality results of the DC and carbon emission confirm the hypothesis, i.e. it implies that 1 index increase in digital development causes 0.0185 metric tons per capita decrease in carbon emissions, all else remain constant. A significant positive correlation between GDP per capita and carbon emission has been confirmed and this relationship implies that countries with higher GDP per capita have already achieved significant progress in energy efficiency, putting them in a comfortable position to pursue pro-growth policies without having to worry about emissions as much (Salahuddin et al., 2016).

A significant and negative correlation has been observed between carbon emission and consumption expenditure. This negative relationship may reflect that higher government spending in our sample is directed more toward public services, social welfare, digital infrastructure, and environmental programs rather than energy-intensive industrial activities. As a result, increased government consumption does not necessarily lead to higher emissions and may even contribute to emission reductions (Dong et al., 2022; Lin and Huang, 2022). Renewable energy has shown a significant and negative correlation with carbon emission suggesting that increases in renewable energy consumption can reduce the carbon emissions. The empirical results presented there show no significant relationship between net trade and carbon emissions.

According to income level, the sample countries are divided into low-income, lower-middle, upper-middle, and high-income countries. The findings demonstrate that the index of digital communications has a negative but insignificant influence on CO_2 emissions for regions with lower income. Having low-income countries relative to high-income countries, a 1 index increase in Digital is associated with a 0.0166 metric tons per capita decrease in carbon emissions, all else constant. On the other hand, for areas with upper-middle incomes, the index of digital communications has a positive but significant impact on CO_2 emissions. Having upper-middle-income countries relative to high-income countries, a 1 index increase in Digital is associated with a 0.042 metric tons per capita increase in carbon emissions, all else constant.

Table 1: Benchmark Model (Model-1) – Fixed Effects

Variable	Coefficient	t-statistic
Digital	−0.0185***	(−5.42)
GDPpc	0.0000509***	(7.10)
Cons_exp	−0.0108*	(−1.82)
Energy	−0.108***	(−12.84)
Trade	−4.17e−13	(−0.31)
_cons	9.652***	(16.77)
R^2	0.190	
N	1142	

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 2: Interaction Model (Model-2) – Fixed Effects with Income Group

Variable	Coefficient	t-statistic
Digital	−0.0402***	(−6.14)
GDPpc	0.0000489***	(6.86)
Cons_exp	−0.0109*	(−1.80)
Energy	−0.112***	(−11.83)
Trade	−7.51e−13	(−0.56)
Low income × Digital	−0.0166	(−0.85)
Lower middle income × Digital	0.0107	(1.04)
Upper middle income × Digital	0.0420***	(5.18)
_cons	10.28***	(17.11)
R^2	0.216	
N	1129	

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6 Conclusion

This study examined the impact of digital communication technologies on carbon emissions across 98 countries, highlighting the heterogeneous effects across income groups. The analysis shows that digitalization can reduce carbon emissions, particularly in high-income countries, while its impact is smaller and statistically insignificant in low-income countries. Upper-middle-income countries exhibit a modest positive association, suggesting that the relationship between digital development and emissions is context-specific.

The findings offer important policy insights. Governments should integrate digital infrastructure development with energy efficiency measures and sustainable practices. Policies promoting low-carbon digital technologies, using digital tools for environmental monitoring, and fostering awareness programs can enhance the environmental benefits of digitalization. These results underscore that digital adoption alone is insufficient; coordinated strategies that link technological advancement with climate and energy policies are essential for achieving sustainable development goals.

Future research could explore more granular data on digital technology types, renewable energy integration, and the role of environmental regulations to better understand how digitalization affects carbon emissions in diverse economic contexts.

Data Availability

The data that support the findings of this study are available from the corresponding author upon request.

Disclosure Statement

Views expressed in this paper are the authors' own and do not necessarily reflect the views of institutions they are affiliated with.

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Appendix 1: Indicators of Digital Communication Technology Index

Indicators	**Source**
Individuals using the Internet (% of population)	ITU
Fixed-telephone subscriptions (per 100 inhabitants)	ITU
Fixed broadband subscriptions (per 100 people)	ITU
Mobile cellular subscriptions (per 100 people)	ITU

Appendix 2: Data Sources and Variable Definitions

Variable	**Data Source**	**Unit**	**Description/Comment**
Per capita CO_2 emissions	World Bank	Metric tons per capita	Carbon dioxide emissions per person
Digital communication technology index	ITU (calculated)	Index	Composite index based on four ICT indicators
Environmental regulation	OECD (calculated)*	% of GDP	Environmental tax revenue as percentage of GDP
Industrial structure	World Bank	% of GDP	Industry value added (including construction)
Foreign trade per GDP	World Bank	% of GDP	Sum of exports and imports as percentage of GDP
R&D expenditure	World Bank	% of GDP	Gross domestic expenditures on research and development
Per capita GDP	World Bank	Current US$	Gross domestic product divided by midyear population

*OECD. (2021). Environmental taxes. OECD.Stat. https://stats.oecd.org
Note: ITU = International Telecommunication Union.