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ICT, technological diffusion and economic growth in Chinese cities

Qing Li[1] · Yanrui Wu[2]

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Abstract
This study uses a rich city-level dataset to analyse the relationship between information and communication technology (ICT) and economic growth in Chinese cities during 2001–2016. It is shown that ICT not only improves the aggregate efficiency of a city but also helps the city absorb technological diffusion from the frontier city. In addition, distance plays little role in technological diffusion process associated with ICT. Cities geographically farther away from or closer to the frontier city can equally benefit from technological diffusion as long as they have the same level of ICT development.

Keywords ICT · Technological diffusion · Economic growth · Chinese cities

JEL Classification O47 · O33 · R11

1 Introduction

Information and communication technology (ICT) is found to improve economic growth through not only capital deepening (or a direct effect) but also "enabling technology" (or an indirect effect) (Jovanovic and Rousseau 2005). The indirect effect of ICT emphasises general-purpose-technology (GPT) features which are vital to technological diffusions and innovation spawning.[1] Empirical evidence from developed

[1] Bresnahan and Trajtenbergb (1995) argued that GPT should have three characteristics: Pervasiveness (The GPT should not be limited within but diffuse to other sectors); Improvement (The GPT should keep lowering the user costs); Innovation spawning (The GPT should make it easier to invent and produce new products or processes).

✉ Yanrui Wu
yanrui.wu@uwa.edu.au

Qing Li
qingli@shu.edu.cn

1 Department of Economics and Finance, SILC Business School, Shanghai University, Shanghai, China

2 Department of Economics, Business School, University of Western Australia, Perth, Australia

economies shows that knowledge, ideas and innovations associated with ICT diffuse across sectors and regions, hence confirming largely the hypothesis of ICT as GPT (see Cardona et al. 2013 as a review). However, studies of ICT as GPT in developing and emerging countries remain quite thin.

ICT has gradually reshaped the economy and mingled with people's daily life in China, especially in urban areas.[2] A strand of literature has investigated the capital deepening effects of ICT in the production process by treating ICT as an independent input factor (Heshmati and Yang 2006; Khuong 2006; Meng and Li 2002; Sun et al. 2012). However, knowledge about how ICT plays its GPT role in China and thus stimulates economic growth is still limited. This paper would like to fill this knowledge gap by examining the indirect effect of ICT on economic growth across Chinese cities. In contrast to directly measure ICT as a stock of capital, we model ICT as a form of public infrastructure that would accelerate economic growth by facilitating the development and adoption of innovation processes and technological progresses.[3] ICT penetration rate, given by the subscription number of ICT, is used as a proxy for the stock of ICT infrastructure (Czernich et al. 2011; Roller and Waverman 2001).

In general, ICT allows the generation and distribution of decentralised information and ideas in production processes that are increasingly rely on information as an input. From the viewpoint of endogenous growth theory, ICT may not differ too much from types of traditional public infrastructure (sewer systems, railways, roads, electricity and so on) that facilitates innovation processes (Czernich et al. 2011). For example, vast improvement in ICT would diffuse knowledge and technological progresses, facilitate efficient work schedule, enhance job matching, create flexible collaboration, and increase the ability to engage in innovative activities. In other words, the economic returns to ICT investment would be much greater than the returns on just the ICT investment itself. If that is the case, ICT is expected to enable technology, shift production possibility frontier and finally boost economic growth at the city level. In addition, given the argument that ICT may lead to a "death of distance" (see Goldfarb and Tucker 2019 for a detailed review), ICT diffusions may or may not be limited within the border of the city. In this paper, we want to explore if ICT can help Chinese cities to absorb technological diffusion from the frontier. Particularly we are interested in whether distance still plays a role in ICT-related diffusion across Chinese cities.

A potential problem of investigating the association between economic growth and ICT development is the existence of reverse causality. In this paper, we address this problem by adopting an instrumental-variable approach and using the historical telephony switchboard system as our instrument candidate. By interacting the instrument with time trend, this strategy bypasses an explicit form of ICT diffusion processes and

[2] The penetration rate of fixed line was under one percent before 1992 when locally made telephony switchboard system (the basic ICT infrastructure element for fixed line connections) was introduced. Nowadays each household in China with fibre connections can easily ask for a fixed line connection without extra costs (or with only a small connection fee). In 1994, China officially introduced the Internet which most Chinese then never heard about. Now, people can access and surf the internet anytime and anywhere through multiple devices.

[3] A direct measure of ICT is to use perpetual inventory method (PIM) to construct ICT capital stock. This strategy requires reliable flows of capital investment, rates of depreciation, and the initial capital stock. Such information is not available in China at the city level. Thus, following existing studies, ICT is modelled as a shift parameter of productivity like other public infrastructures and the penetration rate is used as a proxy.

depicts time-dimensional ICT evolution in the most flexible form. Empirical analysis of 240 Chinese cities over the period of 2001–2016 shows that ICT contributes to city-level annual economic growth by 0.9–1.1 percentage points. It is also shown that ICT can help cities benefit more from ICT-related technological diffusion. In addition, our finding suggests that diffusion associated with ICT is less likely to be weakened by distance.

The rest of the paper begins with Sect. 2 which discusses the background and relevant literature. Section 3 presents the empirical strategy, and Sect. 4 describes the data and investigates the relationship between ICT and economic growth. Section 5 reports the results of empirical analysis and tests the validity of the instrumental variable. We conclude this paper in Sect. 6.

2 Background and literature review

Studies of ICT and economic growth in the developed world are abundant. Since the late 1990s, the USA witnessed an astonished economic and productivity growth and ICT was found to explain much of that. Oliner and Sichel (2000), for example, examined the economic performance in nonfarm business sectors in the USA during 1995–1999, and concluded that computers (as well as the embedded semiconductors) accounted for about two-thirds of the acceleration in productivity growth. van Ark et al. (2002) compared productivity across industries in Europe and the USA and concluded that the key differences between the two economies are in the services sector, especially the intensive ICT-using services. While productivity growth in the USA accelerated, it more or less stalled in Europe.

Early studies on ICT contributions to economic growth follow mainly the growth accounting framework and emphasise the direct effect of ICT on productivity (ICT-centred theory) (Oliner et al. 2008). On the one hand, the rapid technological progress in ICT directly raises productivity in ICT-producing sectors (Timmer and van Ark 2005); On the other hand, ICT implementation triggered by the fall in ICT prices generates substitutions of more productive for less productive inputs and induces accumulation of ICT capital (Jorgenson 2005). Thus, the ICT-centred theory emphasises ICT production and implies that ICT drives economic development mainly through productivity improvement and capital deepening effect in ICT-producing sectors such as sectors of computers, semiconductors, peripherals and so on.

Nevertheless, ICT-centred theory does not capture the full benefits of ICT to economic growth especially after the millennium. For example, Baily and Lawrence (2001) suggested that since 1995, most of the labour productivity acceleration actually took place outside the computer sector. There was supportive evidence that service industries like finance and wholesale and retail trade in the USA, which are major purchasers of ICT, also enjoyed fast growth during the ICT booming period. Basu and Fernald (2007) found that ICT-using industries in the USA recorded high ICT capital growth rates during 1987–2000 and had a faster acceleration in total factor productivity (TFP) growth in the 2000s. Venturini (2009) estimated the elasticity of output with respect to ICT in the US and EU-15 countries in the long run. It is suggested that

ICT generates much higher social returns and the significant spur of ICT on long-run economic growth is not confined to the period of 1990s.

The empirical evidence therefore emphasises the indirect effect of ICT on economic growth. That is, some forces related to ICT drive sustained economic growth (ICT-related theory) (Oliner et al. 2008). It is suggested that ICT acts as a special GPT and impacts on economic growth through technological pervasiveness, innovation spawning and knowledge creation. Therefore, productivity improvement would not be confined in ICT production but also ICT use. At the firm level, better utilisation of ICT is found to reduce communication and coordination costs, facilitate better decision making and arrange new distribution systems that in turn improve ICT-using firms' labour productivity (Arvanitis and Loukis 2009; Cardona et al. 2013; Goldfarb and Tucker 2019); It would also lower the replication costs that help businesses innovate through new products (Bertschek et al. 2013; Brynjolfsson and Saunders 2010).[4] As for consumers, ICT not only releases the normal utility content but acts as a source of learning-by-doing (Venturini 2007). For example, consumption of ICT products and services would generate network externalities, heighten the interactivity between firms and household, and disseminate knowledge.

The GPT conjecture is closely related to the theory of spillovers where social returns exceed private ones (Cardona et al. 2013). Like the spillover-relevant studies, there are two streams of literature on the GPT conjecture of ICT. The first stream of literature attempts to examine whether ICT would diffuse from ICT-producing sectors to ICT-using sectors in support of "vertical" spillovers. For example, service sectors that use ICT intensively were shown to enjoy a sizeable acceleration in productivity and explain large amounts of productivity differentials between the EU and the USA (Bosworth and Triplett 2007; Inklaar et al. 2005; van Ark et al. 2008). The other stream of literature analyses the GPT conjecture through "horizontal" spillovers. It is suggested that knowledge, ideas, and innovations associated with the adoption of ICT could diffuse and generate network externalities among firms and households and thus promote macro-level productivity (Czernich et al. 2011; Roller and Waverman 2001).

Though the direct effect of ICT on economic growth was largely confirmed, there is no consensus on the indirect effect of ICT even in the developed world. One critique is based on the argument that TFP is indeed a residual from production regression analysis, which might reflect only the measurement of ignorance or contributions of unobserved intangible capital. The productivity gains from ICT thus only reflect contributions of organisation capital, R&D, and other unobserved intangibles (Brynjolfsson et al. 2002; Brynjolfsson and Hitt 2003; Chen et al. 2016; Corrado et al. 2017). Those unobserved factors thus can explain some parts or, more extremely, all of the economic externalities of ICT (Acharya 2016).

Meanwhile, positive spillovers of ICT may require advanced "absorptive capabilities". Appropriate level of human capital and flexible organisational structure, among others, are necessary complementarities to fully exploit the benefits of ICT (Niebel 2018). Therefore, conclusions of previous studies regarding developing and emerging economies are rather mixed. While some evidence supports that poorer countries can

[4] A wide range of sectors like transport (Hubbard 2009), health services (Athey and Stern 2002), and banking (Autor et al. 2002) were found to benefit from the application of ICT in the developed countries.

gain more from ICT (Appiah-Otoo and Song 2021; Dimelis and Papaioannou 2010), several studies showed that, due to a lack of absorptive capabilities, developing and emerging economies cannot benefit as much as the developed world from ICT diffusion and therefore fail to "leapfrog" and catch up with the frontier economies (Cheng et al. 2021; Dedrick et al. 2013; Niebel 2018).[5]

We close this section by briefly summarising several studies of ICT and economic growth in China. Obviously, investigation of ICT's GPT conjecture and its contributions to China's economic growth is important. On the one hand, understanding ICT's GPT conjecture helps administrative decisions of investment programs. Only if ICT investment generates greater social returns shall government consider it as the public good and inject resources. On the other hand, evidence collected in the largest developing country has implications for other developing and emerging economies. Particularly, it helps understand if developing countries can benefit from ICT development and exploit its GPT effects. However, unlike the developed economies, evidence of ICT and economic growth in China by now follows mainly the ICT-centred theory, which examines ICT as an input factor to contribute to economic development through capital deepening and substitution effects (Heshmati and Yang 2006; Kumar et al. 2016; Zhan et al. 2014). Whether ICT is a GPT in China is still ambiguous. Cai and Zhang (2015) analysed the pervasiveness effects of ICT in China by using a Granger regression and found a bidirectional relationship during 1977–2012. Guo and Luo (2016) used internet subscription as a proxy for ICT and checked the threshold of subscription to generate network effects. Ward and Zheng (2016) examined the effects of mobile and fixed telecommunications usage on economic growth and investigated the possibility of complementary relationship between the two.

3 Empirical strategy

To estimate the effects of ICT in the production process, we consider the following simple expanded Solow model with physical capital (K_t), human capital (H_t) and labour (L_t) as the three main input factors (Mankiw et al. 1992):

$$Y_t = (K_t)^{\alpha}(H_t)^{\beta}(A_t L_t)^{1-\alpha-\beta} \tag{1}$$

where Y_t is the output and A_t the level of technology or efficiency in year t. α and β represent the income shares of physical capital and human capital, respectively. The evolution of the economy is determined by:

$$\dot{k}_t = s^k y_t - (n + g + \delta)k_t \tag{2a}$$

$$\dot{h}_t = s^h y_t - (n + g + \delta)h_t \tag{2b}$$

[5] The strategy of "leapfrogging" refers to bypassing some of the process of accumulation of traditional production inputs and hence narrowing the gap between the laggards and the frontier much faster (Steinmueller 2001).

where $y_t = Y_t/A_tL_t$, $k_t = K_t/A_tL_t$, and $h_t = H_t/A_tL_t$ are quantities per unit of effective labour. s^k and s^h, respectively, represent the rate of accumulation of physical capital and human capital in the economy. n denotes the population growth rate while g is the exogenous rate of technological progress.[6] It is assumed that human capital depreciates at the same rate of δ as physical capital. For simplicity, these rates are assumed to be constant for the time being. By assuming the constant returns to scale and decreasing returns to all capital, the steady-state economy is defined as:

$$k^* = \left(\frac{(s^k)^{1-\beta}(s^h)^{\beta}}{n+g+\delta}\right)^{1/(1-\alpha-\beta)} \tag{3a}$$

$$h^* = \left(\frac{(s^k)^{\alpha}(s^h)^{1-\alpha}}{n+g+\delta}\right)^{1/(1-\alpha-\beta)} \tag{3b}$$

Substituting (3a) and (3b) into the production function and taking the logarithmic transformation, the output per capita is expressed as:

$$\ln\left(\frac{Y_t}{L_t}\right) = lnA_t - \frac{\alpha+\beta}{1-\alpha-\beta}\ln(n+g+\delta) + \frac{\alpha}{1-\alpha-\beta}\ln\left(s^k\right) + \frac{\beta}{1-\alpha-\beta}\ln(s^h) \tag{4}$$

which depends on the growth rate of population, the accumulation of physical and human capital, and the level of technology. The compact panel data version of Eq. (4) for city i in year t is given by:

$$\ln\left(\frac{Y}{L}\right)_{it} = lnA_{it} + \beta_1 lns_{it}^k + \beta_2 lns_{it}^h + \beta_3 n_{it} \tag{5}$$

where $\beta_s (s = 1, 2, 3)$ are unknown parameters and n_{it} is used to replace $\ln(n_{ij} + g_{it} + \delta_{it})$ (Czernich et al. 2011).

If technology evolves along an exponential growth path which is affected by ICT as a shift factor, A_{it} can be defined as:

$$A_{it} = A_{i0}e^{\varphi_{it}}e^{gt}e^{u_{it}} \tag{6}$$

where A_{i0} represents the time-invariant characteristics of cities like geography that determine a particular technological path, e^{gt} captures the "Hicks neutral" technological evolvement that is indifferent across units and u_{it} is the white noise. Following the existing literature (Fleisher et al. 2010; Benhabib and Spiegel 1994), we postulate that ICT as the shift factor has both a direct effect on efficiency (through innovation) and as well as an indirect spillover effect through ICT-related technological diffusion. Therefore, φ_{it} is expressed as:

$$\varphi_{it} = \gamma_1 ICT_{it} + \gamma_2 ICT_{it}\left[\frac{(Y/L)_{max,t} - (Y/L)_{it}}{(Y/L)_{it}}\right] \tag{7}$$

[6] L and A are assumed to grow exogenously at rates n and g ($L_t = L_0e^{nt}$; $A_t = A_0e^{gt}$) (Mankiw et al. 1992).

where ICT_{it} is an indicator of ICT development in city i at year t and $\left[\frac{(Y/L)_{max,t}-(Ytexforwardslash L)_{it}}{(Y/L)_{it}}\right]$ denotes the output gap with $(Y/L)_{max,t}$ being the highest level of output per capita across the cities (which is typically Shanghai) at year t. The first term on the right of Eq. (7) captures the direct effect of ICT while the second term defines the indirect effect of ICT which is measured by the interaction of ICT indicator and the output gap between a city and the frontier city. Distance is not counted in the ICT-related diffusion process since frictions and costs are not necessarily increasing as cities locate farther to each other. Meanwhile, we impose a time lag to avoid the potential simultaneity from construction of the diffusion variable (Fleisher et al. 2010). By substituting Eqs. (6) and (7) into (5) and taking first differences, the empirical model becomes:

$$
\begin{aligned}
\Delta ln\left(\frac{Y}{L}\right)_{it} &= g + \gamma_1 ICT_{it} + \gamma_2 ICT_{it}\left[\frac{(Y/L)_{max,t} - (Y/L)_{it}}{(Y/L)_{it}}\right] \\
&+ \beta_1 \Delta lns_{it}^{k} + \beta_2 \Delta lns_{it}^{h} + \beta_3 \Delta n_{it} \\
&+ \beta_4 ln\left(\frac{Y}{L}\right)_{i0} + \beta_5 yearnum_{it} + \varepsilon_{it}
\end{aligned} \tag{8}
$$

In Eq. (8), we additionally control the initial income in city i, $ln(\frac{Y}{L})_{i0}$. The inclusion of the initial level of income is widely suggested in convergence analysis (Barro and Sala-i-martin 1992; Mankiw et al. 1992). The number of years ($yearnum_{it}$) since the introduction of ICT in a city is also included to capture the systematically different time trend in the ICT rolling-out process among Chinese cities. Because we cannot trace back to the exact year when ICT was introduced to each city, the benchmark year is set to be the year when the penetration rate of fixed line phones, a traditional ICT service in China, exceeded one per cent. It is argued that, when critical mass is reached, the full impact of ICT on economic growth is realised (Czernich et al. 2011).

Analysis of ICT and economic development suffers from endogeneity problems. One source of endogeneity comes from reverse causality. It is argued that types of ICT services (broadband facilities as the example) are subject to consumers' demand which is correlated with the income level (Briglauer et al. 2018; Roller and Waverman 2001). Another source of endogeneity comes from omitted variables. It is often criticised that state intervention and government subsidies, among others, are associated with both ICT development and economic growth (Briglauer et al. 2021; Czernich et al. 2011). This paper adopts an instrumental variable (IV) strategy. We are primarily inspired by Czernich et al. (2011) who examined broadband's effects on economic growth. In their paper, they argued that the existing telecommunication infrastructure is necessary to reduce deployment costs and very important for broadband roll-out. The extensive margin of the diffusion of broadband technology thus can be described through a logistic curve in which the maximum penetration level of broadband is determined by the volume of voice-telephony and cable-TV networks that existed before the introduction of broadband services.

With the same logic, this paper uses the capacity of telephony switchboard per 100 persons as the instrumental candidate. First, the provision of telephony switchboard, which determines the maximum number in the exchange lines, is necessary for the roll-out of the telecommunication services. Second, given the fact that dial-up connection is the only form of broadband access at the very beginning in China, the existing telephony infrastructure element is also relevant instrument for broadband accessibility. Since China is officially recognised to have broadband access from 20 April 1994, when Sprint Co. from the USA established a full functional linkage, we therefore use the telephony switchboard capacity in year 1993, the year before broadband was officially introduced in China, as the legitimate instrument.

To depict the ICT evolvement over time, city-level telephony switchboard capacity in 1993 is interacted with dummies of rolling-out years ($yearnum_{it}$) (Angrist and Krueger 1991).[7] Because $yearnum_{it}$ is also included in the second-stage equation, the effect of ICT on growth is identified by variation in ICT across cities conditional on each roll-out process (See Appendix A for the detail). In comparison with the nonlinear analysis of Czernich et al. (2011), this strategy does not need to specify an explicit form of ICT diffusion processes and can depict time-dimensional ICT evolvement in the most flexible form.

4 Data and preliminary analysis

According to the definition of International Telecommunication Union (ITU), fixed lines, mobiles and broadband connections are among the most prevalent ICT indicators. Since fixed lines are arguably outdated and might be the driver of new ICT adoptions (Chinn and Fairlie 2007), we use mobiles and broadband as indicators of ICT development. For each indicator, we measure the penetration rate as the number of subscriptions per 100 inhabitants. The data source is China City Statistical Yearbook (CCSY). It started from 1985 and provides detailed information on prefecture-and-above level cities. However, CCSY only started reporting information of mobile and broadband subscriptions in 2001 and stopped collecting information of physical capital investment after 2016. As a result, the final data sample consists of 240 cities across 2001–2016 time period.[8]

Figure 1 illustrates the evolvement of these two ICT indicators across Chinese cities, in which subscriptions of mobiles and broadband connections move largely in tandem. A strong correlation between mobile and broadband subscriptions is also seen in the upper panel of Table 1. To account for the association, we adopt principal component analysis (PCA) first for dimensional reduction. The bottom panel in Table 1 shows the PCA results. Based on Kaiser's rule, we retain the first principal component with an eigenvalue exceeding unity as the proxy for ICT development (Kaiser 1960).[9]

7 Angrist and Krueger (1991) used the interaction of cohorts' birth month and birth year as the instruments for compulsory education.

8 After 2016, CCSY ceased to report the city-level physical capital investment. In total, there are 258 cities with data for the whole period. Among them, 18 cities have no data of telephony switchboard in 1993. The final sample thus only consists of 240 cities.

9 Intuitively, principal components of a collection of points can be understood as a sequence of unit vectors being orthogonal to each other in a real coordinate space. Each data point is projected onto principal components to obtain lower-dimensional data while preserving as much of the data's variation as possible.

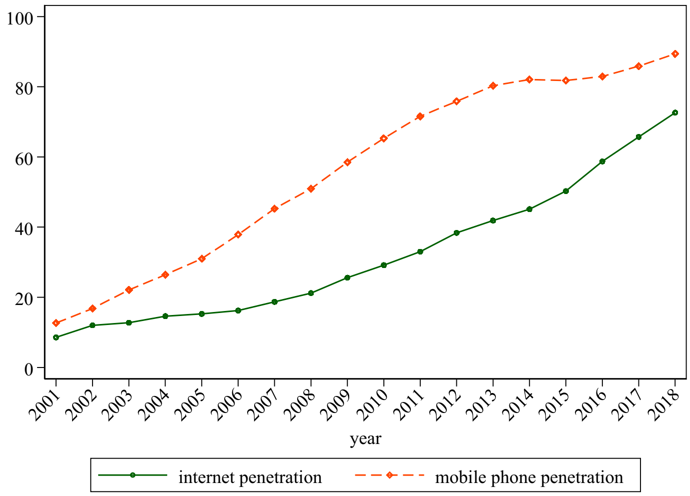


Fig. 1 Penetration rates of broadband and mobiles across Chinese cities during 2001–2018. *Source*: Authors' own work (CCSY)

In addition, real GDP per capita is expressed in 2010 price level and normalised by population. Physical capital accumulation is proxied by the real non-residential fixed capital investment, and human capital accumulation is proxied by the average number of schooling years of the working-age population (Czernich et al. 2011).[10] Table 2 provides descriptive statistics in different years for the cities as a whole and two economic regions, the cost and the interior, for a comparison.[11]

Table 3 reports the results of examining the relationship between ICT penetration and GDP per capita growth in Chinese cities with and without technological diffusion from other cities. The coefficients of ICT penetration rate are positive and significant in all specifications. The magnitude of coefficients suggests that an increase in ICT penetration rate by ten percentage points would be associated with an increase in the annual growth of GDP per capita by 0.3 to 0.5 percentage points. In Column (2), we include physical capital and human capital accumulation to test the assumption of Czernich et al. (2011): Since innovation could be embedded in physical capital and human capital, a smaller coefficient is expected when capital accumulation is incorporated. Nevertheless, evidence is obscure in China. The coefficient remains unchanged

Footnote 9 continued
Mathematically, principal components are often computed by eigen-decomposition of the data covariance matrix. Here, we decompose the covariance matrix of ICT proxies by eigen-decomposition and use uncorrelated and normalised eigenvectors as the proxy for ICT development (ICT penetration rate) [see Jackson (2003) for more details]. We use the covariance matrix because the variables are expressed in the same units.

[10] CCSY provides labour force and China Labour Statistical Yearbook (CLSY) provides the average number of schooling years by sector (2-digit level). The average schooling-year number is then calculated as the summation of the share of sector-level labour force times sector-level schooling years.

[11] The coastal regions include Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The interior regions include Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

Table 1 Correlation matrix and principal component analysis results. *Source*: Authors' own estimates

ICT proxies	Mobiles	Broadband
Mobiles	1.000	
Broadband	0.793	1.000

Principal component	Eigenvalues	% of variance	Cumulative (%)
1	1.792	0.897	0.897
2	0.207	0.103	1.000

Table 2 Descriptive statistics. *Source*: Authors' own estimates

Mean, 2001–2016	All	Coast	Interior
GDP per capita	3.621	5.055	2.697
(10,000 RMB, in 2010 price)	(4.095)	(5.427)	(2.536)
Growth of GDP per capita	10.001	9.658	10.222
(%)	(8.022)	(8.429)	(7.742)
Physical capital per capita	1.698	1.990	1.510
(10,000 RMB, in 2010 price)	(1.683)	(1.813)	(1.565)
Growth of physical capital	18.812	17.480	19.669
(%)	(25.605)	(26.333)	(25.093)
Human capital	10.957	10.943	10.966
(average schooling years)	(1.420)	(1.692)	(1.213)
Growth of human capital	2.266	2.037	2.414
(%)	(9.273)	(10.197)	(8.625)
Population	448.690	483.397	426.344
(10,000 persons)	(318.284)	(278.996)	(339.377)
Broadband penetration rate	29.644	40.018	22.965
(subscription per 100 inhabitant)	(26.646)	(31.084)	(20.772)
Mobiles penetration rate	54.696	63.614	48.954
(subscription per 100 inhabitant)	(32.318)	(32.242)	(31.046)
ICT penetration rate	54.245	64.805	47.517
(subscription per 100 inhabitant, PCA component)	(31.513)	(31.775)	(29.437)
Telephony broadband in 1993	3.174	4.062	2.602
(units per 100 people)	(2.258)	(2.512)	(1.866)
GDP per capita in 2000	1.300	1.847	(0.948)
(10,000 RMB, in 2010 price)	(1.413)	(1.930)	(0.755)
Observation	3840	1504	2336

(even slightly larger) in Column (2) when growth in physical and human capital is controlled. Thus, there is little evidence of capital-embedded or skill-biased technological change. Column (3) introduces a one-year lag of ICT-related technological diffusion from other cities, while Columns (4) adds region dummies to account for regional heterogeneity. Both the direct effects and indirect spillover effects of ICT on growth in GDP per capita are hardly affected. In all columns, time dummies are included for the post-crisis period (pre-crisis period as the reference) to capture the different phases of growth after the external shock.

Table 3 Estimating the relationship between ICT and growth. *Source*: Authors' own estimates

Dep. Growth of GDP per capita	(1)	(2)	(3)	(4)
ICT penetration rate	0.0347***	0.0388***	0.0456***	0.0476***
	(0.0089)	(0.0087)	(0.0081)	(0.0082)
Lagged ICT spillover			0.0092***	0.0089***
			(0.0017)	(0.0018)
Growth of physical capital per capita		0.0552***	0.0547***	0.0545***
		(0.0149)	(0.0147)	(0.0146)
Growth of education years		0.0129	0.0147*	0.0152*
		(0.0086)	(0.0087)	(0.0087)
ΔGrowth of population	− 0.3391***	− 0.3133***	− 0.3104***	− 0.3103***
	(0.0213)	(0.0211)	(0.0206)	(0.0207)
Years since ICT exceeded critical mass	− 0.0052***	− 0.0052***	− 0.0063***	− 0.0064***
	(0.0008)	(0.0007)	(0.0009)	(0.0009)
GDP per capita in 2000	− 0.0057***	− 0.0053***	− 0.0024**	− 0.0023**
	(0.0020)	(0.0020)	(0.0010)	(0.0010)
Post-crisis period	0.0048	0.0090**	0.0046	0.0041
	(0.0041)	(0.0044)	(0.0047)	(0.0047)
Coast				− 0.0039
				(0.0027)
Constant	0.1730***	0.1569***	0.1573***	0.1582***
	(0.0100)	(0.0091)	(0.0100)	(0.0101)
R^2	0.2191	0.2452	0.2542	0.2547
Observations	3600	3600	3600	3600

Robust standard errors are shown in the parenthesis. The sample size is restricted to 3600 in Columns (1) and (2) for comparison purposes

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

5 Discussion of the results

As discussed in Sect. 4, a positive association between ICT and growth cannot lead to a robust conclusion that ICT diffusions cause cities' economic growth. Reverse causality and unobserved omitted variables may bias the OLS results. We now turn to the IV technique for empirical analysis.

5.1 Effects of ICT on city growth

Table 4 reports the second-stage results of the IV model. An endogeneity test rejects the null and suggests the endogeneity of ICT. In all columns, the first-stage F-statistic

Table 4 ICT and growth in GDP per capita: IV technique. *Source*: Authors' own estimates

Dep. Growth of GDP per capita	(1)	(2)	(3)	(4)
Predicted ICT penetration rate	0.0985***	0.1113***	0.0892***	0.0921***
	(0.0182)	(0.0187)	(0.0112)	(0.0116)
Lagged Predicted ICT spillover			0.0203***	0.0200***
			(0.0024)	(0.0024)
Growth of physical capital per capita		0.0585***	0.0558***	0.0555***
		(0.0125)	(0.0118)	(0.0118)
Growth of education years		0.0114	0.0160	0.0167*
		(0.0097)	(0.0098)	(0.0098)
ΔGrowth of population	− 0.3382***	− 0.3115***	− 0.3059***	− 0.3058***
	(0.0312)	(0.0309)	(0.0309)	(0.0310)
Years since ICT exceeded critical mass	− 0.0081***	− 0.0085***	− 0.0094***	− 0.0094***
	(0.0011)	(0.0011)	(0.0009)	(0.0009)
GDP per capita in 2000	− 0.0109***	− 0.0111***	− 0.0019	− 0.0017
	(0.0021)	(0.0021)	(0.0013)	(0.0013)
Post-crisis period	0.0034	0.0077*	− 0.0015	− 0.0020
	(0.0042)	(0.0045)	(0.0045)	(0.0045)
Coast				− 0.0048*
				(0.0028)
Constant	0.1924***	0.1782***	0.1681***	0.1694***
	(0.0098)	(0.0095)	(0.0078)	(0.0079)
First-stage F statistics	27.6303	27.1584	29.0202	28.9130
Endogeneity test (p value)	0.0000	0.0000	0.0000	0.0000
Hansen J test (p value)	0.0644	0.0835	0.1685	0.1785
C-test for $yearnum_{it}$ (p value)	0.0144	0.0042	0.2422	0.2401
R^2	0.1997	0.2203	0.2350	0.2353
Observations	3600	3600	3600	3600

Robust standard errors are shown in the parenthesis. The sample size is restricted to 3600 in Columns (1) and (2) for comparison purposes

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

for the joint significance test is well above 10.[12] Therefore, the instruments are relevant to the endogenous variable and have adequate explanatory power. In addition, the orthogonality conditions are required for the employment of instruments. This restriction is additionally tested by the heterogenous-robust Hansen J statistics in the context of an overidentified model. The large p values of Hansen J statistics in columns (3) and (4) imply that the instruments satisfy the orthogonality conditions required for their employment (Baum et al. 2003). In columns (1) and (2), however, the null is only confirmed marginally as the p values are smaller than 10%. This may imply that the exclusion of spillover effects may lead to omitted variable problems and hence possible correlation between our instruments and the residuals. In other words, the complete specification should be the one with technological diffusions. Finally, we test the exogeneity of $yearnum_{it}$ by conducting the C-test and confirm that the null hypothesis cannot be rejected in columns (3) and (4) of Table 4 when technological diffusions are incorporated.[13] The predicted ICT penetration rate shows a larger and significant effects on cities' economic growth in all columns, indicating a downward bias in the OLS analysis. It is suggested that a ten percentage points increase in ICT penetration rate would lead to about 0.9–1.1 percentage points increase in the annual growth rate. Since the average annual growth rate of GDP per capita in 2001–2016 is about 10 per cent, the direct impacts of ICT would generate magnificent economic effects and account for 9–11 per cent of economic growth. In Columns (3) and (4), the indirect effect of ICT through technological diffusion is considered. In other word, it captures the absorption effects of innovation diffusions from the technological frontier in China. Other things being equal, the development of ICT would help a city to absorb positive technological spillovers and thus in turn improves the city's economic development.

In Table 5, we use a fixed effect model. In this way, only the variation within cities over time is used. Therefore, effects of time-invariant variables like region dummies and initial-year income levels cannot be testified. In general, the coefficients of predicted ICT penetration rate are still positive and significant throughout the table. The magnitude of ICT coefficients in Columns (1) and (2) becomes even larger than those without city fixed effect. However, we interpret the results with caution, since Hansen J and C statistics reject the null in columns (1) and (2) and the instruments fail to pass the orthogonality conditions in these cases. In other words, technological diffusion is an important channel through which ICT contributes to productivity growth in Chinese cities. Ignoring the channel may generate severe omitted-variable problems that dampen the IV results. Therefore, the rest of the analysis is mainly based on the full specification in column (4) of Table 4. After controlling the indirect channel of technological diffusions, the coefficient of ICT direct effects remains positive and highly significant.

The growth-enhancing effect of ICT is investigated further in Table 6. In reality, it may take some time to fully exploit the benefits from ICT development. If so, we would see a larger coefficient when lagged terms are used. Columns (2)-(4) consider

[12] The first-stage results are available upon request.

[13] The p values of the C test in Columns (1) and (2) of Table 4 are relatively small. The exogeneity assumption of $yearnum_{it}$ is not supported. This may imply that the exclusion of technological diffusions could lead to omitted-variable problems and hence the correlation between $yearnum_{it}$ and the residuals.

Table 5 ICT and growth in GDP per capita: fixed effect model. *Source*: Authors' own estimates

Dep. Growth of GDP per capita	(1)	(2)	(3)
Predicted ICT penetration rate	0.3345***	0.3977***	0.1001***
	(0.0418)	(0.0442)	(0.0347)
Lagged Predicted ICT spillover			0.0412***
			(0.0036)
Growth of physical capital per capita		0.0565***	0.0494***
		(0.0125)	(0.0116)
Growth of education years		0.0117	0.0143
		(0.0101)	(0.0097)
ΔGrowth of population	− 0.3358***	− 0.3096***	− 0.3074***
	(0.0278)	(0.0275)	(0.0271)
Years since ICT exceeded critical mass	− 0.0145***	− 0.0151***	− 0.0115***
	(0.0014)	(0.0014)	(0.0014)
Post-crisis period	0.0045	0.0090*	0.0110**
	(0.0046)	(0.0049)	(0.0046)
First-stage F statistics	41.1986	40.8423	18.7703
Endogeneity test (p value)	0.0000	0.0000	0.0003
Hansen J test (p value)	0.0000	0.0000	0.1486
C-test for $yearnum_{it}$ (p value)	0.0069	0.0028	0.2313
City FE	Yes	Yes	Yes
R^2	0.1840	0.2028	0.2847
Observations	3600	3600	3600

Robust standard errors are shown in the parenthesis. The sample size is restricted to 3600 in Columns (1) and (2) for comparison purposes

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

optional estimates with one-year or two-year lagged terms. The coefficients of ICT penetration rate and technological diffusions in these columns are hardly changed in comparison with the baseline results in Column (1).[14] These results may imply that the effects of ICT appear contemporaneous to its diffusion, which are consistent with the findings of Czernich et al. (2011).

When estimating the ICT's indirect effects through technological diffusions, we use the output gap as a measure of technological distance between a city and the technological frontier city in China. Distance is not accounted for in our baseline regressions under the assumption that information and knowledge could diffuse over phones and broadband without spatial-relevant frictions and costs. That is, costs of information transportation are assumed to be extremely low so that distance no longer matters [see Goldfarb and Tucker (2019) for a review]. However, is distance dead? Can cities geographically closer to the technological frontier still gain better access

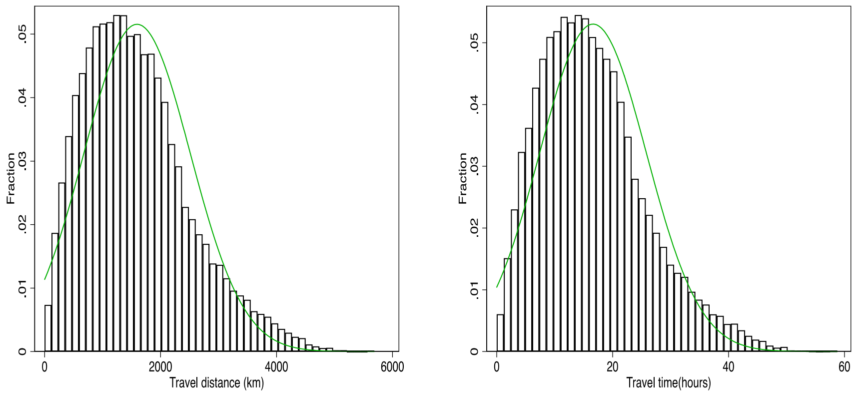
[14] We replicate Table 6 with fixed effects and draw the same conclusion. The results are shown in Table 9, Appendix B.

Table 6 Growth-enhancing analysis: IV technique. *Source*: Authors' own estimates

Dep. Growth of GDP per capita	(1)	(2)	(3)	(4)
Predicted ICT penetration rate	0.0948***		0.0821***	
	(0.0125)		(0.0119)	
Lagged predicted ICT penetration rate		0.0992***		0.0859***
		(0.0138)		(0.0129)
Lagged predicted ICT spillover	0.0207***	0.0223***		
	(0.0026)	(0.0028)		
2Year-Lagged predicted ICT spillover			0.0251***	0.0266***
			(0.0027)	(0.0029)
Growth of physical capital per capita	0.0558***	0.0575***	0.0546***	0.0560***
	(0.0131)	(0.0134)	(0.0124)	(0.0126)
Growth of education years	0.0092	0.0064	0.0092	0.0068
	(0.0126)	(0.0126)	(0.0127)	(0.0128)
ΔGrowth of population	− 0.3081***	− 0.3137***	− 0.3127***	− 0.3179***
	(0.0316)	(0.0317)	(0.0317)	(0.0318)
Years since ICT exceeded critical mass	− 0.0106***	− 0.0109***	− 0.0105***	− 0.0108***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
GDP per capita in 2000	− 0.0011	− 0.0012	0.0005	0.0004
	(0.0013)	(0.0013)	(0.0013)	(0.0014)
Post-crisis period	0.0027	− 0.0004	− 0.0006	− 0.0034
	(0.0049)	(0.0050)	(0.0049)	(0.0050)
Coast	− 0.0045	− 0.0043	− 0.0031	− 0.0030
	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Constant	0.1847***	0.1909***	0.1864***	0.1922***
	(0.0096)	(0.0102)	(0.0096)	(0.0102)
First-stage *F* statistics	26.1380	21.2830	28.3659	24.4960
Endogeneity test (*p* value)	0.0000	0.0000	0.0000	0.0000
Hansen *J* test (*p* value)	0.1064	0.1394	0.4101	0.2716
C-test for $yearnum_{it}$ (*p* value)	0.2314	0.2210	0.1833	0.1018
R^2	0.2414	0.2273	0.2552	0.2457
Observations	3360	3360	3360	3360

Robust standard errors are shown in the parenthesis. The sample size is restricted to 3360 in Columns (1) and (2) for comparison purposes

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$



Mean	S.D.	25p.	50p.	75p.
1594.73	916.90	904.18	1468.34	2113.35

Mean	S.D.	25p.	50p.	75p.
16.61	9.21	9.70	15.39	21.85

Fig. 2 Distribution of travel distance (km) and travel time (hour) across Chinese cities. *Source*: Authors' own estimates

to new technologies through ICT than distant ones? We would like to explore this question further. Briglauer et al. (2021) examined the argument in German counties and used linear distances to weigh regional externalities. Such weighting scheme ignores geographic impediments to a large extent. In contrast, we use "travel distance" and "travel time" to take geographic and geomorphic conditions into account. The travel distance is defined as the number of kilometres one should drive by car from one city's administrative centre to another city's, while the travel time is the number of driving hours under normal traffic conditions.[15] The distribution of the travel distance and travel time across Chinese cities are presented in Fig. 2. In sum, we additionally discount the technological gap with the frontier city by travel distance (time) and examine the ICT-related technological diffusion coefficients. If distance still plays a role in this case, we would expect to see larger effects in the weighting scheme.

Table 7 reports the results. Columns (1) and (4) show the baseline regressions for comparison. Columns (2) and (5) use the travel time as the weighting matrix, while Columns (3) and (6) use the travel distance. After accounting for distance, the magnitudes of technological diffusions through ICT hardly changed. The conclusion thus confirms our conjecture. That is, with the help of ICT development, distance plays a less important role in absorbing technological development. Distant cities would benefit as much as cities closer to the technological frontier from technological diffusions given the same level of ICT development in the cities.

Lastly, we briefly summarise the findings of other controlled variables. There is no surprise to find a positive and significant effect of physical capital accumulation on economic growth. The coefficients remain largely unchanged when IV technique is adopted. For human capital accumulation, its coefficient is positive but insignificant

[15] The routing distance and time is calculated by a user-written command "georoute" in STATA. It allows to retrieve travel distance and travel time between two points defined by their addresses or their geographical coordinates (Weber and Péclat 2017).

Table 7 Distance and ICT spillover: IV technique. *Source*: Authors' own estimates

Dep. Growth of GDP per capita	IV				IV + FE	
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted ICT penetration rate	0.0982***	0.0948***	0.0954***	0.1141***	0.1229***	0.1201***
	(0.0117)	(0.0126)	(0.0127)	(0.0336)	(0.0354)	(0.0357)
Lagged Predicted ICT spillover	0.0207***	0.0225***	0.0221***	0.0404***	0.0407***	0.0410***
	(0.0024)	(0.0031)	(0.0031)	(0.0036)	(0.0036)	(0.0037)
Growth of physical capital per capita	0.0544***	0.0541***	0.0542***	0.0488***	0.0487***	0.0487***
	(0.0117)	(0.0117)	(0.0117)	(0.0116)	(0.0115)	(0.0115)
Growth of education years	0.0146	0.0149	0.0149	0.0119	0.0120	0.0120
	(0.0098)	(0.0099)	(0.0098)	(0.0099)	(0.0099)	(0.0099)
ΔGrowth of population	− 0.3147***	− 0.3143***	− 0.3144***	− 0.3164***	− 0.3161***	− 0.3161***
	(0.0273)	(0.0273)	(0.0274)	(0.0242)	(0.0241)	(0.0241)
Years since ICT exceeded critical mass	− 0.0099***	− 0.0099***	− 0.0099***	− 0.0125***	− 0.0127***	− 0.0127***
	(0.0009)	(0.0010)	(0.0010)	(0.0014)	(0.0014)	(0.0014)
GDP per capita in 2000	− 0.0016	− 0.0007	− 0.0009			
	(0.0013)	(0.0015)	(0.0015)			
Post-crisis period	− 0.0026	− 0.0033	− 0.0031	0.0107**	0.0106**	0.0106**
	(0.0045)	(0.0046)	(0.0046)	(0.0047)	(0.0047)	(0.0047)
Coast regions	− 0.0052*	− 0.0045	− 0.0047			
	(0.0028)	(0.0029)	(0.0029)			
Constant	0.1727***	0.1714***	0.1716***			
	(0.0078)	(0.0079)	(0.0080)			
First-stage F statistics	28.1257	19.8712	19.9437	17.8344	15.1465	14.7609

Table 7 (continued)

Dep. Growth of GDP per capita	IV				IV + FE	
	(1)	(2)	(3)	(4)	(5)	(6)
Endogeneity test (p value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hansen J test (p value)	0.1007	0.1322	0.1034	0.2400	0.2223	0.2227
C-test for $yearnum_{it}$ (p value)	0.1460	0.1446	0.1547	0.0520	0.1346	0.2252
City FE	No	No	No	Yes	Yes	Yes
R^2	0.2368	0.2336	0.2346	0.2862	0.2850	0.2851
Observations	3540	3540	3540	3540	3540	3540

Four cities (Zhoushan, Yongzhou, Haikou, and Sanya) are dropped from the sample due to missing data. Robust standard errors are shown in the parenthesis. The regression specification is $\Delta ln(\frac{Y}{L})_{it} = g + \gamma_1 ICT_{it} + \gamma_2 ICT_{it}\left[\frac{1}{d_{travel\_i}} \cdot \frac{(Y/L)_{max,t}-(Y/L)_{it}}{(Y/L)_{it}}\right] + \beta_1 \Delta lns^k_{it} + \beta_2 \Delta lns^h_{it} + \beta_3 \Delta n_{it} + \beta_4 ln(\frac{Y}{L})_{i0} + \beta_5 yearnum_{it} + \varepsilon_{it}$ where technological gap is discounted by the distance variable d_{travel_i} that is proxied by travel distance and travel time between cities' administrative centres

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

in most cases. This finding is consistent with the conclusions by Czernich et al. (2011) who found a positive but insignificant effect in OECD countries in 1996–2007. The growth rate of population and years after ICT exceeded its critical mass shows the expected negative sign in all specifications. While cities in the interior regions seem to enjoy an even faster growth throughout the period, the differential is not statistically different from zero. Finally, we fail to draw robust conclusions that the post-crisis period witnessed an economic recovery on average and interior cities enjoyed a faster growth throughout the period.

5.2 The instrument validity

The validity of our IV technique depends on the assumption that the capacity of telephony switchboard in 1993 is the legitimate instrument for ICT development. That is, telephony switchboard capacity in 1993 should not have an independent direct effect on cities' economic growth during 2001–2016 and should not be correlated with the error term (ε_{it}) in Eq. (8). While instrumental test statistics confirm largely the satisfaction of the exclusion restriction, we additionally perform a set of robustness checks to defend the validity of our instruments.

The plausible direct effects of telephony switchboard may come from two dimensions. First, it is argued that telephony switchboard is the technology that still affects economic growth in the twenty-first century. To our best knowledge, the mode and function of the telephony switchboard in the twentieth century is quite different from those in the 21st in Chinese cities. Before the introduction of broadband access in 1994, the telephony switchboard is a stored-program-control (SPC) exchange system that provides mainly the voice-transmit services.[16] Since China opened the Internet Protocol (IP) telephony market officially in 1999, the automatic digital switch system (IP exchange), under the Transmission Control Protocol (TCP), quickly replaced the conventional exchange system to provide not only voice but also data and information transmission (Lovelock 2001). Therefore, technologies that embedded in telephony switchboard systems in 1993 are obviously outdated technology that could hardly affect efficiencies in the 21th century.

Second, telephony switchboard in 1993 would possibly generate indirect effects on GDP per capita growth over 2001–2016 through the realisation of the past economic growth. However, the regression model already accounts for the initial level of GDP per capita in 2000. Any effects of telephony switchboard through the above channel should have subsided in this controlled variable. In addition, the nonlinear nature of the instruments allows us to include telephony switchboard capacity in 1993 in the model to check its potential direct effects on economic development. If there is no direct effect from this old-fashioned technology, the coefficient of telephony switchboard capacity should be insignificant. Column (1) in Table 8 confirms this conjecture. After controlling for the channel through ICT development, telephony switchboard shows no direct effects on cities' economic growth during the observed period.

[16] China begun to independently develop her SPC exchange system in the late 1980s and the first self-developed SPC exchange switchboard was put into use in 1992. https://baijiahao.baidu.com/s?id=1612740546396314050&wfr=spider&for=pc.

Table 8 Instrument validity experiments. *Source*: Authors' own estimates

Dep. Growth of GDP per capita	(1)	(2)	(3)	(4)	(5)
Predicted ICT penetration rate	0.0956***	0.1197***	0.0865***	0.1074***	0.0798***
	(0.0118)	(0.0150)	(0.0112)	(0.0129)	(0.0144)
Lagged Predicted ICT spillover	0.0199***	0.0234***	0.0181***	0.0197***	0.0226***
	(0.0024)	(0.0029)	(0.0022)	(0.0024)	(0.0026)
Growth of physical capital per capita	0.0555***	0.0542***	0.0689***	0.0561***	0.0553***
	(0.0118)	(0.0119)	(0.0102)	(0.0120)	(0.0118)
Growth of education years	0.0169*	0.0139	0.0136	0.0164*	0.0139
	(0.0098)	(0.0099)	(0.0096)	(0.0099)	(0.0100)
ΔGrowth of population	− 0.3058***	− 0.3141***	− 0.3039***	− 0.3047***	− 0.3051***
	(0.0310)	(0.0269)	(0.0310)	(0.0309)	(0.0318)
Years since ICT exceeded critical mass	− 0.0095***	− 0.0111***	− 0.0086***	− 0.0096***	− 0.0097***
	(0.0009)	(0.0010)	(0.0009)	(0.0009)	(0.0009)
GDP per capita in 2000	− 0.0015	− 0.0035	− 0.0017	− 0.0016	− 0.0026**
	(0.0013)	(0.0034)	(0.0012)	(0.0013)	(0.0013)
Post-crisis period	− 0.0026	− 0.0053	− 0.0002	− 0.0033	− 0.0015
	(0.0046)	(0.0047)	(0.0043)	(0.0045)	(0.0045)
Coast	− 0.0047	− 0.0045	− 0.0070***	− 0.0058**	− 0.0029
	(0.0029)	(0.0029)	(0.0027)	(0.0029)	(0.0031)
Telephony capacity per capita in 1993	− 0.0006				
	(0.0007)				
Log of FDI investment/GDP			0.0026		
			(0.0023)		

Table 8 (continued)

Dep. Growth of GDP per capita	(1)	(2)	(3)	(4)	(5)
Log of area of paved road per capita				− 0.0040**	
				(0.0016)	
Log of education years					0.0100**
					(0.0049)
Constant	0.1707***	0.1809***	0.1570***	0.1680***	0.1765***
	(0.0079)	(0.0091)	(0.0078)	(0.0080)	(0.0082)
First-stage F statistics	28.8919	24.7284	28.4596	28.0939	30.3279
Endogeneity test (p value)	0.0000	0.0000	0.0000	0.0000	0.0000
Hansen J test (p value)	0.2510	0.2402	0.5544	0.4122	0.3262
C-test for $yearnum_{it}$ (p value)	0.1063	0.0955	0.1131	0.1278	0.1170
R^2	0.2345	0.2268	0.2563	0.2303	0.2348
Observations	3600	3480	3500	3574	3600

Robust standard errors are shown in the parenthesis
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

The validity of the instrument rests on the conjecture that the instrument is not related to the error term in the regression model. On the one hand, the instrument should not impact on economic growth through channels other than ICT development; on the other hand, there exists no confounders that are associated with telephony switchboard and economic growth. Since the telephony switchboard is the telecommunication infrastructure element that serves telecommunication services, no evidence is found that it would exert influences on economic growth through channels other than telecommunication.

One might argue that cities with more market-oriented economies may enjoy more openness and competitiveness, and hence would have had a more developed telephony switchboard system in 1993 and remain strong economic growth in twenty-first century. If that is the case, marketization becomes one confounder which dampens the IV result. To verify this, we conduct two more robustness checks. First, we remove special economic zones (SEZ) and cities with "special status" in China as a check. Specifically, Shenzhen city, Zhuhai city, Shantou city, Xiamen city, and Hainan province as five SEZ regions are excluded from analysis,[17] as well as Beijing and Shanghai, the political and economic centres in China. Column (2) in Table 8 reports the results. The main conclusions from the IV regression remain hardly changed. In addition, Column (3) in Table 8 controls foreign direct investment (FDI) as a portion of GDP in the cities as an additional experiment. This variable shows no effects on improving cities' economic efficiency and hence the main conclusions are hardly affected.

Column (4) in Table 8 includes cities' infrastructure development. The argument is that ICT may only be a proxy for a city's basic infrastructure development like transportation, power supplies, and plants and building. The effects of ICT on efficiency improvement thus capture only the impacts of cities' infrastructure development. To test this, we use the per capita paved road area as a proxy for a city's basic infrastructure development. The inclusion of infrastructure development does not diminish the effects of ICT on economic growth. Furthermore, we follow Czernich et al. (2011) and add the level of schooling years as a robustness check in Column (5) of Table 8. It is argued that human capital would improve innovation capacity and economic development and ICT is only a proxy for advanced human capital. However, both ICT's direct and indirect effects are found to be positive and statistically significant even after the level of schooling years is controlled.

In addition, spatial interdependence may dampen our IV results and generate biased estimates. According to Betz et al. (2020), IV estimates are commonly immune to common sources of bias due to omitted variables, measurement error, simultaneity or reverse causality, but help little with a special case of confounding: unmodeled spatial interdependence. Appendix C shows more details about this argument. To identify the spatial dependence, we use the global Moran's I based on the error terms obtained from our IV estimates. Table 10 in the appendix lists Moran's I index, Z-scores and P-statistics. Accordingly, the null hypothesis cannot be rejected, which implies that no unmodelled spatial interdependence is left in our IV residuals.

[17] In 1979, Shenzhen city (Guangdong province), Zhuhai city (Guangdong province), Shantou city (Guangdong province), and Xiamen city (Fujian province) were established as four SEZ to enjoy more flexible regulations and economic freedom. In 1988, Hainan province was established as the fifth SEZ. In our sample, cities in Hainan provinces include Sanya city and Haikou city.

Finally, it is noticed that the magnitude of our IV estimators is much larger than that of OLS estimators. This may challenge the validity of the instruments. Though a crude comparison in coefficients is pointless,[18] sizeable differences between OLS and IV estimates might be interpreted as evidence of invalid instruments (Ciacci 2021). Here, we adopt the method of Ciacci (2021) and Oster (2019) to make a comparison between our IV and OLS estimates (see more details in Appendix D). A parameter known as the *size of proportionality* is calculated to show how large selection on unobservables relative to observables is needed to support the size difference between the IV and OLS estimators. An extreme large *size of proportionality* would indicate the invalidity of our instruments. According to Table 11 in the Appendix, only if selection on unobservables is about one-sixth to one-fourth of selection on observables, it is enough for the true treatment effect to have the size of our IV estimates. In other words, the difference between the size of our OLS and IV estimators is not sizeable and hence the validity of our instruments is supported.

6 Conclusion

This paper investigates the relationship between ICT development and economic growth in China's context. It shows a positive and significant effect of ICT on city-level economic development. An increase in ICT penetration rate of ten percentage points would lead to about 0.9–1.1 percentage points increase in the annual growth rate in Chinese cities during 2001–2016 and the relationship is robust after the validity of the instruments is checked. In addition, advanced ICT development would improve cities' efficiency by not only generating knowledge and innovation but also absorbing technological diffusions from the frontier city. Technological diffusions in this case are less related to cities' geographic locations after taking geographic and geomorphic conditions into account. In other words, distant cities would benefit as much as cities closer to the technological frontier from technological diffusions should the level of ICT development be the same in the cities.

We conclude by discussing relevant future research directions. First, we did not account for the quality improvement of ICT development. ICT technology evolves fast. The utility of fifth-generation telecommunication, optical fibre, web of things and so on alters the way that ICT affects economic growth. It would be interesting to examine patterns and channels through which different ICT facilities impact on city-level economic development if relevant data is publicly released in the future. Second, we focus only on the extensive margin of ICT use under the assumption that the intensiveness of ICT use distributes equally across cities. When relevant information becomes accessible, this assumption could be relaxed so that the intensive margin of ICT use can be analysed.

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[18] The magnitude of IV estimator also relies on the covariance between the instrumental and instrumented variables.

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Declarations

Conflict of interest The authors have no conflict of interest to declare that are relevant to the content of this article.

Appendix A

Explicitly, the instrumental variable of ICT_{it} is $Tele\_Switch_{1993} \cdot yearnum_{it}$, and the instrumental variable of $ICT_{it}\left[\frac{(Y/L)_{max,t}-(Y/L)_{it}}{(Y/L)_{it}}\right]$ is $Tele\_Switch_{1993} \cdot yearnum_{it} \cdot \left[\frac{(Y/L)_{max,t}-(Y/L)_{it}}{(Y/L)_{it}}\right]$. Thus, the first stage regression is: $\widehat{ICT_{it}} = \delta_0 + \boldsymbol{\delta}_1\mathbf{X_{it}} + \delta_2 IV_{it} + \delta_3 IV_{it} \cdot \left[\frac{(Y/L)_{max,t}-(Y/L)_{it}}{(Y/L)_{it}}\right] + \delta_4 yearnum_{it}$ and $ICT_{it}\widehat{\left[\frac{(Y/L)_{max,t}-(Y/L)_{it}}{(Y/L)_{it}}\right]} = \eta_0 + \boldsymbol{\eta}_1\mathbf{X_{it}} + \eta_2 IV_{it} + \eta_3 IV_{it} \cdot \left[\frac{(Y/L)_{max,t}-(Y/L)_{it}}{(Y/L)_{it}}\right] + \eta_4 yearnum_{it}$, where IV_{it} is $Tele\_Switch_{1993} \cdot yearnum_{it}$ and $\mathbf{X_{it}}$ denotes the set of other covariates such as the growth rate of population, the accumulation of physical and human capital. It is clear that $yearnum_{it}$ is also included in the second-stage equation, the effect of ICT on growth is identified by variation in ICT across cities conditional on each roll-out process.

Appendix B

See Table 9.

Table 9 Growth-enhancing analysis: fixed effect model. *Source*: Authors' own estimates

Dep. Growth of GDP per capita	(1)	(2)	(3)	(4)
Predicted ICT penetration rate	0.1012**		0.1001***	
	(0.0510)		(0.0347)	
Lagged predicted ICT penetration rate		0.1153***		0.0907***
		(0.0409)		(0.0336)
Lagged predicted ICT spillover	0.0456***	0.0483***		
	(0.0048)	(0.0044)		
2Year-Lagged predicted ICT spillover			0.0576***	0.0585***
			(0.0041)	(0.0041)
Growth of physical capital per capita	0.0494***	0.0515***	0.0448***	0.0494***
	(0.0116)	(0.0119)	(0.0116)	(0.0116)
Growth of education years	0.0143	0.0120	− 0.0039	0.0143
	(0.0097)	(0.0098)	(0.0127)	(0.0097)
ΔGrowth of population	− 0.3074***	− 0.3120***	− 0.3240***	− 0.3074***
	(0.0271)	(0.0273)	(0.0278)	(0.0271)
Years since ICT exceeded critical mass	− 0.0115***	− 0.0135***	− 0.0105***	− 0.0115***
	(0.0014)	(0.0016)	(0.0014)	(0.0014)
Post-crisis period	0.0110**	0.0078*	0.0173***	0.0110**
	(0.0046)	(0.0047)	(0.0051)	(0.0046)
First-stage *F* statistics	18.7703	17.2579	16.1801	18.7103
Endogeneity test (*p* value)	0.0000	0.0000	0.0000	0.0000
Hansen *J* test (*p* value)	0.1486	0.1608	0.1876	0.1276
C-test for $yearnum_{it}$ (*p* value)	0.2800	0.3865	0.3515	0.2133
City FE	Yes	Yes	Yes	Yes
R^2	0.2847	0.2679	0.2986	0.2847
Observations	3360	3360	3360	3360

Robust standard errors are shown in the parenthesis. 2. The sample size is restricted to 3360 in Columns (1) and (2) for comparison purposes

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Appendix C

Consider a simple linear-additive model:

$$y = \beta x + e \tag{C1}$$

$$x = \gamma z + v \tag{C2}$$

where y is a vector of outcomes, x the endogenous variables, z a suitable set of instruments. If there exists spatial interdependence that is ignored in the estimation, the disturbance e can be decomposed as $e = \rho \boldsymbol{W} y + u$. In such case, a unit's outcome affects the actions of other units through cross-sectional interdependence that is captured by ρ, while $\boldsymbol{W}$ is the connectivity matrix that identifies the units' relationship. In such case, the probability limit of the IV estimator is expressed as:

$$plim_{n\to\infty}\dot{\beta}_{2sls} - \beta = \frac{\rho \times cov(\boldsymbol{W}y, z)}{cov(x, z)} + \frac{cov(u, z)}{cov(x, z)} \tag{C3}$$

Since z is the suitable instruments, it satisfies the usual assumption that $cov(u, z) = 0$. However, the instruments are still correlated with the term $\boldsymbol{W}y$. Unless $\rho = 0$, the IV estimator violates the exclusion restriction and suffers from the spatial bias (see details in Betz et al. 2020).

Therefore, we use the global Moran's I index to investigate if any spatial autocorrelation is left in the error terms of our IV results in each year. Table 10 displays the results. According to the p values in each year, we cannot reject the null hypothesis and conclude safely that the spatial interdependence is not a big concern in this context.

Table 10 Global Moran *I* Index of error terms. *Source*: Authors' own estimates

Year	Moran' I	$E(I)$	Sd(I)	Z	p value	Year	Moran' I	$E(I)$	Sd(I)	Z	p value
2001		–	–	–	–	2009	− 0.004	− 0.004	0.000	− 0.008	0.497
2002	− 0.004	− 0.004	0.000	− 0.003	0.499	2010	− 0.004	− 0.004	0.000	0.007	0.497
2003	− 0.004	− 0.004	0.000	0.001	0.500	2011	− 0.004	− 0.004	0.000	− 0.001	0.500
2004	− 0.004	− 0.004	0.000	0.012	0.495	2012	− 0.004	− 0.004	0.000	0.010	0.496
2005	− 0.004	− 0.004	0.000	− 0.003	0.499	2013	− 0.004	− 0.004	0.000	0.005	0.498
2006	− 0.004	− 0.004	0.000	− 0.006	0.498	2014	− 0.004	− 0.004	0.000	0.002	0.499
2007	− 0.004	− 0.004	0.000	− 0.002	0.499	2015	− 0.004	− 0.004	0.000	− 0.001	0.500
2008	− 0.004	− 0.004	0.000	− 0.005	0.498	2016	− 0.004	− 0.004	0.000	− 0.004	0.498

The specification in the table is the same as the specification used in Column (4) of Table 4. The binary weights matrix is used

Appendix D

According to Oster (2019), the true treatment effect depends on the relative size of the proportionality between selection on observables and unobservable. Therefore, if IV coefficient is a consistent estimator, we can compute how large the size of the proportionality needs to be to support the difference in size between the OLS and IV estimator (Ciacci 2021). If the size of the proportionality is extremely large, it would imply that super large selection on unobservables, compared to observables, is needed to support the "true effect" of the IV estimates, which would thus indicate the invalidity of the instruments or the heterogenous effects for a subpopulation.

Explicitly, the population regression function is expressed as:

$$y_{it} = \alpha_1 + \beta_1 d_{it} + \gamma w_{it} + \theta_1 X_{it} + \varepsilon_{1it} \tag{D1}$$

where d_{it} indicates the variable of interest, w_{it} the unobserved controls and X_{it} the observed controls. With omitted variables, the regression specification becomes:

$$y_{it} = \alpha_2 + \beta_2 d_{it} + \theta_2 X_{it} + \varepsilon_{2it} \tag{D2}$$

The relative size of the proportionality under the assumption of Oster (2017) is given by:

$$\delta \frac{Cov(d_{it}, X_{it})}{Var(X_{it})} = \frac{Cov(d_{it}, w_{it})}{Var(w_{it})} \tag{D3}$$

and the omitted variable bias is given by:

$$\widehat{\beta_2} = \beta_1 + \gamma \frac{Cov(d_{it}, w_{it})}{Var(d_{it})} \tag{D4}$$

Since IV estimator is the consistent estimator of β_1, we can compute how large δ is needed to support the difference in size between the OLS estimate and the IV estimate by plugging Equation (D3) into Equation (D4):

$$\delta = (\widehat{\beta_2} - \beta_1) \frac{Var(d_{it})Var(X_{it})}{\gamma Var(w_{it})Cov(d_{it}, X_{it})} \tag{D5}$$

A large δ implies a large selection on unobservables, compared to observables, in order to support the true effect of the IV estimator. Therefore, a large δ would indicate either that the instrument is not valid or that there are heterogenous effects in subpopulation.

Table 11 compares the results of Tables 3 and 4 and shows how large δ is needed to support the true effect of our IV estimators. Accordingly, as long as selection on unobservables is about one-sixth to one-fourth of selection on observables, it is enough for the true treatment effect to have the size of our IV estimates. In other words, the difference between the size of our OLS and IV estimators is not sizeable and hence the validity of our instruments is supported.

Table 11 Comparison between OLS and IV coefficients in Tables 3 and 4. *Source*: Authors' own estimates

	OLS coefficient	IV coefficient	δ
Column (1)	0.0347***	0.0985***	0.1437
Column (2)	0.0388***	0.1113***	0.1678
Column (3)	0.0456***	0.0892***	0.2473
Column (4)	0.0476***	0.0921***	0.2533

δ is calculated based on the STATA command "psacalc"

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