ISSN: 2029-4913 / eISSN: 2029-4921

Article in press

TECHNOLOGICAL and ECONOMIC DEVELOPMENT of ECONOMY

https://doi.org/10.3846/tede.2024.21050

SUSTAINABLE DIGITAL TRANSFORMATION: THE NEXUS BETWEEN ICT AND GLOBAL GREEN ECONOMIC GROWTH

Yiwen LI[1], Xia LI[2], Xiaojuan WANG[3], Chao FENG[4]✉

[1,2,3] *School of Economics, Central University of Finance and Economics, 100098 Beijing, China*
[4] *School of Economics and Business Administration, Chongqing University, 400030 Chongqing, China*

Article History:
- received 16 November 2022
- accepted 21 December 2023
- first published online 20 May 2024

Abstract. As a new engine to promote global economic and social development, information and communication technology (ICT) plays a key role in the field of modern economy. The aim of this paper is to investigate the nexus between ICT and green total factor productivity (GTFP) on a global scale. An extended data envelopment analysis model (DEA), named WINDOWS-US-SBM, was constructed for calculating the GTFP of 65 countries from 2007 to 2019. This paper empirically analyzes the spatial effect and the transmission mechanism of ICT development on GTFP in countries from different income groups. The results show a prominent imbalance between ICT development and GTFP in various countries. ICT can effectively improve GTFP and play a crucial role in lower middle-income countries. The development of ICT can improve GTFP through technological progress, energy intensity, and trade openness. This paper is helpful to provide policy guidance for the development of ICT and give a new perspective of global green development.

Keywords: WINDOWS-US-SBM model, ICT development, spatial Durbin model, threshold model, global green development.

JEL Classification: O33, O44, Q56.

✉Corresponding author. E-mail: *littlefc@126.com*

1. Introduction

Rapid industrialization and urbanization have not only brought unprecedented development opportunities to countries around the world, but also caused a series of environmental problems, including climate change and air pollution. How to promote the harmonious integration of environmental protection and economic development has become a widespread topic of concern (Wang et al., 2022; Koseoglu et al., 2022).

In recent years, information and communication technology (ICT) has undergone rapid and remarkable development. ICT profoundly impacts both global industries and human lifestyles, encompassing aspects such as reconstructing traditional industrial models, reducing costs, and enhancing productivity (Hoffert et al., 2002; Higón et al., 2017). ICT can play a crucial role in addressing climate change and other related environmental challenges. The impact of ICT on environmental sustainability has also been extensively discussed (Melville, 2010; Elliot, 2011; Watson et al., 2012; Gholami et al., 2013).

As a key index to evaluate the quality of economic development, total factor productivity (TFP) is considered by the academic community to be of high priority. The lack of "greening" of the traditional extensive economic growth model has resulted in problems such as the depletion of natural resources. The influence of environmental factors should be considered based on traditional productivity research to correctly evaluate the economic development performance. Therefore, the academic circle has gradually shifted its research focus to the study of green TFP (GTFP) and regarded it as an important indicator to measure green development (Sueyoshi et al., 2017; Zhu et al., 2018; Cárdenas Rodríguez et al., 2018; Wang & Feng, 2021).

In the context of an increasingly digitalized global economy, it is of great theoretical and practical significance to explore the coordinating role of ICT in economic development and environmental quality. Based on this, we integrated data on ICT index and green development from 65 countries into a unified research framework. Referring to Zhu et al. (2019), we used the super-slack-based measure (Super-SBM) model combined with the window DEA model to construct an extended DEA model (WINDOWS-US-SBM), and used this model to quantitatively measure the GTFP in different income level groups of countries. The contribution of this paper is mainly reflected in three aspects. Firstly, due to difficulties in data acquisition and other problems, many studies often use a single indicator to measure ICT in empirical analysis (Haldar et al., 2023; Tzeremes et al., 2023), which is not a comprehensive indicator and cannot measure ICT index more comprehensively. This paper employs multiple indicators to quantitatively measure the ICT index. Furthermore, this study investigates the impact of ICT development on GTFP in countries with varying income groups, which helps to propose relevant suggestions based on local conditions. Additionally, this article found that Lahouel et al. (2021) conducted a comprehensive analysis on the non-linear relationship between TFP and CO_2 emissions, considering the ICT threshold effect, while Yu (2022) explores the mediating variables of industrial structure and technological innovation to understand the transmission path of the internet on IGTFP. Based on the relevant findings of Lahouel et al. (2021) and Yu (2022), this paper discusses the driving force and the transmission mechanism of ICT impact on GTFP from the aspects of technological progress, energy intensity and trade openness, which holds significant policy implications for effectively promoting ICT development and achieving global green development.

2. Literature review

ICT promotes information acquisition, dissemination, and sharing, effectively improving the efficiency of resource allocation (Fernández-Portillo et al., 2020). The impact of ICT on GTFP has become a hot topic in research (Amri et al., 2019; Jung & López-Bazo, 2020). Most existing research suggests that ICT contributes to economic development, but the mechanisms of the ICT impact on the environment still need further research. The mechanism of ICT development on environmental pollution is mainly manifested in the scale, technological innovation, structure, and foreign trade effects. The scale effect means that ICT development can contribute to economic development. The technological innovation effect refers to the fact that the progress of ICT will enhance innovation consciousness and thus significantly accelerate the rate of technological innovation. Technological innovation has a bi-directional impact on the environment. On the one hand, it can enhance labour efficiency, improve labour productivity, and reduce environmental pollution. On the other hand, technological innovation has a "rebound effect", whereby it increases the demand for energy, resulting in environmental pollution. The structural effect means that the progress of ICT not only drives the rise of high-tech industries but also upgrades and transforms traditional energy-consuming industries to reduce energy intensity, thus reducing their negative effects on the environment (Huang et al., 2019). The foreign trade effect refers to the development of ICT that can promote foreign trade and improve transaction efficiency. The foreign trade effect also has a two-fold environmental effect. On the one hand, more foreign trade allows the trade in efficient and environmentally friendly technological innovations, while promoting global competition for more resources. On the other hand, foreign trade enables developed countries to shift high-energy-consuming and high-polluting industries to underdeveloped areas, thus aggravating environmental pollution in those areas (Lau et al., 2014; Zhang et al., 2017).

2.1. The ICT scale and GTFP

Countries are becoming increasingly aware of the limitations of the economic development that relies on natural resources. In order to better assess the economic development and environmental quality of a specific region, GTFP has gradually become the focus of attention (Sun et al., 2020). The research of GTFP mainly focuses on aspects such as definition, measurement methods, and influencing factors (Su et al., 2021; Farouq et al., 2021; Tian & Feng, 2022). The current mainstream theories on the relationship between the ICT scale and GTFP can be broadly categorized into two perspectives: positive and negative. Firstly, the "ICT for Green" perspective suggests that the use of smart technologies and tools can alleviate environmental burdens (Majeed, 2018). This theory refers to the role of ICT in enhancing resource efficiency, innovation, and sustainability, thereby contributing to environmental protection and sustainable development. Moreover, it can achieve cleaner and greener sustainable production processes, and improve energy efficiency (Gouvea et al., 2018; Danish, 2019; Zheng et al., 2023).

Another view is that the increase of the ICT scale may have a negative impact on GTFP. The proliferation of ICT leads to enhanced production efficiency and reduced production costs, thereby generating a scale effect due to the rising demand for products. At the same time, the continuous growth of ICT leads to an increase in the manufacturing, transportation, and use of ICT devices, as well as electronic waste, thus challenging the prospects for achieving green growth (Plepys, 2002; Houghton, 2015).

2.2. ICT, technological progress, and GTFP

The influence of ICT on technological progress has been widely discussed in recent years (Cecere et al., 2014). The technological advances brought by ICT are conducive to diverse, innovative, and productive societies. ICT can effectively promote the smooth circulation of regional innovation elements, and strengthen the synergistic interaction between regional innovators (Crişan et al., 2010). Bartel et al. (2007) found that information technology promotes productivity growth by promoting product innovation and employee skills. Androutsos (2011) points out that the internet facilitates the collaboration between R&D, design, and manufacturing enterprises. This spawns a series of new technologies and formats of business, generating significant innovation spillover effects. Some researchers believe that ICT can enhance regional environmental quality by optimizing production processes and raising the bar on green technologies (Feuerriegel et al., 2016). Shahbaz et al. (2016a) proposed that capital flow, globalisation, and technological progress are important tools for dealing with environmental pollution. The development of ICT breaks the space-time constraint of information transmission, and promotes the spillover of cutting-edge technology.

Technological progress plays a crucial role in driving economic growth and development, while also fostering sustainable practices in production processes. Firstly, technological advancements drive innovation in environmental technologies, such as clean energy and resource-efficient practices, leading to greener production processes and increased GTFP (Su & Gao, 2022). Secondly, technological progress improves resource utilization efficiency, reduces waste, and enhances overall resource efficiency, thereby fostering sustainable production practices and contributing to higher GTFP (Miao et al., 2017). Based on panel data from 30 provinces in China between 2000 and 2016, Jin et al. (2019) found that technological innovation enhances the green total factor efficiency of industrial water resources in China. Moreover, under the impetus of technological progress, companies have increased investment in green initiatives, promoting the adoption of environmental practices and driving further improvements in GTFP (Zhang et al., 2022). Furthermore, the knowledge transfer and learning effects brought about by technological progress stimulate the application of environmental technologies, positively influencing GTFP (Wang et al., 2021). Lastly, technological progress improves environmental management and regulatory capabilities, leading companies to prioritize sustainable development practices, hence improving GTFP.

2.3. ICT, energy intensity, and GTFP

The development of ICT is having an increasing impact on production methods and energy consumption. Firstly, changes in energy intensity directly affect a company's energy costs. Higher energy intensity implies greater energy consumption per unit of output, resulting in higher energy expenses during production. Consequently, reducing energy intensity enables companies to decrease energy costs, thereby improving production efficiency and GTFP (Feng et al., 2018). Moyer et al. (2012) found that information networks can improve production efficiency, reduce energy intensity to achieve energy conservation. Additionally, Ishida (2015) analyzed panel data from Japan between 1980 and 2010 using the autoregressive distributed lag bound test method and concluded that ICT investment is helpful in moderately reducing Japan's energy consumption. Secondly, changes in energy intensity are often accompanied by technological innovation and changes in production methods. By introducing more energy-efficient and environmentally friendly technologies and equipment, companies can reduce energy consumption per unit of output, consequently increasing energy efficiency and GTFP (Zhang et al., 2021). Zhou et al. (2018) analyzed the effect of ICT on energy intensity in China using the three-tier structural decomposition analysis (SDA). The results showed that alternative investment in ICT can help reduce the use of energy in production processes. Lastly, the improvement of energy intensity involves the allocation and utilization of resources within a company. Through optimizing resource allocation and enhancing energy utilization efficiency, companies can reduce energy intensity and increase GTFP (Huang et al., 2022).

2.4. ICT, Trade openness, and GTFP

ICT greatly improved the efficiency of information transmission and ensured that traders can closely follow market trends, thus effectively reducing energy consumption per unit of output and improving resource allocation efficiency (Addison & Rahman, 2005; Vemuri & Siddiqi, 2009). Therefore, GTFP can be improved in the long run under ICT development (Liu et al., 2016). ICT breaks the temporal and spatial constraints of traditional trade and reduces the cost of sharing information. It is conducive to builds a bridge for professional division and cooperation in trade. Consequently, international trade is changing in content and form. Lin (2015) showed that when internet users increase by 10 percentage points, foreign trade increases by 0.2 to 0.4 percentage points.

3. Methodology and data

3.1. Model establishment

The purpose of this study was to determine the impact of the ICT index on GTFP. Based on the theoretical research of Greenstein (2020) and Lange et al. (2020), this paper incorporates the ICT index into the analytical framework of GTFP. This research focuses on the following model:

$$\ln GTFP_{it} = \beta_0 + \beta_1 \ln Y_{it} + \beta_2 \ln ICT_{it} + \beta_3 \ln X_{it} + \varepsilon_{it}, \tag{1}$$

where ln$GTFP$ represents the natural logarithm of GTFP, lnICT represents the natural logarithm of ICT development. ln$Y$ represents the natural logarithm of economic growth. X represents other control variables, including the industrialization level, technological progress, energy intensity, trade openness, urbanization level, and population density. The subscripts i and t represent the country and year, respectively; ε_{it} represents a random error vector; β is an unknown parameter vector.

3.2. WINDOW-US-SBM model

We estimate GTFP using the WINDOW-US-SBM model, primarily based on the following considerations. Traditional DEA method may suffer from the issues of an insufficient number of available decision making units (DMUs), applicability limited to cross-sectional data, and the constraint of the highest efficiency value being 1. Tone (2001) presented a non-radial DEA model, namely the SBM model, which eliminates the deviation and influence caused by the difference in radial and angular selection. Tone (2002) presented a super-efficiency SBM model with undesirable output, and comprehensively considered the relationship between input, output, and pollution. Suppose the production system has n DMUs, m inputs x, q_1 desired outputs y^g, q_2 undesired outputs y^b, X, Y, and Z are defined as matrices $X = [x_1, x_2, \cdots, x_n]$, $Y^g = [y_1^g, y_2^g, \cdots, y_n^g]$, $Y^b = [y_1^b, y_2^b, \cdots y_n^b]$, in which the input, desirable, and undesirable outputs x, $y^{g,}$ and y^b are greater than 0. Combined with Tone (2002) and Cooper et al. (2006), the super-efficiency SBM model is as follows:

$$\rho^* = \min \frac{1+\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1-\frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1} s_r^{g+} / y_{rk}^{g} + \sum_{t=1}^{q_2} s_t^{b-} / y_{tk}^{b}\right)}$$

$$\begin{aligned}
\text{s.t.}\quad & \sum_{j=i,j\neq k}^{n} x_{ij}\lambda_j - s_i^- \le x_{ik}, \\
& \sum_{j=1,j\neq k}^{n} y_{rj}\lambda_j + s_r^{g+} \ge y_{rk}^{g}, \\
& \sum_{j=1,j\neq k}^{n} y_{tj}^{b}\lambda_j - s_t^{b-} \le y_{tk}^{b}, \\
& 1-\frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1} s_r^{g+} / y_{rk}^{g} + \sum_{t=1}^{q_2} s_t^{b-} / y_{tk}^{b}\right) > 0, \\
& \lambda, s^-, s^+ \ge 0, \\
& i = 1, 2\ldots, m;\ r = 1, 2\ldots, q;\ j = 1, 2\ldots, n\ (j \neq k),
\end{aligned} \tag{2}$$

where i, r, t, and k denote i th input, r th desirable output, t th undesirable output, and k th DMU, respectively. x_{ik}, y_{rk}^{g}, and y_{tk}^{b} represent the inputs, desirable outputs, and undesirable outputs, respectively. s_i^-, s_r^{g+}, and s_t^{b-} are the slack variables of input and output, λ is the weight vector, and ρ* refers to the relative efficiency; if and only if ρ* > 1, DMUk is effective.

DEA window analysis is a useful method to deal with problems related to the intertemporal comparison of efficiency values that general DEA methods cannot solve (Charnes et al., 1985). It can vertically and horizontally compare the efficiency of different DMUs in various periods (Asmild et al., 2004). In addition to evaluating the efficiency of the DMU, the DEA window analysis could also perform moving averages against time-series indicators. The efficiency value for the same year was the average value of the different window periods. The window DEA model increases the number of effective data points and helps to realize a comprehensive analysis of the changing trend of DMU, thereby achieving realistic efficiency evaluations.

Assume that the sample time length is T and the window width is d. Hence, the number of windows is $T - d + 1$. Suppose that the number of initial DMUs is n and the number of the DMUs under evaluation changes to $d \times n \times (T - d + 1)$.

Referring to Zhu et al. (2019), this research combined window DEA with super-efficiency SBM model carrying undesirable output and obtained the WINDOW-US-SBM model. According to Asmild et al. (2004), within the T period (T = 1, ..., T), assuming N DMUs, using r inputs to obtain s outputs, among which the input vector $X_n^t = \left(x_n^{1t} \cdots x_n^{rt}\right)^T$ and output vector $Y_n^t = \left(y_n^{1t} \cdots y_n^{st}\right)^T$, if the window begins from t ($1 \le t \le T$) and the width is d($1 \le d \le T - d + 1$), the input and output matrix is

$$X_{td} = \begin{pmatrix} x_1^t & x_2^t & \cdots & x_N^t \\ x_1^t & x_2^{t+1} & \cdots & x_N^{t+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{t+d} & x_2^{t+d} & \cdots & x_N^{t+d} \end{pmatrix}; \tag{3}$$

$$Y_{td} = \begin{pmatrix} y_1^t & y_2^t & \cdots & y_N^t \\ y_1^t & y_2^{t+1} & \cdots & y_N^{t+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_1^{t+d} & y_2^{t+d} & \cdots & y_N^{t+d} \end{pmatrix}. \tag{4}$$

The efficiency value in the δth window (δ = 1, 2,…, $T - d + 1$) at the time point γ (γ = 1, 2,…, d) is as follows:

$$\rho^*_{WIN-US-SBM} = \min \frac{1 + \frac{1}{m}\sum_{i=1}^{m} s_i^{-,\varphi\gamma} \,/\, x_{ik}^{\delta\gamma}}{1 - \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1} s_r^{g+,\varphi\gamma} / y_{rk}^{g,\varphi\gamma} + \sum_{t=1}^{q_2} s_t^{b-,\varphi\gamma} / y_{tk}^{b,\varphi\gamma}\right)}$$

$$\text{s.t.} \quad \begin{aligned} & \sum_{j=i, j\neq k}^{n} x_{ij}^{\varphi\gamma}\lambda_j^{\varphi\gamma} - s_i^{-,\varphi\gamma} \le x_{ik}^{\varphi\gamma}, \\ & \sum_{j=1, j\neq k}^{n} y_{rj}^{\varphi\gamma}\lambda_j^{\varphi\gamma} + s_r^{g+,\varphi\gamma} \ge y_{rk}^{g,\varphi\gamma}, \\ & \sum_{j=1, j\neq k}^{n} y_{tj}^{b,\varphi\gamma}\lambda_j^{\varphi\gamma} - s_t^{b-,\varphi\gamma} \le y_{tk}^{b,\varphi\gamma}, \\ & 1 - \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1} s_r^{g+,\varphi\gamma} / y_{rk}^{g,\varphi\gamma} + \sum_{t=1}^{q_2} s_t^{b-,\varphi\gamma} / y_{tk}^{b,\varphi\gamma}\right) > 0, \\ & \lambda^{\varphi\gamma},\ s^{-,\varphi\gamma},\ s^{g+,\varphi\gamma},\ s^{b-,\varphi\gamma} \ge 0, \\ & i = 1, 2\ldots, m;\ r = 1, 2\ldots, q;\ j = 1, 2\ldots, n\ (j \neq k). \end{aligned} \tag{5}$$

$x_{ik}^{\delta\gamma}$, $y_{rk}^{g,\delta\gamma}$, and $y_{rk}^{b,\delta\gamma}$ represent the input, desirable, and undesirable outputs of the δth window in the γth year, respectively. Other variables' definitions are similar to those in Eq. (2).

According to Halkos and Polemis (2018), the window width d was set to 3. In the example provided, the first window included 2007, 2008, and 2009. As the window slides, the original years are removed from the window, and a year is added; the last window includes 2017, 2018, and 2019. This paper adopts the WINDOW-US-SBM model to better alleviate the limitations of the traditional DEA model, so as to better measure GTFP (Meng & Zhao, 2022; Sun et al., 2023).

3.3. Spatial autocorrelation analysis

(1) Spatial weight matrix

The spatial weight matrix was used to describe the relative position relationship of the spatial observation units and measure spatial dependence. Different spatial weight calculation methods generate different spatial autocorrelations and obtain different significance test results. The most commonly used construction method is the inverse distance spatial weight matrix (W_d) (Eq. (6)) based on the principle of geographical distance (Elhorst, 2014). W_d considers the potential differences in the spatial spillover effects of the GTFP at different geographical distances, which can reflect the spatial correlation characteristics more comprehensively and objectively. W_d can be described as follows:

$$W_d = \begin{cases} \frac{1}{d_{ij}} & i \neq j \\ 0 & i = j \end{cases}, \tag{6}$$

where d_{ij} represents the reciprocal of the distance calculated based on the longitude and latitude from the capital of country i to that of country j.

(2) Spatial econometric model

According to Elhorst (2012), common spatial econometric models involve the spatial error model (SEM), spatial lag model (SLM), and spatial Durbin model (SDM), which are shown in Eqs (7)–(9), respectively: SLM considers the spatial lag correlation of the dependent variables. SEM introduces the spatial effect into the disturbance error term and reveals spatial heterogeneity. The SDM considers the lag terms of the explanatory and dependent variables. The SLM, SEM, and SDM can usually be written as

SLM:

$$Y = \alpha I_n + \rho WY + X\beta + \varepsilon,\ \ \varepsilon \sim N\left(0, \delta^2 I_n\right). \tag{7}$$

SEM:

$$Y = \alpha I_n + X\beta + \mu,\ \ \mu = \lambda w\mu + \varepsilon,\ \varepsilon \sim N\left(0, \delta^2 I_n\right). \tag{8}$$

SDM:

$$Y = \alpha I_n + \rho WY + X\beta + WX\theta + \varepsilon,\ \ \varepsilon \sim N\left(0, \delta^2 I_n\right). \tag{9}$$

To select these spatial models, the likelihood ratio (LR) test and Wald test were used in the following two null hypotheses. H_0:δ = 0 and H_0:δ + ρβ = 0. Essentially, SDM is the best model for fitting the data in this study because both hypotheses are rejected (Burridge, 1981).

Since SDM can better estimate the spillover effects across observers and obtain unbiased coefficient estimates, this study adopts a more generalized SDM to study the spatial correlation between the variables and the GTFP. The spatial econometric model is expressed in Eq. (10):

$$\begin{aligned} \ln GTFP_{it} &= \rho W \ln GTFP_{it} + \beta_0 + \beta_1 \ln Y_{it} + \beta_2 \ln ICT_{it} + \beta_3 \ln X_{it} + \\ &\theta_1 W \ln Y_{it} + \theta_2 W \ln ICT_{it} + \theta_3 \ln X_{it} + \varepsilon_{it},\ \ \varepsilon_{it} \sim N(0, \sigma_{it}^2). \end{aligned} \tag{10}$$

W represents the spatial weight matrix of $N \times N$, the subscripts i and t represent the country and year, respectively; ρ is a spatial autoregressive coefficient; ε_{it} represents a random error vector; β and θ are unknown parameter vectors.

3.4. The mediating effect model

In this section, a mediating effect model is constructed to empirically test the mechanism of the effect of the ICT development level on GTFP. This study selected technological progress, energy intensity, and trade openness as the mediating variables. Referring to MacKinnon et al. (2000), mechanism test was conducted in three steps and the complete mediation effect model consists of Eqs (11)–(13):

$$\ln GTFP_{it} = \gamma_1 + \gamma_2 \ln ICT_{it} + \sum \gamma_j X_{it} + \mu_i + \varepsilon_i; \quad (11)$$

$$\ln MED_{it} = \beta_1 + \beta_2 \ln ICT_{it} + \sum \beta_j X_{it} + \mu_i + \varepsilon_i; \quad (12)$$

$$\ln GTFP_{it} = \omega_1 + \omega_2 \ln ICT_{it} + \omega_3 \ln MED_{it} + \sum \omega_j X_{it} + \mu_i + \varepsilon_i. \quad (13)$$

$\ln MED_{it}$ is the mediating variable that includes technological progress, energy intensity, and trade openness. γ_2, β_2, and ω_2 are the coefficients of the ICT development level. ω_3 is the coefficient of the mediating effect variable; X_{it} is other control variable; i = 1, 2, ..., N represents countries, u_{ij} is a normally distributed mean-zero error term; and γ_j, δ_j, ω_j are the coefficients of the control variables.

3.5. The threshold panel model

Due to the involvement of multiple factors in affecting GTFP in real-world economies, and the possible existence of complex interactions and nonlinear effects among these factors, traditional linear regression models may not fully capture this complexity (Wu et al., 2020). Regarding the analysis of the causal mechanism, this paper not only employs the traditional mediation effect model but also adopts the threshold panel model to capture the non-linear relationship between variables. (Lahouel et al., 2021). This study is able to fit linear regression models in different sub-samples and group the sample data based on specific threshold conditions, thereby more accurately exploring the nonlinear impact of technological progress, energy intensity, and trade openness on GTFP under different conditions (Qiu et al., 2021). This research approach contributes to a deeper understanding of the actual effects of ICT on GTFP and provides more targeted guidance for relevant policy formulation (Kremer et al., 2013). Therefore, this study used Hansen's (1999) panel threshold model and considered technological progress, energy intensity, and trade openness as threshold variables to further test this nonlinear relationship. The panel threshold model was set as follows:

$$\ln GTFP_{it} = \beta_0 + \beta_1 \ln ICT_{it} \cdot I(q_{it} \le \lambda_1) + \beta_2 \ln ICT_{it} \cdot I(\lambda_1 \le q_{it} \le \lambda_2) + \\ \beta_3 \ln ICT_{it}(q_{it} > \lambda_2) + \beta_c X_{it} + \varepsilon_{it}, \quad (14)$$

where q_{it} denotes the threshold variable, including technological progress, energy intensity, and trade openness, λ_1 and λ_2 are the thresholds to be estimated. $I(\cdot)$ is the indicator function, β is an unknown parameter vector, and ε_{it} represents a random error vector.

4. Data description

This study uses panel data of 65 countries from 2007 to 2019. Following the existing literature (Pan et al., 2013; Song et al., 2013; Halkos & Polemis, 2018), We classify countries according to the World Bank's income division criteria into four categories: high-income countries (HI), upper-middle-income countries (UMI), lower-middle-income countries (LMI), and low-income countries (LI) (Table A1). Capital stock and GDP data are obtained from the Penn World Table, version 10.0. Energy consumption and CO_2 emission data are obtained from Energy Information Administration (EIA). The variable definitions are listed in Table 1. We use labor force, capital stock, and energy consumption as input variables, GDP as the desirable output, and CO_2 emissions as undesirable outputs (Table 2).

The entropy weight method adopts information entropy to assess the entropy weight of every subdivision index and acquire an objective index weight. Entropy can be used to judge the degree of dispersion of an index. The entropy weight method is used to calculate the comprehensive index of the ICT level. Considering the availability of data, four ICT representative variables are selected: fixed telephone subscriptions (per 100 people), mobile cellular subscriptions (per 100 people), fixed broadband subscriptions (per 100 people), and using the internet (% of population). The four ICT representative variables are all positive (Table 1).

The indicators of trade openness, industrialization level and energy intensity are measured by the ratio of total trade output value, secondary industry output value and energy consumption to GDP, respectively. The total number of patent applications (resident and non-resident) represented the technological innovation variables. The data for import and export value, secondary industry output value, and the total number of patent applications are from *World Bank Development Indicators* (*WBDI*). To reduce the impacts of the inflation change and exchange rate, GDP per capita is converted based on the 2017 constant price using the GDP deflator.

Table 1. Definition of the variables used in this study

Classification	Variables	Description	Units	Source
Economic factors	GDP per capita (*Y*)	Annual Gross Domestic Product (GDP) per capita	at constant 2017 US dollars ($)	Penn World Table version 10.0
Open factors	Trade openness (*TR*)	The sum of exports and imports of goods and services measured as a percentage to GDP	%	WDI
Socioeconomic factors	Industrialization (*IND*)	The proportion of secondary industry value added to GDP	%	WDI
	Population density (*POP*)	Population density	people per sq. km of land area	WDI
	Urbanization (*UR*)	The proportion of urban population in the total population	%	WDI
	Energy intensity (*E*)	The total energy consumption added to GDP	%	EIA
Technological factors	Technical progress (*TP*)	The total number of patent applications (resident and non-resident)	%	WDI
	ICT development index (*ICT*)	It consists of four components: Fixed telephone subscriptions (per 100 people), Mobile cellular subscriptions (per 100 people), Fixed broadband subscriptions (per 100 people), Individuals using the Internet (% of population).	–	WDI

Table 2. Main features of the input-output indicators for analysis

Indicator type	Indicator selection	Units	Source
Input	Capital stock	at constant prices (2017 US$)	Penn World Table version 10.0
	Labor input	10 thousand person	WDI
	Energy input	MM Toe	EIA
Desirable output	GDP	at constant prices (2017 US$)	Penn World Table version 10.0
Undesirable output	CO_2 emissions (CO_2)	MM tonnes	EIA

The Appendix (Table A1) shows the grouping of different income countries and the GTFP values of different countries are shown in Table A2. The GTFP of various countries shows certain characteristics of regional imbalances. The average GTFP of the lower and upper middle-income countries from 2007 to 2019 is lower than that of the high-income countries. Among high-income countries, Iceland, Norway, and Switzerland had high GTFP values throughout the study period. However, Uruguay has a low GTFP among the high-income countries. High-income countries have relatively high GTFP due to their good economic development, high production efficiency and strong environmental awareness (Wu et al., 2020). Zambia has the lowest average GTFP in lower middle-income countries. Due to the low level of economic development, the average GTFP is relatively low in lower middle-income countries.

This study initially presents the distribution of average GTFP across 65 countries from 2007 to 2019 (Figure 1), followed by the creation of a scatter diagram illustrating the relationship between GTFP and ICT development levels, aiming to investigate potential associations (Figure 2).The slope of the optimal fitting line is positive, indicating a positive correlation between the GTFP and ICT development level. This is a preliminary survey that requires more rigorous measurement methods for verification.

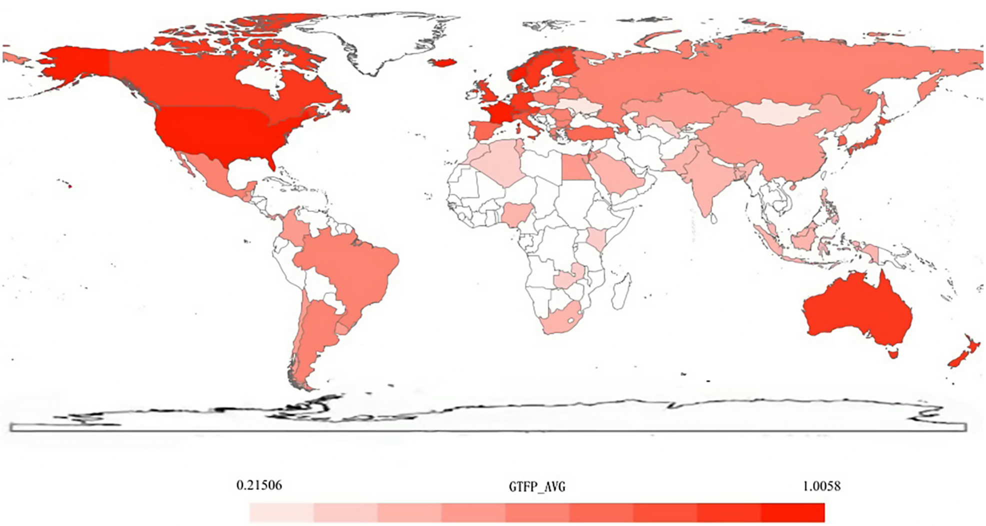

Figure 1. Distribution of average GTFP in 65 countries from 2007 to 2019

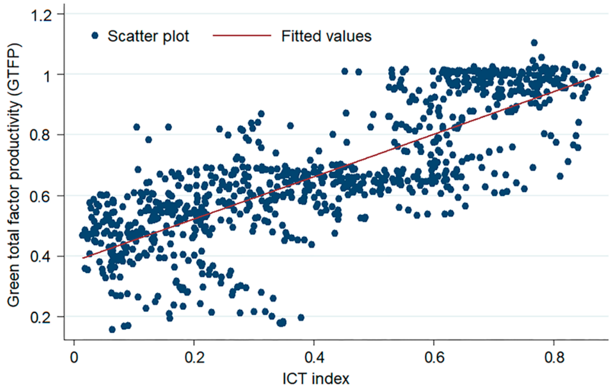

Figure 2. Scatter plot of ICT index and GTFP, 2007–2019

5. Empirical results

5.1. Estimation results of the spatial model

We calculated the effect of the GTFP in the SDM model using the method provided by LeSage and Pace (2009) in Table 3.

With regard to three different matrices, the effect of ln$Y$ on the ln$GTFP$ is significantly positive in high-income and lower middle-income countries, whereas the effect on GTFP is negative in upper middle-income countries. As economic growth rises, the GTFP will increase in lower middle-income and high-income countries but decrease in upper middle-income countries. The relationship between the GTFP and economic growth depends on the stage of development. In lower middle-income countries, economic growth will promote production efficiency to reduce pollutants, thus improving the GTFP. However, with further improvement in economic growth, industrialization process becomes faster and consumes large amounts of fossil energy, leading to more pollutant emissions. When the economic level reaches a certain level, the energy-intensive industries will gradually turn to service and knowledge-intensive industries, and the pollution situation will be alleviated. Therefore, economic growth will boost the GTFP in high-income countries.

The coefficient of lnICT shows significant positive on the ln$GTFP$ of countries with different income level. This denotes that the growth of ICT dependence promoted the GTFP, which is consistent with the study by Lahouel et al. (2021). For instance, lower middle-income countries have the highest coefficient of lnICT on ln$GTFP$ with 0.129 at a 10% significant level, indicating that the growth of ICT development by 1% led to the increase in the GTFP by 0.129%. Compared with that of high- and upper middle- income countries, the ICT level of lower middle- income countries is relatively low. Therefore, the growth of the ICT level is most beneficial to the technological innovation capacity of the lower middle-income group, thus improving the GTFP (Dedrick et al., 2013).

There are several possible reasons. First, the increase in ICT has contributed to the introduction of advanced technology, conducive to pollutant reduction and energy efficiency. Second, ICT circumvents the constraint of geographic space, and production resources in-

Table 3. Results of spatial Model

Variables	Full sample	Lower middle-income countries	Upper middle-income countries	High income countries
	(1)	(2)	(3)	(4)
ln*Y*	0.163***	1.028***	–0.694***	0.173**
	(0.053)	(0.125)	(0.102)	(0.067)
ln*ICT*	0.103***	0.129*	0.119***	0.099***
	(0.021)	(0.068)	(0.036)	(0.038)
ln*E*	–0.237***	0.115	–0.550***	–0.034
	(0.035)	(0.093)	(0.079)	(0.038)
ln*TP*	0.002	0.126***	0.054***	–0.008
	(0.011)	(0.036)	(0.020)	(0.013)
ln*TR*	0.021	–0.004	–0.197***	0.158***
	(0.032)	(0.067)	(0.061)	(0.042)
ln*IND*	–0.149***	–0.037	0.148	–0.140***
	(0.045)	(0.125)	(0.097)	(0.053)
ln*UR*	–1.125***	–1.755***	0.598	–1.379***
	(0.173)	(0.409)	(0.489)	(0.509)
ln*POP*	0.147	–0.584**	–0.554***	0.202
	(0.104)	(0.264)	(0.215)	(0.124)
*W**ln*Y*	0.056	–0.150	–0.231	0.180
	(0.362)	(0.765)	(0.458)	(0.125)
*W**ln*ICT*	–0.445***	–0.081	0.367**	0.262**
	(0.153)	(0.356)	(0.169)	(0.125)
*W**ln*E*	0.248	1.465**	–0.862**	0.054
	(0.331)	(0.639)	(0.352)	(0.133)
*W**ln*TP*	–0.148**	–0.702***	-0.002	0.090
	(0.073)	(0.217)	(0.090)	(0.0586)
*W**ln*TR*	–0.839***	–0.685	0.502**	0.040
	(0.223)	(0.422)	(0.253)	(0.064)
*W**ln*IND*	1.194***	–0.512	0.822	0.367**
	(0.261)	(0.777)	(0.502)	(0.182)
*W**ln*UR*	0.957	6.826***	3.764**	–1.438
	(1.203)	(2.102)	(1.913)	(1.338)
*W**ln*POP*	0.749	–5.831***	–1.896	–0.588
	(0.985)	(1.686)	(1.207)	(0.369)
Spatial rho	–0.706***	–0.963***	–0.537***	–0.287***
	(0.151)	(0.237)	(0.164)	(0.0913)
Log-likelihood	961.0529	215.6854	345.2871	618.769
sigma^2	0.00594***	0.00673***	0.004***	0.00297***
R^2	0.1753	0.5443	0.2865	0.1307
LR test spatial lag	79.29***	45.95***	48.54***	17.47***
LR test spatial error	77.18***	60.01 ***	47.08***	17.38***
Wald test spatial lag	82.94***	50.01***	53.80***	17.31***
Wald test spatial error	80.62***	73.69***	51.46***	17.95***

Note: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

cluding capital, information, and labor can flow freely within the region, therefore correcting the error of resource mismatch in time, and improving resource utilization efficiency. Third, ICT breaks the barrier of information asymmetry, and stakeholders can take advantage of the internet platform to realize information transmission, which significantly lifts the efficiency of information transmission within enterprises, greatly reduces market transaction costs, and notably increases the production efficiency.

The effect of ln*E* is significantly negative at the 1% level in the full sample and upper middle-income group indicating the GTFP decreases with the rise of energy intensity. Boosting the energy intensity can increase energy consumption and enhance pollutant emission, thus decreasing the GTFP (He et al., 2017; Wang et al., 2017; Xu et al., 2019).

The effect of ln*TP* is significantly positive of lower and upper middle-income countries. This indicates that technical progress promotes the GTFP in the lower and upper middle -income countries. Increasing the technological progress will inevitably lead to technology diffusion in the groups. This has promoted the reform of the production technology and independent industrial innovation, rationalized the use of energy, and improved the production efficiency, which is conductive to GTFP (Huang et al., 2019).

The effect of ln*TR* is significantly positive in higher income countries, and it is significantly negative in upper middle-income countries. The trade openness enables higher income countries to acquire and absorb advanced technologies. Increases in the energy efficiency can reduce air pollutants from fossil fuel combustion (Nasreen & Anwar, 2014; Li et al., 2018a; Liobikienė & Butkus, 2019). Meanwhile, trade openness promotes the improvement of trade structure, and this is helpful to reduce pollutant emissions in higher income countries (Shahbaz et al., 2016b). Although the foreign trade structure of upper middle-income countries has been continuously optimized, most of the products imported and exported are still labor-intensive and pollution intensive products, which has an inhibitory effect on GTFP in upper middle-income countries.

The effect of ln*IND* is significantly negative in the entire panel and high-income countries. The growth of the industrialization proportion can decrease the GTFP in the entire panel and high-income countries. At present, industrialization development still needs reasonable adjustment. There are many energy-intensive industries consuming massive fossil energy that are causing serious levels of pollution (Hao & Liu, 2016; Cheng et al., 2017; Li et al., 2018b; Zhang et al., 2019).

The impact of ln*UR* is significantly negative in the full sample, high- and lower middle-income countries. This indicates the rise of urbanization has curbed the GTFP. The development of urbanization consumes a great amount of energy and emits a great amount of pollutants, reducing the GTFP (Liddle & Lung, 2010).

The effect of ln*POP* is significantly negative in the lower and upper middle-income groups indicating that the growth of population density has decreased the GTFP. The rise of the population density emits pollutants emission, which does some damage to the environment.

5.2. Estimation results of mediating effect model

To assess the mechanism of the ICT impact on GTFP, our paper adopts the stepwise regression to construct the mediating effect. Table 4 presents the mechanism test outcomes.

The regression results of columns (1)–(3) suggest that ICT development can significantly improve the technological progress. The technological progress level is partially intermediary in the relationship between ICT development and GTFP; that is, ICT development may enhance its positive influence on GTFP by improving the technological progress level. The development of ICT introduces a range of innovative technologies, including artificial intelligence, big data analytics, and automation (Wang et al., 2021). These technologies have the potential to enhance production processes, thereby increasing production efficiency and output quality, ultimately leading to an improvement in GTFP.

The results in columns (4)–(5) show that ICT development significantly reduces energy intensity. The impact of energy intensity on GTFP is significantly negative, showing that energy intensity plays a partial intermediary role in the relationship between ICT and GTFP. ICT can improve GTFP by reducing the level of energy intensity. The development of ICT introduces novel technologies and tools, such as intelligent energy management systems, energy-efficient equipment, and automation controls (Xie et al., 2021). These innovations have the potential to reduce energy waste and losses, enhance energy utilization efficiency, lower energy intensity levels, and consequently elevate GTFP (Wu et al., 2022).

Table 4. Results of mediating effect model

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln*GTFP*	ln*TP*	ln*GTFP*	ln*E*	ln*GTFP*	ln*TR*	ln*GTFP*
ln*TP*			0.022*				
			(0.012)				
ln*E*					–0.160***		
					(0.036)		
ln*TR*							0.037**
							(0.018)
ln*ICT*	0.083***	0.369***	0.090***	–0.051**	0.074***	0.046**	0.082***
	(0.022)	(0.068)	(0.023)	(0.022)	(0.022)	(0.020)	(0.022)
ln*Y*	0.227***	0.933***	0.207***	–0.540***	0.141***	–0.145**	0.230***
	(0.046)	(0.140)	(0.047)	(0.046)	(0.049)	(0.057)	(0.046)
ln*IND*	–0.128***	–0.076	–0.130***	–0.188***	–0.158***	–0.257***	–0.124***
	(0.044)	(0.134)	(0.044)	(0.043)	(0.044)	(0.054)	(0.044)
ln*UR*	–1.662***	1.045*	–1.685***	0.918***	–1.515***	–0.140	–1.660***
	(0.184)	(0.562)	(0.184)	(0.182)	(0.185)	(0.229)	(0.184)
ln*POP*	–0.269***	0.414	–0.278***	0.872***	–0.129	–0.748***	–0.257***
	(0.084)	(0.258)	(0.084)	(0.083)	(0.089)	(0.105)	(0.087)
Constant	5.203***	–7.289***	5.360***	1.970**	5.519***	8.591***	5.059***
	(0.802)	(2.447)	(0.805)	(0.793)	(0.795)	(0.998)	(0.839)
Observations	845	845	845	845	845	845	845
R^2	0.164	0.079	0.168	0.271	0.185	0.189	0.164

Note: Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The regression results in columns (6)–(7) show that the impact of trade openness level on GTFP is significantly positive at the 5% level, indicating that ICT can improve GTFP by increasing the level of trade openness. ICT enables enterprises to access international markets and engage in cross-border trade more easily (Bollou & Ngwenyama, 2008). This facilitates the expansion of their market coverage, attracting a larger customer base and collaboration partners, ultimately leading to increased sales and output. By elevating the level of trade openness, ICT expands the size of markets, enhances efficiency, and fosters innovation, thereby directly and indirectly elevating GTFP.

To sum up, ICT development promotes GTFP by improving technological progress, reducing energy intensity, and enhancing trade openness.

5.3. Results from threshold analyses

On one hand, the development of ICT will mitigate information asymmetry in energy production, transportation, and consumption processes. It will facilitate resource sharing and reduce transaction costs, thereby enhancing output efficiency and decreasing energy consumption per unit of output. Consequently, this will contribute to the improvement of GTFP (Freire-González et al., 2017). On the other hand, ICT technology can enhance efficiency, it may inadvertently lead to increased consumer reliance on energy due to improved productivity. This rebound effect could result in escalated energy consumption. Therefore, the impact of ICT exhibits a non-linear influence on GTFP. This study used the threshold model to determine whether ICT development indirectly affects the GTFP.

The bootstrap method was used to test for a threshold effect. Through repeated sampling 300 times, the results showed that, when taking technological progress, energy intensity, and trade openness as threshold variables, the double threshold significantly rejected the original hypothesis (Table 5). Therefore, it was more appropriate to adopt a double threshold. Table 6 shows the estimates of the two thresholds and the corresponding 95% confidence intervals. The threshold LR diagram of the technological progress, trade openness, and energy intensity variables is shown in Figure 3.

Table 5. Effects of threshold variables and its confidence interval

Core independent variable	Threshold variable	Model	F-test	P-valve	BS	1%	5%	10%
ln*ICT*	ln*TP*	Single threshold	45.70*	0.070	300	42.792	48.893	64.175
		Double threshold	37.96*	0.093	300	36.182	46.312	61.950
	ln*E*	Single threshold	51.09**	0.043	300	42.974	46.480	59.548
		Double threshold	53.58*	0.073	300	44.706	57.248	72.509
	ln*TR*	Single threshold	45.98**	0.010	300	27.545	32.413	43.660
		Double threshold	27.58*	0.080	300	24.962	34.129	41.212

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

Table 6. Testing for the threshold effects

Core independent variable	Threshold variable	Model	Threshold value	95% confidence interval
ln*ICT*	ln*TP*	Double	6.548	[6.506,6.551]
		threshold	12.254	[12.137,12.272]
	ln*E*	Double	3.382	[3.377, 3.386]
		threshold	5.082	[5.040,5.083]
	ln*TR*	Double	4.451	[4.442,4.452]
		threshold	4.986	[4.981,4.993]

Table 7. Threshold regression results

Variable	(1)	(2)	(3)
	Regime = ln*TP*	*Regime* = ln*E*	Regime = ln*TR*
ln*POP*	-0.152^{*}	-0.354^{***}	-0.235^{***}
	(–1.83)	(–4.36)	(–2.86)
ln*IND*	-0.103^{**}	-0.127^{***}	-0.166^{***}
	(2.42)	(3.04)	(3.90)
ln*UR*	-1.962^{***}	-1.743^{***}	-1.460^{***}
	(–10.00)	(–9.97)	(–8.17)
ln*Y*	0.157^{***}	0.263^{***}	0.271^{***}
	(3.49)	(6.02)	(6.08)
ln*ICT*·I (Regime < C1)	0.147^{***}	0.0135	0.0304
	(6.50)	(0.39)	(1.35)
ln*ICT*·I (C1≤Regime < C2)	0.0616^{***}	0.210^{***}	0.128^{***}
	(2.66)	(7.55)	(5.53)
ln*ICT*·I (Regime≥C2)	0.570^{***}	0.0670^{***}	0.0125
	(6.04)	(3.09)	(0.37)
_cons	6.731^{***}	5.587^{***}	3.640^{***}
	(8.02)	(7.35)	(4.57)
N	845	845	845

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Figures in () are the *t*-values of the coefficients.

Based on determining the double threshold value, the threshold effect was evaluated in Table 7. With a constant rise in technological progress (ln*TP*), the influence of ICT development on GTFP shows a trend of first increasing, then decreasing, and then increasing.

ICT development can significantly improve GTFP through technological progress (Amri et al., 2019). When technological progress (ln*TP*) is lower than the first threshold of 6.548, ICT development can significantly improve GTFP. When ln*TP* reaches the range [6.548, 12.254], the promotion of ICT development to GTFP is the weakest. When ln*TP* exceeds the second threshold of 12.254, the improvement in GTFP by ICT development will reach the strongest level. This shows that technological progress promotes the effect of ICT on the GTFP at the beginning of development, which is related to the contribution of technological progress to improving productivity (Khattak et al., 2020). However, when technological progress reaches a certain level, it promotes the production scale expansion and results in a rise in energy consumption. As a result, the contribution of technological progress to the impact of ICT on GTFP weakens. When technological progress breaks through the maximum threshold, the large-scale application of ICT reduces the cost of information search and information processing, and significantly promotes the resource allocation efficiency. The improvement of relevant environmental technologies also helps improve production efficiency, which strengthens the positive impact of ICT development on GTFP to a certain extent.

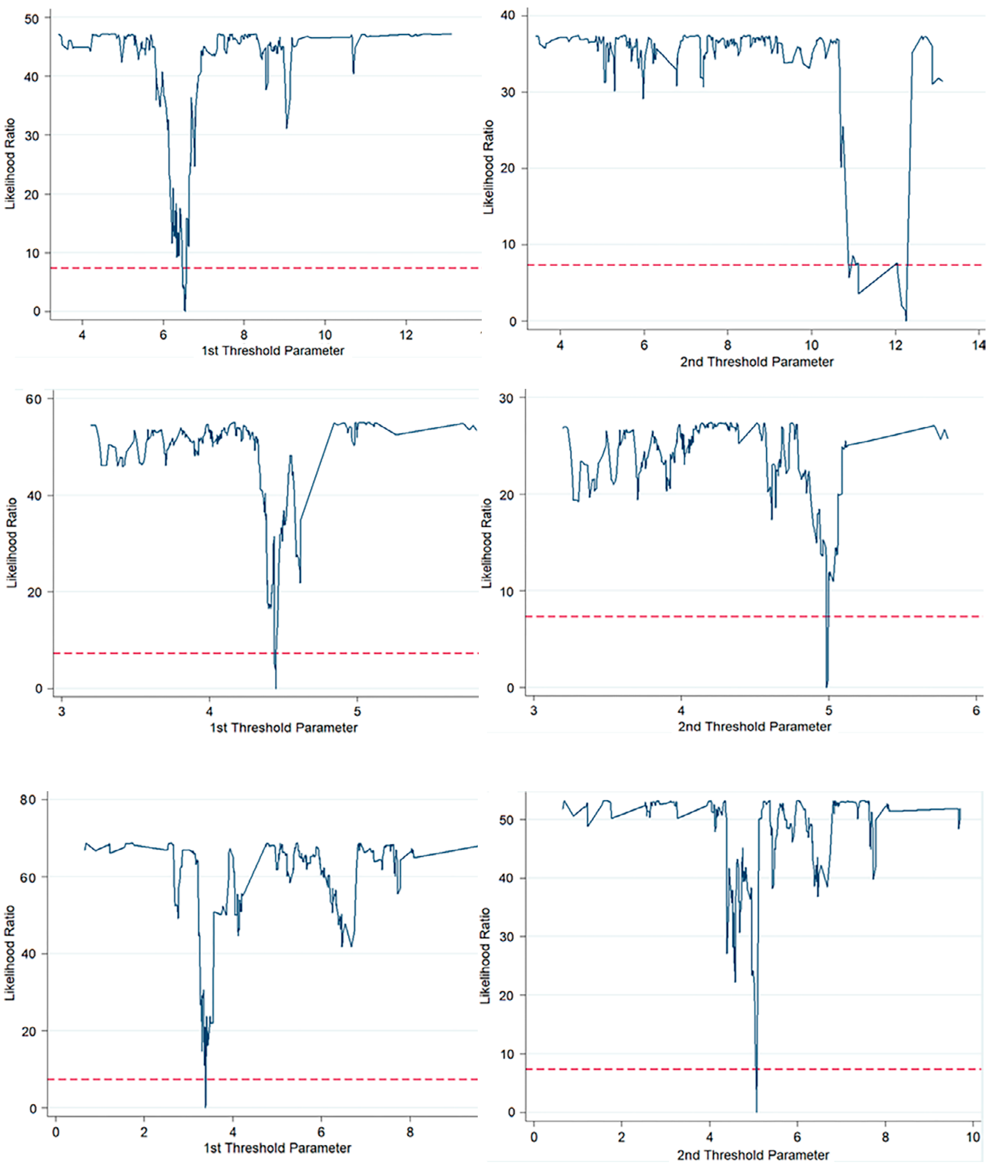

Figure 3. Threshold estimates and confidence intervals for technological progress, trade openness and energy intensity

We can notice that the impact of ICT development on GTFP is not significant when energy intensity (ln*E*) is below the first threshold. This is primarily due to two main reasons. Firstly, in energy-intensive industries, where energy constitutes a significant proportion, the application of ICT can have a pronounced impact on production processes and efficiency. However, in cases of lower energy intensity, where energy constitutes a smaller proportion, other production factors such as labor and capital become relatively more significant. As a result, the impact of ICT on GTFP is not significant. In contrast, when energy intensity is high, improvements in energy efficiency may lead to greater productivity growth, making the impact of ICT more significant. When energy intensity (ln*E*) was in the interval [3.382, 5.082], ICT development had the strongest promoting influence on GTFP. When (ln*E*) exceeds the second threshold of 5.082, the positive impact of ICT development on GTFP is weakened. Initially, a modest increase in energy intensity will inevitably lead to the diffusion of technology among countries, which promotes national production technology reform and industrial-independent innovation, improved production efficiency (Huang et al., 2019). However, when the energy intensity exceeds the threshold, energy consumption increases significantly leads to an increase in pollutant emissions, which weakens the role of ICT development in promoting GTFP.

In each threshold range, the influence of ICT on GTFP is positive. When the trade openness (ln*TR*) is below the first threshold of 4.451, the development of service trade represented by information intensive services is weak. The driving effect of ICT on trade is not strong, so the development of ICT has no significant impact on GTFP. When ln*TR* is in the range [4.451, 4.986], the development of ICT is significantly beneficial for GTFP. When trade openness is within a certain range, it is conducive to resource allocation. Foreign trade can promote the free flow of goods, capital, personnel and knowledge around the world, effectively promote information sharing and knowledge transfer, optimize the allocation of factor resources, and enhance the positive impact of ICT development on GTFP (Asongu et al., 2019). With the continuous enrichment of international trade types and the increase of differentiated products, search costs and information costs are also increasing. Therefore, when the trade openness (ln*TR*) is higher than the second threshold, the effect of ICT development on GTFP is not significant.

5.4. Robustness checks

This paper adopts variable substitution and endogeneity test to ensure the reliability of the conclusion.

5.4.1. Substitution of variables

Referring to the existing research, this paper further adopts four ICT-related indicators, namely fixed telephone subscriptions (per 100 people), mobile cellular subscriptions (per 100 people), fixed broadband subscriptions (per 100 people), using the internet (% of population) to represent ICT index respectively, so as to conduct robustness tests. These four indicators are closely related to the application and development of the internet, and are also important components of ICT. In Table 8, models (1), (2), (3) and (4) replace the measurement indicators of ICT, namely fixed telephone subscriptions (ln*INT1*), mobile cellular subscriptions (ln*INT2*), fixed broadband subscriptions (ln*INT3*), using the internet (ln*INT4*), and then conduct regression analysis respectively. The regression results show that the four indicators all have a significant positive impact on GTFP, but the regression coefficient is smaller than that of the original regression. The possible reason is that the robustness test uses a single indicator to represent the level of ICT, and compared with the comprehensive indicators, the impact of ICT on GTFP will be smaller. Therefore, the basic regression results are robust.

Table 8. Robustness test results

Variables	fixed telephone subscriptions (per 100 people)	mobile cellular subscriptions	fixed broadband subscriptions (per 100 people)	using the internet (% of population)
	(1)	(2)	(3)	(4)
		Main		
ln*Y*	0.1692***	0.1064**	0.1766***	0.1814***
	(3.3237)	(1.9654)	(3.3912)	(3.5148)
ln*INT1*	0.0257**			
	(1.9684)			
ln*INT2*		0.0924***		
		(3.6435)		
ln*INT3*			0.0046**	
			(2.0221)	
ln*INT4*				0.0044**
				(2.1070)
ln*E*	–0.2357***	–0.2376***	–0.2331***	–0.2404***
	(–6.6661)	(–6.7554)	(–6.5081)	(–6.7741)
ln*TP*	–0.0048	–0.0002	–0.0012	–0.0029
	(–0.4545)	(–0.0203)	(–0.1143)	(–0.2700)
ln*TR*	–0.0180	–0.0213	–0.0142	–0.0197
	(–0.5574)	(–0.6672)	(–0.4475)	(–0.6176)
ln*IND*	0.1341***	0.1496***	0.1581***	0.1536***
	(2.9915)	(3.3507)	(3.4779)	(3.4005)
ln*UR*	–0.8849***	–1.1703***	–0.9862***	–1.0425***
	(–4.9768)	(–6.7014)	(–5.9571)	(–6.2088)
ln*POP*	0.2020*	0.1003	0.1650	0.1683
	(1.9597)	(0.9752)	(1.5990)	(1.6292)
		Wx		
*W**ln*Y*	–0.3615	0.1652	–0.0374	–0.0753
	(–1.0687)	(0.4509)	(–0.1008)	(–0.2127)
*W**ln*INT1*	–0.1080			
	(–1.4774)			
*W**ln*INT2*		–0.3928***		
		(–2.6108)		
*W**ln*INT3*			–0.1114**	
			(–2.0553)	

End of Table 8

Variables	fixed telephone subscriptions (per 100 people)	mobile cellular subscriptions	fixed broadband subscriptions (per 100 people)	using the internet (% of population)
	(1)	(2)	(3)	(4)
W*ln$INT4$				-0.2471^{**}
				(–2.5190)
W*ln$E$	0.1739	0.3877	0.1746	0.2415
	(0.5259)	(1.1680)	(0.5278)	(0.7258)
W*lnTP	-0.1480^{**}	-0.1377^{*}	-0.1386^{*}	-0.1614^{**}
	(–1.9641)	(–1.8271)	(–1.8779)	(–2.1895)
W*lnTR	-0.8429^{***}	-0.5655^{**}	-0.7945^{***}	-0.8857^{***}
	(–3.7362)	(–2.4779)	(–3.5673)	(–3.8867)
W*lnIND	1.5262^{***}	1.3350^{***}	1.3876^{***}	1.2036^{***}
	(6.4328)	(5.6297)	(5.6933)	(4.4934)
W*lnUR	–0.4740	0.7062	0.8813	0.3691
	(–0.3298)	(0.5590)	(0.7205)	(0.3096)
W*lnPOP	0.3259	0.7231	0.7291	0.7214
	(0.3220)	(0.7396)	(0.7396)	(0.7334)
Spatial				
Spatial rho	-0.6727^{***}	-0.5863^{***}	-0.6971^{***}	-0.7077^{***}
	(–4.4947)	(–3.9070)	(–4.6437)	(–4.7022)
N	845	845	845	845
R^2	0.1416	0.1732	0.1679	0.1739

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Figures in () are the t-values of the coefficients.

5.4.2. Discussion of endogeneity

ICT and GTFP have a two-way causal relationship. To avoid biased and inconsistent estimation results due to endogeneity problem, we use the instrumental variable two-stage least square method (IV-2SLS) to deal with endogeneity and the results are shown in Table 9. According to the literature of Thompson and Garbacz (2011) and Jung and López-Bazo (2020), we use international bandwidth as the instrumental variable. Network connection speed and bandwidth will affect the penetration rate of the internet, reflecting the basic level of ICT development, so this instrumental variable is relevant to the ICT index (Pejovic et al., 2012). However, international bandwidth has no direct impact on GTFP, indicating that this instrumental variable is exogenous. Table 8 reveals the results based on IV-2SLS method, where column (1) examines the influence of instrumental variables on ICT development. The first-stage regression results show that instrumental variables have a significant positive impact on ICT development. The F statistic is greater than 10, and the test indicates that the selected instrumental variables do not have weak instrumental variables. The second stage regression results show that the rise of ICT development level promotes GTFP. In other words, after the adoption of instrumental variables to overcome the possible endogeneity problem, the estimated coefficient of ICT on ln$GTFP$ and its statistical significance did not change substantially, demonstrating the robustness of the above estimated results.

Table 9. Testing for IV estimation

Variable	First stage regression	Second stage regression
	ln*ICT*	ln*GTFP*
ln*LB*	0.1108***	
	(12.6737)	
ln*ICT*		0.1025**
		[2.0095]
ln*Y*	0.3755***	0.3699***
	(14.3206)	[12.2819]
ln*E*	–0.0756***	0.0222*
	(–3.8173)	[1.8488]
ln*TP*	0.0193	–0.0237**
	(1.3741)	[–2.4638]
ln*TR*	0.1145***	–0.1509***
	(3.6326)	[–6.6266]
ln*IND*	–0.2226***	–0.1466***
	(3.6718)	[3.8870]
ln*UR*	0.4031***	–0.0735*
	(7.1801)	[–1.8184]
ln*POP*	–0.0267***	0.0396***
	(–2.8486)	[5.7573]
_cons	–8.5774***	–3.6465***
	(–22.6640)	[–7.1691]
N	845	845
R^2	0.8552	0.6850
F	465.1112	

Note: ***, **, and *indicate significance at the 1%, 5%, and 10% levels, respectively. Figures in () and [] are the *t*-values and *z*-values of the coefficients, respectively.

6. Conclusions and policy implications

Based on panel data from 2007 to 2019, this study examines the impact of ICT on the GTFP of 65 countries and gives a new perspective of global green development. In addition to ICT, our regression analysis also considers the effects of GDP per capita, industrialization level, urbanization level, technological progress, trade openness, energy intensity, and population density on GTFP. We used the inverse distance spatial econometric model to analyse the impact of ICT development on the GTFP of countries from different income groups and used the mediation effect model, panel threshold model to explore the driving mechanism of ICT impact on GTFP. Through empirical research, we draw the following conclusions and policy recommendations:

(1) This study found that compared with high-income countries, the average value of GTFP in lower countries from 2007 to 2019 is relatively low. With higher economic growth, the GTFP of lower middle-income and high-income countries rises, while the

GTFP of upper middle-income countries declines. It shows that the middle-income countries should improve the quality of economic development as well as constantly optimize the economic structure, thereby improving the GTFP.

(2) The imbalance between ICT development and GTFP in various countries is still significant. ICT can effectively improve GTFP, and has the largest effect in lower middle-income countries. This shows that lower middle-income countries should vigorously promote the construction and improvement of ICT systems, strengthen investment in basic research on information technology. They also should focus on strengthening ICT infrastructure, ensuring that ICT can cover and access a wider range of regions, and comprehensively improve the development level of ICT. Additionally, lower middle-income countries need to make full use of their comparative advantages according to their own development directions and formulate ICT development strategies according to local conditions. High-income and upper middle-income countries should consolidate their existing foundation of ICT and continue to promote relevant research and innovation in ICT. All countries should also continue to improve the capacity for sustainable development to effectively improve the environment and reduce pollution.

(3) Technological progress promoted GTFP in lower and upper middle-income countries. With the gradual improvement of technological progress, the positive effect of ICT development on the GTFP shows a trend of first strengthening, then weakening, and then strengthening in the overall panel. In terms of the distribution of ICT, lower and upper middle-income countries should promote technological innovation by increasing innovation investment and infrastructure construction. Governments should optimise role of ICT channels and promote the improvement of innovation ability. To improve GTFP, governments should make large-scale use of core low-carbon technologies and promote the free flow of ICT resources.

(4) Increases in trade openness promote GTFP in high-income countries but inhibit GTFP in upper middle-income countries. Considering that ICT has the potential to become a new competitive advantage in trade, high-income countries should further promote ICT development in conjunction with opening up to international trade and make full use of ICT to promote regional co-operation.

(5) Energy intensity inhibits the GTFP of the overall panel and upper middle-income countries. As energy intensity increases, the impact of ICT development on the GTFP shows a trend of first strengthening and then weakening. Countries should make full use of ICT to strengthen the supervision and assessment of regional energy conservation and green development. In addition, high-income countries have strong economic strength and the ability to continue to promote the development of the renewable energy industry. They should continue to increase and expand the proportion of renewable energy application, vigorously promote the deep integration of ICT with energy production and consumption, and change the way of energy production and consumption through information networks.

(6) The increase of industrial proportion has an inhibitory effect on the GTFP of the overall panel and high-income countries. Governments should recognize the importance of internet technology in the process of industrial upgrading, and actively aim to transform low-technology, low-productivity industries to high-tech and knowledge-intensive industries. Countries should promote sustainable industrial development, improve productivity, and curb pollutant emissions. Countries can promote sustainable development by promoting the integration of ICT with traditional industries, continuously optimising production processes, and promoting industrial transformation and upgrades.

(7) The increase of urbanization level has restrained the GTFP of the overall panel and lower middle-income and high-income countries. Lower middle-income and high-income countries should promote the rational layout of urban spaces, enhance the deep integration of ICT into urban developments, and improve the sustainability of urban construction to reduce pollutant.

(8) Increases in population density have an inhibitory effect on GTFP in lower and upper middle-income countries. Lower and upper middle-income countries should utilise ICT to optimise the population structure, and improve residents' awareness of environmental protection to improve the GTFP.

References

Addison, T., & Rahman, A. (2005). Capacities to globalize: Why are some countries more globalized than others? In G. W. Kolodko (Ed.), *Globalization and social stress* (pp. 4–5). Nova Science Publishers.

Amri, F., Zaied, Y. B., & Lahouel, B. B. (2019). ICT, total factor productivity, and carbon dioxide emissions in Tunisia. *Technological Forecasting and Social Change*, *146*, 212–217. https://doi.org/10.1016/j.techfore.2019.05.028

Androutsos, A. (2011). Access link bandwidth externalities and endogenous internet growth: A long run economic approach. *International Journal of Network Management*, *21*(1), 21–44. https://doi.org/10.1002/nem.771

Asmild, M., Paradi, J. C., Aggarwall, V., & Schaffnit, C. (2004). Combining DEA window analysis with the malmquist index approach in a study of the Canadian banking industry. *Journal of Productivity Analysis*, *21*(1), 67–89. https://doi.org/10.1023/B:PROD.0000012453.91326.ec

Asongu, S. A., Nwachukwu, J.C., & Pyke, C. (2019). The comparative economics of ICT, environmental degradation and inclusive human development in Sub-Saharan Africa. *Social Indicators Research*, *143*, 1271–1297. https://doi.org/10.1007/s11205-018-2009-x

Bartel, A., Ichniowski, C., & Shaw, K. (2007). How does information technology affect productivity? Plant-level comparisons of product innovation, process improvement, and worker skills. *Quarterly Journal of Economics*, *122*(4), 1721–1758. https://doi.org/10.1162/qjec.2007.122.4.1721

Burridge, P. (1981). Testing for a common factor in a spatial auto regression model. *Environment and Planning A: Economy and Space*, *13*(7), 795–800. https://doi.org/10.1068/a130795

Bollou, F., & Ngwenyama, O. (2008). Are ICT investments paying off in Africa? An analysis of total factor productivity in six West African countries from 1995 to 2002. *Information Technology for Development*, *14*(4), 294–307. https://doi.org/10.1002/itdj.20089

Cárdenas Rodríguez, M., Haščič, I., & Souchier, M. (2018). Environmentally adjusted multifactor productivity: Methodology and empirical results for OECD and G20 countries. *Ecological Economics*, *153*, 147–160. https://doi.org/10.1016/j.ecolecon.2018.06.015

Cecere, G., Corrocher, N., Gossart, C., & Ozman, M. (2014). Technological pervasiveness and variety of innovators in green ICT: A patent-based analysis. *Research Policy*, *43*(10), 1827–1839. https://doi.org/10.1016/j.respol.2014.06.004

Charnes, A., Clark, C. T., & Cooper, W. W., B. (1985). A developmental study of data envelopment analysis in measuring the efficiency of maintenance units in the U.S. air forces. *Annals of Operations Research*, *2*, 95–112. https://doi.org/10.1007/BF01874734

Cheng, Z., Li, L., & Liu, J. (2017). Identifying the spatial effects and driving factors of urban PM2.5 pollution in China. *Ecological Indicators*, *82*, 61–75. https://doi.org/10.1016/j.ecolind.2017.06.043

Cooper, W. W., Seiford, L. M., & Tone, K. (2006). *Introduction to data envelopment analysis and its uses: With DEA-Solver software and references*. Springer. https://doi.org/10.1007/0-387-29122-9

Crişan, D. A., Preda, A. M., Coculescu, C., & Altăr-Samuel A. N. (2010). Some aspects concerning the correlation between ICT and innovation in Europe. *Annals of the University of Oradea Economic Science*, *1*(2), 1183–1189.

Danish. (2019). Effects of information and communication technology and real income on CO_2 emissions: The experience of countries along Belt and Road. *Telematics and Informatics*, *45*, Article 101300. https://doi.org/10.1016/j.tele.2019.101300

Dedrick, J., Kraemer, K. L., & Shih, E. (2013). Information technology and productivity in developed and developing countries. *Journal of Management Information Systems*, *30*(1), 97–122. https://doi.org/10.2753/MIS0742-1222300103

Elhorst, J. P. (2012). Dynamic spatial panels: Models, methods, and inferences. *Journal of Geographical Systems*, *14*, 5–28. https://doi.org/10.1007/s10109-011-0158-4

Elhorst, J. P. (2014). *Spatial econometrics: From cross-sectional data to spatial panels*. Springer. https://doi.org/10.1007/978-3-642-40340-8

Elliot, S. (2011). Transdisciplinary perspectives on environmental sustainability: A resource base and framework for IT-enabled business transformation. *Management Information Systems Quarterly*, *35*(1), 197–236. https://doi.org/10.2307/23043495

Farouq, I. S., Sambo, I. S., Ahmad, A. U., Jakada, A. H., & Danmaraya, I. A. (2021). Does financial globalization uncertainty affect CO_2 emissions? Empirical evidence from some selected SSA countries. *Quantitative Finance and Economics*, *5*(2), 247–263. https://doi.org/10.3934/QFE.2021011

Feng, C., Huang, J. B., & Wang, M. (2018). Analysis of green total-factor productivity in China's regional metal industry: A meta-frontier approach. *Resources Policy*, *58*, 219–229. https://doi.org/10.1016/j.resourpol.2018.05.008

Fernández-Portillo, A., Almodóvar-González, M., & Hernández-Mogollón, R. (2020). Impact of ICT development on economic growth. A study of OECD European union countries. *Technology in Society*, *63*, Article 101420. https://doi.org/10.1016/j.techsoc.2020.101420

Feuerriegel, S., Bodenbenner, P., & Neumann, D. (2016). Value and granularity of ICT and smart meter data in demand response systems. *Energy Economics*, *54*, 1–10. https://doi.org/10.1016/j.eneco.2015.11.016

Freire-González, J., Vivanco, F. D., & Puig-Ventosa, I. (2017). Economic structure and energy savings from energy efficiency in households. *Ecological Economics*, *131*, 12–20. https://doi.org/10.1016/j.ecolecon.2016.08.023

Gholami, R., Sulaiman, A., Ramayah, T., & Molla, A. (2013). Senior managers' perception on green information systems (IS) adoption and environmental performance: Results from a field survey. *Information & Management*, *50*(7), 431–438. https://doi.org/10.1016/j.im.2013.01.004

Gouvea, R., Kapelianis, D., & Kassicieh, S. (2018). Assessing the nexus of sustainability and information & communications technology. *Technological Forecasting and Social Change*, *130*, 39–44. https://doi.org/10.1016/j.techfore.2017.07.023

Greenstein, S. (2020). The basic economics of internet infrastructure. *Journal of Economic Perspectives*, *34*(2), 192–214. https://doi.org/10.1257/jep.34.2.192

Liobikienė, G., & Butkus, M. (2019). Scale, composition, and technique effects through which the economic growth, foreign direct investment, urbanization, and trade affect greenhouse gas emissions. *Renewable Energy*, *132*, 1310–1322. https://doi.org/10.1016/j.renene.2018.09.032

Halkos, G. E., & Polemis, M. L. (2018). The impact of economic growth on environmental efficiency of the electricity sector: A hybrid window DEA methodology for the USA. *Journal of Environmental Management*, *211*, 334–346. https://doi.org/10.1016/j.jenvman.2018.01.067

Haldar, A., Sucharita, S., Dash, D. P., Sethi, N., & Chandra Padhan, P. (2023). The effects of ICT, electricity consumption, innovation and renewable power generation on economic growth: An income level analysis for the emerging economies. *Journal of Cleaner Production*, *384*, Article 135607. https://doi.org/10.1016/j.jclepro.2022.135607

Hao, Y., & Liu, Y. M. (2016). The influential factors of urban $PM_{2.5}$, concentrations in China: A spatial econometric analysis. *Journal of Cleaner Production*, *112*, 1443–1453. https://doi.org/10.1016/j.jclepro.2015.05.005

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics*, *93*(2), 345–368. https://doi.org/10.1016/S0304-4076(99)00025-1

He, Z. X., Xu, S. C., Shen, W. X., Long, R. Y., & Chen, H. (2017). Impact of urbanization on energy related CO_2 emission at different development levels: Regional difference in China based on panel estimation. *Journal of Cleaner Production*, *140*, 1719–1730. https://doi.org/10.1016/j.jclepro.2016.08.155

Higón, D. A., Gholami, R., & Shirazi, F. (2017). ICT and environmental sustainability: A global perspective. *Telematics and Informatics*, *34*(4), 85–95. https://doi.org/10.1016/j.tele.2017.01.001

Hoffert, M. I., Caldeira, K., Benford, G., Criswell, D. R., Green, C., Herzog, H., Jain, A. K., Kheshgi, H. S., Lackner, K. S., & Lewis, J. S. (2002). Advanced technology paths to global climate stability: Energy for a greenhouse planet. *Science*, *298*(5595), 981–987. https://doi.org/10.1126/science.1072357

Houghton, J. W. (2015). ICT, the environment, and climate change. In *The international encyclopedia of digital communication and* society (pp. 39–60). Wiley. https://doi.org/10.1002/9781118767771.wbiedcs015

Huang, J. B., Liu, C. H., Chen, S. X., Huang, X., & Hao, Y. (2019). The convergence characteristics of China's carbon intensity: Evidence from a dynamic spatial panel approach. *Science of the Total Environment*, *668*, 685–695. https://doi.org/10.1016/j.scitotenv.2019.02.413

Huang, X., Feng, C., Qin, J., Wang, X., & Zhang, T. (2022). Measuring China's agricultural green total factor productivity and its drivers during 1998–2019. *Science of the Total Environment*, *829*, Article 154477. https://doi.org/10.1016/j.scitotenv.2022.154477

Ishida, H. (2015). The effect of ICT development on economic growth and energy consumption in Japan. *Telematics and Informatics*, *32*(1), 79–88. https://doi.org/10.1016/j.tele.2014.04.003

Jin, W., Zhang, H., Liu, S., & Zhang, H. (2019). Technological innovation, environmental regulation, and green total factor efficiency of industrial water resources. *Journal of Cleaner Production*, *211*, 61–69. https://doi.org/10.1016/j.jclepro.2018.11.172

Jung, J., & López-Bazo, E. (2020). On the regional impact of broadband on productivity: The case of Brazil. *Telecommunications Policy*, *44*(1), Article 101826. https://doi.org/10.1016/j.telpol.2019.05.002

Koseoglu, A., Yucel, A.G., & Ulucak, R. (2022). Green innovation and ecological footprint relationship for a sustainable development: Evidence from top 20 green innovator countries. *Sustainable Development*, *30*(5), 976–988. https://doi.org/10.1002/sd.2294

Khattak, S.I., Ahmad, M., Khan, Z.U., & Khan, A. (2020). Exploring the impact of innovation, renewable energy consumption, and income on CO_2 emissions: New evidence from the BRICS economies. *Environmental Science and Pollution Research*, *27*, 13866–13881. https://doi.org/10.1007/s11356-020-07876-4

Kremer, S., Bick, A., & Nautz, D. (2013). Inflation and growth: New evidence from a dynamic panel threshold analysis. *Empirical Economics*, *44*, 861–878. https://doi.org/10.1007/s00181-012-0553-9

Lahouel, B. B., Taleb, L., Zaied, B. Y., & Managi, S. (2021). Does ICT change the relationship between total factor productivity and CO_2 emissions? Evidence based on a nonlinear model. *Energy Economics*, *101*, Article 105406. https://doi.org/10.1016/j.eneco.2021.105406

Lange, S., Pohl, J., & Santarius, T. (2020). Digitalization and energy consumption. Does ICT reduce energy demand? *Ecological Economics*, *176*, Article 106760. https://doi.org/10.1016/j.ecolecon.2020.106760

Lau, L. S., Choong, C. K., & Eng, Y. K. (2014). Investigation of the environmental Kuznets curve for carbon emissions in Malaysia: Do foreign direct investment and trade matter? *Energy Policy*, *68*, 490–497. https://doi.org/10.1016/j.enpol.2014.01.002

LeSage, J. P., & Pace, R. K. (2009). *Introduction to spatial econometrics* (1st ed.). CRC Press. https://doi.org/10.1201/9781420064254

Li, M., Li, C., & Zhang, M. (2018a). Exploring the spatial spillover effects of industrialization and urbanization factors on pollutants emissions in China's Huang-Huai Hai region. *Journal of Cleaner Production*, *195*, 154–162. https://doi.org/10.1016/j.jclepro.2018.05.186

Li, K., Fang, L.T., & He, L. R. (2018b). How urbanization affects China's energy efficiency: A spatial econometric analysis. *Journal of Cleaner Production*, *200*, 1130–1141. https://doi.org/10.1016/j.jclepro.2018.07.234

Lin, F. (2015). Estimating the effect of the internet on international trade. *The Journal of International Trade & Economic Development*, *24*(3), 409–428. https://doi.org/10.1080/09638199.2014.881906

Liu, G., Wang, B., & Zhang, N. (2016). A coin has Two Sides: Which one is driving China's green TFP growth? *Economic Systems*, *40*(3), 481–498. https://doi.org/10.1016/j.ecosys.2015.12.004

Liddle, B., & Lung, S. (2010). Age-structure, urbanization, and climate change in developed countries: Revisiting STIRPAT for disaggregated population and consumption-related environmental impacts. *Population & Environment*, *31*, 317–343. https://doi.org/10.1007/s11111-010-0101-5

Majeed, M. T. (2018). Information and communication technology (ICT) and environmental sustainability in developed and developing countries. *Pakistan Journal of Commerce and Social Sciences*, *12*(3), 758–783. https://www.jespk.net/publications/4314.pdf

MacKinnon, D. P., Krull, J. L., & Lockwood, C. M. (2000). Equivalence of the mediation, confounding and suppression effect. *Prevention Science*, *1*(4), 173–181. https://doi.org/10.1023/A:1026595011371

Melville, N. P. (2010). Information systems innovation for environmental sustainability. *Management Information Systems Quarterly*, *34*(1), 1–21. https://doi.org/10.2307/20721412

Meng, F., & Zhao, Y. (2022). How does digital economy affect green total factor productivity at the industry level in China: From a perspective of global value chain. *Environmental Science and Pollution Research*, *29*, 79497–79515. https://doi.org/10.1007/s11356-022-21434-0

Miao, C., Fang, D., Sun, L., & Luo, Q. (2017). Natural resources utilization efficiency under the influence of green technological innovation. *Resources*, *Conservation and Recycling*, *126*, 153–161. https://doi.org/10.1016/j.resconrec.2017.07.019

Moyer, J. D., & Hughes, B. B. (2012). ICTs: DO they contribute to increased carbon emissions? *Technological Forecasting & Social Change*, *79*(5), 919–931. https://doi.org/10.1016/j.techfore.2011.12.005

Nasreen, S., & Anwar, S. (2014). Causal relationship between trade openness, economic growth and energy consumption: A panel data analysis of Asian countries. *Energy Policy*, *69*, 82–91. https://doi.org/10.1016/j.enpol.2014.02.009

Pan, H., Zhang, H., & Zhang, X. (2013). China's provincial industrial energy efficiency and its determinants. *Mathematical and Computer Modelling*, *58*(5–6), 1032–1039. https://doi.org/10.1016/j.mcm.2012.09.006

Pejovic, V., Johnson, D. L., Zheleva, M., Belding, E., Parks, L., & Van Stam, G. (2012). Broadband adoption| The bandwidth divide: Obstacles to efficient broadband adoption in rural sub-Saharan Africa. *International Journal of Communication*, *6*, 1–25. https://ijoc.org/index.php/ijoc/article/view/1795/807

Plepys, A. (2002). The grey side of ICT. *Environmental Impact Assessment Review*, *22* (5), 509–523. https://doi.org/10.1016/S0195-9255(02)00025-2

Qiu, S., Wang, Z., & Geng, S. (2021). How do environmental regulation and foreign investment behavior affect green productivity growth in the industrial sector? An empirical test based on Chinese provincial panel data. *Journal of Environmental Management*, *287*, Article 112282. https://doi.org/10.1016/j.jenvman.2021.112282

Shahbaz, M., Solarin, S. A., & Ozturk, I. (2016a). Environmental Kuznets curve hypothesis and the role of globalization in selected African countries. *Ecological Indicators*, *67*, 623–636. https://doi.org/10.1016/j.ecolind.2016.03.024

Shahbaz, M., Loganathan, N., Muzaffar, A. T., Ahmed, K., & Jabran, M. A. (2016b). How urbanization affects CO_2 emissions in Malaysia? The application of STIRPAT model. *Renewable & Sustainable Energy Reviews*, *57*, 83–93. https://doi.org/10.1016/j.rser.2015.12.096

Song, M., Zhang, L., An, Q., Wang, Z., & Li, Z. (2013). Statistical analysis and combination forecasting of environmental efficiency and its influential factors since China entered the WTO: 2002–2010–2012. *Journal of Cleaner Production*, *42*, 42–51. https://doi.org/10.1016/j.jclepro.2012.11.010

Su, Y., & Gao, X. (2022). Revealing the effectiveness of green technological progress and financial innovation on green economic growth: The role of environmental regulation. *Environmental Science and Pollution Research*, *29*, 72991–73000. https://doi.org/10.1007/s11356-022-20978-5

Su, Y., Li, Z., & Yang, C. (2021). Spatial interaction spillover effects between digital financial technology and urban ecological efficiency in China: An empirical study based on spatial simultaneous equations. *International Journal of Environmental Research and Public Health*, *18*(16), Article 8535. https://doi.org/10.3390/ijerph18168535

Sueyoshi, T., Yuan, Y., & Goto, M. (2017). A literature study for DEA applied to energy and environment. *Energy Economics*, *62*, 104–124. https://doi.org/10.1016/j.eneco.2016.11.006

Sun, X., Jiang, K., Cui, Z., Xu, J., & Zhao, X. (2023). Exploring the impact of the digital economy on green total factor productivity in China: A spatial econometric perspective. *Frontiers in Environmental Science*, *10*, Article 1097944. https://doi.org/10.3389/fenvs.2022.1097944

Sun, Y., Ding, W., Yang, Z., Yang, G., & Du, J. (2020). Measuring China's regional inclusive green growth. *Science of the Total Environment*, *713*, Article 136367. https://doi.org/10.1016/j.scitotenv.2019.136367

Thompson, H. G., & Garbacz, C. (2011). Economic impacts of mobile versus fixed broadband. *Telecommunications Policy*, *35*(11), 999–1009. https://doi.org/10.1016/j.telpol.2011.07.004

Tian, Y., & Feng, C. (2022). The internal-structural effects of different types of environmental regulations on China's green total-factor productivity. *Energy Economics*, *113*, Article 106246. https://doi.org/10.1016/j.eneco.2022.106246

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, *130*(3), 498–509. https://doi.org/10.1016/S0377-2217(99)00407-5

Tone, K. (2002). A slacks-based measure of super-efficiency in data envelopment analysis. *European Journal of Operational Research*, *143*(1), 32–41. https://doi.org/10.1016/S0377-2217(01)00324-1

Tzeremes, P., Dogan, E., & Alavijeh, N. K. (2023). Analyzing the nexus between energy transition, environment and ICT: A step towards COP26 targets. *Journal of Environmental Management*, *326*, Article 116598. https://doi.org/10.1016/j.jenvman.2022.116598

Vemuri, V. K., & Siddiqi, S. (2009). Impact of commercialization of the internet on international trade: A panel study using the extended gravity model. *The International Trade Journal*, *23*(4), 458–484. https://doi.org/10.1080/08853900903223792

Wang, H., Cui, H., & Zhao, Q. (2021). Effect of green technology innovation on green total factor productivity in China: Evidence from spatial Durbin model analysis. *Journal of Cleaner Production*, *288*, Article 125624. https://doi.org/10.1016/j.jclepro.2020.125624

Wang, M., & Feng, C. (2021). Revealing the pattern and evolution of global green development between different income groups: A global meta-frontier by-production technology approach. *Environmental Impact Assessment Review*, *89*, Article 106600. https://doi.org/10.1016/j.eiar.2021.106600

Wang, M. L., Ntim, V. S., Yang, J. M., Zheng, Q. J., & Geng, L. M. (2022). Effect of institutional quality and foreign direct investment on economic growth and environmental quality: Evidence from African countries. *Economic Research-Ekonomska Istraživanja*, *35*(1), 4065–4091. https://doi.org/10.1080/1331677X.2021.2010112

Wang, Y., Zhang, C., Lu, A., Li, L., He, Y. M., ToJo, J., & Zhu, X. D. (2017). A disaggregated analysis of the Environmental Kuznets curve for industrial CO_2 emissions in China. *Applied Energy*, *190*, 172–180. https://doi.org/10.1016/j.apenergy.2016.12.109

Watson, R. T., Corbett, J., Boudreau, M. C., & Webster, J. (2012). An information strategy for environmental sustainability. *Communications of the ACM*, *55*(7), 28–30. https://doi.org/10.1145/2209249.2209261

Wu, H., Ren, S., Yan, G., & Hao, Y. (2020). Does China's outward direct investment improve green total factor productivity in the "Belt and Road" countries? Evidence from dynamic threshold panel model analysis. *Journal of Environmental Management*, *275*, Article 111295. https://doi.org/10.1016/j.jenvman.2020.111295

Wu, J., Xia, Q., & Li, Z. (2022). Green innovation and enterprise green total factor productivity at a micro level: A perspective of technical distance. *Journal of Cleaner Production*, *344*, Article 131070. https://doi.org/10.1016/j.jclepro.2022.131070

Xie, F., Zhang, B., & Wang, N. (2021). Non-linear relationship between energy consumption transition and green total factor productivity: A perspective on different technology paths. *Sustainable Production and Consumption*, *28*, 91–104. https://doi.org/10.1016/j.spc.2021.03.036

Xu, S. C., Miao, Y. M., Gao, C., Long, R. Y., Chen, H., Zhao, B., & Wang, S. X. (2019). Regional differences in impacts of economic growth and urbanization on air pollutants in China based on provincial panel estimation. *Journal of Cleaner Production*, *208*, 340–352. https://doi.org/10.1016/j.jclepro.2018.10.114

Yu, B. (2022). The impact of the internet on industrial green productivity: Evidence from China. *Technological Forecasting and Social Change*, *177*, Article 121527. https://doi.org/10.1016/j.techfore.2022.121527

Zhang, J., Lu, G., Skitmore, M., & Ballesteros-Pérez, P. (2021). A critical review of the current research mainstreams and the influencing factors of green total factor productivity. *Environmental Science and Pollution Research*, *28*(27), 35392–35405. https://doi.org/10.1007/s11356-021-14467-4

Zhang, L., Saydaliev, H. B., & Ma, X. (2022). Does green finance investment and technological innovation improve renewable energy efficiency and sustainable development goals. *Renewable Energy*, *193*, 991–1000. https://doi.org/10.1016/j.renene.2022.04.161

Zhang, Z., Zhu, K., & Hewings, G. J. D. (2017). A multi-regional input-output analysis of the pollution haven hypothesis from the perspective of global production fragmentation. *Energy Economics*, *64*, 13–23. https://doi.org/10.1016/j.eneco.2017.03.007

Zhang, W. W., Sharp, B., & Xu, S. C. (2019). Does economic growth and energy consumption drive environmental degradation in China's 31 provinces? New evidence from a spatial econometric perspective. *Applied Economics*, *51*(42), 4658–4671. https://doi.org/10.1080/00036846.2019.1593943

Zheng, H., Feng, C., & Yang, J. (2023). Examining the internal-structural effects of internet development on China's urban green total factor productivity. *Emerging Markets Finance and Trade*, *59*(15), 4174–4193. https://doi.org/10.1080/1540496X.2023.2190843

Zhou, X., Zhou, D., & Wang, Q. (2018). How does information and communication technology affect China's energy intensity? A three-tier structural decomposition analysis. *Energy*, *151*, 748–759. https://doi.org/10.1016/j.energy.2018.03.115

Zhu, W., Xu, L., Tang, L., & Xiang, X. (2019). Eco-efficiency of the western Taiwan straits economic zone: An evaluation based on a novel eco-efficiency model and empirical analysis of influencing factors. *Journal of Cleaner Production*, *234*, 638–652. https://doi.org/10.1016/j.jclepro.2019.06.157

Zhu, X., Chen, Y., & Feng, C. (2018). Green total factor productivity of China's mining and quarrying industry: A global data envelopment analysis. *Resource Policy*, *57*, 1–9. https://doi.org/10.1016/j.resourpol.2017.12.009

APPENDIX

Table A1. List of countries by group

Grouping of countries at different income levels	
Income level	Countries (or Regions)
HI	Austria, Canada, Chile, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Israel, Italy, Japan, Lithuania, Luxembourg, New Zealand, Norway, Panama, Poland, Romania, Republic of Korea, Saudi Arabia, Singapore, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States, Uruguay.
UMI	Argentina, Azerbaijan, Belarus, Brazil, Bulgaria, China, Colombia, Dominican Republic, Guatemala, Indonesia, Jamaica, Jordan, Kazakhstan, Malaysia, Mexico, Russian Federation, South Africa, Turkey.
LMI	Algeria, Bangladesh, Egypt, India, Kenya, Mongolia, Morocco, Nigeria, Pakistan, Philippines, Sri Lanka, Tunisia, Ukraine, Uzbekistan, Zambia.

Table A2. Values of GTFP during 2007–2019

Income level	country	2007	2019	Average value
High income	Australia	0.9146	1.0002	0.9685
	Austria	1.0026	1.0069	0.9741
	Canada	0.9925	1.0026	0.9657
	Chile	0.6347	0.5503	0.5893
	Denmark	0.9372	1.0028	0.9709
	Estonia	0.6037	0.5925	0.6130
	Finland	1.0106	1.0167	0.9551
	France	1.0090	1.0108	0.9805
	Germany	1.0111	1.0153	0.9748
	Greece	0.7146	0.6210	0.6745
	Hungary	0.6527	0.6839	0.6524
	Iceland	0.9898	1.0272	1.0058
	Israel	0.7746	0.8502	0.8253
	Italy	1.0084	0.6943	0.8737
	Japan	0.8338	0.9837	0.8912
	Lithuania	0.6442	0.6844	0.6550
	Luxembourg	0.9717	0.9523	0.9679
	New Zealand	0.9904	0.9007	0.9553
	Norway	1.0105	1.0239	0.9855
	Panama	0.5723	0.4649	0.6146
	Poland	0.6641	0.6211	0.6557
	Republic of Korea	0.7259	0.8413	0.7562

End of Table A2

Income level	country	2007	2019	Average value
High income	Romania	0.6683	0.6835	0.6498
	Saudi Arabia	0.5525	0.5220	0.5479
	Singapore	0.7613	0.7421	0.7556
	Slovenia	0.6348	0.6686	0.6489
	Spain	0.8262	0.7502	0.7648
	Sweden	1.0109	1.0071	0.9733
	Switzerland	0.9821	1.0081	0.9838
	United Kingdom	1.0045	1.0179	0.9675
	United States	1.0077	0.9924	0.9828
	Uruguay	0.5661	0.5396	0.6038
Upper middle income	Argentina	0.6907	0.6386	0.6656
	Azerbaijan	0.8241	0.6236	0.7721
	Belarus	0.6589	0.6128	0.6309
	Brazil	0.6858	0.6348	0.6758
	Bulgaria	0.6835	0.6680	0.6822
	China	0.5503	0.6160	0.5869
	Colombia	0.6658	0.6107	0.6189
	Dominican Republic	0.6076	0.5265	0.5853
	Guatemala	0.5960	0.5308	0.5776
	Indonesia	0.5098	0.5400	0.5289
	Jamaica	0.1948	0.2605	0.2939
	Jordan	0.5975	0.4839	0.6090
	Kazakhstan	0.4448	0.5714	0.5635
	Malaysia	0.6166	0.4365	0.5410
	Mexico	0.6715	0.6471	0.6592
	Russian Federation	0.6339	0.6233	0.6331
	South Africa	0.4624	0.4700	0.4830
	Turkey	0.7992	0.6318	0.7533
Lower middle income	Algeria	0.4963	0.2967	0.4128
	Bangladesh	0.4672	0.4728	0.4879
	Egypt	0.6851	0.6289	0.5834
	India	0.5265	0.4219	0.4929
	Kenya	0.4722	0.2753	0.3667
	Mongolia	0.1573	0.2949	0.2532
	Morocco	0.3973	0.3369	0.3790
	Nigeria	0.5751	0.3746	0.5049
	Pakistan	0.5441	0.3980	0.4826
	Philippines	0.5710	0.5267	0.5449
	Sri Lanka	0.3968	0.6915	0.5308
	Tunisia	0.4078	0.5127	0.4822
	Ukraine	0.2343	0.1957	0.2151
	Uzbekistan	0.3434	0.4511	0.4434
	Zambia	0.3593	0.3297	0.3949