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Time-varying impact of information and communication technology on carbon emissions

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内容摘要： To investigate the time-varying net environmental impact of Information and Communication Technology (ICT), we apply the local linear dummy variable estimation (LLDVE) method using a panel data consisting of 63 countries for the period 1995–2017. Our analysis reveals that ICT increases CO2 emissions until 2004, while reducing them after 2008, regardless of the national income level. We further uncover that the positive environmental impact of ICT on high-income countries is about 10 times greater than that on middle-income countries over time. These findings indicate that the development of ICT should be encouraged to alleviate carbon emissions on a global scale, especially for middle-income countries, given the benefits of an improved technology absorption rate on the mitigation effect in high income countries.

一、Introduction

Greenhouse Gas (GHG) emissions generated by economic growth have contributed to the global warming, which in turn lead to more fre quent extreme weather conditions (e.g., drought, wildfires, heat waves) that impose immense risks on society, businesses and ecosystems (IPCC, 2018). These alarm the urgent need for striving a sustainable develop ment by mitigating carbon emissions. There is growing evidence shows that advanced technologies, especially the information and communi cation technology (ICT), have the potential to facilitate the transition to a low-carbon society.

Theoretically, ICT may mitigate carbon emissions mainly through its optimization and substitution effects (Zhang and Liang, 2012). The optimization effect is derived from innovations in green ICT. The application of ICT in other social sectors has improved economic output and optimized the allocation of energy resources, thus en hancing energy efficiency (Lahouel et al., 2021; Usman et al., 2021).This can be achieved through, i.e., the usage of more energy-saving products1 (see, e.g., Servaes, 2012; Bieser and Hilty, 2018), the au tomation of industrial process2 (see, e.g., Yi and Thomas, 2007; Zhang and Liang, 2012; Reimsbach-Kounatze, 2009), among others. For the substitution effect, ICT have replaced traditionally carbon-intensive activities with low-carbon activities through the process of digitiza tion (Berkhout and Hertin, 2004; Zhang and Liang, 2012; Sun and Kim, 2021). Tele-conferences and paperless offices are typical examples of virtual mobility and the dematerialization process (Bieser and Hilty, 2018; Tariq, 2018).

However, the direct and rebound effects of ICT may increase carbon emissions and lead to environmental degradation (Zhang and Liang, 2012). The direct effect arises from the life cycle of ICT products. According to the Climate Group,3 materials and productions related to ICT account for 0.35 Gt4 of carbon emissions (about a quarter of the overall carbon footprint), with 1.08 Gt of emissions coming from its usage. Moreover, ICT may transform the manufacturing process to higher energy efficiency and stimulate economic growth. As a result,diminished production costs and rising demand support an increase in overall energy use. This so-called rebound effect could hinder potential energy savings (see, e.g., Plepys, 2002; Galvin, 2015; Lange et al., 2020).

The overall impact of ICT on carbon emissions depends on which of these conflicting channels prevail. Extant studies have mainly applied linear models to panel data but have provided inconclusive results. Some authors have reported that ICT mitigates climate change by reducing carbon emissions (Salahuddin and Alam, 2016; Asongu et al., 2017; Añón Higón et al., 2017; Lu, 2018; Ozcan and Apergis, 2018; Tariq, 2018; Danish, 2019; Haseeb et al., 2019; Chien et al., 2021; Zheng and Wang, 2021), whereas others have shown opposite con clusions and suggested ICT as a contributor to carbon emissions (Lee and Brahmasrene, 2014; Lee et al., 2015; Salahuddin and Alam, 2016), or exhibiting an insignificant effect (Amri et al., 2019). However, point estimations in linear models merely reflect the average effect of ICT on carbon emissions in a certain period, which may result in inconsistent and biased results. A small strand of studies finds a nonlinearity between ICT and CO2 emissions based on the time series of a single country (Godil et al., 2020; Lahouel et al., 2021). Their results suggest that the relationship between ICT and carbon emissions is rather complex, whereas linear models may not reveal it appropriately.

There are several reasons to believe that the direction of this overall environmental impact could be time dependent. First, innovations in ICT over time could be decisive drivers of boosting productivity while reducing carbon emissions per unit of output (Nguyen et al., 2020; Lahouel et al., 2021). Second, changes in policies related to the de velopment of ICT also trigger and incentivize low-carbon activities in households and businesses (Reimsbach-Kounatze, 2009; Sun and Kim, 2021). For example, research and development (R&D) expenditures allocated by policy makers usually update production technologies and thus curb emissions (Dinda, 2018). Moreover, ICT facilitates people's access to environmental news at a higher exposure, which nudges them to take part in more environmental-friendly activities (Wang and Hao, 2018; Gong et al., 2020). Advancements in technologies, changes in policies for environmental protection, structural and behavioural shifts in society toward climate change, and other unknown factors may all serve as determinants of the net effect of the opposite impact mechanism of ICT. Therefore, it is natural to ask how ICT affects carbon emissions over time and what mechanism dominants the net impact. To model the time-varying relationship between these two variables and ensure the degree of freedom and estimation efficiency, we propose to employ a Local Linear Dummy Variable Estimation (LLDVE). This approach allows us to clearly identify the role of ICT and provide more testable implications for its development.

This study contributes to the existing literature in the following ways. First, we investigate the time-varying relationship between ICT and carbon emissions over global panel data using the LLDVE method. In contrast to previous studies that simply assume a linear relationship between ICT and CO2 in panel models or report a nonlinear relationship but use single-country data, we consider the smooth transition of coefficients over time without conjecturing their functional form. This novel nonparametric approach allows the data to tailor the pattern of the underlying relationship, thus avoiding misspecification of models and providing more robust estimations (Silvapulle et al., 2017; Ren et al., 2022). Second, we provide a unified framework to explain the environmental impact of ICT. Given the multiple impact mecha nisms of ICT, we integrate time effect to provide further insights in analysing the driving factors of this time-varying net environmental impact, which is an unresolved issue. Third, we highlight the neces sity for considering heterogeneity when formulating more targeted policies in different income-level countries. Due to significant discrep ancies in the accumulation of human capital and investment between developed and emerging markets, developing countries may face signif icant barriers in absorbing and utilizing ICT to hinder environmental degradation (Niebel, 2018). Our test on different national income groups[5] suggests that the mitigation effect of ICT on high-income economies are greater than that on middle-income economies. There fore, middle-income countries should invest both financial funds and human capital to bring out more of ICT’s positive effect in decoupling carbon emissions from economic growth.

Prior to commencing with the nonparametric method, we adopt a two-way fixed-effect model as a benchmark and choose the proportion of internet users in the population as an indicator of ICT development. All variables are at a logarithmic first-order difference to ensure the stationarity of the panels. We then apply the sample sets into the LLDVE model to examine the common trend and coefficient smoothing functions. The results are then discussed and compared between sample groups and across different models to verify the time-variant effect lying in the relationships. Moreover, energy consumption, gross domestic product (GDP) per capita, and foreign direct investment are added to the panel as control variables to reinforce the degree of model fitness and reduce bias.

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The results from the parametric method suggest that internet penetration and mobile subscriptions, as proxies of ICT development, show statistically no significant effect on environment. However, the LLDVE method presents a significant N-shaped trend of ICT over time. The findings reveal that ICT reduces carbon emissions with its relief effect since 2008. The disparities between results across these two approaches indicate that the LLDVE model has the ability to capture the entire spectrum of variable relationships. Furthermore, the results show similar N-shaped coefficient trends between ICT and carbon emissions across the high-income and middle-income groups, but the extent of the effect is not identical.

This research highlights the need to accelerate the development and diffusion of ICT in a global context. High-income and middle income countries should collaborate to innovate ICT towards higher productivity to increase its mitigation effect. Furthermore, the heterogeneity of environmental consequences across different national incomes offers new evidence for more targeted policy implications over various regions. For instance, ICT has a greater positive impact on high-income countries than on middle-income countries. Middle income countries should expand and advance their ICT development to gain more favourable carbon reductions.

This paper is organized into six sections. Section 2 provides a brief overview of the related literature. Section 3 introduces the methodology used in this study. Section 4 presents the findings by analysing the results of the parametric and nonparametric tests. Section 5 conducts robustness checks for potential missing variables and endogeneity issues. The conclusions are provided in the last section.

二、Literature review

Our study is related to the literature that focuses on the impact of ICT on the environment. One strand of studies has mainly clarified the theoretical mixed effects of ICT on the environment (i.e., direct effects, indirect effects, structural and behavioural effects) (see, e.g., Berkhout and Hertin, 2004; Yi and Thomas, 2007; Fichter, 2008; Zhang and Liang, 2012). Direct effects refer to the impacts of the manufacture, use, and disposal of ICT on climate change (see, e.g., Berkhout and Hertin, 2004; Erdmann and Hilty, 2010; Zhang and Liang, 2012). Previous literature based on life cycle assessment shows that the ICT manufacturing and use stages contribute predominant damage to the environment (see, e.g., Choi et al., 2006; Zhou and Schoenung, 2007; Weber et al., 2010). The manufacturing processes of ICT products components introduce significant emissions such as GHG emissions and acid fumes (Berkhout and Hertin, 2004). The transportation of ICT products via different transportation modes through a global supply chain can also generate significant GHG emissions. In addition, the utilization of ICT products can be energy-intensive since it consumes significant amount of electricity.

The indirect effects arise from the applications of ICT in other sectors, such as the manufacture, transportation, design, and operation of products (Berkhout and Hertin, 2004; Yi and Thomas, 2007; Erdmann and Hilty, 2010). These indirect effects are expected to mitigate the effect of climate change via substituting high-carbon products and activities with low-carbon alternatives through the digitization processes and optimizing energy use (Yi and Thomas, 2007; Zhang and Liang, 2012; Bieser and Hilty, 2018). The data acquisition, storage, and computational capacities of ICT are considered to enable a larger added value gained by other economic activities through the optimization of fixed resources, which can simultaneously save energy and increase productivity (Berkhout and Hertin, 2004; Erdmann and Hilty, 2010; Zhang and Liang, 2012).

The structural and behavioural effects are twofold. On one hand, by shifting to a dematerialization lifestyle in the long run can ICT signifi cantly lower emissions. Specifically, knowledge utilization can create more value through the reallocation of resources and energy rather than the exploration of new resources (Berkhout and Hertin, 2004). On the other hand, increased energy efficiency scales up economic growth and reduces the price of a unit product or service, thus, leading to the "rebound effect" to the expansion of energy consumption and demand (Plepys, 2002; Galvin, 2015; Lange et al., 2020). This rebound effect of ICT can offset some of the energy savings realized by the increased efficiency (Arushanyan et al., 2014; Galvin, 2015).

Given the paradoxical nature of ICT based on these theories, exten sive empirical studies have examined the relationship between ICT and carbon emissions using country-level data. These studies have mainly established parametric panel models to identify a linear relationship, that is, whether ICT could mitigate carbon emissions. However, con tradictory or insignificant results have been reported.

A large number of studies have found a negative relationship be tween ICT and carbon emissions (see for example, Ishida, 2015; Asongu et al., 2017; Lu, 2018; Ozcan and Apergis, 2018; Danish, 2019; Haseeb et al., 2019; Godil et al., 2020; Ulucak et al., 2020; Chien et al., 2021; Zheng and Wang, 2021). The CO2 mitigation effect can arise from gains in energy efficiency, which seems to surpass the additional energy demand caused by the direct and rebound effects of ICT (Ozcan and Apergis, 2018; Danish, 2019; Haseeb et al., 2019). Conversely, several authors have shown that the contribution effect of ICT suggests that stimulated energy consumption may impede the development of a low carbon economy (e.g., Lee and Brahmasrene, 2014; Lee et al., 2015; Salahuddin and Alam, 2016; Danish et al., 2018; Park et al., 2018; Kouton, 2019). Using both static and dynamic models, they have shown that the expansion of ICT could prompt electricity demand overall, thus leading to an increase in carbon emissions (Salahuddin and Alam, 2016; Park et al., 2018; Kouton, 2019). In addition, an insignificant effect is reported by N’dri et al. (2021) as a result of the balance between the mitigation and contribution effects of ICT across high-income developing countries. A similar outcome has also been discovered in Tunisia, Australia, and western regions of China (Salahuddin and Alam, 2015; Zhang and Liu, 2015; Amri et al., 2019; N’dri et al., 2021). The inconsistent findings point out a lack of consensus in the literature on either the mitigation or the contribution mechanism exerting a dominant impact on the environment.

The mixed results encourage the hypothesis of an environmental Kuznets curve (EKC) relationship between ICT and CO_2. Therefore, another strand of studies has put forward modifications to unify the mitigation and contribution effects under the framework of a nonlinear relationship to further illustrate the environmental impact of ICT. In these studies, a square term of ICT is added into their empirical models and an inverted U-shaped relationship is captured (Añón Higón et al., 2017; Faisal et al., 2020; Anser et al., 2021). This indicates that ICT increases carbon emissions before a threshold but enhances the quality of the environment once that threshold is reached.

Existing studies have constructed different parametric linear models for use in investigations, including mean-group estimator, augmented mean group, continuously-updated fully modified estimator, continuously-updated bias corrected estimator, full modified ordinary least square, generalized method of moments, and so on. These linear models may not provide consistent results on the environmental impact of ICT when unknown events occur alongside its complex and multi-directional influential channels. Therefore, a more appropriate model setting may be important to capture the precise relationship between ICT and CO_2. However, parametric estimators rely heavily on the hypotheses of functional form and parameter distributions, which may result in model misspecifications and, therefore, failures to fully understand the interaction between the variables. Unlike previous methodologies, the LLDVE method we use requires no prior knowledge about parameters and model settings, thus capturing the time transition coefficient functions tailored by the data.

Another potential caveat with these parametric methods is that they generally produce the average effects of ICT based on a particular sample period. They may obscure the potential changes in the direction of ICT effects over time and lead to inconsistent findings. Therefore, the results need to be interpreted carefully with respect to the selection of countries, regions, and sample periods. This also helps to explain the non-unified findings. Notably, we incorporate potential changes in the coefficients over the course of our study period. This enables us to identify the driving factors of the time-varying nexus and to provide a unified framework for interpreting the impact of ICT and its corresponding channels, which has not yet been clarified.

三、Methodology and data

In this section, we describe the data set and introduce the LLDVE model conducted in our paper. Besides, the two-way fixed effect model is constructed as a benchmark to compare with the results from LLDVE model.

（一）Data and description

This paper aims at examining the extent to which ICT, energy con sumption, economic growth, and foreign direct investment (FDI) affect carbon emissions. The sample in our study consists of 63 countries, which is further categorized into 34 high-income and 29 middle-income countries. The income levels of the countries in the sample groups are defined by the World Bank, with all of the high-income countries chosen being OECD countries. Given the availability of data, the sample covers 22 consecutive years from 1995 to 2017. We use the percentage of the population using the internet (internet penetration) and mobile cellular subscription (per 100 people) as proxies of ICT intensity, which is applied in the extant works (e.g., Sadorsky, 2012; Asongu et al., 2017). As for measuring the impact on the environment, carbon dioxide emissions per capita is chosen as the dependent variable. Data for carbon emissions, internet penetration, mobile subscriptions, GDP per capita and foreign direct investment per capita are derived from the World Bank’s World Development Indicators (WDI). Data for the energy consumption volume are drawn from BP’s Statistical Review of World Energy, which provides and analyses data on world energy communities. A detailed description is summarized in Table 1.

（二）Parametric panel model

In order to explore how ICT, economic growth, and other driving force impact on the environment, we construct a parametric model under the STIRPAT framework (Dietz and Rosa, 1997). It models the relationship between socioeconomic changes and the environment with regard to stochastic impacts in the following form:

$$I_{it} = a_i P_{it}^b A_{it}^c T_{it}^d , \tag{3.1}$$

Where a_i is a constant intercept term, I_{it}, P_{it}, A_{it}, and T_{it} represent the environmental effect, population, affluence, and technology, respectively. b, c and d are the coefficients of the environmental impact.

In addition, we incorporate energy consumption per capita and foreign direct investment (FDI) into the STIRPAT model to study the impact of energy usage and financial activities on carbon emissions. We choose the above two factors because energy consumption can positively or negatively impact on carbon emissions (Fang et al., 2019), while FDI may affect environmental quality by the interaction between inflows of financial investments, industrial output, and technology (Oz can and Apergis, 2018; Park et al., 2018; Nguyen et al., 2020). To eliminate the heteroscedasticity, we take the logarithm of the formula. Divided by the total population at both sides, Eq. (3.1) could be rewritten as:

$$\begin{aligned} \ln CE_{it} = \alpha_i + \beta_1 \ln INT_{it} + \beta_2 \ln MOB_{it} + \beta_3 \ln EnergyCon_{it} \\ + \beta_4 \ln GDP_{it} + \beta_5 \ln FDI_{it} + \lambda_t + \epsilon_{it}, \end{aligned} \tag{3.2}$$

where CE_{it} denotes per capita carbon emissions. INT_{it} and MOB_{it} are the internet penetration and mobile cellular subscription per 100 people, which indicate the level of technology. $EnergyCon_{it}$ refers to the per capita energy consumption. GDP_{it} represents the per capita gross domestic product. FDI_{it} is the per capita foreign direct investment. Moreover, α_i, λ_t, and ε_{it} represent the unobserved time invariant individual heterogeneity, individual invariant time heterogeneity, and stochastic error term, respectively. Considering the stationarity of panels, we process all variables to the first difference according to the results of the CIPS test. Thus, our two-way fixed effect parametric panel model is established as follows:

$$\begin{aligned} \triangle \ln CE_{it} &= \alpha_i + \beta_1 \triangle \ln INT_{it} + \beta_2 \triangle \ln MOB_{it} + \beta_3 \triangle \ln EnergyCon_{it} \\ &+ \beta_4 \triangle \ln GDP_{it} + \beta_5 \triangle \ln FDI_{it} + \lambda_t + \epsilon_{it}\,, \end{aligned} \tag{3.3}$$

It functions as a benchmark to the results in the LLDVE method after wards. To avoid the problem of omitting variables, we also introduce additional control variables such as trade openness in the robustness test.

Table 1
Description of variables and data source.

Variables	Description	Source
CE	Carbon dioxide emissions(metric tons per capita).They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring.	WDI
INT	Individuals using the Internet (% of population). Internet users are individuals who have used the Internet (from any location) in the last 3 months.	WDI
MOB	Mobile cellular subscriptions (per 100 people). Mobile cellular telephone subscriptions are subscriptions to a public mobile telephone service that provide access to the PSTN using cellular technology.	WDI
EnergyCon	Primary energy consumption per capita. Primary energy comprises commercially-traded fuels, including modern renewables used to generate electricity.	BP's Statistical Review of World Energy
GDP	Per capita GDP (constant 2010$)	WDI
FDI	Per capita foreign direct investment, net inflows (BoP, current US$)	WDI

（三）Parametric panel model

1.Non-parametric panel data model with time-varying coefficients approach

The local linear dummy variable estimation (LLDVE) method (Li et al., 2011) allows us to delve into the time-varying environmental consequences exerted by ICT in the long term. Assume i(i = 1,2,...,N) different cross-section and a time period t(t = 1,2,...,T) given, the dependent and explanatory variable sets are represented by Y_{it} X_{it}.The common time trend panel model with time-varying coefficients is constructed in the form below:

$$\begin{aligned} & Y_{it} = f_t + \beta_t X_{it}^{\top} + \alpha_i + e_{it}, i = 1, 2, \ldots, N, t = 1, 2, \ldots, T\,, \\ & X_{it} = (\triangle \ln INT_{it}\,, \triangle \ln MOB_{it}\,, \triangle \ln EnergyCon_{it}, \\ & \qquad \triangle \ln GDP_{it}, \triangle \ln FDI_{it}\ )\,, \\ & \beta_t = \left(\beta_{t,1}, \beta_{t,2}, \beta_{t,3}, \beta_{t,4}\right)\,. \end{aligned} \tag{3.4}$$

Here,Y_{it} represents the first difference of $\ln CE_{it}$,$f_t=f(t/T)$ denotes the unknown common trend function,$\beta_{t,j}=\beta_j(t/T)$ is the time-varying coefficients under prediction,alpha$_i$ stands for unobserved individual effect and e$_{it}$ for the error term. For the sake of simplicity, Eq. (3.4) can be rewritten as the matrix notations below:

$$\tilde{Y} = \tilde{f} + \widetilde{B}(X,\beta) + \widetilde{D}\alpha + \tilde{e}\,, \tag{3.5}$$

Where

$$\begin{aligned}
\tilde{Y} &= \left(Y_1^\top, \dots, Y_N^\top\right)^\top \text{ with } Y_i = \left(Y_{i1}, \dots, Y_{iT}\right)^\top, \\
\tilde{e} &= \left(e_1^\top, \dots, e_N^\top\right)^\top \text{ with } e_i = \left(e_{i1}, \dots, e_{iT}\right)^\top, \text{for } i = 1,2,\dots,N, \\
\tilde{f} &= \bar{I}_N \otimes \left(f_1, \dots, f_T\right)^\top = \bar{I}_N \otimes f, \\
\tilde{B}(X,\beta) &= \left(X_{11}^\top\beta_1, \dots, X_{1T}^\top\beta_T, X_{21}^\top\beta_1, \dots, X_{NT}^\top\beta_T\right)^\top, \\
\alpha &= \left(\alpha_1, \dots, \alpha_N\right)^\top \\
\tilde{D} &= I_N \otimes \bar{I}_T,
\end{aligned}$$

where $\bar{I}_k$ is a $k \times 1$ vector of ones, $\otimes$ represents the Kronecker product.

To identify and motivate the estimator, we assume $\sum_{i=1}^{N} \alpha_i = 0$, then Eq. (3.5) is further developed as:

$$\tilde{Y} = \tilde{f} + \widetilde{B}(X,\beta) + \widetilde{D}^*\alpha^* + \widetilde{e}, \tag{3.6}$$

where

$$\alpha^* = \left(\alpha_2, \dots, \alpha_N\right)^\top, \ \widetilde{D}^* = \left(-\bar{I}_{N-1}, I_{N-1}\right)^\top \otimes \bar{I}_T.$$

We further define $\beta_*(\cdot) = [f(\cdot), \beta_1(\cdot), \dots, \beta_d(\cdot)]^\top$ as the varying coefficients and common trend function which are being estimated. Thus, $\tilde{f} + \widetilde{B}(X,\beta)$ can be approximated by Taylor expansion as:

$$\beta_*(t/T) \approx \beta_*(\tau) + \beta_*'(\tau)(\frac{t}{T} - \tau) + o[(\frac{t}{T} - \tau)^2]\,. \tag{3.7}$$

It follows:

$$\tilde{f} + \widetilde{B}(X,\beta) \approx \widetilde{M}(\tau)\{\beta_*^\top(\tau), h[\beta_*'(\tau)]^\top\}^\top, \tag{3.8}$$

where h is the bandwidth, τ is the point at which $\tilde{f} + \widetilde{B}(X,\beta)$ is approximated and $\widetilde{M}(\tau)^\top = [M_1^\top(\tau), \dots, M_N^\top(\tau)]$ with

$$M_i^\top(\tau) = \begin{pmatrix} 1 & X_{i1}^\top & \frac{1-\tau T}{Th} & \frac{1-\tau T}{Th}X_{i1}^\top \\ \vdots & \vdots & \vdots & \vdots \\ 1 & X_{iT}^\top & \frac{T-\tau T}{Th} & \frac{T-\tau T}{Th}X_{iT}^\top \end{pmatrix}$$

where $i = 1, 2, \dots, N$.

2.Bandwidth selection

We follow Sun et al. (2009) and Silvapulle et al. (2017) to select the bandwidth by kernel-based weights in our model, which is considered as an upgraded least-squared cross-validation method since it select the optimal bandwidth in an automatic way.

We define the local weight matrix $W(\tau) = \text{diag}\left\{\frac{1}{h}K(\frac{1-\tau T}{Th}), \ldots, \frac{1}{h}K(\frac{1-\tau T}{Th})\right\}$, for K is the kernel function and h is the bandwidth. Thus, our objective transfers to solve the optimization problem with respective to $[\beta_*^\top(\tau), h(\beta_*'(\tau))^\top]^\top$ and α^*:

$$\min_{[\beta_*^\top(\tau), h(\beta_*'(\tau))^\top]^\top, \alpha^*} \left\{\widetilde{Y} - \widetilde{M}(\tau)[\beta_*^\top(\tau), h(\beta_*'(\tau))^\top]^\top - \widetilde{D}^*\alpha^*\right\}^\top \widetilde{W}(\tau)\left\{\widetilde{Y} - \widetilde{M}(\tau)[\beta_*^\top(\tau), h[\beta_*'(\tau)]^\top\}^\top - \widetilde{D}^*\alpha^*\right\}, \tag{3.9}$$

where $\widetilde{W}(\tau) = I_N \otimes W(\tau)$ to fit the dimension in calculation. Taking the first-order conditions on α^*, we have

$$\hat{\alpha}^*(\tau) = [\widetilde{D}^{*\top}\widetilde{W}(\tau)\widetilde{D}^*]^{-1}\widetilde{D}^{*\top}\widetilde{W}(\tau)\left\{\widetilde{Y} - \widetilde{M}(\tau)[\beta_*^\top\tau, h(\beta_*'(\tau))^\top]^\top\right\}, \tag{3.10}$$

Replacing α with $\hat{\alpha}^*(\tau)$ in Eq. (3.9), we obtain the optimization formula with respect to $[\beta_*^\top\tau, h(\beta_*'(\tau))^\top]^\top$:

$$\min_{[\beta_*^\top(\tau), h(\beta_*'(\tau))^\top]^\top} \left\{Y - \widetilde{M}(\tau)[\beta_*^\top\tau, h(\beta_*'(\tau))^\top]^\top\right\}^\top \widetilde{K}^\top(\tau)\widetilde{W}(\tau)\widetilde{K}(\tau)\left\{Y - \widetilde{M}(\tau)[\beta_*^\top\tau, h(\beta_*'(\tau))^\top]^\top\right\}^\top, \tag{3.11}$$

where $\widetilde{K}(\tau) = I_{N\times T} - D^*(D^{*^\top}\widetilde{W}(\tau)D^*)^{-1}D^{*\top}\widetilde{W}(\tau)$. Define $\widetilde{K}^\top(\tau)\widetilde{W}(\tau)\widetilde{K}(\tau)$ as $\widetilde{W}^*(\tau)$, the unknown smooth coefficient function is attained through Eq. (3.12):

$$\hat{\beta}_*(\tau) = (I_{d+1}, \mathbf{0}_{d+1})[\widetilde{M}^\top(\tau)\widetilde{W}^*(\tau)\widetilde{M}(\tau)]^{-1}\widetilde{M}^\top(\tau)\widetilde{W}^*(\tau)\widetilde{Y}. \tag{3.12}$$

Here, $\hat{\beta}_*(\tau)$ is the local linear dummy variable estimator of $\beta_*(\cdot)$.

3.Bootstrapping confidence intervals

The bootstrapping developed by Mammen (1993) is included in order to generate the confidence intervals for the varying coefficient functions and common trend. To be specific, first, the de-trended residuals is calculated from formula $\hat{\varepsilon_{it}} = \hat{e}_{it} - \hat{m}_{it}(\tau; b)$, whereby $\hat{m}_{it}(\tau; b)$ is the country-specific trend functions. $\hat{m}_{it}(\tau; b)$ is a local linear estimation of $\hat{e}_{it}$ on τ. Then, the residuals are resampled as $\hat{\varepsilon_k}$, where k is selected at random among $1, \ldots, T$ with replacement and a sample of Y_{it} is collected forward. Next, estimates of the unknown common trend $\hat{f}^*(t/T)$ and coefficient functions $\hat{\beta}_t^*$ are derived for $i = 1, 2, \ldots, N$. Finally, confidence bands at 90% level are evaluated by a consecutive reiteration of the above steps for 1000 times.

四、Empirical results and discussions

In this section, we describe and discuss the empirical results in parametric and nonparametric models in detail.

（一）Parametric panel model

1.Cross-sectional dependence test

The CD test proposed by Pesaran (2021) is carried out to examine the cross-sectional dependence among each panel group. As shown in Table 2, the null hypothesis of cross-sectional independence across countries in the panel is rejected at 1% level of significance. Thus, there exists cross-sectional dependence across countries in all groups.

2.Unit root test

Unit root test for panel data is considered necessary for the con struction of regression model, since a stationary panel basically guide to trusted results. According to the result in Table 2, cross-sectional dependent is found in all of the sample groups, thus the CIPS test is employed in testing the panel stationarity (Pesaran, 2007). CIPS test is cross-sectionally augmented to detect the unit root in lagged level and first-differences of individual series. The result in Table 3 implies that all 3 panels reject the null hypothesis of a unit root at 1% level significance. Therefore, the panels in this paper are proved to be stationary.

Table 2
The result of cross-sectional dependence test.

	CD-test	p-value	corr	abs(corr)
Panel A: full sample				
dCE	25.84	0.000	0.125	0.230
dINT	125.81	0.000	0.607	0.607
dMOB	136.49	0.000	0.658	0.659
dEnergyCon	24.79	0.000	0.120	0.220
dGDP	61.35	0.000	0.296	0.347
dFDI	19.54	0.000	0.094	0.217
Panel B: high-income				
dCE	28.12	0.000	0.253	0.295
dINT	75.71	0.000	0.682	0.682
dMOB	89.80	0.000	0.808	0.808
dEnergycon	25.49	0.000	0.229	0.279
dGDP	62.34	0.000	0.561	0.562
dFDI	10.06	0.000	0.091	0.225
Panel C: middle-income				
dCE	7.08	0.000	0.075	0.193
dINT	49.18	0.000	0.520	0.520
dMOB	55.72	0.000	0.590	0.590
dEnergyCon	8.27	0.000	0.087	0.207
dGDP	22.36	0.000	0.237	0.279
dFDI	11.46	0.000	0.121	0.217

Note:(i) CD test for cross-sectional correlation developed by Pesaran (2004).(ii) Under the null hypothesis of cross-section independence CD $\sim N(0,1)$.

Table 3
The result of unit root test.

	CIPS	Critical value		
		10%	5%	1%
Panel A: full sample				
dCE	−4.453	−2.52	−2.58	−2.69
dINT	−4.759	−2.52	−2.58	−2.69
dMOB	−3.542	−2.52	−2.58	−2.69
dEnergyCon	−4.478	−2.52	−2.58	−2.69
dGDP	−3.060	−2.52	−2.58	−2.69
dFDI	−5.299	−2.52	−2.58	−2.69
Panel B: high-income				
dCE	−4.543	−2.54	−2.61	−2.73
dINT	−4.872	−2.54	−2.61	−2.73
dMOB	−4.527	−2.54	−2.61	−2.73
dEnergyCon	−4.835	−2.54	−2.61	−2.73
dGDP	−3.140	−2.54	−2.61	−2.73
dFDI	−5.731	−2.54	−2.61	−2.73
Panel C: middle-income				
dCE	−4.368	−2.58	−2.66	−2.81
dINT	−4.723	−2.58	−2.66	−2.81
dMOB	−3.393	−2.58	−2.66	−2.81
dEnergyCon	−4.214	−2.58	−2.66	−2.81
dGDP	−3.708	−2.58	−2.66	−2.81
dFDI	−4.642	−2.58	−2.66	−2.81

Note: CIPS test for unit roots in heterogeneous panels developed by Pesaran (2007).

2.Two-way fixed-effect model test

A two-way fixed-effect model is applied in this research to launch an estimation benchmark among the three sample groups. As reported in Table 4, the coefficients of ICT in the full sample appear to be insignificant at 5% statistical significance level over 1996–2017. We observe that the impacts of internet penetration and mobile subscrip tion are opposite in direction. They imply that increasing penetration of internet is positively correlated with CO_2 while mobile develop ment mainly eases the burden of environment. For subsample groups, high-income countries have significantly negative coefficients for ICT, whereas middle-income countries reach on insignificant positive-to zero coefficients. These results reveal that the average impact of ICT development on the environment among different income-level coun tries is in the opposite direction. According to Niebel (2018), the difference lies in the absorptive capacity of high- and middle-income countries, which intervenes the process of realizing energy efficiency gains from ICT usage.

Our results demonstrate that energy consumption plays a critical role to countries' emissions. To be more specific, a 1% increases in en□ergy consumption increases a 0.613% (0.494%, 0.714%, respectively) of CO_2 emissions for the full sample (high-income, middle-income countries, respectively). Furthermore, GDP per capita also significantly affects environmental quality, especially in the full sample and the high-income group. However, the estimated relationship between for eign direct investment and carbon emissions is insignificant in the full sample and high-income countries, while it assists the environmental degradation among middle-income ones. Recall that the effect of time could not be captured in the relationship between variables in a point estimation, we add an arbitrary break point between the sample period at year 2006. We find some evidence for an inconsistent estimation by the parametric model in different time spans. As shown in Table 5, the coefficient on internet penetration is positive during time span 1996– 2006, while reported as negative over 2007–2017 in the full sample. The effect of mobile subscription on carbon emissions is also opposite in direction during two periods. Thus, the LLDVE approach is employed to capture the potential time-varying relationship between ICT and carbon emissions.

Table 4
The results of point estimation.

	Full sample	High-income	Middle-income
dINT	0.0001	−0.0230**	0.0066
	(0.0045)	(0.0091)	(0.0049)
dMOB	−0.0045	−0.0233**	0.0037
	(0.0059)	(0.0093)	(0.0081)
dEnergyCon	0.6131***	0.4944***	0.7137***
	(0.0931)	(0.1414)	(0.0728)
dGDP	0.1961**	0.3413***	0.0850
	(0.0941)	(0.0899)	(0.1171)
dFDI	−0.0016	−0.0021	0.0514***
	(0.0028)	(0.0031)	(0.0162)
Constant	0.0160*	0.0423***	0.0035
	(0.0093)	(0.0097)	(0.0138)
Observations	1386	748	638
Number of id	63	34	29
R-squared	0.3876	0.4303	0.4086
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Cluster	Yes	Yes	Yes
Adjusted R-squared	0.376	0.410	0.383

Note: (i) This table reports the estimations of fixed effect and time fixed effect for the impacts of internet penetration, energy consumption, GDP, and foreign direct investments on carbon emission, respectively. (ii) Robust standard errors are in parentheses.
*Denotes the 10% significance level.
**Denotes the 5% significance level.
***Denotes the 1% significance level.

（四）Nonparametric model results

1.The time-varying effect of internet penetration and mobile subscription

Fig. 1 presents the time-varying smooth transition trends between each explanatory variable and carbon emissions per capita in 63 coun tries using the LLDVE method. Fig. 2(a) shows that internet penetration is positively correlated with carbon emissions from 1996 to 2004, but the relationship gradually shifts to negative thereafter. The coefficient of mobile subscription is positive to zero and statistically insignificant until 2008 and then moves to below zero afterwards.

Overall, the impact of ICT was to rise carbon emissions before 2008, yet impeded environmental degradation after 2008. Although mobile service contributed insignificantly to CO2 before 2004, it seems that the diffusion of the internet has notably increase the level of carbon.The contribution effect of this period was driven by the direct effect of ICT. As noted in Romm (2002), the internet era (1996–2000) witnessed a boost in the production and usage of the internet in the United States. The development further triggered the construction of infrastructures, such as optical fibre, cable, and so on. Therefore, the promotion of this energy-intensive industry has accelerated the increase in carbon emissions.

The mitigation effect came in 2008. Since then, the coefficients of internet and mobile service have been significantly negative, showing that ICT can decrease the level of carbon emissions. On the basis of extant literature (Erdmann and Hilty, 2010; Zhang and Liang, 2012; Galvin, 2015; Wang et al., 2022a), we attribute the mitigation effect during this period to several factors, including technological innovations, shifts in industrial structure, and changes in policies.

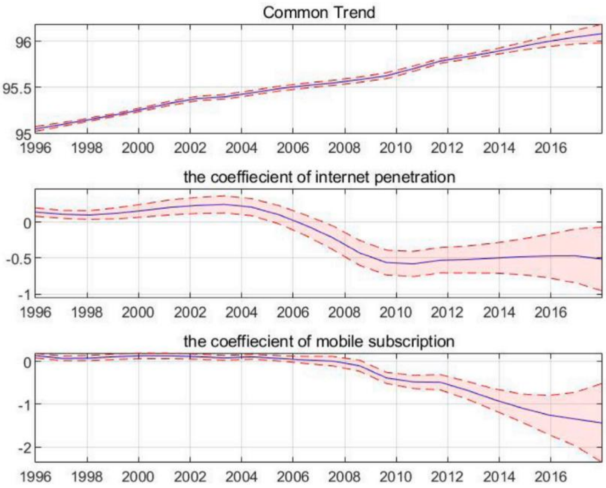
First, advances in technological innovations can prompt the development of more energy-efficient products related to ICT over time, decreasing the energy consumed in ICT products and other domains to curb emissions (Wang et al., 2022b). Adhering to Moore’s law,6 computers are becoming more empowered with chips and processors that enable them to consume less electricity while maintaining impressive performance. Battery operation constraints, along with sleep and off modes, also contribute to the energy savings of ICT-equipped devices. According to Heddeghem et al. (2014), the electricity consumption of a computer from 2006 to 2012 grew less than its popularity. Moreover, compared to the steep decline in the period of 2007–2010, a steady negative trend is captured during 2012–2016, which may be due to the slowed-down development in the ICT industry (Malmodin and Lundén, 2018). Aside from upgrading ICT-related devices, the application of ICT in other social sectors also alleviates carbon emissions due to technological transformation. ICT has been developed to monitor, transfer and analyse the real-time data on energy consumption (e.g., Hledik, 2009; Zhang and Liang, 2012; Sakshi et al., 2021). For example, ICT enables the optimization of energy usage in motor systems through the use of intelligent motor controllers, and the information processing ability also advances the design of transport networks and delivery routines in the transportation sector. Under the transformation of ICT, machines, platforms, and systems can be connected via the internet to message each other and allocate resources smartly. From this perspec tive, ICT can be embodied directly as a carbon reduction technique that stimulates productivity with less emissions (Cheng et al., 2021). Moreover, because ICT has changed the process of acquiring and storing knowledge online, business and study activities have been substituted with relatively low-carbon-intensive activities. The so-called demateri alization or digitization of life patterns (e.g., paperless society, virtual meetings and so on) has helped to mitigate carbon emissions (Zhang and Liang, 2012; Tariq, 2018; Bieser and Hilty, 2018; Yi and Thomas, 2007).

The second channel for the reduction effect in this period would be shifts in industrial structure due to the diffusion of ICT. ICT has the characteristics to drive the dissemination of information, thus enabling the achievement of the knowledge-based and skill-based production with an efficient output through the acceleration of industrial con vergence (Geum et al., 2016; Can and Gozgor, 2017; Dong et al., 2021). The accumulation of ICT can reduce information asymmetry and expand knowledge spillovers in the economy, causing upswings in emerging or tertiary industries, such as e-commerce, automotive electronics, and so on (Can and Gozgor, 2017; Fang et al., 2019). The structural transformation from energy-intensive sectors, including mining, manufacturing, and construction, etc., into those that are not particularly dependent on carbon emissions can not only reduce the negative impact on the environment, but also create additional valued output (e.g., Hledik, 2009; Wang et al., 2022c).

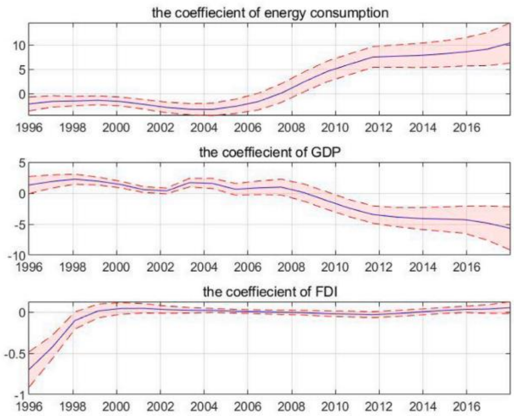
Third, we attribute the broader mitigation effect to the promotion of policies (Ren et al., 2021; Yu and Zhang, 2022) . Governments in the Organization for

Economic Cooperation and Development (OECD) and major non-OECD countries have launched a range of policies related to ICT since 2008, which have prompted green ICT innovations and raised awareness of ICT applications in reducing carbon emissions (Reimsbach-Kounatze, 2009; Sun and Kim, 2021). This is exemplified in Denmark's Action Plan for Green IT,7 which focuses mainly on the education of greener IT use and IT solutions for a sustainable future. Japan has set up the Green IT Project,8 which involves devel oping energy-efficient technologies in collaboration with industry and academia. Similar cases can be seen in Australia, Korea, the United Kingdom, the United States, and the European Union. Overall, the nonparametric estimations prove that the LLDVE method can better capture the time-varying effect of ICT on carbon emissions.

In Fig. 1(b), the increase in energy consumption stimulates carbon emissions most of the time within our sample period, especially af ter 2008. Economic growth is positively related to carbon emissions from 1996 to 2004, with 1% of the GDP growth associated with a 2% increase in carbon emissions at its peak due to manufacturing expansion fuelled by informational technologies. Interestingly, these countries then gradually transitioned to a low-carbon development path after 2010. Our finding suggests that carbon emissions are pro cyclical in the economy, which is consistent with Gozgor et al. (2019). The decelerated impact of economic growth partially supports the EKC hypothesis that carbon emissions negatively react with per capita income when a country reaches the upper-middle (or high) income level. The effect of FDI on the environment presented is statistically insignificant after 1998, which is consistent with the point estimation results. Therefore, FDI in general has not taken place at the expense of environmental deterioration.

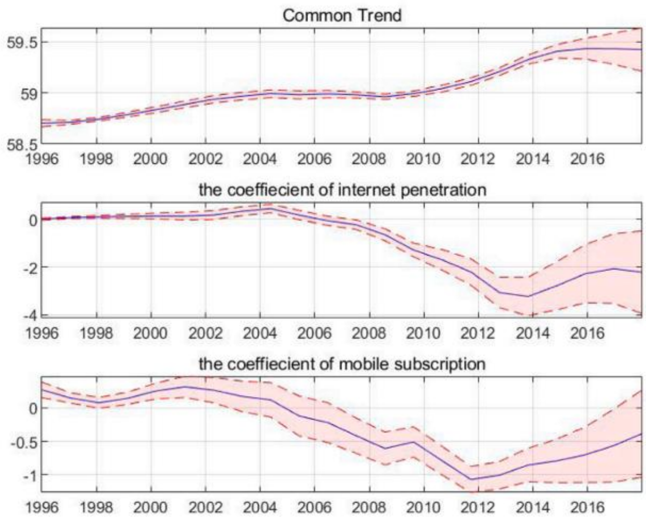


(a)

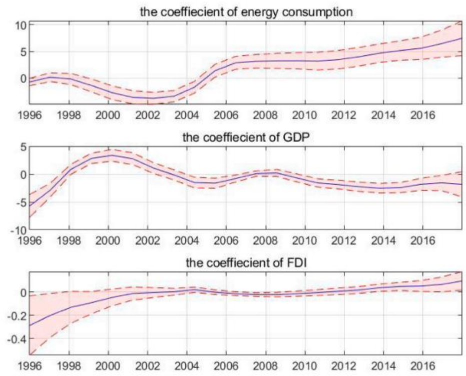


(b)

Fig. 1. Full sample: local linear dummy variable estimates of the common trend and coefficients along with 90% confidence intervals.

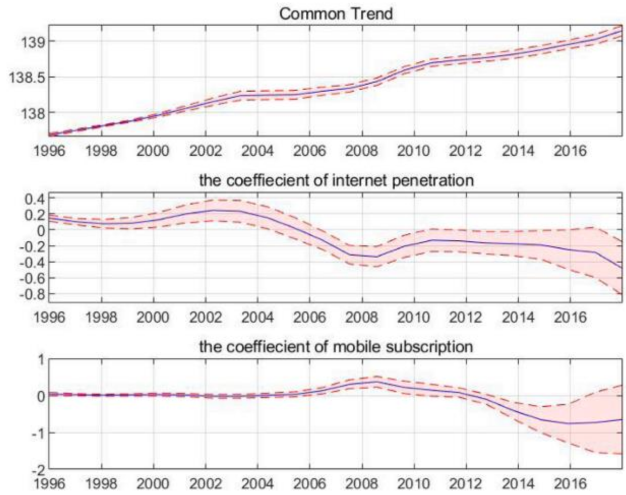


(a)

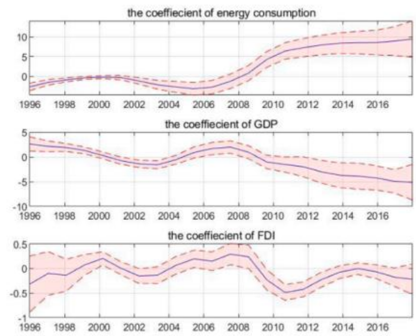


(b)

Fig. 2. High-income countries: local linear dummy variable estimates of the common trend and coefficients along with 90% confidence intervals.



(a)



(b)

Fig. 3. Middle-income countries: local linear dummy variable estimates of the common trend and coefficients along with 90% confidence intervals.

2.Heterogeneous impacts on different income-level countries

Figs. 2 and 3 depict the time-varying relationship between ICT penetration and carbon emissions in high-income and middle-income countries. These results extend previous works by providing time□evolving insights into the heterogeneity of ICT’s environmental impact across countries that vary in income. Overall, a similar N-shaped trend is observed between ICT and carbon emissions in both high-income and middle-income countries. In contrast to Khan et al. (2020), we find that middle-income countries can also develop toward a lower carbon economy with the aid of internet diffusion. Specifically, the reduction effect of internet penetration is substantially greater in high-income countries, which is about 10 times larger than that in middle-income countries at the lowest point.

The mitigation effect variation could be mainly due to the fact that the level of R&D investments and human capital in middle-income economies is not as that sufficient as in high-income economies. The relative shortage of R&D investments further leads to lower absorptive ates of technologies among middle-income countries (Can and Goz gor, 2017; Niebel, 2018). Inadequate investments have been suggested to restrain the innovations in environmentally friendly technologies and hinder the process of structural transformation to more energy efficient industries in middle-income countries. This is also evidenced by Fang et al. (2019), which states that developing economies tend to conduct pollution-intensive productions and export them to advanced economies. Human capital is another component that enhances the effectiveness in implementing the technology and reaping its benefits (Haini, 2021). A lack of skilled experts and workers is a barrier to making use of technology in middle-income countries. Additionally, as companies are rather sensitive to revenue loss, they may be reluctant to be equipped with ICT for fear of any possible manufacturing disruptions caused by installing new equipment. Governments in middle-income countries should be aware that energy efficiency is not a decisive factor for companies in developing production plans during rapid growth periods (Fang et al., 2019). Therefore, apart from financial supports, policies and regulations regarding emission standards can be enacted to inhibit aggressive carbon emissions from energy-intensive production processes and to monitor their production behaviours.

We also observe that the contribution effect of mobile subscriptions in middle-income countries comes later than in high-income countries at about 6 years.

This latency also implies the diffusion lag in mobile services in different per capita income countries. At the end of our study period, the coefficients of mobile service subscriptions in both subsamples show a sign of a transition from negative to positive.

Moreover, the impact of economic growth on carbon emissions in high-income countries fluctuates during the observed time span. The negative relationship discovered after 2010 show that countries in Europe and North America actively promote the global decoupling process (Yang et al., 2021). The negative phase can also be explained by the complementary economy structures among countries (Ren et al., 2021). This is exemplified in EU countries, which are mostly included in our high-income subgroup, as their reliance on comparative advantages triggers the negative spatial spillover effects of economic growth. As a result, economic growth in local carbon emissions.

五、Robustness test

（一）Test for missing variables

We perform an alternative estimation to verify the robustness of our test, where trade openness is added as another control variables to mitigate the problem of missing variable (see Figs. 4–6).

The trend scrutinized in Fig. 4 agrees with the previous section, illustrating a positive interaction between ICT and carbon emissions in the full sample panel before 2004, while stabilizing at the negative region over 2008–2017. This result further affirms the potential of ICT in mitigating climate change through development at a global level. Thus, the reliance of the LLDVE method has been placed in our paper, whereby a time-varying trend between ICT development and carbon emissions is presented. It is also identified that the nonparametric method fits better in depicting the relation in our model, avoiding the offset effect that occurs in point estimations.

（二）Endogeneity test

The main challenge of the proposed ICT and carbon emissions model is the potential endogeneity due to missing variables and re verse causality. To mitigate this issue, we check our ICT and carbon emissions model by employing instrumental variables. We treat internet penetration and mobile subscriptions as two endogenous variables instrumented by the historical urbanization process and fixed tele phone subscriptions, respectively. First, historical urbanization process reflected by the share of urban populations over the total population from 1972 to 1994 may provide necessary infrastructures to facilitate the development and diffusion of internet. At the same time, the degree of urbanization twenties years ago hardly determines carbon emissions at current stage. Second, the fixed telephone subscriptions is regarded as a proxy to capture the historical communication level since a shift from fixed telephone line use to mobile cellular telephone use has been witnessed (Lee and Brahmasrene, 2014). The traditional communica tion facilities may contribute to the development of communication technology onward, whereas causing negligible carbon emissions due to a low usage frequency.

While these instrumental variables are clearly correlated with the endogenous variables, the exclusion restriction is not testable given the unobservable behaviour of the error term (Conley et al., 2012). Thus, we apply the union of all confidence intervals (UCI) technique following (Conley et al., 2012; Clarke and Matta, 2018; Phan et al., 2022). This approach allows the direct effect of instrument variables on the dependent variable to range within some intervals instead of restricting it to zero. Thus, it is feasible in estimating the reasonable value range of coefficient on the endogenous variable with imperfect instruments.

As shown in Fig. 7(a), the range of estimated internet penetration coefficient lies between −0.01 and 0.09 within a 95% confidence inter□val when the direct effect of historical urbanization process on carbon emissions is assumed in a range [-0.2,0.2]. Similarly, the range of estimated mobile subscriptions coefficient resides in −0.18 to 0.24, as exhibited in Fig. 7(b). The results from UCI indicates that the effects of our endogenous variables on carbon emissions are significant, varying in an interval across zero.

We further conduct kinky least squares (KLS) as a second check on endogeneity (Kiviet, 2020; Kripfganz and Kiviet, 2021; Phan et al., 2022). This method imposes flexible assumptions on the correlation between the endogenous variables and error terms, yielding feasible confidence intervals for the coefficients of the endogenous variables. As unobservables may bias the estimate downward or upward, internet penetration and mobile subscriptions can be negatively and positively correlated with the error term. Therefore, we specify the degree of endogeneity within the range between −0.75 to 0.75. Fig. 8 shows the KLS confidence intervals for the two estimated coefficients. The results are consistent with the findings from both the LLDVE approach and UCI test, indicating that the impact of ICT on carbon emissions can be either positive or negative.

In sum, our results on the impact of ICT are robust to alternative specifications and endogeneity.

六、Robustness test

Our paper proposed the LLDVE method to investigate how ICT diffusion affected carbon emissions over time based on 63 countries from 1995 to 2017. The empirical results are summarized as below.

First, the N-shaped coefficient curves generated from our panels implied that the environmental impacts of ICT could vary in response to the unknown events behind time, rather than remaining constant. Specifically, our results highlighted that progress in technologies, shifts in industrial structure, and policies could contribute to the reduction effect of ICT on CO2 emissions. Hence, the effect of time should be considered when analysing the relationship between ICT and carbon emissions. The comparison between the LLDVE and benchmark estima tions also suggested that the LLDVE approach provided more accurate and reasonable results. Otherwise, the conflicting effects of ICT are offset during the sample period and was exhibited to be insignificant.

Second, our full sample result demonstrated that ICT diffusion played a mitigating role after 2008, although the boom of the internet could induce the growth of emissions before 2004. With ICT developed to be more efficient, we found the mitigation effect on carbon emissions outweighed the pollution caused by the process of consuming energy. This mitigation effect can be achieved by the upgrade of energy saving products and the structural transformation to a knowledge-based and technological-intensive economy, with the assistant of ICT-friendly policies. Our findings suggest that countries all over the world should establish alignment in bringing out the positive effects of ICT on the environment while restraining its negative effects.

Third, we observed that the mitigation effect of internet penetration in high-income countries was about 10 times greater than that in middle-income countries. This indicates that income level played a critical role in reaping benefits from the diffusion of ICT. The discrepancy may result from the varied technology absorptive rates across countries, as innovations in ICT take time to transfer from countries with higher R&D expenditures and human capital resources, usually high-income countries, to technology-deficit countries (Niebel, 2018; Haini, 2021).

The potential of ICT in reducing the level of carbon emissions throughout economic activities provides useful insights for policy making. Firstly, governments around the world should enhance the mitigation effect of ICT via the investments in more energy-saving green innovations among traditional industries. Financially, more funds could be raised in support of researches and adoptions of these technologies. It is also necessary to make up for the technical gaps by updating systems and infrastructures that carry out ICT in manufacturing, transportation, and other sectors. Subsidies and technical supports could be offered to companies to encourage the implement of ICT-equipped machines that promote the efficient use of resources. Secondly, the heterogeneous results indicate that middle-income countries should strengthen their intake and development of ICT to gain better mitigation effect. Besides the direct investments into ICT, they could also enhance human capital in the digitalization process to stimulate the innovations of this technology and acquire the skills to make use of it. This in turn relates to the support in educating both researchers and technical workers and the introduction of foreign capitals to accelerate the diffusion of ICT. Last, but not least, it is urgent for the world to create internationally accepted standards to popularize ICT applications in production processes over the world. This will increase the efficiency of ICT spillovers from technologically advanced countries to less developed ones. The collaborate cooperation in promoting ICT development would finally facilitate to keep up the pace of sustainable development in the global community.

As our study mainly focus on the time-transition coefficient func tions of the overall panel, we suggest that future investigations could propose some heterogeneity estimators to explore the potential differed regional time-varying impacts of ICT on carbon emissions. Additionally, the time-varying nexus between ICT and CO2 could be more accurate when the data of low-income countries are available. We shall leave these issues for future work.

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