Economic Journal of Emerging Markets, 18(1) 2026, 41-53

EJEM
Econ.J.Emerg.Mark.

Economic Journal of Emerging Markets
Available at https://journal.uii.ac.id/jep

Modelling the impact of Information and Communication Technology (ICT) trade, economic complexity and energy structure on carbon neutrality: Evidence from BRICS

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Article history:
Received 01 December 2025
Accepted 13 April 2026
Published 30 April 2026

JEL Classification Code:
F18; Q43; Q56

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DOI:
10.20885/ejem.vol18.iss1.art4

Abstract

Purpose — This study investigates the impact of Information and Communication Technology (ICT) trade flow components, specifically ICT service exports, ICT goods exports, and ICT goods imports, alongside economic complexity and renewable energy share on carbon emissions.

Methodology — A panel of BRICS countries from 2000 to 2022 is estimated using a second-generation cross-sectional autoregressive distributed lag (CS-ARDL) model that accounts for cross-sectional dependence and slope heterogeneity across countries.

Findings — Gross domestic product per capita and economic complexity are positively associated with carbon emissions. ICT trade flows have heterogeneous effects on emissions. ICT services, exports, and renewable energy consumption significantly reduce carbon emissions. However, ICT goods exports and imports have an insignificant effect on carbon emissions.

Implications — The results suggest that the BRICS countries must emphasise policy measures that promote the export of ICT services, accelerate renewable energy adoption, and promote industrial transformation policies towards sustainable production practices.

Originality — This study focuses on supply-side ICT trade channels and disaggregates them into ICT goods exports, imports, and service exports. Furthermore, this study applies second-generation estimation techniques that are robust to cross-sectional dependence and slope heterogeneity.

Keywords — ICT Trade Flows; Economic Complexity; Renewable Energy; CS-ARDL

Introduction

Balancing economic growth with environmental sustainability remains a significant challenge for emerging economies undergoing structural transformation (Shekhawat et al., 2025). Despite rapid economic and technological advancements characterised by the rapid growth of information and communication technology (ICT) and an evolving production structure marked by rising economic complexity and an increasing renewable energy transition, BRICS economies are experiencing a significant rise in carbon emissions. In recent years, these economies have accounted for about 42% of global carbon emissions (Erkılıç et al., 2025). This raises concerns regarding the environmental effects of their developmental pathways.

P ISSN 2086-3128 | E ISSN 2502-180X

These structural changes affect carbon emissions via different mechanisms. ICT may reduce emissions by facilitating technological innovations and digital solutions, promoting efficiency gains across industries (Kashif et al., 2024), whereas it may increase emissions by increasing overall energy demand (Irfan et al., 2025). Economic complexity may reduce emissions through industrial upgrading towards higher value-added and knowledge-intensive exports, whereas it may increase emissions through energy-intensive exports (Balsalobre-Lorente et al., 2023). Renewable energy reduces emissions through the energy substitution channel by substituting fossil fuels with cleaner energy sources (Shekhawat et al., 2025). While ICT development, an evolving production structure, and energy transition are viewed as catalysts for low-carbon and sustainable growth, their environmental implications yield mixed empirical evidence.

The empirical evidence examining the impact of ICT on carbon emissions remains inconclusive (Appiah-Otoo et al., 2023). Studies that measure ICT using demand-based indicators, such as internet adoption rates and mobile and telephone subscription rates, report mixed findings regarding its impact on carbon emissions. One strand of literature reports that ICT significantly improves environmental quality (Sun et al., 2026; Wen et al., 2025). These studies suggest that ICT reduces emissions by enabling resource optimisation, improves energy efficiency, and directs economic activity towards low-carbon service-based sectors (Zuo & Ren, 2025). Whereas other studies found that the growth of ICT increases electricity demand for digital infrastructure and related services, thereby increasing emissions (Adebayo et al., 2025; Le et al., 2025). The literature primarily focuses on demand-side indicators as proxies for digitalisation. It captures ICT adoption usage intensity and efficiency impacts.

However, these demand-side indicators of ICT do not account for the production and supply aspects of ICT, where energy consumption and emissions may be embedded. Thus, it may underestimate the sector's total environmental impact. However, the empirical literature on ICT focuses primarily on the supply side. Empirical studies have reported heterogeneous effects of ICT trade components on carbon emissions. Mhlanga (2025) found that ICT goods exports significantly increase carbon emissions in the case of BRICS countries. The finding is consistent with the energy-intensive nature of ICT goods production, including digital hardware, telecommunications devices, and electronic equipment, which depend on carbon-based inputs and energy-intensive production methods, thereby increasing carbon emissions (Irfan et al., 2025). Whereas Kashif et al. (2024) found that ICT services exports significantly reduce carbon emissions in the case of OECD countries. ICT services, including digital platforms, software, and cloud solutions, enhance environmental quality through dematerialisation and resource efficiency. It also boosts energy efficiency and facilitates sustainable production practices (Wen et al., 2025). F. Khan et al., (2025) investigated the impact of the ICT trade index (measured by using exports and imports of ICT goods and ICT services export indicators) on carbon emissions in the case of five selected Asian countries. The findings indicate that ICT significantly reduces carbon emissions.

However, studies either use individual ICT trade measures or an aggregated measure, neither of which reflects the significant variation among components of ICT trade associated with different energy intensities and production processes. While ICT services exports represent knowledge-based activities with lower carbon intensity, ICT goods trade is associated with energy-intensive production and embodied carbon emissions (Kim, 2024; Lange et al., 2020). It is therefore important to analyse the varying impact of components of ICT trade on carbon emissions. To address this, the present study examines the impact of disaggregated ICT trade channels, including ICT goods exports, ICT goods imports, and ICT services exports, on carbon emissions. Beyond digitalisation, the study has examined structural transformation through the concept of economic complexity. The Economic Complexity Index (ECI) was developed by Hidalgo & Hausmann (2009). It measures the productive knowledge, skills, and know-how embedded in the economy's production structure, as reflected in its capacity to manufacture and export a wide range of sophisticated goods.

Empirical evidence on the environmental impact of economic complexity remains mixed. Some studies found that economic complexity is associated with increased carbon emissions (Balsalobre-Lorente et al., 2023; Feng et al., 2024). These studies suggest that in the early stages of development, increasing economic complexity indicates a shift from agriculture-based exports towards energy-intensive manufacturing-based exports. This transition increases industrial activity and energy demand, leading to higher fossil fuel consumption and, in turn, higher carbon emissions. Whereas other studies found that economic complexity is associated with reduced carbon emissions (Haciimamoglu, 2025; Tabash et al., 2024). Countries with a greater level of complexity specialise in higher-value-added knowledge-intensive exports. Their accumulation of advanced capabilities facilitates technological innovations and energy-efficient, cleaner production methods, thereby reducing carbon emissions. This contrasting evidence suggests that the environmental impact of economic complexity depends on the prevalent production structure and energy mix. In parallel, the renewable energy transition has been widely regarded as a crucial strategy for reducing carbon emissions. Studies have consistently found that renewable energy significantly reduces carbon emissions (Balsalobre-Lorente et al., 2023; Zuo & Ren, 2025).

Despite a growing body of literature, existing literature largely examines information and communication technology (ICT), economic complexity, and renewable energy separately, with limited attention to their combined influence on carbon emissions. This fragmented approach limits understanding of how ongoing structural transformations influence carbon emissions. In addition, most ICT-related studies rely on general ICT adoption metrics, such as internet access and subscription rates. However, these metrics do not capture the supply-side ICT trade flows, which influence production efficiency, technology diffusion, and carbon emissions differently across economies. Therefore, these limitations highlight the need of an integrated analytical framework that accounts for ICT trade, the complexity of economic systems, and the energy structure to provide a comprehensive understanding of how these interconnected factors influence environmental quality.

In this context, the present study extends the STIRPAT model framework to examine the impact of ICT trade flows (exports of ICT services, exports of ICT goods, and imports of ICT goods), economic complexity, and renewable energy on carbon emissions across BRICS economies. The present study contributes to the existing literature in several ways. First, the study includes supply-side ICT trade variables comprising ICT services exports, ICT goods exports and ICT goods imports to assess their environmental impact, thereby moving beyond demand-side ICT usage indicators and providing fresh insights on the impact of ICT trade components on environmental quality. Second, the study includes economic complexity as a structural transformation variable, providing a novel perspective on the impact of evolving productive knowledge and capability structure on environmental quality. Third, the study includes the share of renewable energy (% of total final energy consumption) to analyse the impact of the economy's prevalent energy mix on environmental quality. The study contributes theoretically by extending the STIRPAT model to include ICT trade, economic complexity, and renewable energy as key technological variables, and by analysing how technological progress, underlying production capabilities, and energy structure influence carbon emissions. Additionally, as a methodological advancement, the study employs a cross-sectional autoregressive distributed lag (CS-ARDL) model that accounts for cross-sectional dependence and slope heterogeneity. This is particularly relevant for highly interconnected economies like BRICS, where cross-sectional dependence and slope heterogeneity are prevalent.

The analysis is essential for understanding the development pathways of BRICS economies in the digital era. From a policy perspective, understanding the environmental trade-off associated with ICT-driven industrialisation is essential, as the BRICS economies strive for sustainable growth and greater integration into the global digital trade network. It provides policy insights on how emerging economies might leverage ICT and technological advancement while ensuring environmental sustainability.

Methods

Data Source and Description

The study is conducted on a sample of BRICS countries, namely Brazil, Russia, India, China, and South Africa, for the period 2000 to 2022, based on data availability. Table 2 provides a brief description of the variables employed and data sources.

Table 1. Description of Variables and Data Sources

Variables	Symbols	Units	Sources
Carbon emissions per capita	COEPC	Tonnes per person	Our World in Data
Urban Population	URB	Per cent of total population	Our World in Data
Gross domestic product per capita	GDPPC	constant 2021 US$	Our World in Data
Exports of ICT Services	ICTSER	Per cent of total services exports	World Development Indicators
Exports of ICT goods	ICTEXP	Per cent of total goods exports	World Development Indicators
Imports of ICT goods	ICTIMP	Per cent of total goods exports	World Development Indicators
Economic complexity index	ECI	Index	Atlas of Economic Complexity
Renewable energy share	RES	Per cent total final energy consumption	Our World in Data

Theoretical Framework and Model Specification

The study analyses the determinants of carbon emissions using the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model framework to determine the role of human activities on environmental quality (Dietz & Rosa, 1997). The model can be described using the following equation:

$$I_{it} = aP_{it}^{b}A_{it}^{c}T_{it}^{d}\varepsilon_{it} \tag{1}$$

where *I* represents environmental impact, *P* represents population, *A* represents affluence, and *T* represents the technology variable; ε_{it} represents the error term; *a* is the constant term; *b*, *c*, and *d* are parameters associated with population, affluence and technology variables; *i* is the cross-section unit, and *t* is the time period.

To estimate equation 1, all variables are transformed to their natural logarithms to account for heteroskedasticity and to allow interpretation of the coefficients in elasticities. For the empirical analysis, the model is transformed into log-linear form:

$$lnI_{it} = \alpha + blnP_{it} + clnA_{it} + dlnT_{it} + \varepsilon_{it} \tag{2}$$

In the study, environmental impact is represented by carbon emissions per capita $LnCOEPC_{it}$. Within the STIRPAT framework, the population effect measures the population concentration. It is represented by using the urban population (% of total population), indicated by $LnURB_{it}$. Higher urbanisation is expected to increase carbon emissions ($\beta_1 > 0$) due to increased energy demand, infrastructure expansion and transportation requirements in BRICS (Singh et al., 2024; Wang et al., 2024). Affluence measures the intensity of economic activity per person. It is represented by using gross domestic product per capita, indicated by $LnGDPPC_{it}$. In BRICS countries, higher economic growth is characterised by rapid industrialisation and energy-intensive economic activities. Economic growth increases overall output production and energy consumption, which in turn increases carbon emissions (Singh et al., 2024; Ullah et al., 2023). Therefore, the study hypothesizes positive relationship between GDPC and COEPC ($\beta_2 > 0$).

The study extends the technological component of the STIRPAT model framework to capture ongoing structural transformations in economies characterised by rapid digitalisation (ICT goods exports, ICT goods imports, and ICT services exports), evolving production structures (economic complexity), and the energy transition (renewable energy share). The digitalisation aspect is represented by disaggregated ICT trade components i.e. ICT services exports (% of total services exports) indicated by $LnICTSER_{it}$, ICT goods exports (% of total goods exports) indicated by $LnICTEXP_{it}$ and ICT goods imports (% of total goods exports) indicated by $LnICTIMP_{it}$.

ICT services exports (% of total services exports) reflect an economy's ability to export knowledge-based digital services. The export of ICT services, such as computer programming, consulting, and information services, supports low-carbon and energy-efficient technologies. It also facilitates industrial structure upgrading as economies move away from heavy industrial production towards cleaner, knowledge-intensive industries (Kashif et al., 2024). They are less energy-intensive and resource-intensive than the manufacturing of ICT goods. Thus, it is hypothesised that the expected sign of ICT services exports on carbon emissions is negative (beta sub 3 less than 0).

ICT goods exports (as % of total exports) represent technology diffusion through the trade channel. However, the production of ICT goods such as computers, phones, semiconductors, and other hardware is energy-intensive. Additionally, the manufacturing and disposal of ICT equipment pose challenges for electronic waste management and resource depletion (Ghulam & Abushammala, 2023). Thus, higher ICT goods exports lead to greater production and, hence, an increase in carbon emissions (Mhlanga, 2025). Thus, it is hypothesised that the expected sign of ICT goods exports with carbon emissions is positive in BRICS $(\beta_4 > 0)$.

ICT goods imports (% of total goods exports) facilitate the adoption of advanced energy-efficient digital technologies within the economy. Hence, it reflects the technique effect. Imports of ICT goods reduce emissions through the adoption of cleaner manufacturing processes, energy-efficiency improvements, and dematerialisation within the economy (A. Khan & Ximei, 2022). However, ICT goods imports may also increase energy consumption and emissions (Irfan et al., 2025). Thus, it is hypothesised that the expected sign of ICT goods imports with carbon emissions is ambiguous $(\beta_5 > 0 \text{ or } \beta_5 < 0)$.

In addition to ICT-based digitalisation, the technology component encompasses structural transformation in production, as measured by the Economic Complexity Index. It is indicated by ECI_{it}. It measures the diversity and sophistication of the production structure, as reflected in the economy's export composition of the economy. A higher economic complexity reflects an economy's ability to produce technologically advanced and knowledge-intensive exports that are less carbon-intensive. A lower economic complexity reflects a production structure characterised by resource- and energy-intensive manufacturing, leading to increased carbon emissions (Haciimamoglu, 2025). In the study, Economic complexity in the BRICS economies is often associated with energy-intensive exports, which leads to a rise in emissions (Balsalobre-Lorente et al., 2023). Therefore, ECI is hypothesised to have a positive impact on emissions $(\beta_2 > 0)$.

Further technology components are extended to include the adoption of renewable energy. The study uses the renewable energy share (% of total final energy consumption) indicated by $LnRES_{it}$. It reflects the transition from a carbon-intensive energy structure towards a more sustainable energy mix. Thus, it represents clean energy technology that reduces carbon emissions, as it has a lower life-cycle carbon footprint (Shekhawat et al., 2025). Thus, it is hypothesised that the expected sign of the Renewable energy share (% of total final energy consumption) and carbon emissions is negative $(\beta_6 < 0)$.

Thus, the extended model is specified as:

$$LnCOEPC_{it} = \alpha_0 + \beta_1 LnURB_{it} + \beta_2 LnGDPPC_{it} + \beta_3 LnICTSER_{it} + \beta_4 LnICTEXP_{it} + \beta_5 LnICTIMP_{it} + \beta_6 ECI_{it} + \beta_7 LnRES_{it} + \varepsilon_{it} \quad (3)$$

In equation (3), α_0 represents the constant term, and $\beta_1; \beta_2; \beta_3; \beta_4; \beta_5; \beta_6; \beta_7$ are the model coefficients to be estimated in the model analysis and ε_{it} represents the error term.

Panel Estimation Technique

The study conducts various pre-diagnostic tests, including the cross-sectional dependence test, slope homogeneity test, and panel unit root test, to select the appropriate methodology for the empirical analysis.

Cross-Sectional Dependence (CSD) test

Cross-sectional dependence arises because of unobserved common factors, global shocks or local spillovers which affect all the individual units (e.g. countries or firms) simultaneously. Hence, the residuals are correlated across individual units in a panel data model. To check the cross-sectional dependence across the panel, the study uses the cross-sectional dependence (CSD) test developed by Pesaran (2004). It can be expressed as,

$$Pesaran\ CSD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \tag{4}$$

Here, N represents the number of cross-sectional units, T represents the time period, and $\hat{\rho}_{ij}$ represents the pairwise correlation of residuals between unit i and unit j. The hypothesis of the test is that the null hypothesis states that there is no cross-sectional dependence among the cross-sectional units, while the alternative hypothesis states that there is cross-sectional dependence.

Second-Generation Panel Unit-Root Test

To determine the stationarity properties of the variables, the study uses the second-generation Cross-Sectional Augmented Im, Pesaran, and Shin (CIPS) test (Pesaran, 2007). The test statistics of CIPS is calculated as:

$$CIPS(N,T) = \frac{1}{N}\sum_{i=1}^{N} CADF_i(N,T) \tag{5}$$

Here N is the cross-sections, T is the time and $CADF_i(N,T)$ is the Cross-sectionally augmented Dickey-Fuller statistic for i[th] cross-section. It is obtained from the regression:

$$\Delta Y_{i,t} = \alpha_i + \beta_i Y_{i,t-1} + c_i\bar{Y}_{t-1} + \sum_{j=0}^{p} d_{ij}\Delta\bar{Y}_{t-j} + \sum_{j=1}^{p}\phi_{ij}\,\Delta Y_{i,t-j} + \varepsilon_{it} \tag{6}$$

The hypothesis of the test is that the null hypothesis states that there is a unit root present in the variable, while the alternative hypothesis states that there is no unit root present in the variable.

Slope Homogeneity Test

The Slope homogeneity test is used to determine if the slope coefficient is constant across various cross-sectional units within a dataset. In panel data analysis, it is used to choose between the pooled estimation technique, which assumes identical slopes across cross-sectional units in the panel, and the estimation technique that accounts for slope heterogeneity (Pesaran & Yamagata, 2008). It is represented by the following equations:

$$\Delta_{SH} = (N)^{\frac{1}{2}}(2k)^{\frac{1}{2}}\left(\frac{1}{N}\tilde{S} - k\right) \tag{7}$$

$$\tilde{\Delta}_{ASH} = (N)^{\frac{1}{2}}\left(\frac{2k(T-k-1)}{T+1}\right)^{-\frac{1}{2}}\left(\frac{1}{N}\tilde{S} - 2k\right) \tag{8}$$

where Δ_{SH} is delta tilde and $\tilde{\Delta}_{ASH}$ represents the adjusted delta tilde test statistic. $\tilde{S}$ is swamy test statistic, K is the number of independent variables, and N is the number of cross-sectional units. The hypothesis of the test is that the null hypothesis states that the slope coefficients are homogeneous across all units, while the alternative hypothesis states that they are heterogeneous across units.

Cross-Sectionally Augmented Autoregressive-Distributed Lag (CS-ARDL) Model

Finally, to estimate long-run coefficients, the study uses a second-generation cross-sectionally augmented autoregressive distributed lag (CS-ARDL) model (Chudik & Pesaran, 2015). The model addresses the cross-sectional dependence and accounts for slope heterogeneity. The generalised form of the model can be represented by the following equation:

$$y_{it} = \alpha_i + \sum_{l=1}^{p_y}\phi_{il}y_{i,t-l} + \sum_{l=0}^{p_x}\beta'_{il}x_{i,t-l} + \sum_{l=0}^{p_{\bar{z}}}\gamma'_{il}\,\bar{z}_{t-l} + \varepsilon_{it} \tag{9}$$

Where, y_{it} is carbon emissions per capita, $x_{i,t}$ is vector of explanatory variables and $\bar{z}_t$ is cross-sectional averages of both dependent and independent variables. Furthermore, to ensure robustness of the baseline model, the study employs a fully modified ordinary least squares (FMOLS) estimator, which corrects for endogeneity of regressors and serial correlation in cointegrated panels (Phillips & Hansen, 1990).

Results and Discussion

The findings of Pesaran, (2004) test for the presence of cross-sectional dependence in the panel are reported in Table 2. For most of the variables, including COEPC, URB, GDPPC, ICTSER, ICTEXP and RES, the CD test statistic is significant at the 1% level of significance (p-value < 0.01). So, we reject the null hypothesis (H_0) for the test, i.e. the series is cross-sectionally independent. Thus, the CSD test confirms that the countries are cross-sectionally dependent. Because CSD is present, the conventional first-generation panel unit root test may yield biased and inconsistent estimates. Therefore, the study proceeds with a second-generation unit-root test that accounts for CSD.

Table 2. Cross-sectional dependence test

Variable	CD-test	p-value	Average joint T	mean ρ	Mean abs ρ
COEPC	5.68	0.00	23.00	0.37	0.59
URB	14.35	0.00	23.00	0.95	0.95
GDPPC	13.48	0.00	23.00	0.89	0.89
ICTSER	9.19	0.00	23.00	0.61	0.61
ICTEXP	-2.37	0.01	23.00	-0.16	0.30
ICTIMP	1.86	0.06	23.00	0.12	0.43
ECI	-1.95	0.05	23.00	-0.13	0.68
RES	6.80	0.00	23.00	0.45	0.46
H_0: Series is cross-sectionally independent.					

The findings of the second-generation panel CIPS unit-root test are reported in Table 3. At the level form, the variables COEPC, GDPPC, ICTEXP, ECI and RES do not display statistically significant CIPS statistic (p-value > 0.05). These variables are therefore non-stationary in level form, as we fail to reject the null hypothesis (i.e., the presence of a unit root). In the first difference, the variables COEPC, GDPPC, ICTEXP, ECI, and RES show statistically significant CIPS statistics (p-values < 0.05). This indicates that these variables become stationary after first differencing; thus, they are integrated of order I(1). ICTSER and ICTIMP report statistically significant CIPS statistics at the level (p-value < 0.05). Whereas URB shows a statistically significant CIPS statistic at the 10% level of significance. Thus, these variables are integrated of order I (0). Overall, the findings confirm a mixed order of integration across variables.

Table 3. Second-generation CIPS unit root test

Variable	CIPS statistic at the level	CIPS statistic at First-difference	Order of Integration
COEPC	-1.14	-3.34***	I (1)
URB	-2.26*	-	I (0)
GDPPC	-1.93	-2.90***	I (1)
ICTSER	-2.86***	-	I (0)
ICTEXP	-1.54	-3.55***	I (1)
ICTIMP	-2.58***	-	I (0)
ECI	-1.31	-4.79***	I (1)
RES	-1.93	-5.04***	I (1)
H_0: There is a unit root.			

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

The findings of the Pesaran & Yamagata (2008) slope homogeneity test are reported in Table 4. It indicates that both the delta statistic and the adjusted delta test statistic are statistically significant at the 1% level (p-value < 0.01). Thus, we reject the null hypothesis and confirm that the slope coefficients are heterogeneous across the panel.

The diagnostic test in Table 4 is used to select the appropriate estimation method. The panel shows cross-sectional dependence, slope heterogeneity and mixed order of integration across variables. Conventional panel estimation models that rely on homogeneous slope coefficients and cross-sectional independence may not provide robust estimates. Thus, to account for unobserved common factors, heterogeneous slope coefficients, and variables exhibiting mixed orders of integration, the study uses a second-generation cross-sectionally augmented autoregressive distributed lag (CS-ARDL) model (Chudik & Pesaran, 2015). The findings are reported in Table 5.

Table 4. Slope heterogeneity test

Test	Statistic	p-value
Delta	6.46	0.00
Delta Adj.	8.28	0.00
H_0: Slope coefficients are homogeneous.		

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

Table 5. Long-Run and Short-Run Estimates from the CS-ARDL Model

LNCOEPC	Coef.	Std. Err.	z	P > |z|	[95% Conf. Interval]	
Short Run Est.						
Mean Group:						
LNURB	0.469	2.27	0.21	0.83	-3.980	4.919
LNGDPC	0.812	0.341	2.38	0.01	0.142	1.482
LNSERV	-0.088	0.040	-2.18	0.02	-0.167	-0.009
LNEXP	-0.001	0.050	-0.02	0.98	-0.100	0.097
LNIMP	0.082	0.065	1.26	0.20	-0.045	0.210
ECI	0.088	0.034	2.56	0.01	0.020	0.155
LNRES	-0.381	0.148	-2.57	0.01	-0.671	-0.090
Adjust. Term						
Mean Group:						
lr_LNCOEPC	-1.04	0.090	-11.52	0.00	-1.21	-0.865
Long Run Est.						
Mean Group:						
lr_LNURB	0.172	1.962	0.09	0.93	-3.673	4.017
lr_LNGDPC	0.689	0.315	2.18	0.02	0.070	1.308
lr_LNSERV	-0.088	0.041	-2.14	0.03	-0.169	-0.007
lr_LNEXP	0.002	0.048	0.05	0.95	-0.091	0.096
lr_LNIMP	0.092	0.071	1.29	0.19	-0.048	0.232
lr_ECI	0.095	0.035	2.70	0.00	0.026	0.164
lr_LNRES	-0.359	0.145	-2.47	0.01	-0.644	-0.074
F (85,25) = 3.88						
Prob > F = 0.00						
R-squared (MG) =0.99						
CD Statistic = -1.26 (p-value = 0.206)						

Note: The CD test statistic indicates no significant cross-sectional dependence in the residuals (p-value > 0.05), thus confirming the reliability of the estimates.

The findings show that GDPPC has a positive and statistically significant effect on COEPC in both the short and long run. The estimated coefficient indicates that a 1-unit increase in GDPPC is associated with a 0.68-unit increase in carbon emissions per capita in the long run. This suggests that an increase in economic growth is associated with rising environmental pressures in the case of BRICS countries. This pattern indicates the structural reliance of these countries on energy-intensive industrialisation, infrastructure development, and continued reliance on fossil fuels, resulting in increased carbon emissions. The finding is consistent with the recent studies by Singh et al., (2024) and Ullah et al., (2023).

Furthermore, the findings reveal the differing impacts of ICT goods exports, ICT goods imports, and ICT services exports on per capita carbon emissions across BRICS countries. While ICT services exports reduce emissions, ICT goods exports and imports show no significant effect.

The findings show that ICT service exports have a negative and statistically significant effect on per capita carbon emissions in both the short and long run. The estimated coefficient indicates that a unit increase in ICT services exports decreases carbon emissions per capita by 0.08 units in the long run. The findings support the hypothesis that the integration of digital services into the economy facilitates the transition towards a less carbon-intensive economy. ICT services such as telecommunications, consultancy, courier and information services, and software solutions promote energy efficiency and reduce emissions. Exports of ICT services shift economic activity towards lower-emission, knowledge-intensive sectors, thereby reducing structural dependence on energy-intensive sectors. Further, ICT services enable industries to adopt digital technologies that enhance production efficiency and reduce energy use per unit of output, representing a technique effect. The findings of this study are consistent with the study by Kashif et al., (2024). Thus, the expansion of ICT services exports in international trade can be a viable strategy to decouple economic growth from emissions, as these services have a comparatively lower carbon footprint than manufacturing ICT goods, indicating a sustainable, technology-driven development pathway.

The findings show that economic complexity has a positive and statistically significant effect on carbon emissions per capita both in the short and long run. The estimated coefficient indicates that with a one-unit increase in economic complexity, carbon emissions per capita increase by 0.09 units in the long run. This implies that rising economic complexity in these countries is associated with resource-intensive manufacturing, which increases emissions. Our results are consistent with the previous studies by Balsalobre-Lorente et al., (2023) and Haciimamoglu, (2025).

The findings show that renewable energy has a negative and statistically significant effect on per capita carbon emissions in both the short and long run. The findings indicate that with a one-unit increase in the renewable energy share, carbon emissions per capita decrease by 0.35 units in the long run. The reason could be that renewable energy resources have lower life cycle emissions than fossil fuels. The finding supports the anticipated environmental advantage of switching towards cleaner energy sources. The results align with the work published by Shekhawat et al., (2025).

Table 6. Robustness Analysis Using the FMOLS Model

Variable	Coefficient	Std. Error	t-statistic	prob
LNURB	-2.72	0.58	-4.67	0.000
LNGDPC	1.520	0.269	5.651	0.000
LNSERV	-0.578	0.084	-6.813	0.000
LNEXP	-0.083	0.120	-0.688	0.492
LNIMP	-0.245	0.342	-0.716	0.475
ECI	0.614	0.274	2.238	0.027
LNRES	-0.169	0.060	-2.787	0.006
R-Squared	0.751			
Adjusted R-Squared	0.736			

Further, the findings of the robustness analysis are provided in Table 6. The findings are broadly consistent with the baseline model. Gross domestic product per capita and economic complexity reveal a positive and significant correlation with emissions. Renewable energy share and ICT services exports reveal a negative and significant correlation with emissions. Whereas ICT goods exports and imports remain statistically insignificant. However, the effect of urbanisation on emissions becomes negative and significant in the robustness model, whereas it was insignificant in the CS-ARDL model, indicating its effect is sensitive to model specification.

Conclusion

The present study examined the impact of individual components of ICT trade (ICT services exports, ICT goods exports and ICT goods imports), economic complexity index (ECI) and renewable energy share (RES) on carbon emissions per capita (COEPC) using the STIRPAT model framework. Methodologically, to account for cross-sectional dependence, heterogeneity of slope coefficients, and mixed order of integration, the panel study used a second-generation cross-sectionally augmented autoregressive distributed lag (CS-ARDL) model for the panel of BRICS over the period 2000-2022. The findings reveal that ICT service exports and renewable energy significantly reduce carbon emissions, indicating their positive role in improving environmental quality. Whereas gross domestic product per capita and economic complexity index significantly increase carbon emissions, indicating their harmful effects on environmental sustainability. However, ICT goods exports and imports have no significant effect on carbon emissions. The findings suggest that increasing the adoption of renewable energy and ICT services can help reduce carbon emissions. However, their impact on emissions reduction remains limited relative to the emissions pressure associated with economic growth and rising economic complexity. Therefore, a more effective decarbonization pathway requires aligning these mitigation channels with structural changes in the production system, such as reducing the carbon intensity of complex industries and integrating renewable energy into high-value-added sectors. Thus, renewable energy and ICT services can be an enabling factor in a more comprehensive transition strategy to achieve carbon neutrality objectives in BRICS countries (Balsalobre-Lorente et al., 2023).

Our findings present the following policy implications for enhancing environmental quality in selected economies through ICT trade and the adoption of renewable energy. First, the findings indicate that exports of ICT services are negatively correlated with carbon emissions, suggesting that the expansion of digital services improves environmental quality. Policies should be formulated to facilitate the growth of ICT service industries by building an enabling environment through investment in digital infrastructure and digital skills development. In addition, promoting ICT-related services, including software development, cloud computing, IT consulting, e-governance, and digital banking, promotes dematerialisation and is less energy-intensive. Thus, exports of ICT services can serve as a low-carbon growth strategy for the BRICS economies. Second, the detrimental effect of economic complexity on environmental quality suggests that countries must integrate industrial upgrading strategies with environmental objectives. Policies should be formulated to channelise investments in the development of green technological capabilities, such as research and development (R&D) in renewable energy technologies and energy-efficient manufacturing methods. Further, the study highlights the positive role of renewable energy in environmental sustainability. Policymakers should prioritise investments in renewable energy infrastructure, enhance renewable energy subsidies, and implement regulatory frameworks that encourage business transition towards sustainability.

In conclusion, our findings suggest that ICT-driven growth, characterised by ICT services exports, can promote sustainability and must be integrated with renewable energy technologies, energy-efficient measures, and innovation-driven industrial upgrading strategies.

Funding

The Authors declare that no funds, grants, or other support were received during the preparation of the manuscript.

Acknowledgment

Not applicable

Author contribution

All authors contributed to the conception and design of the study, data collection, analysis and interpretation of the results, and the writing of the manuscript. All authors read and approved the final version of the manuscript.

Use of AI tools declaration

Artificial intelligence tools were used to assist with language editing and to enhance the clarity and readability of the manuscript. The authors remain fully responsible for the content and conclusions of this study.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and material

The dataset analysed during the current study is available from the corresponding author on reasonable request.

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