Pol. J. Environ. Stud. Vol. 31, No. 4 (2022), 3677-3686
DOI: 10.15244/pjoes/147197 ONLINE PUBLICATION DATE: 2022-05-20

Original Research

Does an Inverted U-shaped Relationship Exist between ICT and CO_2 Emissions in China? Evidence from Unconditional Quantile Regression

Gan Liu*, Sanyu Wan

College of Economics, Hangzhou Dianzi University, Hangzhou, People's Republic of China 310018

Received: 26 January 2022
Accepted: 7 March 2022

Abstract

Information and communication technology (ICT) has experienced rapid development in recent decades, which exerts profound impacts on environmental sustainability. The positive and negative environmental impacts of ICT are widely debated. Some scholars point that some negative environmental impacts have arisen due to the production, use and disposal of ICT. While others consider that ICT has exerted favorable impacts on environmental sustainability by building smarter cities, transportation systems, electrical grids and industrial processes. These two effects are opposite, resulting in an inverted U-shaped relationship between ICT and CO_2 emissions. The existing literature abound in the relationship between ICT and CO_2 emissions in developed countries, but little attention has been paid to China. Therefore, the aim of this study is to investigate the non-linear relationship between ICT and CO_2 emissions in China. Applying China's urban panel data covering period 2004-2017 and employing unconditional quantile regression with fixed effect to estimate the benchmark model, we confirm the inverted U-shaped relationship between ICT and CO_2 emissions at all quantiles. Considering the regional differences, there is an inverted U form between ICT and CO_2 emissions at all quantiles for the eastern cities. Whereas, for non-eastern cities, the inverted U form only exists below the medium-high quantiles and does not exist at high quantiles. The findings not only contribute to the existing literatures, but also provide some policy implications to China and other developing countries.

Keywords: ICT, CO_2 emissions, environmental Kuznets curve, unconditional quantile regression, regional differences

Introduction

Recent decades have witnessed the rapid development and application of information and communication technology (ICT). Many previous studies have shown a significantly positive impact of ICT on economic growth [1-4] and productivity [5, 6]. Recently, a growing number of scholars have paid close attention to explore the relationship between ICT and environmental sustainability. However, different from the influence of ICT on economic growth and productivity, the effect of ICT on the environment is contradictory. ICT can have both unfavorable

*e-mail: hieescdcs@hdu.edu.cn

and favorable impacts on the environment. Moreover, ICT has been considered part of the environmental problem, but also part of the solution [7]. Undoubtedly, the production, use and disposal of ICT have an adverse effect on the environment [8-11]. The production of ICT-related equipment and running of ICT-related infrastructure increase the energy consumption, and the application of ICT has direct impacts on electricity consumption [12-14]. The main concern with the disposal of ICT devices is hazardous materials. They are liberated or generated after disposal in three ways: leaching from landfills, incineration and recycling, which causes environmental pollution [10]. But ICT can exert favorable impacts on the environment by building smarter cities, transportation systems, electrical grids and industrial processes, promoting green and sustainable development [15-17].

Since the reform and opening up, China, the largest developing country in the world, has experienced rapid economic growth over the past forty years, becoming the world's second largest economy [18]. However, China's rapid economic growth, has been achieved at the expense of the over-exploitation of resources and seriously environmental pollution [7]. The increasing number of environmental problems, especially air and water pollution, pose great threat to public health and damage China's economy sustainable development. It is imperative for China to balance economic development and environmental sustainability. As a party to the United Nations Framework Convention on Climate Change (UNFCCC), China promises to reach the peak of carbon emissions around 2030 and increase the proportion of non-fossil energy in primary energy consumption to 20%. At the same time, ICT industry has been increasingly booming since the beginning of the twenty-first century. To boost the development of ICT, Chinese government has developed and implemented a new set of ICT strategies, such as "Broadband China", "Internet plus" and "National Informatization Development Strategy 2006–2020". The wider application of ICT, especially in the conventional industries, can optimize the energy structure, which exerts profound impacts on energy efficiency and environmental sustainability.

Although the existing studies have explored the relationship between ICT development and environmental sustainability in China [19, 20], their benchmark models are all linear models. However, ICT can have both negative and positive impacts on the environment, and the relationship between ICT development and environmental sustainability may be non-linear. Hence, to bridge the gap in the existing literatures, we focus on the non-linear model and employ China's urban balanced panel data from 2004 to 2017 to investigate the relationship between ICT development and CO_2 emissions. Furthermore, due to the regional differences in China, the data may not follow the normal distribution. Therefore, this paper applies the unconditional quantile regression (UQR) model proposed by Firpo, Fortin, and Lemieux to estimate the benchmark model [21].

The remainder of the paper is organized as follows. Section 2 outlines a brief review of relevant literature, presents the model and discusses the data, while the empirical results and robustness analysis are presented in Section 3. Finally, the paper concludes the empirical results and provides some policy implications to China and other developing countries.

Material and Methods

Theoretical Background and Hypothesis

In the digitalized era, ICT plays an essential role in digitalized production, trading and transportation, which can greatly boost the productivity and economic development. ICT's contributions to productivity and economic growth are now widely accepted [1-6]. Economic growth indicates that a nation can produce more goods and services, and ICT makes goods and services more productive [22]. As for the relationship between economic growth and environmental sustainability, the environmental Kuznets curve (EKC) hypothesis implies that with the development of the country, pollution per capita begins to deteriorate, but eventually improves with economic growth through the scale effect, output effect, input effect and technology effect [23-25]. Therefore, the studies on the impacts of ICT on the environment are rather mixed.

The existing studies have not reached an agreement on this issue. Some scholars held the view that the application of ICT would increase global electricity consumption and be detrimental to the environment. Malmodin et al. forecast that the rapid development of the ICT will cause the carbon footprint to achieve 1.1 Gt by 2020 [26]. Moreover, Belkhir and Elmeligi conducted a detailed analysis of the ICT global carbon footprint, including the production of ICT and operational energy of ICT devices and infrastructure. They compared this contribution to the global 2016-level Green House Gas emissions (GHGE) and found that ICT-related GHGE contribution could increase from 1-1.6% of the 2007-level to more than 14% of the 2016-level worldwide GHGE [27]. While some scholars argued that the application of ICT would make contributions to decrease GHGE and be beneficial to form an environmental-friendly society. Lee and Brahmasrene applied the panel data of the Association of Southeast Asian Nations over the period 1991 to 2009 to examine the relationships among ICT, CO_2 emissions, and economic growth, identifying the significant favorable effects of ICT on both economic growth and CO_2 emissions [28]. Aldakhil et al. examined the role of ICT on carbon-fossil emissions in South Asia using a time series data from 1975 to 2016 and concluded that the wide application of ICT in diversified economic restructuring could help reduce carbon-fossil emissions to achieve environmental sustainability [29]. Haseeb et al. applied 1994-2014 panel data of BRICS economies to investigate the relationship between ICT and environmental quality, which suggests that ICT positively contributes towards environmental quality [30]. Additionally, N'dri et al. used a panel pooled mean group autoregressive distributive lag (PMG-ARDL) model for 58 developing countries from 1990 to 2014 and found that ICT can have favorable impacts on the environment for relatively low-income developing countries, while no evident relationship exists for relatively high-income developing countries [31].

Being motivated by the EKC hypothesis [32], some scholars suggested that there may be a non-linear relationship between ICT and the environment. Referring to the EKC hypothesis, Barış-Tüzemen et al. employed the autoregressive distributed lag (ARDL) analysis to determine the relationship between environmental degradation and ICT in Turkey [33]. The results confirmed the validity of inverted N-shaped EKC hypothesis; however, the results of the quantile regression test were inconsistent with those of ARDL. Faisa et al. examined the effects of electricity consumption, financial development, economic growth, trade and ICT on CO_2 emissions in the fast-emerging countries, which indicates that there is an inverted U-shaped relationship between ICT and CO_2 emissions [34]. Furthermore, through the production theory and EKC hypothesis, Higón et al. theoretically analyzed the relationship among ICT, economic growth and environmental sustainability. Then, on a global scale, they used a panel data consisting of 142 countries over the period 1995–2010 and confirmed that the relationship between ICT and CO_2 emissions is an inverted U form in both developed countries and developing countries [22].

The existing literature abound in the relationship between ICT and CO_2 emissions in developed countries. There has been little attention paid to developing countries, such as China. In the Chinese context, the initial study on the impact of ICT on the environment is conducted by Zhang and Liu, who used provincial panel data in China during 2000-2010 and employed the Feasible Generalized Least Square (FGLS) method to estimate the benchmark model [19]. And they found that ICT industry contributes to reducing China's CO_2 emissions. Chen et al., using China's provincial panel data covering period 2001-2016 and employing quantile regression method to estimate the benchmark model, found that ICT has a significant negative effect on CO_2 emission [20]. However, employing fixed effect model with Driscoll and Kraay standard errors [35], Higón et al. identified an inverted U-shaped relationship in developing countries including China [22]. The empirical results of Zhang and Liu, Chen et al. and Higón et al. are inconsistent [19, 20, 22].

Different from the existing literature, this paper investigates the non-linear relationship between ICT and CO_2 emissions in China combined with the unconditional quantile regression (UQR) model with fixed effect. Therefore, compared with previous studies, the marginal contributions of this study are in the following three aspects. Firstly, considering the favorable and unfavorable impacts of ICT on CO_2 emissions, it is more reasonable to assume the non-linear relationship between ICT and CO_2 emissions in China. Secondly, to deal with estimation problems for abnormal distribution and covariates effects, we employ the UQR model rather than the conventional fixed effect model or random effect model. Moreover, fixed effect indicator is added to control possible unseen covariates across varied cross-section at constant time. Thirdly, China's cities rather than provinces are selected as our sample to better reflect regional differences. Based on the above discussion on the relationship between ICT and CO_2 emissions, we propose the following hypothesis.

Hypothesis 1. There is an inverted U-shaped relationship between ICT and CO_2 emissions. With the development of ICT, CO_2 emissions are expected to increase; however, when ICT development achieves a more advanced stage, CO_2 emissions may decrease.

Benchmark Regression Model

Following the standard EKC framework [32], this study investigates the impact of ICT development on CO_2 emissions by using the following regression model:

$$\mathrm{CO2PC_{it}} = \alpha_0 + \alpha_1 \mathrm{ICT_{it}} + \alpha_2 \mathrm{ICT_{it}^2} + \alpha_3 \mathrm{GDPPC_{it}} + \alpha_4 \mathrm{GDPPC_{it}^2} + \mathrm{X_{it}}\beta + \mu_i + \varepsilon_{it} \quad (1)$$

where the subscripts i and t refer to city and time, respectively. CO2PC is the dependent variable measured by carbon dioxide (CO_2) emissions in metric tons per capita, which represents environmental sustainability. ICT is the key explanatory variable referring to ICT development level. GDPPC is per capita real gross domestic product, representing the level of economic development. α_0 is the constant. α_1, α_2, α_3 and α_4 are the coefficients of variables. β is the column vector of coefficients. Furthermore, μ_i represents city-specific effects and ε_{it} is the stochastic error term. We suppose that CO_2 emissions per capita (CO2PC) are influenced by the ICT development (ICT) and its squared term, per capita real gross domestic product (GDPPC) and its squared term, and a vector of control variables (X_{it}) that includes the different characteristics of cities.

On the basis of the EKC framework, with the development of economy, pollution levels are expected to increase to a threshold level beyond which pollution levels are expected to decrease when income is much higher ($\alpha_3>0$, $\alpha_4<0$). In an effort to broaden the concept of EKC framework, we investigate the relationship between CO_2 emissions and ICT development and assume that the relationship is an inverted U-shaped between the variables. With the development of ICT,

CO_2 emissions are expected to increase (α_1>0); however, when ICT development achieves a more advanced stage, CO_2 emissions may decrease (α_2<0).

Variable Setting

Different methods are used to measure ICT development in the existing literatures, including gross output of electronic and information manufacturing industry [19], Internet penetration and mobile phone penetration [20, 36-38], and ICT index [22, 28]. Considering the data availability and representativeness, we employ a similar method proposed by Higón et al. to construct the ICT index [22]. The ICT index used in this study consists of three components, including mobile phone users per 100 people, Internet users per 100 people and total telecommunications business per capita, respectively. To construct the composite index of ICT development, Higón et al. used average scores of indicators [22]. Different from this approach, we employ the entropy weight method proposed by Shannon to construct the ICT index [39]. In addition, as suggested by the existing literatures, the other covariates used in this model include: population density [22, 40, 41] and industrial structure [19, 42].

Estimation Method Selection

A methodological issue concerns the appropriate estimator. In general, the majority of estimation methods used in panel data analysis include the Pooled Ordinary Least Squares (POLS) model, the Feasible Generalized Least Square (FGLS), the fixed effect (FE) model and random effect (RE) model. Similarly, these methods are commonly used in empirical analysis to investigate the relationship between ICT and CO_2 emissions [19, 22, 28, 30]. Nevertheless, the ordinary panel models only study the relationship between conditional expectations of independent variables and dependent variables. However, as pictured in Fig. 1, the distribution of CO_2 emission per capita has significant right deviation, which indicates the estimation results may be biased when fitting the ordinary panel models.

In this paper, the UQR model proposed by Firpo, Fortin, and Lemieux is employed to investigate the relationship between ICT and CO_2 emissions [21]. Compared with OLS, the estimation results of quantile regression are more robust to outliers, and quantile regression does not require strong assumptions for error terms. Therefore, for abnormal distribution, the quantile regression coefficient estimator is more robust. Furthermore, compared with conditional quantile regression (CQR) model, the quantiles of UQR model are defined before regression; therefore, the model is not influenced by any right-hand-side variables [43]. Finally, fixed-effect estimator is added to the model to control some possible unseen covariates across varied cross-section at constant time. As a result, we apply UQR model with fixed effect to estimate the benchmark model [44].

Data and Description

The data applied in this paper consists of 282 cities at the level of municipality or above in mainland China (Hong Kong, Macao and Taiwan are excluded), split into 86 cities in eastern region (developed region) and 196 cities in non-eastern region (underdeveloped region), over the period 2004 to 2017. This results in a balanced panel with 3948 observations for analysis. Lhasa, Tongren, Mudanjiang, Zhangzhou, Chaohu and Qiqihar is also excluded due to the serious lack of data. The majority of the data is collected from the China City Statistical Yearbook (2005-2018). To impute the missing values, we use linear interpolation methods or look up statistical yearbooks of each city. The data of CO_2 emissions is calculated by the dataset of CO_2 emissions in Atmospheric Composition Analysis Group (ACAG) of Dalhousie University.

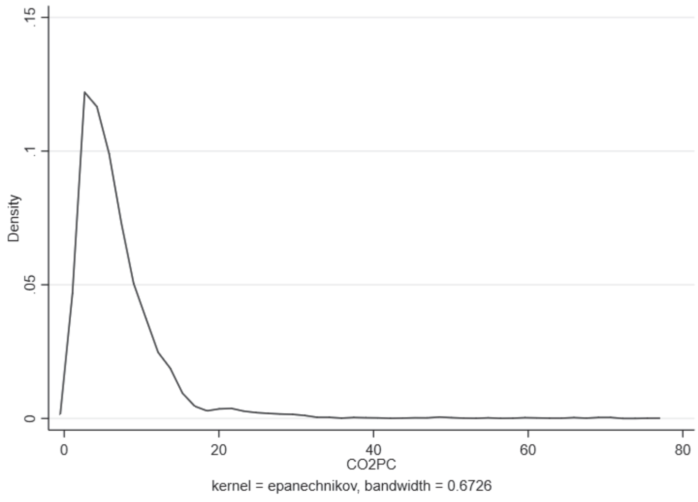

Fig. 1. Kernel density distribution of CO_2 emission per capita (CO2PC).

Table 1. Description of variables and data sources.

Variable	Description	Source
CO2PC	Carbon dioxide (CO_2) emissions in metric tons per capita	ACAG
ICT	ICT index: mobile phone users per 100 people, Internet users per 100 people, total telecommunications business per capita	China City Statistical Yearbook (2005-2018)
GDPPC	Per capita real gross domestic product based on purchasing power parity in 2004 CNY	
Pop	Population density: population per square kilometer	
Structure	Industrial structure: added value of tertiary industry/ added value of secondary industry	

Table 2. Descriptive statistics of the 282 cities (2004-2017).

Variable	Observations	Mean	Std. Dev.	Min	Max
CO2PC	3948	6.991	6.498	0.153	76.32
ICT	3948	0.045	0.048	0.003	0.682
GDPPC	3948	2.914	2.468	0.009	36.621
Structure	3948	0.850	0.454	0.094	9.482
Pop	3948	428.227	329.335	4.700	2661.54

Table 3. Descriptive statistics of the eastern and non-east region (2004-2017).

Variable	Eastern region (Developed region)		Non-eastern region (Underdeveloped region)	
	Mean	Std. Dev.	Mean	Std. Dev.
CO2PC	7.223	4.184	6.889	7.284
ICT	0.068	0.075	0.035	0.0023
GDPPC	4.047	3.151	2.417	1.898
Structure	634.466	384.289	337.735	253.85
Pop	0.896	0.488	0.83	0.437
Number of cities	86		196	
Observations	1204		2744	

Table 2 and Table 3 present some descriptive statistics of all variables employed in the total sample and sub-samples models. Table 2 shows that CO_2 emissions per capita and ICT index have a large degree of dispersion, which indicates that there are great differences in different cities. Additionally, we observe significant differences between developed region and underdeveloped region in Table 3. On average, CO_2 emissions per capita and ICT index are much higher in developed region. As for economic level, real GDP per capita of developed region is 4.047 ten thousand yuan, whereas for underdeveloped region is 2.417 ten thousand yuan. Moreover, the average values of other control variables are greater in developed region.

Results and Discussion

Analysis of UQR Model Results

In this section, in order to avoid pseudo regression and ensure the effectiveness of the estimation results, we conduct panel unit root tests and panel cointegration tests before regression. The unit root tests and cointegration tests show that there is a stationary cointegration relationship between all variables, which can be used for empirical analysis. After stationary test, we apply UQR model with fixed effect to investigate the relationship between ICT development and CO_2 emissions. As a comparison, we use the two-way fixed effect (TFE) model with Driscoll and Kraay standard errors to estimate the benchmark model.

Table 4 presents the influence of ICT on CO_2 emissions for whole sample by applying UQR model with fixed effect. In this paper, the quantile regression reports the estimation results at seven quantiles of 0.2, 0.3, 0.4, 0.5, 0.6, 0.7 and 0.8. It can be seen that estimated coefficients of ICT and ICT squared term are statistically significant at all quantiles and at the 1% level. Specifically, the results confirm the Hypothesis 1 that there is an inverted U form between ICT development and CO_2 emissions ($\alpha_1>0$; $\alpha_2<0$). When ICT industry is underdeveloped, further ICT investments contribute to the CO_2 emissions. But CO_2 emissions begin to decrease after reaching a threshold level of ICT development. The estimated turning point for the ICT is about 0.3 at 20th quantile distribution to 60th quantile distribution and about 0.5 at 70th quantile distribution to 80th quantile distribution. The results indicate that the higher the CO_2 emissions, the greater the turning point of ICT in cities. By comparison, the estimated turning point for the ICT in TFE model is about 0.48, which may not be applicable for all cities. Specifically, the estimated turning point for the ICT is above the average level of ICT for the total sample, indicating that China needs to boost the development of ICT industry to reach a threshold level of ICT.

As shown in Table 4, the influence of control variables is distinct at different quantiles. It can be found that estimated coefficients of GDPPC and its squared term are statistically significant at all quantiles (($\alpha_3>0$, $\alpha_4<0$), which confirms the EKC curve. In addition, the coefficients of industrial structure are significantly negative at 20th quantile distribution to 30th quantile distribution, showing that the upgrading of industrial structure have a great negative impact on CO_2 emissions at the low quantiles. Finally, population density has a significant positive impact on CO_2 emissions at 20th quantile distribution to 30th quantile distribution, but significant negative impact on CO_2 emissions at 80th quantile distribution.

Robustness Analysis

In this section, to make robustness tests, we apply UQR model with fixed effect in sub-samples, solve endogenous problems by introducing the instrumental variable and deal with the outliers.

China is vast in territory and resources but its development is unbalanced. The gap between developed regions and underdeveloped regions has become a serious issue. So, it is essential to investigate whether the impact of ICT on CO_2 emissions differs across different regions in China. Considering the differences in geographical advantages and economic development level, the whole sample is divided into two regions: the eastern region and the non-eastern region. The eastern region is regarded as a developed region, while the non-eastern region is considered as an underdeveloped region. Table 5 presents the results for these two regions.

Table 4. Estimation results of TFE and UQR model with fixed effect for whole sample.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	TFE	Q20	Q30	Q40	Q50	Q60	Q70	Q80
ICT	68.45***	31.27***	36.72***	37.38***	46.20***	51.47***	58.60***	96.12***
	(23.17)	(4.872)	(5.155)	(5.657)	(6.873)	(7.366)	(8.799)	(13.50)
ICT2	-70.69***	-49.53***	-58.08***	-60.84***	-72.11***	-73.79***	-64.36***	-90.44***
	(26.05)	(13.77)	(15.11)	(15.39)	(17.79)	(16.21)	(16.90)	(28.87)
GDPPC	0.822**	0.223***	0.379***	0.626***	0.663***	0.580***	0.792***	0.729***
	(0.404)	(0.0701)	(0.0879)	(0.125)	(0.131)	(0.136)	(0.204)	(0.258)
GDPPC2	-0.0164*	-0.00919***	-0.0139***	-0.0211***	-0.0216***	-0.0184***	-0.0214***	-0.0213***
	(0.00851)	(0.00310)	(0.00411)	(0.00583)	(0.00601)	(0.00510)	(0.00707)	(0.00700)
Structure	-0.0750	-0.929***	-0.946***	-0.441	-0.515	-0.244	-0.200	-0.0305
	(0.154)	(0.238)	(0.288)	(0.343)	(0.368)	(0.304)	(0.335)	(0.407)
Pop	-0.00294*	0.00123***	0.00107**	0.000820	-0.000872	-0.000566	-0.00122	-0.00533***
	(0.00175)	(0.000464)	(0.000541)	(0.000705)	(0.000800)	(0.000775)	(0.000926)	(0.00166)
Constant	3.026***	1.471***	1.726***	1.580***	2.882***	3.469***	4.094***	6.202***
	(0.967)	(0.316)	(0.377)	(0.481)	(0.509)	(0.465)	(0.573)	(0.935)
N	3948	3948	3948	3948	3948	3948	3948	3948

Note: Standard errors are in parentheses. Model (1) uses TFE model with Driscoll-Kraay standard errors, Model (2)-(8) use UQR model with robust clustered standard errors. *, ** and *** represent significance at 10%, 5% and 1%.

Table 5. Estimation results of the eastern region and the non-eastern region.

Variables		Q20	Q30	Q40	Q50	Q60	Q70	Q80
East	ICT	33.72***	28.05***	32.58***	40.74***	47.24***	61.25***	82.63***
		(7.636)	(6.851)	(7.436)	(7.308)	(8.068)	(9.879)	(13.72)
	ICT2	-49.41***	-43.91***	-48.70***	-56.37***	-53.82***	-62.39***	-75.03***
		(14.93)	(13.97)	(14.88)	(14.51)	(16.53)	(19.54)	(25.21)
	Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	N	1204	1204	1204	1204	1204	1204	1204
	Cities	86	86	86	86	86	86	86
Non-east	ICT	74.60***	72.73***	73.62***	64.02***	77.54***	53.89**	84.34**
		(16.59)	(15.76)	(14.41)	(15.95)	(16.69)	(22.24)	(34.95)
	ICT2	-367.3***	-349.8***	-329.7***	-265.9***	-279.7***	-97.04	-38.77
		(133.7)	(122.1)	(100.9)	(80.93)	(76.46)	(101.6)	(173.5)
	Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	N	2744	2744	2744	2744	2744	2744	2744
	Cities	196	196	196	196	196	196	196

Note: Robust clustered standard errors are in parentheses. *, ** and *** represent significance at 10%, 5% and 1%.

For eastern region, at all the quantiles, the estimate coefficients of ICT are significantly positive at the 1% level and the estimate coefficients of its squared term are significantly negative at the 1% level, which indicates an inverted U-shaped relationship. The results are in consistent with the above conclusions at the national level. For non-eastern region, at 20th quantile distribution to 60th quantile distribution, the estimate coefficients of ICT are significantly positive and the estimate coefficients of its squared term are significantly negative at the 1% level. At 70th quantile distribution to 80th quantile distribution, although the estimate coefficients of ICT are significantly positive at the 5% level, the coefficients of its squared term are negative and insignificant. The results show that there is an inverted U form between ICT development and CO_2 emissions below the medium-high quantiles. But ICT development has a positive impact on CO_2 emissions at high quantiles, which is in line with Chen et al. [20].

Generally speaking, ICT is a typical general-purpose technology [6]. Therefore, the impact of ICT on efficiency improvement and environmental sustainability may be lagging. Consequently, following Zhang et al. and Chen et al., we replace ICT and its squared term with ICT lagging by 1 year and its squared term in the model to reduce the endogeneity existing in the benchmark model [20, 45]. Due to the lack of ICT index data in 2003, the data applied in this part is from 2005 to 2017. Table 6 shows the estimation results considering the endogeneity. Clearly, there is an inverted U-shaped relationship between ICT

Table 6. Estimation results for lagging ICT and its squared term for 1 year.

Variables	Q20	Q30	Q40	Q50	Q60	Q70	Q80
L.ICT	15.22***	11.46***	7.284*	18.24***	13.23**	22.44***	43.89***
	(3.610)	(3.561)	(4.283)	(5.850)	(5.905)	(8.226)	(12.55)
L.ICT2	-28.24***	-25.27***	-22.59**	-36.06***	-27.67**	-44.94***	-77.23***
	(10.06)	(9.584)	(10.34)	(13.52)	(11.62)	(10.76)	(17.59)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3666	3666	3666	3666	3666	3666	3666

Note: Robust clustered standard errors are in parentheses. *, ** and *** represent significance at 10%, 5% and 1%.

Table 7. Estimation results after excluding outliers.

Variables	Q20	Q30	Q40	Q50	Q60	Q70	Q80
ICT	39.55***	40.86***	39.84***	44.64***	51.66***	53.29***	108.8***
	(7.117)	(7.095)	(7.535)	(9.133)	(9.836)	(13.40)	(19.31)
ICT2	-86.20**	-84.55***	-79.38***	-79.22***	-83.64***	-55.37*	-146.1***
	(33.25)	(29.48)	(26.28)	(29.80)	(28.91)	(32.55)	(45.25)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3822	3822	3822	3822	3822	3822	3822

Note: Robust clustered standard errors are in parentheses. *, ** and *** represent significance at 10%, 5% and 1%.

development and CO_2 emissions at all quantiles, which is consistent with the above conclusion.

Quantile regression model reduces the influence of outliers to a great extent, but the following abnormal situation still exists in the sample data. Some cities in China are experiencing rapid economic development. Due to the resource endowment, geographical advantages and policy factors of some cities, their ICT has been developing rapidly. The relationship between ICT development and CO_2 emission in such cities may be inconsistent with other cities. Therefore, referring to Zhang and Dai, this paper excludes four municipalities directly under the central government (Beijing, Shanghai, Tianjin, and Chongqing) and five municipalities with independent planning status (Dalian, Qingdao, Ningbo, Xiamen and Shenzhen) [46]. As shown in Table 7, there is an inverted U-shaped relationship between ICT development and CO_2 emissions at all quantiles, which is in accordance with the above conclusions. Additionally, the estimated value of ICT turning point after excluding outliers is lower than that of original sample, indicating that if the outliers are not considered, the turning point will be overestimated.

After three robustness tests, the empirical results are in line with the original estimation model. Consequently, the basic conclusion of this paper is robust.

Conclusions

Being inspired by the EKC framework, we construct a non-linear model to investigate the impact of ICT development on CO_2 emissions from a national perspective. Furthermore, we apply the panel data of 282 cities in mainland China during the period 2004 to 2017. The unconditional quantile regression model with fixed effect is employed to estimate the benchmark model, which can describe the overall characteristics of sample distribution. Our estimates are not only on a national scale but on two sub-samples of cities, including 86 developed cities and 196 underdeveloped cities, respectively. Sub-samples estimations are beneficial to explore the heterogeneity and test the robustness of the relationship between ICT development on CO_2 emissions. Finally, we consider the influence of endogenous problems and outliers, re-estimating the benchmark model to make robust tests.

The empirical results show that when a threshold level of ICT development has been achieved, the ICT development can exert a positive impact on the reduction of CO_2 emissions. Specifically, there is an inverted U form between ICT development and CO_2 emissions for the total sample as well as the developed cities. Whereas, for underdeveloped cities, the inverted U form only exists below the medium-high quantiles and does not exist at high quantiles.

The above conclusions not only contribute to the existing literature, but also provide China and other developing countries with some policy implications. First, although ICT may pollute the environment at low levels of development, the reasonable path to a sustainable environment may be achieved by greater development of ICT and a change in the structure of the economy, shifting from energy intensive industries to industries with low energy density. Second, when formulating and implementing ICT-related policies, developing countries should consider regional diversities and economic differences. More attention should be paid to underdeveloped regions. As for developed regions, relevant policies should be made to promote the sustainable development of green ICT and further reduce the unfavorable impacts of ICT on the environment. For future research, with the update and enrichment of the data, scholars can select a longer sample period to confirm the conclusions.

Acknowledgments

The authors would like to express their gratitude to all peer reviewers for their reviews and comments.

Conflicts of Interest

The authors have no relevant financial or non-financial interests to disclose.

References

1. O'MAHONY M., VECCHI M. Quantifying the Impact of ICT Capital on Output Growth: A Heterogeneous Dynamic Panel Approach. Economica, **72**, 615, **2005**.
2. DIMELIS S.P., PAPAIOANNOU S.K. ICT growth effects at the industry level: A comparison between the US and the EU. Information Economics and Policy, **23** (1), 37, **2011**.
3. HWANG W.S., SHIN J. ICT–specific technological change and economic growth in Korea. Telecommunications Policy, **41**, 282, **2017**.
4. NIEBEL T. ICT and economic growth – Comparing developing, emerging and developed countries. World Development, **104**, 197, **2018**.
5. CARDONA M., KRETSCHMER T., STROBEL T. ICT and productivity: conclusions from the empirical literature. Information Economics and Policy, **25** (3), 109, **2013**.
6. LIAO H., WANG B., LI B., WEYMAN-JONES T. ICT as a general-purpose technology: The productivity of ICT in the United States revisited. Information Economics and Policy, **36**, 10, **2016**.
7. ZHANG J., LIANG X.J. Promoting green ICT in China: A framework based on innovation system approaches. Telecommunications Policy, **36** (10-11), 997, **2012**.
8. ERDMANN L., HILTY L. Scenario Analysis: Exploring the Macroeconomic Impacts of Information and Communication Technologies on Greenhouse Gas Emissions. Journal of Industrial Ecology, **14** (5), 826, **2010**.
9. MALMODIN J., MOBERG A., LUNDÉN D., FINNVEDEN G., LÖVEHAGEN N. Greenhouse Gas Emissions and Operational Electricity Use in the ICT and Entertainment and Media Sectors. Journal of Industrial Ecology, **14** (5), 770, **2010**.
10. WILLIAMS E. Environmental effects of information and communications technologies. Nature, **479** (7373), 354, **2011**.
11. RIVERA M.B., HKANSSON C., SVENFELT S., FINNVEDEN G. Including second order effects in environmental assessments of ICT. Environmental Modelling and Software, **56**, 105, **2014**.
12. RØPKEA I., CHRISTENSEN H.T. Energy impacts of ICT – Insights from an everyday life perspective. Telematics and Informatics, **29** (4), 348, **2012**.
13. HAMDI H., SBIA R., SHAHBAZ M. The nexus between electricity consumption and economic growth in Bahrain. Economic Modelling, **38**, 227, **2014**.
14. SALAHUDDIN M., ALAM K. Information and communication technology, electricity consumption and economic growth in OECD countries, a panel data analysis. International Journal of Electrical Power and Energy Systems, **76**, 185, **2016**.
15. ZHOU X., ZHOU D., WANG Q. How does information and communication technology affect China's energy intensity? A three-tier structural decomposition analysis. Energy, **151**, 748, **2018**.
16. BASTIDA L., COHEN J.J., KOLLMANN A., MOYA A., REICHL J. Exploring the role of ICT on household behavioral energy efficiency to mitigate global warming. Renewable and Sustainable Energy Reviews, **103**, 455, **2019**.
17. LAHOUEL B.B., TALEB L., ZAIED B.Y., MANAGI S. Does ICT change the relationship between total factor productivity and CO_2 emissions? Evidence based on a nonlinear model. Energy Economics, **101**, 1, **2021**.
18. AN Q., WU Q., LI J., XIONG B., CHEN X. Environmental efficiency evaluation for Xiangjiang River basin cities based on an improved SBM model and Global Malmquist index. Energy Economics, **81**, 95, **2019**.
19. ZHANG C., LIU C. The impact of ICT industry on CO_2 emissions, A regional analysis in China. Renewable and Sustainable Energy Reviews, **44**, 12, **2015**.
20. CHEN X., GONG X., LI D., ZHANG J. Can information and communication technology reduce CO_2 emission? A quantile regression analysis. Environmental Science and Pollution Research, **26** (32), 32977, **2019**.
21. FIRPO S., FORTIN M. N., LEMIEUX T. Unconditional quantile regressions. Econometrica, **77**, 953, **2009**.
22. HIGÓN A.D., GHOLAMI R., SHIRAZI F. ICT and Environmental Sustainability: A Global perspective. Telematics and Informatics, **34** (4), 85, **2017**.
23. DINDA S. Environmental Kuznets Curve Hypothesis: A Survey. Ecological Economics, **49** (4), 431, **2004**.
24. STERN D.I. The Rise and Fall of the Environmental Kuznets Curve. World Development, **32** (8), 1419, **2004**.
25. GHOSH S., YAMARIK S. Do Regional Trading Arrangements Harm the Environment? An Analysis of 162 Countries in 1990. Applied Econometrics and International Development, **6** (2), 15, **2006**.
26. MALMODIN J., BERGMARK P., LUNDÉN D. The future carbon footprint of the ICT and E&M sectors. ICT4S 2013, **2013**.
27. BELKHIR L., ELMELIGI A. Assessing ICT global emissions footprint, Trends to 2040 & recommendations. Journal of Cleaner Production, **177**, 448, **2018**.
28. LEE J. W., BRAHMASRENE T. ICT, CO_2 Emissions and Economic Growth, Evidence from a Panel of ASEAN. Global Economic Review, **43**, 93, **2014**.
29. ALDAKHIL A.M., ZAHEER A., YOUNAS S., NASSANI A.A., ABRO M.M.Q., ZAMAN K. Efficiently managing green information and communication technologies, high-technology exports, and research and development expenditures, A case study. Journal of Cleaner Production, **240**, 1181641, **2019**.
30. HASEEB A., XIA E., SAUD S., AHMAD A., KHURSHID H. Does information and communication technologies improve environmental quality in the era of globalization? An empirical analysis. Environmental Science and Pollution Research, **26**, 8594, **2019**.
31. N'DRI L.M., ISLAM M., KAKINAKA M. ICT and environmental sustainability, Any differences in developing countries? Journal of Cleaner Production, **297** (2), 126642, **2021**.
32. GROSSMAN G.M., KRUEGER A.B. Economic Growth and the Environment. Quarterly Journal of Economics, **110**, 353, **1995**.
33. BARIŞ-TÜZEMEN Ö., TÜZEMEN S., ÇELIK K. Does an N-shaped association exist between pollution and ICT in Turkey? ARDL and quantile regression approaches. Environmental Science and Pollution Research, **27**, 20786, **2020**.
34. FAISAL F., AZIZULLAH, TURSOY T., PERVAIZ R. Does ICT lessen CO_2 emissions for fast-emerging economies? An application of the heterogeneous panel estimations. Environmental Science and Pollution Research, **27**, 10778, **2020**.
35. DRISCOLL J.C., KRAAY A.C. Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. The Review of Economics and Statistics, **80** (4), 549, **1998**.

36. ALI M.S.B., GASMI A. Does ICT diffusion matter for corruption? An economic development perspective. Telematics and Informatics, **34**, 1445, **2017**.
37. ASONGU A. ICT, Openness and CO_2 emissions in Africa. Environmental Science and Pollution Research, **25** (10), 9351, **2018**.
38. TCHAMYOU V.S., ERREYGERS G., CASSIMON D. Inequality, ICT and financial access in Africa. Technological Forecasting and Social Change, **139**, 169, **2019**.
39. SHANNON C.E. A mathematical theory of communication. Bell System Technical Journal, **27** (3), 3, **1948**.
40. KLICK J. Autocrats and the Environment or it's Easy Being Green. Social Science Electronic Publishing, **2002**.
41. WANG F., CHAI W., LIU J., REN J., SHAN J., LIU Z. City Size, Urban-Rural Income Gap and Environmental Pollution, Empirical Evidence from 283 Cities in Chin. Polish Journal of Environmental Studies, **30** (4), 3297, **2021**.
42. LI Z., LI N., WEN H. Digital Economy and Environmental Quality, Evidence from 217 Cities in China. Sustainability, **13**, 8058, **2021**.
43. KILLEWALD A., BEARAK J. Is the motherhood penalty larger for low-wage women? A comment on quantile regression. American Sociological Review, **79**, 350, **2014**.
44. BORGEN N.T. Fixed effects in unconditional quantile regression. Stata Journal, **16** (2), 403, **2016**.
45. ZHANG L., RONG P., QIN Y., JI Y. Does Industrial Agglomeration Mitigate Fossil CO_2 Emissions? An Empirical Study with Spatial Panel Regression Model. Energy Procedia, **152**, 731, **2018**.
46. ZHANG S., DAI Y. Heterogeneity, Fiscal Decentralization and Urban Economic Growth. Journal of Financial Research, **1**, 103, **2012**.