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THE EFFECTS OF ICT ON ENVIRONMENT QUALITY: THE ROLE OF GREEN TECHNOLOGICAL INNOVATION IN ASIAN DEVELOPING COUNTRIES

Johora Tahsin[1,2]

[1]*School of Economics, Zhongnan University of Economics and Law, Wuhan, China.*
[2]*Planning Cell, Mongla Port Authority, Mongla, Bagerhat, Bangladesh.*
[1,2]*Email: tahsin.johora@yahoo.com Tel: +8613367272441*

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ABSTRACT

To address the existing environmental challenges, the contributions of ICT and green technological innovation have gained considerable scholarly attention in recent decades. Therefore, this study investigates the effects of ICT penetration including green technological innovation on environmental quality in selected Asian developing countries, using data spanning the period 1990-2018. The long-run relationships among the variables are confirmed using panel ARDL and robust least squares techniques. The results suggest that environmental pollution diminishes after a threshold level of ICT development is attained. However, a significantly decreasing influence of green technological innovation is found on carbon emissions, leading to increased energy efficiency by promoting carbon-peaking and carbon neutrality goals. Furthermore, a bidirectional causality running from carbon emissions to ICT penetration and green technological innovation is affirmed by the Dumitrescu-Hurlin causality test. Therefore, more sound fiscal incentives must be implemented to further strengthen the efficient use of ICT products along with green technological innovation.

Contribution/ Originality: This study applies different second-generation econometrics techniques to examine the effect of the degree of ICT penetration, assessed using the ICT index, and green technological innovation on environment quality in selected Asian developing countries, as other studies have not considered these issues in combination.

1. INTRODUCTION

The environmental phenomenon of ICT penetration has garnered considerable attention from environmental scholars because of the rise in greenhouse gases (GHGs) resulting from the heavy energy use of ICT products. ICT's contribution to GHGs was predicted to rise from 1-1.6% in 2007 to 3-3.6% by 2020 and will exceed 14% of the 2016 level by 2040 if this upward trend continues (Belkhir & Elmeligi, 2018). The emission of GHGs contributes to climate change and global warming (Kutlu, 2020). Moreover, an increase in carbon emissions has been shown to significantly degrade the environment in recent years (Li & Wei, 2021). During the second half of the 20th century, a significant amount of CO2 was emitted by Asia and particularly China. Currently, China is the world's largest emitter of CO2, releasing nearly 10.29 billion tons in 2018. India has become the 2nd highest emitter, discharging around 2.60 billion tons in 2018 (Ritchie & Roser, 2020). The other main contributors in Asia are Iran, Saudi Arabia, Turkey, and Indonesia with 9.8 billion tons, 2.5 billion tons, 672 million tons, and 635 million tons, respectively, in 2017. These emissions affect the average temperatures in the various regions of the world and ultimately increase the frequency, magnitude, and impact of floods and droughts, with adverse effects on human life (Lashkarizadeh & Salatin, 2012).

Furthermore, these emissions are predicted to increase in the coming decades, in which intensified industrialization and economic diversification will contribute to the energy crisis. To tackle these adverse effects, a global response to climate change has been adopted in the 2015 Paris agreement, which commits to limiting the global average temperature rise to well below 2°C (Ibrahiem, 2020).

ICT has a dual effect on climate change; it increases energy usage and GHGs emissions, yet it can improve the environment through its dematerialization effects. To lower GHG emissions, a modern, automatic and digital production process is needed to promote ICT adoption and raise concerns about its effect on the environment (Avom, Nkengfack, Fotio, & Totouom, 2020). Additionally, the magnitude of CO2 emissions can be diminished by shifting from the delivery of physical products to the delivery of services, improving the productivity of manpower, innovating and replacing older technology, and choosing virtual mobility (Shabani & Shahnazi, 2019). The utilization of ICT can stimulate innovation and increase productivity by creating new business ideas; it can reduce transaction costs and provide advanced global information (Barıs-Tuzemen, Tüzemen, & Celik, 2020). Thus, green communication technologies must be adopted to lower carbon emissions (Vereecken, Van Heddeghem, Colle, Pickavet, & Demeester, 2010), as well as green procurement processes, disposal of e-waste, and e-regulatory reforms for sustained business growth (Elliot & Binney, 2008). Besides, technological innovation makes a significant contribution to abating global warming and ensuring sustainable development (Fernández, López, & Blanco, 2018). The improvement of technological innovation can enhance energy efficiency and reduce the intensity of energy consumption (Zhong & Li, 2020). It also helps to attain sustainable development by reducing the production costs of renewable energy (Ellabban, Abu-Rub, & Blaabjerg, 2014), along with the development of clean and low-carbon production processes (Ockwell, Haum, Mallett, & Watson, 2010). Although technological innovation has a powerful effect on energy efficiency, green technology innovation is more appropriate to attain sustainable development (Li & Liao, 2020) because it takes the external effects on the environment into account (Wagner, Bachor, & Ngai, 2014). Moreover, green technological innovation contributes significantly to reducing carbon emissions by promoting carbon-peaking and carbon neutrality goals (Sezgin, Bayar, Herta, & Gavriletea, 2021). However, less attention is given to green technological innovation than to pure technological innovation, which is associated with increased CO2 emissions. The global energy and climate change crises are expected to be balanced by green technologies in the future (Morris, Paltsev, & Ku, 2019). Therefore, to check these emissions and attain sustainable development, advanced green technologies must be invented that can help to concentrate GHGs. So, an extensive analysis is needed to investigate whether ICT penetration and green technological innovation can help to improve environmental quality in selected Asian developing countries.

To the best of our knowledge, no previous studies have considered the effects of ICT penetration on environmental quality while considering the role of green technological innovation in selected Asian developing countries from the period of 1990 to 2018. The present study attempts to discover the effects of green technological innovation and the ICT Index on environmental quality. So, to fill the gaps in the literature, this study investigates the effects of ICT penetration and green technological innovation on environmental quality measured through CO2 emissions in selected Asian developing countries in the context of the EKC framework. In doing so, the study intends to achieve the following secondary goals:

1. To determine the impact of ICT penetration and green technological innovation on CO2 emissions in selected countries.
2. To ascertain the causal linkages among CO2 emissions, ICT penetration, and green technological innovation in selected countries.

To achieve these objectives, the study seeks to answer the following research questions:

i. How do ICT penetration and green technological innovation influence the environmental quality in the sample countries?
ii. Is there an inverted U-shaped association between ICT penetration and CO2 emissions in selected countries?

iii. Do ICT penetration and green technological innovation granger cause CO_2 emissions?

The panel autoregressive distributed lag (ARDL) and robust least squares techniques (RLS) are applied to examine the long-run relationships among the variables to answer the first question. The study uses the Environmental Kuznets Curve (EKC) framework proposed by Grossman and Krueger (1991) (inverted U-shaped relationship between per capita CO_2 emissions and per capita GDP) to fulfill the second objective. To broaden the concept of the EKC, the relationship between the environment and ICT is investigated by assuming that after reaching an initial development level of ICT can reduce CO_2 emissions in selected countries. Besides, the Dumitrescu-Hurlin causality test is used to analyze the causality links among the concerned variables to answer the third question.

The rest of the article is structured as follows. Section 2 discusses the relevant theoretical framework and pertinent literature. Section 3 covers the research methodology, including a description of the data, the empirical model, and the econometric procedures. Section 4 analyses the empirical results. Finally, Section 5 draws the major conclusions and suggests some policy implications.

2. LITERATURE REVIEW

2.1. Theoretical Framework: Economic Growth and Technology

The long-run relationship between economic growth and technology was first investigated by Robert Solow, who represented how the evolution of capital accumulation, labor force, and technology affect a country's overall production (Mankiw, 2002). However, an endogenous growth model appears necessary, as no hints are found about the development of technology in this exogenous model. According to the endogenous growth model, technological progress is an outcome of firms making investment decisions for profit maximization. The effects of technological progress on economic growth are broadly discussed by Joseph Schumpeter, who defined economic growth as a process of creative destruction, in which one party gains while others suffer (Greiner, Semmler, & Gong, 2005). Furthermore, economic growth is driven by innovations, which are the outcomes of investments made by entrepreneurs for profit maximization, and these new technologies replace older ones with decreasing profits (Schumpeter, 1935).

2.2. Empirical Review

2.2.1. ICT and the Environment

The impacts of ICT penetration on environmental quality have been examined, though different results have been found. Accordingly, some studies argue that the use of ICT products improves environmental quality by decreasing emissions, such as Ozcan and Apergis (2018), who studied 20 emerging economies from 1990 to 2015; Park, Meng, and Baloch (2018), who studied 23 EU countries from 2001 to 2014; Asongu, Le Roux, and Biekpe (2018) in 44 Sub-Saharan African countries from 2000 to 2012, and Haseeb, Xia, Saud, Ahmad, and Khurshid (2019) in BRICS countries from 1994 to 2014. On the other hand, the production of IT-related products degrades the climate by releasing a massive amount of CO_2 emissions, as most are produced in an energy-intensive way that results in high pollution. This conclusion was drawn by Khan, Baloch, Saud, and Fatima (2018) for the Next-11 countries from 1990 to 2014; Tsaurai (2019) for the emerging markets from 1994 to 2014; Arshad, Robaina, and Botelho (2020) for the south and southeast Asian region from 1990 to 2014; Avom et al. (2020) for 21 Sub-Saharan African countries from 1996 to 2014, and Raheem, Tiwari, and Balsalobre-Lorente (2020) for the G7 countries from 1990 to 2014. Other studies have been conducted on poor e-waste management, which is also a burden on the environment (Widmer, Oswald-Krapf, Sinha-Khetriwal, Schnellmann, & Böni, 2005). The highest quantity of e-waste in 2019 was generated in Asia, where only 11.7% of e-waste was formally collected and properly recycled (Forti, Balde, Kuehr, and Bel, 2020). Moreover, some studies found that ICT development has a mixed effect on the environment. For instance, Higón, Gholami, and Shirazi (2017) examined the existence of an inverted U-shaped relationship between ICT and CO_2 emissions for sub-panels of developed and developing countries. They found that developed countries have reached an initial level of ICT penetration but developing countries need to improve further. Faisal, Tursoy, and

Pervaiz (2020) also explored an inverted U-shaped relationship between ICT and CO_2 emissions in fast-emerging economies from 1993 to 2014. Majeed (2018) concluded that ICT contributed to decreasing CO_2 emissions in developed economies but not in developing economies, after studying 132 developed and developing economies over the period 1980-2016. Shabani and Shahnazi (2019) discovered a positive effect of ICT penetration on CO_2 emissions in the industrial sector but a negative effect in the transportation and services sectors in Iran from 2002 to 2013. Khan, Sana, and Arif (2020), studying 91 sample countries from 1990 to 2017, also found that the ICT index contributed to decreasing CO_2 emissions in developed countries, but they found a negative and significant impact in developing countries. However, no significant relationship between ICT and CO_2 emissions was found for Tunisia in the period 1975-2014 (Amri, 2018).

2.2.2. Green Technological Innovation and the Environment

The potential of technological innovation to help achieve sustainable development and address the effects of climate change has gained considerable attention in the literature. Technological innovation has played a great role in promoting the development of human society, as well as in economic development, (D'Attoma & Ieva, 2020). A significant aspect of technological innovation, green technological innovation concentrates on environmentally friendly and energy-saving solutions (Deng, You, & Wang, 2019). In the process of modernizing economic activity, the pressure on resources and the environment can be effectively diminished by green technological innovation (Zhang, Liu, Zheng, & Xue, 2017). Green technological innovation is considered an essential tool in promoting green and sustainable development by alleviating the internal conflicts between economic growth and environmental degradation. Recently, the relationship between environmental quality and green technological innovation has been extensively investigated, and mixed results have been found. Accordingly, Lee and Min (2015) investigated whether green R&D has a significant impact on the CO_2 emissions of Japanese manufacturing firms. The study revealed a negative association between green R&D and carbon emissions from 2001 to 2010. Díaz, Fernández, Gibbins, and Lucquiaud (2016) analyzed the effect of carbon capture technology on CO_2 emissions in the refining industry in the United States and found that carbon capture technology can effectively reduce carbon emissions. Su and Moaniba (2017) found that the number of climate-change-related innovations has an increasing effect on the levels of carbon emissions from gas and liquid fuels and a decreasing effect on emissions from solid fuel consumption as well as other GHG emissions. Cho and Sohn (2018) measured the effects of green R&D investment and related patent generation on CO_2 emissions. The study concluded that green patent application reduces carbon emissions in the case of Italy, Germany, France, and the United Kingdom from 2004 to 2012. López, Ruíz-Benítez, and Vargas-Machuca (2019) also found that technological innovations, such as electric and emission-free buses, should be prioritized to achieve greater performance in the environmental dimension. Moreover, based on the panel data of 30 provinces and municipalities in China, Ye and Cheng (2019) examined whether green technological innovation efficiency affected the financial ecological environment from 2006 to 2016. The results revealed that the efficiency of green technology innovation has a significant spatial autocorrelation, although the overall efficiency of green technological innovation is not that significant. Besides, the financial ecological environment and its components can effectively promote the efficiency of green technology innovation. To combat global warming and related problems, Toebelmann and Wendler (2020) analyzed the effect of environmental innovation on CO_2 emission reductions in the EU-27 countries between 1992 and 2014. The empirical study found that environmental innovation has a reducing effect on CO_2 emissions; however, general innovative activity has an increasing effect on CO_2 emissions in the sample countries. Furthermore, Zeng, Li, Wu, and Dong (2022) analyzed the spatial spillover and nonlinear effects of green technology innovation on carbon emissions at the regional level in China from 2001 to 2019. The study found that the spatial spillover of green technology innovation has a reducing effect on CO_2 emissions in the selected regions, mainly in the underdeveloped areas in China. In the previous literature, spending on R&D, the global innovation index, the total number of resident and non-resident patents, the number of scholarly articles published per 1000 people in a country, venture capital per $1000 of GDP, etc. have mostly been used to examine the effects of technological innovation on environmental degradation (Youssef, Boubaker, & Omri, 2018). Moreover, patent applications have been widely used to analyze the effect of green technologies (Kwon, Cho, & Sohn, 2017). The present study uses patent applications, as the most suitable proxy for innovation, to examine the effects of green technological innovation on environmental quality (Hascic & Migotto, 2015). In the context of the prior contradictory findings, it is important to carry out new research on the effects of ICT adoption on CO2 emissions in selected Asian developing countries, focusing on the role of green technological innovation for a better understanding of this emerging issue.

3. RESEARCH METHODOLOGY

3.1. Data and Study Variables

The current study investigates the effects of ICT penetration, including green technological innovation, on environmental quality in 34 selected Asian developing countries* from 1990 to 2018. The dependent variable is CO2 emissions (metric tons per capita) as a proxy for environmental quality, which is most often used to analyze the association between ICT and the environment in macroeconomic studies (Melville, 2010). The data on CO2 emissions are collected from the World Bank Indicator, WDI (2020). The explanatory variables used in this study are discussed below:

(i) ICT index: The ICT index consists of the four sub-components of ICT penetration, i.e., mobile subscriptions, internet users, fixed broadband subscriptions, and fixed telephone subscriptions. These are shown in Figure 1 following Higón et al. (2017) and Khan et al. (2020). The data for this index are collected from WDI (2020).

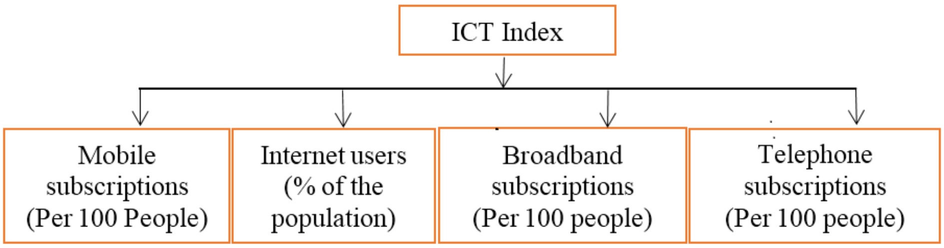

Figure 1. The four components of the ICT index.

(ii) Green technological innovation: The percentage of patents in environment-related technologies is used in this study as a proxy for green technological innovation. These data are collected from OECD (2020), in accordance with Toebelmann and Wendler (2020) and Hascic and Migotto (2015).

The control variables used in this study are (i) Economic growth, measured as GDP per capita (constant 2010 US$) (ii) Energy consumption (kg of oil equivalent per capita) (iii) Trade openness, measured as the sum of export and import (% of GDP). The data for these variables are retrieved from WDI (2020).

*Azerbaijan, Armenia, Georgia, Kazakhstan, Kyrgyzstan, Turkmenistan, Tajikistan, Uzbekistan, China, Mongolia, Bangladesh, Pakistan, India, Nepal, Sri Lanka, the Philippines, Myanmar, Vietnam, Thailand, Brunei, Cambodia, Indonesia, Malaysia, Bahrain, Iran, Iraq, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Turkey, the United Arab Emirates. The statistical description of the selected variables is summarized in Table 1.

Table 1. Summary statistics of the variables.

Variables	Observations	Mean	Std. Dev.	Min.	Max.
LnCO2	986	1.526	0.997	0.000	3.886
LnICT	986	0.614	0.357	0.407	2.113
LnGTI	986	1.548	1.376	0.000	4.615
LnEC	986	6.137	2.779	0.000	10.004
LnY	986	7.994	1.749	0.000	11.152
LnTO	986	4.070	1.135	0.000	5.400

3.2. The Empirical Strategy and Model

The present study investigates the effects of ICT penetration and green technological innovation on environmental quality in selected Asian developing countries, following the methodology of Faisal et al. (2020), Avom et al. (2020), and Higón et al. (2017). Consequently, the constructed model is described in Equation 1:

$$\ln CO2_{it}=\alpha_0+\alpha_1\ln ICT_{it}+\alpha_2\ln ICT^2_{it}+\alpha_3\ln GTI_{it}+\alpha_4\ln Y_{it}+\alpha_5\ln EC_{it}+\alpha_6\ln TO_{it}+\mu_{it} \quad (1)$$

Where CO2 is the carbon emissions, ICT and ICT^2 denote the ICT index and its square term, respectively, GTI is green technological innovation, Y shows economic growth, EC is the energy consumption, and TO is trade openness. The subscripts t, i, and μ show the period, cross-sections, and error terms, respectively. To reduce the effects of heteroscedasticity and data sharpness, all variables are transformed into a logarithmic form. The principal component analysis (PCA) is applied to construct ICT index to avoid multicollinearity problems (Lu, 2018). These indicators are selected for PCA because every nation has different levels of economic growth and R&D, thus a single indicator ICT component might not represent the actual ICT scenario in the sample countries. The computed principal components eigenvectors of the ICT index are shown in Table 2.

Table 2. Principal components eigenvectors of the ICT index.

Variables	Comp 1	Comp 2	Comp 3	Comp 4	Unexplained
Broadband subscription	0.533	-0.161	-0.748	0.362	0.000
Mobile subscription	0.532	-0.255	0.660	0.465	0.000
Internet users	0.570	-0.154	0.049	-0.806	0.000
Telephone subscription	0.328	0.941	0.060	0.056	0.000

Moreover, the expected sign of the coefficients of ICT and ICT^2 may be positive, negative, or insignificant (Haseeb et al., 2019). If the coefficients of ICT and ICT^2 are positive and negative, respectively, it expresses that high-level ICT usage is associated with a decrease in CO2 emissions. Conversely, positive coefficients of ICT and ICT^2 show that CO2 emissions monotonically increase with higher levels of ICT penetration. The coefficient of green technological innovation is expected to be negative as it should improve environmental quality by decreasing CO2 emissions. The expected signs of the coefficients of economic growth and energy consumption are positive, and that of trade openness is negative.

3.3. Estimation Procedures

Different advanced and second-generation econometric techniques are applied in this study to check for issues of endogeneity, non-stationarity, cross-sectional dependency, and heterogeneity, following Faisal, Tursoy, and Pervaiz (2020); Ahmed, Ahmad, and Yusup (2020), and Sabir, Qayyum, and Majeed (2020). These second-generation advanced econometric procedures are discussed in detail below:

3.3.1. Cross-Sectional Dependency Test

To check the cross-sectional dependence (CD) among the variables, this study utilizes (a) the Pesaran scaled LM test by Pesaran, Ullah, and Yamagata (2008), (b) the bias-corrected scaled LM test by Baltagi, Feng, and Kao (2012), and (c) the Pesaran CD test by Pesaran (2004) as the number of the cross-section is greater than the period (N>T). The null hypothesis supposes that there is no CD in the panel data. It is essential to check for this issue; otherwise, a biased value of the unit root and cointegration test may be found in the panel data (Khan, Sana, and Arif., 2020)

3.3.2. Slope Homogeneity Test

The slope homogeneity test (Pesaran & Yamagata, 2008) is applied to find out the slope heterogeneity between the cross-sections. Ambiguous results can be found if slope homogeneity exists in the data (Ozcan & Apergis, 2018). The model for this test is presented in Equation 2 and Equation 3.

$$\tilde{\Delta}_{SH} = (N)^{1/2}(2K)^{-1/2}\left(\frac{1}{N}\tilde{S} - k\right) \quad (2)$$

$$\tilde{\Delta}_{ASH} = (N)^{1/2}\left(\frac{2k(T-k-1)}{T+1}\right)^{-1/2}\left(\frac{1}{N}\tilde{S} - k\right) \quad (3)$$

Where $\widetilde{\Delta}SH$ and $\widetilde{\Delta}ASH$ are the delta tilde and the adjusted delta tilde, respectively.

3.3.3. Panel Unit Root Tests

The second-generation unit roots test, CADF, and CIPS test developed by Pesaran (2007) are applied to check for cross-section dependency and heterogeneity problems. The dynamic linear heterogeneous model with N cross-section of countries is written in Equation 4:

$$\Delta y_{it} = \alpha_i + b_i y_{i;t-1} + \beta_i \bar{y}_{t-1} + \sum_{j=0}^{k} \gamma_{ij} \Delta \bar{y}_{t-j} + \sum_{j=1}^{k} \delta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \quad (4)$$

Where y_{t-1} is the lagged level of cross-sectional averages and t is the period. $\bar{Y}_{t-j}$ is the first order of integration for every cross-section. The CIPS unit root test is based on CADF, which is expressed in Equation 5:

$$CIPS = N^{-1} \sum_{i=1}^{N} CADF \quad (5)$$

3.3.4. Panel Cointegration Test

To analyze the long-run association among the variables, the Westerlund panel cointegration test (Westerlund, 2007) is applied to check for both cross-sectional dependency and heterogeneity issues. This test involves two group statistics (G_t and G_a) and two panel statistics (P_t and P_a). The null hypothesis states that there is no cointegration for at least one cross-section for the G_t, and all cross-sections for P_t. The ECM-based cointegration test presumes that all variables are integrated of I(1), as shown in Equation 6:

$$\Delta y_{it} = \delta'_i d_i + \alpha_i (y_{i,t-1} - \beta'_i x_{i,t-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \Delta x_{i,t-j} + u_{it} \quad (6)$$

Where d_t is the deterministic component and p_i and q_i are the lag lengths and lead orders, which vary across individual cross-sections. The two group-mean test statistics G_t and G_a and the two panel test statistics P_t and P_a are shown in Equations 7 to 10:

$$G_t = N^{-1} \sum_{i=1}^{N} \frac{\hat{\alpha}_i}{SE(\hat{\alpha}_i)} \quad (7)$$

$$G_a = N^{-1} \sum_{i=1}^{N} \frac{T\hat{\alpha}_i}{\hat{\alpha}_i(1)} \quad (8)$$

$$P_t = \frac{\hat{\alpha}_i}{SE(\hat{\alpha}_i)} \quad (9)$$

$$P_a = T(\hat{\alpha}) \quad (10)$$

Where the adjustment speed/short- to long-run equilibrium is denoted by $\hat{\alpha}_i$.

3.3.5. Long-Run Estimation

3.3.5.1. Panel Autoregressive Distributed Lag (ARDL) Method

The panel autoregressive distributed lag (ARDL) method developed by Pesaran, Shin, and Smith (1999) is used to calculate the long-run and short-run association among the chosen variables. This test assumes that all the selected variables are I(1) and cointegrated for individual countries, making the error term an I(0) process for all i. The panel ARDL technique can be written as in Equation 11:

$$\ln CO2_{it} = \beta_0 + \sum_{j=1}^{\rho} \beta_{i1} \ln CO2_{it-j} + \sum_{j=0}^{q} \beta_{i2} \ln ICT_{it-j} + \sum_{j=0}^{q} \beta_{i3} \ln ICT^2_{it-j} + \sum_{j=0}^{q} \beta_{i4} \ln GTI_{it-j} + \sum_{j=0}^{q} \beta_{i5} \ln EC_{it-j} + \sum_{j=0}^{q} \beta_{i6} \ln Y_{it-j} + \sum_{j=0}^{q} \beta_{i7} \ln TO_{it-j} + \mu_i + u_{it} \quad (11)$$

Where $\ln CO2_{it}$ is the dependent variable expressed in natural logarithm, β_{1i}, β_{2i}, β_{3i}, β_{4i}, β_{5i}, β_{6i}, and β_{7i} are the unknown parameters of the logarithm form of CO2 emissions, ICT and ICT^2, green technological innovation, energy consumption, GDP per capita, and trade openness, respectively. Besides, μ_i indicates fixed effects, u_{it}, i, and t are the error term, the number of entities, and time span, respectively. Equation 11 can be modified into an error correction model, which is presented in Equation 12:

$$\Delta \ln CO2_{it} = \delta_i ECT_{it-1} + \sum_{j=1}^{\rho} \gamma_{i1} \Delta \ln CO2_{it-j} + \sum_{j=0}^{q} \gamma_{i2} \Delta \ln ICT_{it-j} + \sum_{j=0}^{q} \gamma_{i3} \Delta \ln ICT^2_{it-j} + \sum_{j=0}^{q} \gamma_{i4} \Delta \ln GTI_{it-j} + \sum_{j=0}^{q} \gamma_{i5} \Delta \ln EC_{it-j} + \sum_{j=0}^{q} \gamma_{i6} \Delta \ln Y_{it-j} + \sum_{j=0}^{q} \gamma_{i7} \Delta \ln TO_{it-j} + \mu_i + u_{it} \quad (12)$$

Where γ_{1i} is the unknown parameter of lagged dependent variable ($lnCO2_{it-j}$).
The error correction term, $ECT_{it} = lnCO2_{it-1} - \beta_0 - \sum_{j=0}^{q} \beta_{i2} lnICT_{it-j} - \sum_{j=0}^{q} \beta_{i3} lnICT^2_{it-j} - \sum_{j=0}^{q} \beta_{i4} lnGTI_{it-j} - \sum_{j=0}^{q} \beta_{i5} lnEC_{it-j} - \sum_{j=0}^{q} \beta_{i6} lnY_{it-j} - \sum_{j=0}^{q} \beta_{i7} lnTO_{it-j}$

And $\delta_i = 1 - \sum_{j=1}^{\rho} \gamma_{1i}$, where δ_i is the coefficient of the speed of adjustment towards the stable (long-run equilibrium) point, and the negative sign of this coefficient determines the convergence towards long-run equilibrium.

3.3.5.2. Robust Least Squares (RLS) Method

The robust least squares method is used in this study because it is more reliable in producing the long-run estimator. Moreover, this technique also helps to check cross-sectional dependency and heterogeneity issues (Faisal et al., 2020).

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3.3.6. Dumitrescu and Hurlin Causality Test

The Dumitrescu and Hurlin (2012) causality test is applied to analyze the directional flow in heterogeneous panels. This test is helpful for correcting cross-sectional dependency and heterogeneity issues, which are based on W-bar and Z-bar statistics. The null hypothesis assumes that no causality exists between variables. This causality test is given in Equation 13:

$$z_{i,t} = \alpha_i + \sum_{j=1}^{p} \beta^j_i z_{i,t-j} + \sum_{j=1}^{p} \gamma^j_i T_{i,t-j} + \mu_{it} \quad (13)$$

Where the lag length is j, and the autoregressive parameter is $\beta^j(j)$.

4. RESULTS AND DISCUSSION

4.1. Cross-Section Dependence Test

The results of three CD tests, the Pesaran scaled LM test, the bias-corrected scaled LM test, and the Pesaran CD test, are portrayed in Table 3. The null hypothesis of no CD between countries is rejected at a 1% level of significance, which confirms that a disturbance in one country can affect other countries.

Table 3. Cross-section dependence test results.

Variables	Pesaran scaled	Bias-corrected scaled	Pesaran CD
LNCO2	165.655***	165.048***	22.0431***
LNICT	323.578***	322.971***	104.473***
LNGTI	18.445***	17.838***	21.325***
LNEC	409.503***	408.896***	118.684***
LNY	254.663***	254.056***	67.900***
LNTO	68.209***	67.602***	13.358***

Note: *** indicates significance at the 1% level.

4.2. Slope Homogeneity Test

The results of the slope homogeneity test are described in Table 4. The results unveil the presence of heterogeneity in the panel data. As the coefficients of the model are heterogeneous and the slope is different across the countries.

Table 4. Slope homogeneity test results.

Statistics	Value	P-value
-Δ	26.677 ***	0.000
Δ-adjusted	30.629 ***	0.000

Note: *** indicates significance at the 1% level.

4.3. Panel Stationary Tests

The results of second-generation panel unit root tests, CADF, and CIPS are presented in Table 5. The CIPS results indicate that LnTO and LnGTI are stationary at both levels and their first difference, and LnCO2, LnICT, LnY, LEC, and LnTO are stationary at their first difference, confirming rejection of the null hypothesis of no stationarity among the variables. Also, the CADF unit root results, LnCO2, LnGTI, and LnTO are stationary at both levels and their first difference, and all other variables are stationary at their first difference. This outcome reveals that all variables in this study are stationary and that makes it suitable to check long-run cointegration among the variables in the sample countries.

Table 5. Panel unit root test results.

Variables	CIPS		CADF	
	At level	1st difference	At level	1st difference
LnCO2	1.071	-19.732***	96.679***	474.313***
LnICT	129.939	-2.393***	75.709	173.439***
LnGTI	-12.377***	-33.178***	286.901***	757.036***
LnEC	5.696	-23.204***	20.884	548.722***
LnY	5.536	-15.389***	53.782	356.246***
LnTO	-6.525***	-27.203***	317.320***	555.125***

Note: *** indicates significance at the 1% level.

4.4. Panel Cointegration Test

The Westerlund panel cointegration test is employed to check the long-run association among the concerned variables. The bootstrap approach of Westerlund is also applied to determine the long-run relationship that governs the CD issue. The bootstrap results reject the null hypothesis of no cointegration, as shown by the robust p-values in Table 6, which affirm the long-run relationship among the concerned variables. The results of cointegration among the variables are similar to the results of Faisal et al. (2020) and Arshad et al. (2020).

Table 6. Westerlund bootstrap cointegration test results.

Test	Stat.	Z-value	P-value	Robust p-value
Gt	-3.061*	0.296	0.384	0.100
Ga	-10.372***	5.624	1.000	0.033
Pt	-16.939*	0.698	0.243	0.067
Pa	-12.392***	2.126	0.983	0.033

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

4.5. Long-Run Elasticity Estimates

4.5.1. Panel ARDL Technique

The long-run estimations of the variables are determined by the cointegration test. Therefore, the panel ARDL technique is applied to estimate the long-run (LR) and short-run (SR) relationship among the variables, and the result is presented in Table 7. The long-run coefficient of the ICT is positive and significant, and the ICT^2 is negative and significant, supporting an inverted U-shaped relationship between ICT penetration and CO2 emissions. It indicates that after arriving at a threshold level, ICT users contribute to reducing pollution through the use of environmentally friendly ICT equipment. This could increase energy efficiency and encourage effective use of the internet (Faisal et al., 2020). Moreover, when a combination of output, input, and technology effects of ICT overcomes the scale effect of ICT, a negative effect of ICT on CO2 emissions is found (Danish, 2019; Higón et al., 2017), also indicating technological advancement and efficient energy use. These results support Higón et al. (2017) and Faisal et al. (2020) and contrast with Avom et al. (2020) and Raheem et al. (2020). As anticipated, the long-run coefficient of green technological innovation has a significant negative effect on emissions by promoting green technology in the sample countries. Green technological innovation enhances the transition to clean energy by improving energy efficiency and cuts the costs of energy production, resulting in reduced carbon emissions (Vidadili, Suleymanov, Bulut, &

Mahmudlu, 2017). Moreover, this innovation assists in reducing CO_2 emissions by promoting carbon peaking and carbon neutrality goals (Zeng et al., 2022). However, more policies should be implemented to ensure better outcomes from green technological innovation in the sample countries. This result supports the findings of Costantini, Crespi, Marin, and Paglialunga (2017); Ghisetti and Quatraro (2017); Toebelmann and Wendler (2020). Furthermore, a significantly increasing effect of energy consumption on CO_2 emissions is found in LR. This implies that energy consumption increases CO_2 emissions through the excessive and inefficient utilization of ICT equipment. It is also argued that developing countries need more energy because of their involvement in older production processes that cause disadvantages to the environment (Khan et al., 2020). This finding is broadly consistent with Lu (2018) and Arshad et al. (2020).

The coefficient of economic growth has a significant increasing effect on CO_2 emissions, both in LR and SR. This effect can be broadly explained by the scale effect, in which more energy is needed to produce more goods and products that have negative effects on the environment (Dinda, 2004). Moreover, this high production level also assists in developing more industrial sectors, leading to the use of more fossil fuels and thus CO_2 emissions (Sohag, Al Mamun, Uddin, & Ahmed, 2017).

These findings parallel those of Ozcan and Apergis (2018) and Lu (2018) but are inconsistent with Haseeb et al. (2019) and Faisal et al. (2020). Moreover, the long-run coefficient of trade openness is negative and statistically significant, supporting the factor endowment theory. This theory describes that the effect of trade openness on the environment depends on countries' capital-labor intensity. It is argued that developing countries are well-endowed with natural resources, and labor will focus on the production and export of less-polluting goods (Avom et al., 2020). This result is in line with the findings of Arshad et al. (2020) and Faisal et al. (2020) but inconsistent with Tsaurai (2019) and Omri and Hadj (2020).

Table 7. Panel ARDL results.

Variables	Coefficient	Std. Error	t-Statistic	P-value
Long-Run Relationship				
LnICT	0.848***	0.129	6.580	0.000
$LnICT^2$	-0.175**	0.073	-2.395	0.017
LnGTI	-0.032***	0.006	-5.294	0.000
LnEC	0.020***	0.005	3.989	0.000
LmY	0.285***	0.005	55.102	0.000
LnTO	-0.049***	0.017	-2.819	0.005
Constant	-0.124***	0.038	-3.234	0.001
Threshold level of ICT	2.426			
Short-Run Relationship				
ECT	-0.126***	0.047	-2.672	0.008
ΔLnICT	-521.017	780.996	-0.667	0.505
$ΔLnICT^2$	636.907	954.630	0.667	0.505
ΔLnGTI	0.038	0.036	1.045	0.296
ΔLnEC	0.025	0.020	1.243	0.215
ΔLnY	0.291***	0.071	4.094	0.000
ΔLnTO	0.023	0.025	0.937	0.349

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

4.5.2. Robust Least Squares (RLS)

The robustness of the Panel ARDL technique is also confirmed using robust least squares (RLS), as shown in Table 8. The long-run coefficients of the RLS model are strongly aligned with the results of the panel ARDL estimates and confirm an inverted U-shaped relationship between ICT penetration and CO_2 emissions. Energy consumption and economic growth are positive and significant, and the effects of trade openness and green technological innovation on CO_2 emissions are found to be negative and significant.

Table 8. Robust Least Squares (RLS) results.

Variables	Coefficient	Std. Error	Z-Statistic	P-value
LnICT	0.832***	0.201	4.152	0.000
$LnICT^2$	-0.191*	0.102	-1.872	0.061
LnGTI	-0.021**	0.010	-2.037	0.042
LnEC	0.031***	0.006	5.524	0.000
LnY	0.609***	0.009	67.467	0.000
LnTO	-0.061***	0.012	-4.907	0.000
Constant	-3.812***	0.090	-41.438	0.000
R^2	0.657			
Adjusted R^2	0.655			

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

Table 9. Dumitrescu-Hurlin panel causality results.

Null Hypothesis	W-Stat.	Z-Stat.	P-value
LnICT does not granger cause LnCO2	4.796***	6.222	0.000
LnCO2 does not granger cause LnICT	5.748***	8.506	0.000
LnGTI does not granger cause LnCO2	3.386***	2.843	0.005
LnCO2 does not granger cause LnGTI	3.328***	2.705	0.007
LnEC does not granger cause LnCO2	3.273**	2.5726	0.010
LnCO2 does not granger cause LnEC	3.126**	2.2192	0.027
LnY does not granger cause LnCO2	8.830***	15.8950	0.000
LnCO2 does not granger cause LnY	7.738***	13.2757	0.000
LnTO does not granger cause LnCO2	6.215 ***	9.6251	0.000
LnCO2 does not granger cause LnTO	3.352***	2.7604	0.006
LnGTI does not granger cause LnEC	2.083	-0.2804	0.7792
LnEC does not granger cause LnGTI	2.107	-0.2232	0.823
LnICT does not granger cause LnEC	15.374***	31.5837	0.000
LnEC does not granger cause LnICT	34.185***	76.6806	0.000
LnTO does not granger cause LnEC	2.053	-0.3521	0.725
LnEC does not granger cause LnTO	24.110***	52.527	0.000
LnY does not granger cause LnEC	3.354***	2.768	0.0056
LnEC does not granger cause LnY	1.698	-1.203	0.2292
LnICT does not granger cause LnGTI	7.412***	12.496	0.000
LnGTI does not granger cause LnICT	1.710	-1.174	0.240
LnTO does not granger cause LnGTI	2.977*	1.864	0.062
LnGTI does not granger cause LNTO	3.586***	3.322	0.001
LNY does not granger cause LNGTI	5.293***	7.415	0.000
LnGTI does not granger cause LNY	2.444	0.584	0.560
LNTO does not granger cause LNICT	2.853	1.566	0.118
LNICT does not granger cause LNTO	4.496***	5.504	0.000
LNY does not granger cause LNICT	5.050***	6.832	0.000
LNICT does not granger cause LNY	2.611	0.984	0.325
LNY does not granger cause LNTO	4.512***	5.544	0.000
LNTO does not granger cause LNY	3.123**	2.214	0.268

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

4.6. Dumitrescu-Hurlin Panel Causality Test

The results of the Dumitrescu-Hurlin panel causality test are presented in Table 9. According to the results, a bidirectional causality association is found from CO2 emissions to ICT, from CO2 emissions to green technological innovation, from CO2 emissions to energy consumption, from CO2 emissions to economic growth, from CO2 emissions to trade openness, from ICT to energy consumption, from trade openness to green technological innovation, and from trade openness to economic growth in the selected countries. In contrast, a unidirectional causality association is found from energy consumption to trade openness, economic growth to energy consumption, ICT to green technological innovation, economic growth to green technological innovation, ICT to trade openness, and economic growth to energy consumption.

5. CONCLUSION AND POLICY SUGGESTIONS

This article has investigated the effects of ICT penetration and green technological innovation on environmental quality in terms of CO_2 emissions in selected Asian developing countries, using data from 1990 to 2018. The results of the empirical study reveal that attaining a threshold level of ICT penetration contributes to diminishing environmental degradation in the sample countries. As it is argued that ICT makes a significant contribution to environmental quality in the present age of industrial revolution and technological advancement, the decline in CO_2 emissions indicates that technological advancement and efficient use of energy could contribute to environmental sustainability in the latter stages of development, even with ICT diffusion. Likewise, green technological innovation reduces CO_2 emissions by energy efficiency, which can further help to achieve carbon peaking and carbon neutrality goals. Additionally, economic growth, energy consumption, and trade openness play crucial roles in the nexus of the environment and ICT penetration. Accordingly, the outcomes of this study suggest that green technological innovation could be used more efficiently and effectively through the adoption of different clean energy resources and ICT products. Therefore, to mitigate the adverse effects of ICT on environmental quality, governments should design policies to improve energy efficiency and promote renewable energy and provide more fiscal incentives for green technological innovation along with enforcing environmental laws and regulations.

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