Article

Heterogeneous Effects of ICT across Multiple Economic Development in Chinese Cities: A Spatial Quantile Regression Model

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Abstract: Most previous articles estimate the effects of information communication technologies (ICTs) on economic growth average using national data without consideration of heterogeneity of ICT effects on cities across multiple economic development. The heterogeneity of ICT effects is confirmed to promote both the sustainability and equitableness of the whole cities. In order to investigate the heterogeneous effects of ICT between developed and less developed cities, a quantile spatial autoregressive (QSAR) model is applied to estimate coefficients at different quantiles while accounting for the spatial dependence of urban economy. We find significantly positive effects of ICT in local and neighboring cities after controlling the spatial dependence of urban economy. We have further found larger coefficients of ICT-related variables in cities with lower gross domestic product (GDP) per capital suggesting that digital dividend from ICT prefer the less developed cities over developed cities. Our conclusions indicate there would be “double dividend” from ICT, namely an improvement of both overall economic growth and balanced economic development among cities.

Keywords: information communication technologies; heterogeneity; economic growth; spatial dependence; quantile regression

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1. Introduction

A widely accepted argument is that information communication technologies (ICTs) raise economic growth [1] by fostering productivity growth and, consequently, changing how business and international trade is done in manifold ways [2]. The charm of ICT gave rise to the adoption of corresponding ICT policies in developed and developing nations. Global connectivity is at an all-time high, and more users than ever before are participating in Internet [3]. In China, the State Council formally declared the “Internet Plus” action plan in 2015, which is to make use of ICT, including the Internet of Things, big data, and cloud computing, to support China’s economic growth. The number of Internet users in China had reached 854 million, with an Internet penetration rate of 61.2 percent by 2019 according to the report of China Internet Network Information Center (CNNIC). During the Coronavirus Disease 2019 (COVID-19) pandemic, ICT supported online life model to meet “non-contact” epidemic prevention requirements and might be a key to restore economic growth after epidemic in China.

However, not all regions and cities shared the same digital dividend from ICT in the world. In the case of China, investment of ICT in small cities lagged behind metropolis at the beginning of ICT springing up characterized by a decline of ICT development index values from the east to the west as well as from core cities to more peripheral ones [4]. The digital divide would shift to differences in usage [5], while China’s infrastructure miracle filled the “access gap” among cities. The diverse economic conditions and great digital divide in usage in Chinese cities imply that the national-level analysis of ICT effect on economic growth would generate misleading results as it might hide the heterogeneous impacts of ICT on economic performance. Knowledge and information are posited the panacea to

drive sustainable and equitable growth [6], but heterogeneous impacts of ICT might hide a risk or an opportunity of sustainability and equitableness for the whole cities. In the worst case, according to selection effects proposed by Ottaviano [7], we can guess that ICT would only have effect on developed cities and increase the concentration of human capital with high digital literacies in just a few urban areas, while the other cities would lose or obtain a less sustainable developing driver of ICT. In the meantime, ICTs enable to overcome the barrier of geographical distance and improve the distribution of knowledge [8]. In the best case, whole cities obtain sustainable power of economic growth from knowledge sharing driven by ICT, and undeveloped cities would reap more knowledge spillover from ICT as a result of the catch-up role. To the urban development path of sustainability and equitableness, or to the other path, depending on the empirical study on heterogeneous economic effects of ICT across different cities.

The ICT-related story can go back to the Solow Paradox saying, “You can see the computer anywhere but in the productivity statistics”. Many empirical articles studied quantify the impact of ICT on economic growth at the national level [2,9] and evaluate the general purpose technology (GPT) hypothesis, which implies that ICT has an influence on economic development beyond the effect of normal capital investment [10,11].

As the world’s most productive economy and the largest market for ICT goods and services, USA is an important object of studying the ICT–economy relationship. Colecchia and Schreyer [12] compared the impact of ICT capital accumulation on output growth between USA and some developed nations and ICT contributed between 0.3 and 0.9 percentage point per year to economic growth during the second half of 1990s. Varnavskii [13] noted that the large-scale investments into the ICT provided a great portion of U.S. economic growth and productivity since mid-1990, but then, the contribution of ICT reduced from its maximum value in 1995–2004. Sarmir [14] concluded the “new economy” driven by ICT is more a myth than a reality. A study on OECD (Organization for Economic Co-operation and Development) authored by Maggi [15] considered ICT capital as a driver of economic growth. Ceccobelli et al. [16] conducted a non-parametric analysis on 14 OECD countries and the results indicated that ICT capital would cause a technological regress due to the absence of complementary investments and temporal lags to achieve a productivity benefit. Most European countries experienced a significant impact of this component, while the USA suffered the least from the impact. Edquist and Henrekson [17] estimated output elasticity based on data for 47 different industries in Swedish and found that ICT is associated with greater value added. Based on the fixed effects model, the study found heterogeneous interaction effects between hours worked by high-skill versus low-skill employees and ICT. Ishida [18] performed an autoregressive distributed lag (ARDL) bounds testing approach to estimate the long-run relationship between ICT, energy consumption, and economic growth in Japan during a period from 1980 to 2010. The results indicated that ICT investments contribute directly to energy consumption reductions, not to GDP growth. Fukao et al. [19] investigated why ICT investment in Japan stagnated and concluded that smaller and older firms, which play a much greater role in Japan, tend to have a lower ICT intensity than other firms. Moshiri [20] focused on the heterogeneous impacts of ICT on productivity across provinces and industries over time in Canada. This research performed a panel data model based on the Cobb–Douglas production function and found the effect of ICT on productivity is weak in some provinces owing to the dominance of agricultural and natural resource sectors in their economic structures.

Compared with developed countries, developing countries reaped less from ICT as the return to ICT is smaller [21]. Haftu [22] empirically analyzed the impact of mobile phone and the Internet on per capita income of Sub-Saharan Africa (SSA) of 40 countries. The study using the robust two-step system GMM (Generalized Method of Moments) reported that a 10% increase in mobile phone penetration results in a 1.2% change in GDP per capita, while the Internet has not contributed to the per capita GDP. David and Grobler [23] used a single index for ranking ICT development in 46 African countries and confirmed that ICT penetration has more impact on economic growth in South Africa,

which has the highest average real GDP than other countries. Kumar et al. [24] used ARDL bounds approach to cointegration and granger non-causality tests to examine short-run and long-run contribution of ICT on economic growth of China over the sample period 1980–2013. They explored that ICTs are co-integrated with economic growth, duly supporting the presence of a long-run association, and a 1% change in ICT will result in changes in output per worker between 0.01 and 0.08 percent.

Research on the effect of ICT on economic growth in developed and developing countries is already extensive, and most empirical results indicate a larger digital dividend in developed countries than in developing countries. However, the heterogeneity of the ICT effect across cities has been only minimally explored. A large number of articles have investigated differences in ICT adoption globally owing to complementary factors, such as education, culture, and policy. Nevertheless, it is not easy to control for those factors in ICT adoption studies at the national level. The case of cities can help us better understand the ICT–economy relationship because all cities share the same education system, culture, and national strategy. Therefore, any heterogeneity of the ICT effect on economy across cities can be attributed to differences of urban economy.

Gaspar and Glaeser [25] raised the question two decades ago of whether will ICTs make the cities obsolete. We see both fast development of ICT and growth of metropolis, which seemingly has answered the question, but the answer becomes uncertain if we focus on ICT and less developed cities. The hypothesis of this research considers that contributions of ICT to urban economy vary significantly across urban economic development. Two inverse results may happen under heterogeneity of the ICT effect: (1) ICT contributes more to less developed cities than developed cities versus (2) ICT contributes more to developed cities than less developed cities. We hope the former would happen, which means not only will ICT promote economic development for the whole cities, but also it would be an antidote to the great economic gap between rich and poor cities. The aim of this research is to estimate the effect of ICT on urban economy, and to explore the heterogeneous effect across Chinese cities. Specifically, the article addresses the following questions: (1) Have local ICTs contributed to urban economic growth? (2) Is there an intercity spillover or siphonic effect of ICT in Chinese cities? (3) How has the ICT effect varied across urban economic development levels? The answers to these questions help to deeply understand the relationship between ICT and economic development at the city level. Though a large number of articles find evidence on ICT promoting economic development in developed and developing nations, we still cannot clearly investigate the possible “dark side” of ICT as new energy of economic development, namely would ICT be more beneficial to the rich or the poor.

Some possible contribution of this paper is as follows. Firstly, using city data from China as a case is particularly interesting, because China has expanded Internet access quickly. The number of Internet users reached 854 million in 2019, with an Internet penetration rate of 61.2% according to CNNIC, and China’s first regional 5G network has been completed and put into trial use in Shanghai, indicating the beginning of the 5G age in China. At the same time, China faces great digital divide and diversified economic development across its cities. Most developed cities are concentrated in the East of China and the Internet penetration rate in these cities is much higher than in less developed cities. Additionally, some empirical issues are considered in the paper to answer the questions above. We consider the spatial dependence of the urban economy, which is usually necessary in a large number of relevant studies for a high degree of accuracy. The paper further investigates the value of ICT in local and neighboring cities at different quantiles rather than the average effect. Therefore, we study the heterogeneity of ICT effects on urban economy across multiple economic development levels in cities, which is seldom studied. As far as the authors know, only few articles consider both spatial dependence and the heterogeneous effects of ICT in one empirical study [2,9,26].

This paper is structured as follows. Section 2 defines the analytical framework and traces some empirical models including spatial autoregressive (SAR) model and quantile

spatial autoregressive (QSAR) model. Variables description and summary statistics are provided in Section 3. Section 3 also describes the economic development distribution of China to account for the necessity to induce the quantile estimation method. Econometric issues and results are presented in Section 4. The final section concludes the study.

2. Methodology

This study estimates the economic effects of ICT on developed cities and metropolis, compared with those on less developed cities. For this purpose, we introduce a conventional Solow framework in which the total production of a city i (Y_i) is dependent on the aggregate stock of technology A_i , capital stock K_i , and labor stock L_i of a city i . The initial equation is defined as follows:

$$Y_i = A_i K_i^{\beta_K} L_i^{\beta_L} \quad (1)$$

where β_K and β_L are the capital and labor shares and $\beta_K + \beta_L = 1$. Using (1) with the Hicks-neutral technical progress, the output per capital (y_i) is defined as

$$y_i = A_i k_i^{\beta_K} \quad (2)$$

where k_i is the capital per worker. As ICT can drive total factor productivity (TFP) from externalities related to the use of ICT [27,28], A_i in Equation (2) can be augmented with ICT as a shift variable, which is proxied by the Internet penetration rate of a city i (% of Internet users of total population). Hence,

$$A_i = A_0 ICT_i^{\beta_{ICT}} \quad (3)$$

where A_0 refers to the stock of knowledge enjoyed by the whole cities including other catch-all factors related to TFP and β_{ICT} refers to the externality of ICT. Consequently,

$$y_i = A_0 ICT_i^{\beta_{ICT}} k_i^{\beta_K} \quad (4)$$

Taking the log of Equation (4), we obtain the basic multiple log-linear regression model. Under the basic model, the output per capital of a city i (y_i) is regressed on ICT and the capital per capital in city i using Equation (5).

$$\ln y_i = \beta_0 + \beta_1 \ln ICT_i + \beta_2 \ln k_i + \mu_i \quad (5)$$

Equation (5) can be estimated using ordinary least square (OLS) with assumption of homoscedasticity that $V(\mu_i) = \sigma^2$ for all i .

However, there are some possible drawbacks to using OLS. Initially, ignorance of the spatial dependence results in biased coefficient estimates, especially, the spatial nature of data increases the likelihood of spatial lag dependence. For example, in this study, the output per capital in city i might be influenced by the output per capital in its neighboring cities owing to the spatial interaction. The presence of spatial lag dependence violates the assumptions of uncorrelated errors as well as the independence of observations, so it could induce biased and inefficient estimates. Therefore, it is necessary to test for spatial independence using the global Moran's I statistic, which is defined as follows:

$$I = \frac{n \sum_i \sum_{j \neq i} w_{ij} (\ln y_i - \overline{\ln y}) (\ln y_j - \overline{\ln y})}{(\sum_i \sum_{j \neq i} w_{ij}) \sum_i (\ln y_i - \overline{\ln y})^2} \quad (6)$$

where w_{ij} is the element of standard spatial matrix W ; W is an $n \times n$ spatial matrix for n observation; and $\overline{\ln y}$ is the mean of explained variable. As ICT overcomes the limitation of geographical distance on the spatial interaction to a great extent, we use the differences

in the economies of neighboring cities to reflect their “economic distance”, which can be calculated by

$$w_{ij} = \frac{z_{ij}}{\sum_{j=1}^n z_{ij}}$$

and

$$z_{ij} = \begin{cases} 0, & i = j \\ 1/|G_i - G_j|, & i \neq j \end{cases}$$

where G_i refers to aggregate economic output of city i represented by GDP. The magnitude of weight decays with economic distance more than with geographic distance owing to ICT; thus, the cities with a similar economic scale are assigned higher weights than those with economic gaps. Hence, the element w_{ij} of W describes the strength of spatial economic inaction between cities i and j .

Additionally, for our case, ICTs have a spillover or siphonic effect on neighboring cities. The spatial autocorrelation and network effect of ICT is likely to be complex and significant [29]. On the one hand, ICT may construct a channel of knowledge spillover to promote adjacent regions to quickly absorb and adopt the new technology for economic development [26]. On the other hand, developed cities would attract more intelligent manufacturing enterprises and ICT providers with excellent Internet infrastructure, while less developed cities may lose some Internet business attracted by neighboring developed cities. In rare cases, Noh and Yoo [30] and Billon et al. [31] report that ICTs have a negative effect on economic growth in countries with high economic inequality or high educational inequality. The logical divergence is called “the paradoxical geographies of the digital economy”. Thus, we need to estimate the spatial lag of ICT and spatial lag of the dependent variable in our spatial model. In our case, a spatial autoregression (SAR) model can be used in Equation (7):

$$\ln y_i = \beta_0 + \rho \ln y_i^* + \theta \ln ICT_i^* + \beta_1 \ln ICT_i + \beta_2 \ln k_i + \mu_i \quad (7)$$

where $\ln y_i^* = \sum_{j=1}^n w_{ij} \ln y_j$ is a spatially lagged dependent variable for the spatial weight matrix W ; $\ln ICT_i^* = \sum_{j=1}^n w_{ij} \ln ICT_j$ is a spatially lagged independent variable; and ρ and θ are spatially lagged parameters.

Furthermore, SAR suffers from the same limitations as OLS. Both SAR and OLS only measure the average relationship between $\ln y$ and $\ln X$ based on the conditional mean function $E(\ln y | \ln X)$, but the result does not describe the relationship at different points in the distribution of $\ln y$. Because the quantile regression approach can effectively describe a complete picture of the heterogeneous effects of the driving forces, the paper uses it to investigate how ICTs contribute to urban economy. For instance, if coefficients of ICT-related variables under different quantiles vary greatly, it means that the influence of ICT on urban economy is significantly diverse under different quantiles. The τ th quantile of $\ln y$ is represented by $\ln y(\tau)$, which means the probability that $\ln y$ is less than or equal to $\ln y(\tau)$ is τ , and the larger the τ , the larger the $\ln y(\tau)$.

Following the quantile spatial autoregressive (QSAR) model proposed by Kostov [32] and Mathur [33], we embed the quantile regression theory into the spatial model and the quantile spatial Durbin (QSAR) model can be written as follows:

$$\ln y_i = \beta_{0,\tau} + \rho_\tau \ln y_i^* + \theta_\tau \ln ICT_i^* + \beta_{1,\tau} \ln ICT_i + \beta_{2,\tau} \ln k_i + \mu_{i,\tau} \quad (8)$$

where $\beta_{0,\tau}$, ρ_τ , θ_τ , $\beta_{1,\tau}$, and $\beta_{2,\tau}$ are a group of coefficients estimated from a quantile regression at τ th quantile, $\tau \in (0, 1)$.

In spite of the advantages, standard quantile regression approach cannot address the spatial lag dependence because of the clear endogeneity issue of $\ln y_i^*$. As spatial lag terms of explanatory variables and other explanatory variables are exogenous, standard quantile regression can address them. Therefore, we implement two-stage quantile regression (2SQR) proposed by Kim and Muller [34], which has been broadly applied in spatial

study [35,36]. In the first stage of 2SQR, we use explanatory variables and their spatial lag terms to perform quantile regression on $\ln y_i^*$. The predicted value $\ln \hat{y}_i^*$ of $\ln y_i^*$ at each quantile is calculated with the first stage. In the second stage of 2SQR, $\ln y_i^*$ is replaced by $\ln \hat{y}_i^*$ at the same quantile. The initial QSAR model of interpreted variable $\ln y_i$ performed by $\ln \hat{y}_i^*$ and exogenous variables.

3. Data

The Chinese data of 275 cities in year 2017 are obtained from China City Statistical Yearbook of 2018. The yearbook is published by National Bureau of Statistics of China and supported by departments at the provincial and county level. The dependent variable $\ln y_i$ is the log of constant regional GDP per capital, referring to the final products at market prices produced by all resident units in a city divided by the number of resident units. The capital per worker variable $\ln k_i$ is the log of fixed asset stock per worker referring to the total fixed assets, which is the ending balance after deducting the depreciation and impairment divided by the average number of employed staff and workers.

The key explanatory variable $\ln ICT_i$ is the log of all subscribers at year-end who have gone through registration procedures in the operation points of enterprises engaged in telecommunications and are hence connected to Chinese Internet. The spatial lagged term $\ln ICT_i^*$ is to examine the spatial effect of ICT—whether the local ICTs promote the economy of neighboring cities. If the estimated parameter of $\ln ICT_i^*$ is greater than 0, there is a positive spillover effect of ICT; otherwise, there is a negative siphonic effect of ICT. The spatial lagged term of dependent variable $\ln y_i^*$ is similar with $\ln ICT_i^*$. The variable definitions seen in Tables 1 and 2 show the summary statistics on the major variables used in the research.

Table 1. Variable definitions. GDP, gross domestic product; ICT, information communication technology.

Variable	Definition
$\ln y$	log of constant regional GDP per capital one year, in yuan
$\ln ICT$	log of subscribers of Internet service, in ten thousand persons
$\ln k$	log of fixed asset stock per worker, in yuan
$W\ln y$	spatial spillover of other cities' economy on the local, in yuan
$W\ln ICT$	spatial spillover of other cities' Internet service on the local

Table 2. Summary statistics of variables.

Variable	Mean	SD	Min	Max
$\ln y$	10.97	0.29	10.21	12.27
$\ln ICT$	4.46	0.80	2.64	6.52
$\ln k$	11.47	0.79	8.72	13.83

Further insights into economy distribution of Chinese cities can be obtained based on the rank–frequency distribution model. There are a large number of applications of the rank–frequency distribution model as a method to investigate the distribution and overall gap of economy between cities. Eaton and Eckstein [37] use the model to describe relative populations of the top 40 urban areas of Japan from 1876 to 1990 and 39 urban areas of France, and urbanization consequently appears to have taken the form of the parallel growth of cities consistent with Zipf's Law. According to Zipf's Law, the indicator frequency changes following its sort order change in different units [38]. Similarly, Sharma [39] describes the scale distribution of cities in India and Black and Henderson [40] estimate urban scale distribution in the USA from 1900 to 1990, and their results are also consistent with Zipf's Law. Following the previous studies, when we change the linear x – y coordinate system into a $\log(x)$ – $\log(y)$ coordinate system, the curve of point range in the x – y coordinate system usually becomes the beeline, namely $\log(y) = c - \alpha \log(x)$

where $\alpha > 0$. For instance, we map out the rank–frequency distribution of GDP per capital of cities in China in the double logarithmic coordinate system. Figure 1 shows the frequency distribution of urban economy in China in 2017, where the horizontal coordinate denotes the rank of $\log(x)$ and the vertical coordinate the logarithm of the frequency value. As shown in Figure 1, the head of the point range is sparse and smooth, while there is a sharp drop in the tail of the point range, proving great distribution diversity of economic development in Chinese cities. Such a great diversity shows that Chinese cities might be differentiated as far as economic development is concerned. Liu and Sun [41] compare the spatial distribution of innovation activities, which is highly correlated with economic development in China and the United States, and the spatial distribution of patent distribution at the province level in China is similar to Figure 1. Consequently, using only the classical statistical methods that mainly focus on mean values (like SAR model) might lead to false results. Therefore, it is necessary for this research to extend the SAR model using the QSAR model.

Figure 1. The rank–frequency distribution of economic development of Chinese cities in 2017.

4. Results and Discussion

4.1. Econometric Issues

A number of statistical tests have to be performed before estimating the results of SAR and QSAR for the reliability and accuracy. Initially, the test for spatial independence is necessary to check the assumption that the spatial distribution pattern of economy is clustered, but not random. A spatial autocorrelation tool, Global Moran's I , defined as Equation (6), is used to study the global spatial association based on both the location factor w_{ij} and economy factor y_i . Table 3 reports the Global Moran's I statistic for 275 cities in China in 2017. As the Global Moran's I statistic is nearer to the positive one and the p -value for Global Moran's I statistic is less than 1% in Table 3, there is a strong positive global spatial association of economy among cities. The spatial distribution of urban economy reveals obvious characteristics of spatial dependence, so we reject the null hypothesis of spatial autocorrelation, which confirms the significance of spatial interaction effects related to economic proximity of cities. Consequently, it is necessary to apply the spatial econometric method.

Table 3. Spatial regression model estimations ($n = 275$). SAR, spatial autoregressive; SEM, spatial error autocorrelative; LM, Lagrange multiplier.

Variable	SAR		SEM	
	Coeff	Prob	Coeff	Prob
Wlny	0.305	0.004		
W μ			0.286	0.000
WlnICT	0.479	0.000	0.638	0.000
lnICT	0.081	0.091	0.098	0.034
lnk	0.191	0.000	0.180	0.000
Constant	3.062	0.001	5.780	0.000
Moran's I	0.299	0.000		
LM	7.207	0.001	4.042	0.044
Robust LM	3.802	0.051	0.638	0.425

Additionally, two possible forms of spatial dependence between cities should be considered: spatial lag dependence, which we use in this research, and spatial error autocorrelation. Different from spatial lag dependence, the spatial error autocorrelative (SEM) model assumes there is an autoregressive process in the residuals, namely $\mu = \lambda W\mu + \varepsilon$, where μ is the vector of regression residuals, λ is the estimated autocorrelation parameter, and ε is a white-noise disturbance term. Two Lagrange multiplier tests, namely the Lagrange multiplier (LM) and robust Lagrange multiplier (robust LM), are used to examine whether the form of spatial dependence is spatial lag dependence or spatial error autocorrelation. The methodological details of the two tests can be seen in the article by Anselin et al. [42]. In the present paper, the tests for the form of spatial dependence are performed using the same spatial weights matrix W , which is based on the economic distance between cities. The spatial diagnostic results of spatial regression models show that (1) the LM of spatial lag dependence has a larger value and passes the significance test of 1% level; (2) the robust LM of spatial lag dependence passes the significance test (the p -value equals 0.051), while the robust LM of spatial error autocorrelation does not pass the significance test (the p -value equals 0.425). These indicate that the SAR model is more suitable for the analysis of urban economic development influencing factors than the SEM model in this research. Therefore, we focus on the homogeneous and heterogeneous effects of ICT and other influencing factors on urban economy based on the SAR model.

4.2. Homogeneity Analysis of ICT on Urban Economy

Because of the examination of spatial dependence form above, we mainly analyze the influencing factors of homogeneity effects on the dependent variable based on the SAR model. In fact, the results of both the SAR and SEM models show that the regression coefficients of explanatory variables are positive and pass the significance test at the 10% level (Table 3). This suggests that our estimation results can corroborate the conclusions of most relevant studies.

SAR results show that the regression coefficient of the spatial lag term is 0.305 and passes the significance test at the 1% level (Table 3), suggesting the economic interaction of cities plays an important role in urban economic development. Some cities may generate a high–high or low–low concentration cluster, namely the richest cities relying on nature conditions and agglomeration advantages may only facilitate economic development of similar cities in the economy through spatial spillover. Such results are consistent with those of relevant studies [43].

We have more interest in the effects of ICT on economic development. The SAR results show the regression coefficients of ICT-related variables are significantly positive. The regression coefficient of local ICT is 0.081, suggesting that each additional unit of local ICT will increase local city's GDP per capital by a 0.081 units. Meanwhile, the regression coefficient of spatial lag of ICT is 0.479, suggesting that each additional unit of ICT in cities in close economic proximity to a local city will increase the local city's GDP per capital by

0.479 units. Such results indicate that local ICT and spillovers from global ICT have certain contributions to urban economic development, which is consistent with the empirical research using Japanese data [44]. Compared with the capital investment effect, the local ICT effect is smaller, while global ICT has a much larger effect. This may be attributable to the critical mass of ICT infrastructure [45]. When the number of ICT users is beyond the critical mass, a significant ICT effect can be found. Anyhow, local ICT contribute to urban economic growth, while the spatial spillovers of ICT are even larger.

However, the SAR model analyzes influencing factors of homogeneity effects on urban economic development, which may be not accurate. As mentioned in the introduction of this article, the effects of ICT on economic development would be varied in different regions and different periods. In order to detect heterogeneity effects of influencing factors, we apply the QSAR model to further investigate the differences in the effects of urban differences of ICT-related factors on urban economic development.

4.3. Heterogeneity Analysis of ICT on Urban Economy

To simplify the interpretation of the QSAR estimation results, we mainly observe 0.1, 0.2, ... to 0.9 quantiles, which represent cities with different economic development levels. Table 4 clearly shows the QSAR estimated coefficients of ICT-related variables at different quantiles. To observe the trend of ICT-related variables' coefficients at different quantiles more clearly, we generate the trend curves of ICT-related variables (Figure 2). The QSAR model estimation results in Figure 2 indicate that the ICT-related factors effects on urban economic development vary across the economy spectrum of whole cities. The full curve shows the regression coefficients of ICT-related factors by 2SQR.

Table 4. Quantile spatial autoregression model estimations ($n = 275$).

Variable	lnICT		WlnICT	
	coeff	prob	coeff	prob
0.1 quantile	0.643	0.000	0.583	0.006
0.2 quantile	0.621	0.000	0.562	0.002
0.3 quantile	0.609	0.000	0.550	0.002
0.4 quantile	0.598	0.000	0.540	0.002
0.5 quantile	0.588	0.001	0.529	0.004
0.6 quantile	0.576	0.003	0.518	0.008
0.7 quantile	0.559	0.016	0.501	0.027
0.8 quantile	0.544	0.030	0.488	0.058
0.9 quantile	0.527	0.066	0.471	0.116

Figure 2. Regression coefficients of ICT-related factors based on the quantile SAR (QSAR) model. (a) lnICT (local ICT effect) (b) WlnICT (spatial spillovers of ICT).

Firstly, it can be seen clearly that coefficients of both the local ICT and ICT spatial lag terms at most quantiles are positive and pass the significance test at the 10% level,

except the ICT spatial lag term coefficient at 0.9 quantile (the p -value is larger than 10%). The results further confirm the conclusion above, that ICTs of local and neighboring cities contribute to economic development.

Secondly, the local ICT effects on less developed cities are larger than those on developed cities. Table 4 shows that the coefficient of local ICT at 0.1 quantile is 0.643, while the coefficient at 0.9 quantile is 0.527, which is obviously smaller than the former. Figure 2a also shows that the coefficients of local ICT have a downward trend with the increase of the quantiles. The results suggest that local ICTs contribute to economic development, while it is relatively more important for less developed cities. This may be not in line with the observation on nations of relevant studies. The developed nations with a higher income usually tend to enjoy a higher ICT development status and more digital dividends than developing nations [46]. The results are also not in line with the study by Haini [47], who found that the effect of Internet penetration on economic growth is stronger for developed countries. The difference might be attributed to geographical range. Lin et al. [26] argue that Internet dispersion is positively associated with economic growth and the spillover effect varies significantly in Eastern, Central, and Western regions in China, which is in line with the QSAR results, but Internet dispersion is more pronounced in developed regions, which is not in line with our results. The main reasons are as follows. Firstly, differences of cities in one nation are mainly reflected in the economy and the divergences of education, culture, and government, which have great influences on the ICT economic effect, are much smaller than those between nations. Though the previous studies separate different regions, they use mean regression, ignoring heterogeneity of cities in region, which can be considered by QSAR. Therefore, the divergence of the ICT effect between cities can be much smaller than that between nations and regions. Secondly, Chinese big-scale ICT infrastructure construction, especially in developed cities, induces that the Internet penetration rate in metropolis is close to saturation level, while the less developed cities have great ICT development potential. Consequently, the overall performance is that the local ICT economic effects in less developed cities are more significant than those in developed cities. It is not only beneficial to reduce the economic gap between cities, but it is also more beneficial to overall economic development to strengthen the ICT in less developed cities.

Thirdly, the spatial spillover effects of ICT can be obtained by less developed cities more than developed cities. Specifically, Table 4 and Figure 2b show that the coefficients of ICT spatial lag term monotonically decrease from 0.583 at 0.1 quantile to 0.471 at 0.9 quantile, which suggests that spatial positive spillovers of ICT on economic development in less developed cities are larger than those in developed cities. Compared with the richest cities, such as Nanchong, Dongying, Shenzhen, Daqing, Zhuhai, Baotou, Yantai, Zhenjiang, Zhenjiang, Changsha, and so on, the less developed cities, such as Dingxi, Bazhong, Longnan, Jixi, Yichun, Hegang, Fuxin, Fuyang, Pingliang, Lvliang, and so on, reap a greater spillover effect of ICT from neighboring cities. Therefore, establishing an economic network of cities through ICT can effectively reduce the economic gap between developed and less developed cities.

5. Conclusions

In this article, SAR and QSAR models were established for ICT effects on urban economic development, including the spatial dependence of urban economy. We first test whether there is spatial dependence and which form of spatial dependence should be used in our model. The test results indicate that spatial lag dependence is necessary and suitable for this research rather than spatial error autocorrelation. Therefore, using SAR and QSAR is reasonable statistically. Homogeneity analysis using the SAR model suggests that, not only do local ICTs contribute directly to urban economy, but also city can reap ICT spatial positive spillover from its neighboring cities. Then, heterogeneity analysis using the QSAR model further confirm directive and spatial spillover effects of ICT on urban economic development. Additionally, the results of QSAR indicate that estimated coefficients of local and neighboring cities' ICT are slightly larger at low quantile and the

coefficients decrease monotonically with the increase of quantile. Therefore, we conclude that the less developed cities in China can reap more digital dividends than developed cities, which would help to reduce the economic gap between cities. Generally, the most important contribution of this research is that we provide empirical evidence that (1) ICTs have positive economic effects on local and neighboring cities; and (2) ICTs are more benefitable to the economic development of less developed cities than that of developed cities in China.

Our conclusions may give good news for China that we can obtain a “double dividend” from ICT. It is possible to obtain an improvement of both overall economic growth and balanced economic development among cities. Especially, in China, it is challenging to exploit fresh economic growth energy and to eliminate regional poverty. Additionally, we conclude that ICT economic effects are larger in less developed cities, which is not consistent with the relevant research at the national level. This reminds us that the economic paradox of ICT may be beyond the economy, namely developing countries’ demand matched the education and policy system to reap digital dividends rather than the economy.

The “double dividend” from ICT can be obtained by other countries where there is a clear-cut geographical divide. The spatial inequalities in the digital development of households and individuals in Europe at the regional level have been identified [48]. In the scenario, ICT penetration would also have a dividend on narrowing the regional gap. Musolino [49] is concerned the “perception gap” would contribute to the regional development gap because Italian entrepreneurs have a stereotyped, far too negative image of Southern Italy. Through bridge communication channels beyond barriers of geographical distance, ICT would help to tear down the “wall in the head” of entrepreneurs. Similarly, poor peripheries grow faster than richer ones throughout Germany [50], which could contribute to ICT development strategy partly based on the empirical study of China.

Owing to the unavailability of data, we do not take the new generation of ICT, such as cloud computing and the Internet of Things, into consideration in this article. The ICT revolution is dynamic and the new technologies will play an increasingly important role in urban economy. In future research, we will continue to accumulate data to conduct a more comprehensive and accurate analysis of ICT economic effects on cities. Additionally, a panel data QSAR model is worthy of consideration on the issue because the urban fixed effect in the panel data model could allow researchers to control the time-invariant unobserved urban characteristic.

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