# Is Information and Communication Technology a Productivity Drain or Gain? Evidence from the Health Services Sector in China

Philip Arestis[1], Mianshan Lai[2], Lu Miao[3]

Received: 8 February 2024. Paper by invitation

**Abstract:** This contribution investigates the impact of information and communication technology (ICT) on health service performance and considers the issue of income inequality. It provides empirical evidence that the development of ICT helps to mitigate the negative impact of income inequality on health and thereby providing support for the vigorous development of ICT. Specifically, by using the Driscoll-Kraay standard error estimation, Generalized Method of Moments, and a panel threshold model, a nonlinear relationship is detected, and the results show that: (1) ICT can significantly promote the performance of the health service sector. As income inequality increases, the effects of ICT on health care performance become larger. (2) With the increase from a lower to a higher income inequality level, the positive impact of ICT development on health service enables productivity to increase significantly. Finally, policy recommendations for promoting health service productivity, based on our theoretical contribution and empirical results, are provided.

**Keywords:** Health service performance, ICT, Income inequality, Panel threshold regression
**JEL Classification:** H51, I18, O3

## 1. Introduction

“Health services are one of the fundamental sectors of society and the economy. Providing social health protection and equal access to quality health care has significant positive effects on individual and public health, economic growth and development” (International Labor Organization, 2022, p. 1). The importance of health service is also highlighted in the 17 Sustainable Development Goals (SDGs), which is integrated in the post-2015 United Nations (UN) agenda that was adopted by governments at the UN General Assembly. These goals seek to eliminate poverty, minimize inequality, and promote inclusive economic growth; and population health is a crucial contributor

[1] University of Cambridge, CB3 9EP Cambridge, UK. Email: pa267@cam.ac.uk

[2] Correspondence: China Centre for Special Economic Zone Research, Shenzhen University, 518060 Shenzhen, China. Email: laimianshan@live.cn

[3] Correspondence: School of Economics，Guangxi University, 530004, Nanning, China. Email: miaolu_nagoya@163.com

and beneficiary of them all. Particularly, health is explicitly articulated in the post-2015 agenda: SDG 3 ("Ensure healthy lives and promote well-being for all at all ages"; Pettigrew et al., 2015). Aside from SDG 3, in the 17 SDGs, health is positioned in a broad context and treated as a key feature of human development, with emphasis on human health, which guarantees implementation of the SDGs for all three pillars (society, economy, and environment) and in turn is affected by other SDGs (WHO, 2015).

Abundant literature has highlighted the crucial role of Information and Communication Technology (ICT) in health and productivity promotion (Lee et al., 2016; He et al., 2019). ICT is a general-purpose type of technology that covers all communication devices or applications and a series of related services and software (Zhu et al., 2020). While the penetration of ICT has reached saturation in developed provinces, it still has development potential in the majority of China's regions. It is noteworthy that owing to different economic structures and development phases, when compared with developed countries, the effects of ICT penetration in promoting the productivity of China's health sector remains unclear (He et al., 2019). To address the increasing difficulty and cost of access to medical treatment in China, ICT presents new and cost-effective ways for both doctors and patients (Ueckert et al., 2003). In recent years, with the popularity of wireless technologies, emerging health service systems (e.g., internet hospitals) can effectively attend to long-term health care needs and expenditures, as well as promote the efficiency of traditional hospitals.

However, despite many studies confirm the positive relationship between ICT and health (Lee et al., 2016; Fareed et al., 2021), the influence of ICT on health service productivity is unclear since there are studies illustrating some negative impacts of ICT development on the health services sector. For example, the displacement theory (Kouton et al., 2021) emphasizes the negative effects of technology and holds that people's excessive time investment reduces their time for other activities, such as sports activities, which lead to health problems such as bone pain and sleep difficulties. Newby (2019) pointed out that paying too much attention to online health information can easily cause people to have online health anxiety, making them overly concerned about their health. Marques et al. (2015) found that long-term exposure to screens can also make teenagers feel depressed or irritable. Do et al. (2020) pointed out that quite a lot of people in Vietnam feel obviously anxious after stopping the use of electronic devices.

Therefore, the development of ICT has been hampered by the negative impacts of ICT on the health sector. As the research on the impact of ICT development on health service performance is still in its infancy, this paper aims to bridge this gap by providing relevant theoretical framework and relevant empirical research to alleviate concerns about conflicts between ICT development and the health service sector. By employing the Driscoll and Kraay (1998) estimator, the Generalized Method of Moments, and a panel threshold model, this paper shows that the development of ICT helps to mitigate the negative impact of income inequality on health. This supports our theoretical contribution to the vigorous development of ICT. In summary, we believe that although developing ICT may have side effects, ICT development can benefit low-income groups, thereby improving health service performance. By revealing the positive correlation between ICT development and health, we provide the empirical evidence to also support the United Nations SDG policy.

In view of the existing literature, this study contributes in three ways. First, we integrate the research on the effects of ICT on health and productivity to investigate the influence of ICT on health service productivity. Second, we innovatively investigate the nonlinear relationships between ICT development and health service productivity with respect to inequality by using a threshold regression model. Third, the mainstream of existing research focuses on the relationship either between ICT and health or income inequality and health, whereas this study clarifies the threshold effect of income inequality on the influence mechanism between ICT and health service productivity; thus enhancing the literature streams on both income inequality and health.

The rest of this paper is organized as follows. Section 2 discusses background issues. Section 3 provides the theoretical and empirical background and proposes the hypothesis of our research; section 4 discusses the methodology and data used in the study; section 5 elaborates on the empirical results, and section 6 summarizes the main conclusions and policy implications.

## 2. Background Issues

In light of the post-2015 agenda, the central government and Chinese scholars agree on the importance of health in realizing sustainable development. In 2016, the State Council issued the "Healthy China 2030" plan outline, which pointed out that "health is a priority development strategy" and that "health should be placed in a strategic position of priority development" (CPC Central Committee and State Council, 2016). Since the reform and opening, the average life expectancy of Chinese residents has increased from 67.9 years in 1981 to 76.4 years in 2019; indicators such as infant mortality, maternal mortality, and infectious disease incidence have been significantly reduced (WHO, 2019). However, with the high pace of economic development and promotion of the income level, some new health problems have emerged such as smoking and alcohol abuse and chronic disease due to pressures in life, environmental pollution and so on. Moreover, the unbalanced economic growth and urbanization has been accompanied by long-term increases in income and wealth inequalities (Luo et al., 2020). According to the Wilkinson hypothesis, the larger the income inequalities, the higher the mortality rate and the worse human health will be (Wilkinson and Pickett, 2006). Moreover, to improve residents' health, the government has increasingly invested social resources in health production. From 2009 to 2020, China's total medical and health expenditure increased from 1,754.2 billion yuan (5.03% of GDP) to 7,230.6 billion yuan (7.1% of GDP; National Bureau of Statistics of China, 2020). Although health investment in China has been promoted significantly in the past forty years, the difficulty and high cost of access to medical treatment are becoming more serious. Despite the growth in expenditures on health care services, irrationality and profligacy have led to inefficiency in China's health care system (Yip et al., 2008). With China's economic growth shifting from high-speed to medium-to-high speed, it is unrealistic to rely solely on expanding health inputs to improve residents' health. Thus, considering China's development status, improving the productivity of the health service system by leveraging on Information and Communication Technology (ICT) development and reducing income inequality might be more effective in realizing SDG 3 and a healthy China. However, the agenda does not explain whether the development of ICT will contribute to improved performance in health services.

## 3. Relevant Literature and Hypothesis

### 3.1 ICT and health

Does ICT enhance and improve health service and health behaviour? Theoretically, Kouton et al. (2021) concluded three theories that explain the influence mechanism between ICT and health, including use and gratification, technology acceptance, displacement, and health behavior change, as well as the health-belief model. From the positive side, the use and gratification theory holds that people can obtain satisfaction through social interaction, opinion expression, information search and communication, and other behaviors when using technology, which result in the improvement of health. Technology acceptance theory is mainly based on the research of Davis (1989), suggesting that internet technology is useful and easy to use. If people get the same information from doctors, then people are more willing to use the Internet to obtain health information, because information from the internet is instant and easy to obtain. Ahadzadeh et al. (2015) proved that the technology acceptance theory plays an important intermediary role when people use health-related information from the internet. Health behavior-change theory suggests that health professionals can use ICT to help people improve their health behaviors, thereby enhancing the health of patients. Cook (2013) found that ICT-based assistive technology can help improve the quality of life of some dementia patients. As a widely used technology, ICT cannot only achieve point-to-point matching, but also achieve a larger range of connections, strengthen inter-regional connections, make medical resources flow better to underdeveloped areas, and enhance the efficiency of medical resource. From the negative side, the displacement theory emphasizes the negative effects of technology and holds that people's excessive time investment reduces their time for other activities such as sports activities, which lead to health problems such as bone pain and sleep difficulties. For example, Do et al. (2020) pointed out that quite a lot of people in Vietnam felt obviously anxious after stopping the use of electronic devices. Newby (2019) pointed out that paying too much attention to online health information could easily cause people to have online health anxiety, making them overly concerned about their health.

Empirical research on the impact of ICT development on health focuses on several aspects. One is the relationship between ICT and health. Lee et al. (2016) studied the impact of Internet and communication equipment penetration rates in 61 countries on various health indicators; they found that the penetration rate was positively correlated with life expectancy and related to the decline in infant mortality and tuberculosis incidence. However, they also found that the popularity of the Internet was related to the high prevalence of AIDS. By comparing developed and developing countries, Văidean and Achim (2022) demonstrate that the impact of ICT on health outcomes is nonlinear. They suggest that the growth of ICT infrastructure in developed countries cannot effectively improve health outcomes. Kouton et al. (2021) studied economic development, ICT, and child mortality in Africa and found that there was a complementary relationship between economic development and ICT, and their complementary effects on child mortality were negative. Another focus is the influence mechanism of the impact of ICT on health. Zhao and Li (2020) found that access to the Internet helped people gain more health knowledge to improve their living conditions and promote health. Zhang et al. (2022) argue that the ICT can improve health outcome through increasing government's health expenditure. The third focus is the communication mechanism (psychological mechanism) of the impact of ICT on health. Lu and Wang (2020) also studied the impact of internet use on residents' self-evaluated health and found a positive promotion effect, indicating that the mechanism of action was mainly information acquisition. The empirical research has verified that both positive and negative impacts exist between ICT and health.

3.2 The relationship between income and health

There are three main views on the impact of income on health, represented by the absolute income, relative income, and income inequality hypotheses.

The absolute income hypothesis holds that a high income is a prerequisite for a healthier environment and better medical services. Preston (1975) and Rodgers (1979) put forward this point early on and empirically proved that there is an obvious relationship between absolute income and mortality or life expectancy. Preston (1975) also proposed that an increase in income helps improve health, but its marginal effect diminishes. The absolute income hypothesis has been proven and examined in depth by later researchers. For example, Li and Zhu (2006) studied the impact of per capita income and residents' self-assessed health in China to prove that increased income had a diminishing positive impact on health. Celeste and Nadanovsky (2009) studied the relationship between Brazilian adolescent's health and income and found a positive correlation between the two, but a 'threshold' exists. Apouey and Geoffard (2014) studied the relationship between child health and family income in France and found a significant positive correlation between them.

Relative income influences health through several paths. One is through material channels (i.e., absolute income channels). People with relatively low incomes have difficulty in obtaining health-improving nutrition and medical resources and are less likely to cope with poor material conditions (Qi and Lu, 2015). The second is through psychological stress. When individuals are in a disadvantaged position in the economy and society, they typically harbor negative emotions, stress, and anxiety, which may cause bad habits such as smoking and alcoholism. Long-term stress may also lead to diseases such as high blood pressure, directly or indirectly affecting health (Huang et al., 2019; Lu and Wu, 2019). The third is through the erosion of social capital. Social capital refers to networks, trusts, and norms that can improve economic efficiency through coordinated actions (Putnam et al., 1993); that is, having trust between citizens, rules of mutual benefit between domestic groups, and so on are conducive to increasing social cohesion and promoting relations of mutual cooperation among citizens (Feng et al., 2007). The fourth is through the reduction of public goods. When inequality intensifies, low- and high-income groups are more likely to have inconsistencies in interests, which cause under-estimation of the value of public goods, resulting in a decrease in public policies, public services, and public goods. This means that the poor will have fewer opportunities to improve their physical environment and obtain public medical resources (Simpson et al., 2021). After the reform and opening, China has experienced rapid economic development. Although the overall absolute income has increased significantly, the development between different provinces and cities is extremely unbalanced, and the problem of income inequality is becoming increasingly prominent.

### 3.3 The relationship between ICT and income inequality

Research in recent years has shown that the application of ICT in some areas can help reduce inequality. Tchamyou et al. (2019) studied how the application of ICT technology in the financial sector in African countries affected inequality. They found that ICT reduced inequality through the development of a formal financial sector. Adams et al. (2021) studied the relationship between ICT development and inequality in Africa and the impact of governance capabilities on the relationship between the two. They found that the development of ICT significantly reduced inequality, and good governance could strengthen the relationship between the two. However, the positive role of ICT has some economic thresholds. Asongu and Odhiambo (2020) studied the impact of ICT development in Africa on women's economic participation. They found that ICT development had a certain threshold for alleviating inequality and increasing the positive role of women's economic participation. Only when the penetration rate of ICT reached this threshold would its positive effect begin to appear. There are also some documents that have studied the impact of income inequality on the diffusion of ICT. Ali et al. (2019) used Australian household panel data to study the impact of income distribution and socio-economic inequality on ICT affordability (where the affordability of ICT was considered to reflect partly the diffusion of ICT). They found that income inequality in high-income groups reduced the ICT affordability of the group, while that in low-income groups was positively correlated with ICT affordability for the group. The reason is that for the high-income groups, the average income of low-income households is not enough to cover the ICT costs, and when income inequality increases, higher-income households in this group will be able to afford the ICT costs. Meanwhile, high-income groups are able to afford such costs, and when income inequality among the group members increases, a larger number of lower-income households in this group will no longer be able to afford these costs. Ma et al. (2019) studied the digital divide among youth groups in various countries and found that income inequality exacerbated the digital divide, but when national income was introduced, its negative impact became insignificant.

The aforementioned studies may indicate that there are thresholds for the diffusion and use of ICT, and a low absolute income is an important reason for limiting ICT diffusion. It can be suggested that income inequality in high-income countries will make it difficult for low-income people to bear the cost of ICT and limit the positive impact of ICT on these people, while income inequality in low-income countries will make ICT affordable for some high-income people, thereby improving the overall benefits. In other words, once the established income threshold is crossed, greater equality will allow more people to benefit from the development of ICT. As shown in the above-mentioned literature, for the countries with different development level, the ICT shows a threshold effect on income inequality.

In summary, the above research has investigated the links between ICT and health outcomes, ICT and economic inequality, as well as income inequality and health outcomes. Focusing on the relationship between ICT and health outcomes, some research concludes that there is a peak in the impact of ICT on health and that the positive impact of ICT on health outcomes gradually decreases once a certain level of economic development is reached. On the one hand, the aforementioned study (Văidean and Achim, 2022) takes an absolute income perspective and evaluates the impact of ICT on average health level, ignoring the positive impact of ICT on health equity. In fact, even in developed economies, the problem of limited access to health care for low-income groups persists. On the other hand, the current literature ignores the impact of ICT on the productivity of the health services sector. The health service sector is typically less productive in developing countries. For example, despite the fact that the Chinese government has significantly increased health-care expenditure in recent years, irrational and ineffective spending has resulted in inefficiency in the health-care sector. Therefore, based on the above relevant literature review and the potential research gap, we make the following hypothesis:

**Hypothesis:** In China, ICT can diminish the negative effects of income inequality on health service productivity and a threshold effect exists among different levels of inequality.

## 4. Empirical Methodology and Data

### 4.1 Estimation strategy

First, using the provincial panel data, we examine to begin with the impacts of ICT on health service productivity denoted by total factor productivity (*TFP)*. The baseline model is:

$$TFP_{it} = a_0 + a_1 ICT_{it} + X^{'}\beta + u_i + \delta_i + \varepsilon_{it} \qquad (1)$$

where $TFP_{it}$ denotes the technological progress of province *i* in period *t*; $a_0$ is the intercept term; $ICT_{it}$ includes the internet penetration and mobile phone penetration; $X$ represents a set of control variables; $u_i$ denotes the province-specific effect; $\delta_i$ represents the time-specific effect, and $\varepsilon_{it}$ denotes the regression disturbance.

Further, this study investigates the transmission mechanism among *TFP, ICT,* and income inequality (*GINI*). Then we center the multiplication term to address the collinearity problem. The extended model is as follows:

$$TFP_{it} = a_0 + a_1 ICT_{it} + a_2 ICT_{it} \times GINI_{it} + a_3 GINI_{it} + X^{'}\beta + u_i + \delta_i + \varepsilon_{it} \qquad (2)$$

Due to the spillover effects among different regions, the potential issue of cross-sectional dependence (CD) should be considered for otherwise it will lead to biased estimation. The CD test of Pesaran (2004) is conducted to detect the simultaneous correlation among different regions. Confirming the existence of CD issues (as shown in Table A.1 in the appendix), we then conduct the unit roots test by second generation panel unit roots (CIPS) (Pesaran, 2007). As shown in Table A.2 (in the appendix), all of the variables are stationary at I (1). In addition to the issue of CD and CIPS, we further conduct the correlation test of Wooldridge (2003) to check the serial correlation. Wooldridge test F statistics for internet and mobile penetration models are 36.67 and 46.66, respectively. The calculated results are significant at the 1% level, showing that serial correlation exists. Finally, the heteroscedasticity test is used to discover heteroscedasticity using the modified Wald test. The Wald test F values for internet and mobile penetration models are 16.84 and 13.25, respectively, and are significant at the 1% level. As a result, the heteroscedasticity problem is proven.

To guarantee an unbiased statistical inference, a 'robust' error term is crucial. Basically, the White (1980) estimator is proper to deal with the problem of heteroscedasticity; however, it is not appropriate for panel data owing to the existence of autocorrelation. Further, Rogers (1993) was able to deal with the simultaneous heteroscedasticity and autocorrelation of panel data but could not address the issue of CD. As shown in Table A1, all variables have CD issues. To consider the issue of cross-sectional and temporal dependence, Driscoll and Kraay (1998) modified the above-mentioned covariance matrix estimator to overcome the deficits of the White and Roger estimators in the presence of CD, serial correlation, and heteroscedasticity. Therefore, we conduct the Driscoll and Kraay (1998) estimator to investigate the influence mechanism of income inequality and ICT on health care performance (as shown in Table 2 below).

4.2 Panel Threshold Model

To estimate further the nonlinear effects of ICT on TFP, the panel threshold model developed by Hansen (1999, 2000) is applied. By applying income inequality as the threshold variable, the panel threshold model is constructed. Moreover, by using the panel threshold model, the structural change of the relationship among ICT development, income inequality, and health care service productivity, can be explored to determine if there is a nonlinear relationship. A single threshold model is constructed as follows:

$$TFP_{it} = a_0 + a_1 ICT_{it} \times I(GINI_{it} < \gamma) + a_2 ICT_{it} \times I(GINI_{it} \geq \gamma) + X^{'}\beta + u_i + \delta_i + \varepsilon_{it} \qquad (3)$$

where GINI represents the threshold variable, denoting the inequality; $\gamma$ denotes the value of the threshold; $I(\cdot)$ depends on GINI and $\gamma$, and if the function in the parentheses is true then $I(\cdot) = 1$ or $I(\cdot) = 0$. This model is emerged from our hypothesis discussed in section 3.

4.3 Generalized method of moments (GMM)

In this study, we further use GMM estimation to guarantee the robustness of the baseline estimation. There are four reasons that motivate us to adopt a GMM estimation strategy. First, in terms of endogeneity, during the process of instrumentation, GMM can deal with unobserved endogeneity by controlling simultaneity and time invariant omitted variables. Second, the number of provinces (N = 30) is larger than the corresponding number of periods (T = 13), which meets the criteria for GMM. Third, GMM can deal with the persistence of technological progress, that is, the correlation between its levels and the first difference series are higher than the rule of thumb of confirming the existence of persistence 0.800 (Asongu et al., 2019 and Tchamyou et al., 2019). Finally, in the estimation process, the structure and characteristics of the panel data is in line with the GMM estimation that can account for cross-regional differences. To address the problem of cross-sectional dependence and to constrain the proliferation of an instrument through collapsing instruments, we adopt the difference GMM estimation developed by Roodman (2009a, 2009b).

The equations of a standard system GMM in level and in the first difference is as follows:

$$TFP_{it} = a_0 + a_h TFP_{i,t-\tau} + a_1 ICT_{it} + a_2 ICT_{it} \times GINI_{it} + a_3 GINI_{it} + \sum_{m=1}^{k} \beta_m X_m + u_i + \delta_i + \varepsilon_{it} \quad (4)$$

$$\begin{aligned} TFP_{it} - TFP_{i,t-\tau} = & a_4(TFP_{i,t-\tau} - TFP_{i,t-2\tau}) + a_1(ICT_{it} - ICT_{i,t-\tau}) \\ & + a_2(ICT_{it} \times GINI_{it} - ICT_{i,t-\tau} \times GINI_{i,t-\tau}) \\ & + a_3(GINI_{it} - GINI_{i,t-\tau}) + \sum_{m=1}^{k} \beta_m (X_{m,i,t} - X_{m,i.t-\tau}) \\ & + (u_i - u_{t-\tau}) + (\delta_i - \delta_{t-\tau}) + (\varepsilon_{it} - \varepsilon_{i,t-\tau}) \end{aligned} \tag{5}$$

where $\tau$ is the coefficient of the auto-regression that equals to one.

Identification, simultaneity, and exclusion restrictions are three fundamental issues in guaranteeing the robustness of the GMM specification.

Identification is defined as the procedure for distinguishing dependent, endogenous, and strictly exogenous variables. Following mainstream studies that are based on GMM, all explanatory variables are treated as potentially endogenous or predetermined indicators, whereas years are considered strictly exogenous variables. Following Roodman (2009b), it is not feasible for time-invariant variables to become endogenous in the first difference; therefore, the years are only considered as exogenous.

To solve the issue of simultaneity, a lagged dependent variable is used as the instrument. To diminish the correlation between fixed-effects and error terms, Helmet conversions are applied to avoid biased estimation results (Arellano and Bover, 1995; Love and Zicchino, 2006; Arestis et al. 2023). Instead of subtracting prior observations from current ones, the transformation deducts forwarding mean-variations from prior observations (Roodman, 2009b). The conversion process allows the conditions of orthogonal or parallel between lagged dependent and forward difference variables.

Regarding the exclusion restrictions, the selected strictly exogenous variables of time-invariant variables have an effect on the explanatory variables exclusively through the potential endogeneity. Moreover, the difference-in-Hansen test (DHT) for instruments is applied to detect whether the exclusion restrictions is statistically valid. Theoretically, the exclusion restriction is statistically valid if only the null hypothesis of DHT could not be rejected. The results are reported in the Tables of Section 4. These results show that we cannot reject the null hypothesis of DHT, indicating that the statistical validity of exclusion restrictions is verified. The results of the Sargan (1975) and Hansen (1982) in terms of the overidentifying restrictions (OIRs) test, indicates that the health care performance is exclusively explained by the instruments through predetermined variables (Beck et al., 2003).

## 4.4 Variable Description

### 4.4.1 Explained variables

Total factor productivity of the health service sector (*TFP*): following mainstream research, this study uses *TFP* to indicate the level of technological advancement. The Malmquist productivity Index was constructed by Malmquist (1953) and developed by Caves et al. (1982), which is based on data envelop analysis (DEA) and applied to estimate the *TFP* of the health care service sector. In the input-oriented DEA model, the health service sector of each province is treated as a decision-making unit. The Malmquist productivity index is constructed based on the following distance function:

$$TFP_i = M_i^{t+1}(x^{t+1}, y^{t+1}; x^t, y^t) = \left[\frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^t(x^t, y^t)}\right]\left[\frac{D_i^{t+1}(x^t, y^t)}{D_i^t(x^{t+1}, y^{t+1})}\right]^{1/2} \tag{6}$$

where $x^t$ represents the vector of inputs in year *t,* and $y^t$ denotes the vector of outputs in year *t*. To calculate equation 6, the vectors of inputs and outputs should be confirmed. The Malmquist productivity index is performed on two inputs and two outputs. For the input variables, we select hospital beds per 1,000 population and hygienic personnel per 1,000 population. For the output variables, the infant mortality and maternal mortality are selected, which are core indicators of sustainable development. All the data are derived from the Yearbook of Health of the People's Republic of China.

4.4.2 Explanatory variables

In this study, mobile capacity and internet penetration are the two core variables that denote the ICT development level of each province. The internet penetration ratio is derived from China's Statistical Report on Internet Development, and mobile capacity is derived from China Statistical Yearbook. Income inequality, denoted by the GINI coefficient, is calculated based on the method of Zhang and Zhao (2014). Following the literature, this study also uses a set of explanatory variables as control variables, namely, the urbanization rate, medical insurance coverage, the proportion of education and medical care costs, and the ratio of educated female. Table 1, below, provides a summary of the descriptive statistics for the variables based on the data available for 30 Chinese provinces between 2006 and 2018. The data for each variable are derived from China Statistical Yearbook and Yearbook of Health of the People's Republic of China.

According to Table 1, the estimated TFP for the health services sector ranges from 0.614 to 2.604 with an average value of 1.106, indicating that there is a significant regional disparity in the productivity of health services across the various Chinese provinces and that some provinces are experiencing a decline in health services sector productivity. Regarding the expansion of ICTs, internet access and mobile phone coverage have likewise grown extremely unevenly. Our research indicates that places with higher levels of economic development also have higher levels of ICT development; for instance, Beijing has the highest level of internet development and Guangdong has the highest level of mobile phone development. Gansu has the lowest level of internet development, and Qinghai has the lowest level of mobile phone development. In 2018, Beijing had the highest level of income inequality, as measured by the GINI coefficient, at 0.644, while Hainan had the lowest level of income inequality, at 0.45. The GINI coefficients of most coastal and central regions with higher absolute incomes are more than 0.5. Comparatively, provinces in the west with lower absolute incomes have a GINI coefficient smaller than 0.5.

Table 1: Descriptive statistics

| Variables | Description | N | mean | sd | min | max |
|---|---|---|---|---|---|---|
| TFP | The change of total factor productivity | 390 | 1.106 | 0.263 | 0.614 | 2.604 |
| Internet | Internet penetration | 390 | 37.72 | 17.69 | 3.779 | 78 |
| Mob | Mobile capacity | 390 | 5,503 | 4,142 | 172 | 23,038 |
| ur | Urbanization rate | 390 | 0.535 | 0.137 | 0.275 | 0.896 |
| edu | Female education rate | 390 | 28.02 | 14.29 | 6.543 | 79.30 |
| GINI | GINI coefficient | 390 | 0.463 | 0.0473 | 0.334 | 0.624 |
| coverage | Medical insurance coverage | 390 | 0.382 | 0.254 | 0.0500 | 1 |
| proportion | Education and medical costs proportion | 390 | 0.232 | 0.0347 | 0.148 | 0.306 |

**Source: Own estimations**

## 5. Empirical Results and Relevant Discussion

### 5.1 Driscoll–Kraay standard error estimation

The Driscoll–Kraay estimator is applied to examine the influence mechanism among TFP, ICT and the GINI coefficient. Models (1) and (4) in Table 2 below, show the impact of internet and mobile penetration on TFP, respectively. The results reveal that the estimated coefficient of internet penetration is 0.009 and is significant at the 1% level, indicating that the effect of internet penetration is positive and statistically significant. Meanwhile, the estimated coefficient of mobile capacity is −0.019 and is not significant at the 10% level, indicating that the influence of mobile capacity on TFP is not significant. However, the approach of only regressing two variables will ignore the possible heterogeneity; therefore, the different effects of ICT on TFP attributable to different income inequalities may not be detected.

Thus, we further introduce the intersection term of income inequality and ICT as shown in models (2) and (3). The results show that the coefficient of both Internet and Mob are negative while the coefficient of Internet * GINI and Mob * GINI are positive and significant at the 1% and 5% levels. The results show that as income inequality increases, the effects of ICT on health care performance become larger. Thus, the results support our hypothesis.

Table 2: Results of the Discoll–Kraay estimator

| | Dependent Variable: TFP | | | |
|---|---|---|---|---|
| | （1） | （2） | （3） | （4） |
| Variable | Internet penetration | | Mobile penetration | |
| Internet | 0.009*** | –0.041*** | | |
| | (6.40) | (-2.86) | | |
| Mob | | | –1.147** | –0.019 |
| | | | (–2.31) | (–0.78) |
| GINI | | –3.759** | –0.312 | |
| | | (–2.37) | (–0.59) | |
| Mob * GINI | | | 2.495** | |
| | | | (2.46) | |
| Internet * GINI | | 0.104*** | | |
| | | (3.55) | | |
| ur | –1.780*** | –1.274*** | –0.974*** | –1.199*** |
| | (–9.11) | (–6.40) | (–5.64) | (–8.04) |
| edu | 0.016*** | 0.011*** | 0.014*** | 0.017*** |
| | (5.76) | (5.22) | (6.37) | (5.55) |
| proportion | –0.634** | –0.393 | 0.078 | –0.186 |
| | (–2.15) | (–1.18) | (0.31) | (–0.83) |
| coverage | –0.280*** | –0.289*** | –0.269*** | –0.255*** |
| | (–5.57) | (–5.44) | (–5.36) | (–4.98) |
| Constant | 1.555*** | 3.055*** | 1.251*** | 1.255*** |
| | (14.50) | (4.36) | (4.19) | (16.43) |
| Year FE | Yes | Yes | Yes | Yes |
| Observations | 390 | 390 | 390 | 390 |
| R-squared | 0.261 | 0.354 | 0.270 | 0.230 |
| Number of groups | 30 | 30 | 30 | 30 |
| Year FE | Yes | Yes | Yes | Yes |

Notes: t-statistics are in parentheses; ***, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively. **Source: Own estimations**

The GMM estimation is widely used to check the potential endogeneity issue of the regression model. System GMM is further used to check the robustness of the model. Table 3 shows the results of the system GMM estimation, which are consistent with the estimation of the Driscoll–Kraay estimator. The reliability and validity of the GMM estimation are confirmed by the serial correlation test statistics denoted by AR (1) and AR (2) and the Hansen test statistic. The table shows that for all the models, the presence of a serial correlation is in the second order rather than the first order. Moreover, according to the Hansen (1982) and Sargan (1975) OIR tests, the existence of over identification is denied. Therefore, the instrumental variables selected in the model are considered valid.

Table 3: The estimation results of system GMM

| | Dependent variable: TFP | | | |
|---|---|---|---|---|
| | (1) | （2） | （3） | （4） |
| Variable | Internet penetration | | Mobile phone penetration | |
| TFP(−1) | 1.024*** | 0.791*** | 0.829*** | 0.880*** |
| | (0.000) | (0.000) | (0.012) | (0.000) |
| Internet | –0.001 | –0.046*** | | |
| | (0.463) | (0.001) | | |
| GINI coefficient | | –4.654*** | | –0.599 |
| | | (0.004) | | (0.458) |
| Internet*GINI | | 0.102*** | | |
| | | (0.001) | | |
| Mob | | | 1.081 | –1.251* |
| | | | (0.521) | (0.058) |
| Mob*GINI | | | | 2.783* |
| | | | | (0.053) |
| Constant | | 2.202*** | | 0.284 |
| | | (0.006) | | (0.415) |
| Control Variables | Yes | Yes | Yes | Yes |
| Time effects | Yes | Yes | Yes | Yes |
| AR(1) | (0.005) | (0.001) | (0.000) | (0.001) |
| AR(2) | (0.362) | (0.453) | (0.100) | (0.386) |
| Sargan OIR | (0.024) | (0.162) | (0.932) | (0.291) |
| Hansen OIR | (0.137) | (0.363) | (0.955) | (0.362) |

| | | | | |
|---|---|---|---|---|
| DHT for instruments | | | | |
| (a) Instruments in levels | | | | |
| H excluding group | (0.087) | (0.763) | (0.925) | (0.417) |
| Dif（null, H = exogenous） | (0.450) | (0.077) | (0.717) | (0.295) |
| (b) IV(years, eq(diff)) | | | | |
| H excluding group | | (0.025) | | (0.159) |
| Dif（null, H = exogenous） | | (0.813) | | (0.493) |
| Instruments | 19 | 27 | 19 | 27 |
| Provinces | 30 | 30 | 30 | 30 |
| Observations | 360 | 360 | 360 | 360 |

**Source: Own estimations**

5.2 Panel threshold regression analysis

Following Wang (2015), a panel threshold regression model is used to examine the threshold effects of income inequality on the influence mechanism between the ICT and TFP of the health service sector. As shown in Table 4, below, the income inequality shows a significant single threshold effect. The threshold values are 0.5601 and 0.5596 for ICT and TFP, respectively. In terms of internet development, the threshold value of GINI coefficient is 0.5601. From the lower income inequality level to higher inequality level, the coefficient of internet increases from 0.009 and 0.016, which are both significant at the 1% significance level. Regarding mobile capacity, the coefficient increased from 0.186 to 0.894 with the increase from a lower to a higher income inequality level. The above results confirm the estimated results of Driscoll–Kraay and GMM estimations, which further reinforce the reliability of our results. Therefore, our hypothesis is verified.

In summary, the panel threshold estimation provides some interesting results. At the low-income inequality level, the effects of ICT development on the performance of the health service sector are lower but show a statistically positive impact. When the income inequality level increased to a high level of inequality, the impacts of ICT increased sharply, indicating that ICT can help eliminate the negative impacts of income inequality on the TFP of the health service sector. The main reasons are elaborated below. Our findings contradict Asongu et al.'s (2020) contention that the favourable impact of ICT on health declines as income inequality increases. In locations with a high GINI index, the expansion of ICT can improve health care sector efficiency and increase social fairness, according to our findings.

Firstly, our results confirm the positive impacts of ICT on health outcomes. Abbott and Coenen (2008) concluded that ICT development can help in the globalization of information, which can facilitate health service delivery in remote areas and thereby promote health at a larger scale. Kouton et al. (2021) investigated the relationship between ICT and economic development and argued that the complementary relationship between the two could help decrease the infant mortality rate.

Secondly, the economic development of China's provinces is accompanied by long-term income inequality; the higher the economic development, the higher the income inequality (Luo et al., 2020). As indicated in the research of Ali et al. (2019), the majority of the population with a low-income level cannot afford ICT facilities, and with income inequality, the high-income group of this population can afford ICT facilities, which enhance the effects of ICT on the health care service sector. Sone et al. (2020) confirmed these results in China, showing that in the low-income provinces of China, especially in the central and western China, the digital development level is low. As discussed by Ma (2019) the absolute low-income level limits the advantages of ICT development, which indicates that in high-income countries the increase of income inequality hinders the positive impacts of ICT development on health care service performance, while in low-income countries, the same will increase the application of the availability of ICT facilities in the high-income groups.

Thirdly, our findings offer new data that differ from earlier research. In comparison research of industrialized and developing countries, Văidean and Achim (2022) have demonstrated that the impact of ICT on health outcomes is nonlinear. They contend that more ICT infrastructure will result in less for people's health outcome in nations with high incomes. Their findings are based on the theory of absolute income and disregard the unequal distribution of ICT infrastructure caused by income inequality. Our empirical findings provide additional evidence that while developing ICT infrastructure, both absolute and relative income should be considered. In regions with high relative income disparities, the growth of ICT plays a crucial role in enhancing the efficiency of the health service sector. In addition, a number of studies imply that ICT improves health outcomes by increasing government spending on health care (Zhang et al., 2022). Our empirical evidence indicates that China's health expenditures are inefficient due to the sector's low productivity. Compared to the promotion of government health expenditure, the most significant contribution of ICT to the health services sector is the rise in productivity, which in turn improves health outcomes. Our findings reassure the government that boosting ICT investment is an effective means of promoting health outcome, and social justice, as opposed to just increasing health expenditures and investments.

Table 4: The estimation of the threshold regression

| | (1) | (2) |
|---|---|---|
| Variable | TFP | TFP |
| Threshold estimation | 0.5601 | 0.5596 |
| P-value | 0.0050 | 0.0033 |
| Mob (GINI < threshold) | 0.186*** | |
| | (5.43) | |
| Mob (GINI > threshold) | 0.894*** | |
| | (8.65) | |
| Internet (GINI < threshold) | | 0.009*** |
| | | (6.62) |
| Internet (GINI> threshold) | | 0.016*** |
| | | (9.18) |
| ur | –2.086*** | –2.376*** |
| | (–4.37) | (–5.03) |
| edu | 0.009*** | 0.004* |
| | (3.89) | (1.68) |
| proportion | –0.152 | –0.360 |
| | (–0.31) | (–0.73) |
| coverage | –0.077 | –0.119** |
| | (–1.36) | (–2.09) |
| Constant | 1.995*** | 2.024*** |
| | (9.22) | (10.16) |
| Year FE | Yes | Yes |
| Observations | 390 | 390 |
| R-squared | 0.285 | 0.291 |
| Number of id | 30 | 30 |

Notes: t-statistics are in parentheses; ***, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively. **Source: Own estimations**

The estimated TFP verifies the government expenditure on health sector that does not efficiently promote health outcome. Only considering the direct relationship between ICT and health or health-service sector will lead biased estimation that will result in ineffective health policies. Considering income disparities, our analysis demonstrates that there is a threshold effect of ICT on the efficiency of health service sector. In contrast to previous studies that have focused on the attenuating effect of income inequality on the health impact of ICT, the findings of this paper suggest that the efficiency of the local health services sector, and thus health, can be increased to a greater extent by enhancing ICT development in areas with a greater income disparity than in areas with lower levels of income inequality. The estimated results confirm our hypothesis that, even though the influence of ICT on health output falls as income inequality increases, ICT can be used for more than only improving health outcome. Faced with income inequality, local governments can enhance the productivity of the health services industry through ICT development, thereby improving the population's health.

## 6. Summary, Conclusions and Policy Implications

With the increasing need to promote public health in China, this study innovatively includes ICT development, income inequality, and the TFP of the health service sector in a unified research framework. To investigate further the non-linear impacts of ICT development on the performance of the health service sector, a panel threshold regression method is applied. This study further clarifies how ICT helps to improve public health and offers empirical basis for realizing SDG 3 in developing countries.

Based on the data of China’s 30 provinces for the period 2006–2018, the linear and non-linear impacts of ICT development on the TFP of the health service sector are examined. Two indicators are used to represent ICT development in China: the internet penetration and mobile switch capacity. The results show that both internet and mobile development can significantly promote the performance of the health service sector. With the increase of income inequality from a low to a high level, the positive impacts of ICT development increases, meaning that ICT can help eliminate the negative impacts of income inequality on health outcomes. In China, the economic growth is always accompanied by the increase of income inequality (see, Luo et al., 2020). With the increase of income inequality in China’s provinces, the ICT facilities become affordable for the high-income group, and the spillover effects of ICT could enhance the positive effects of ICT development on health outcomes. Finally, compared with the increase of investment in health-related infrastructure, promoting the availability of ICT facilities is less costly, and more effective.

According to the empirical findings, the role of ICT development on health service performance is confirmed to be crucial. To realize SDG 3 and the objectives of ‘Health China 2030’, the respective policies should highlight the importance of ICT development in the health service sector and actively promote health care consumer engagement in remote areas through digital hospitals. The government can provide subsidies to low-income groups to encourage the consumption of basic ICT facilities. Subsidies can also be provided to the communication company to construct a base station in developing areas. Moreover, in remote areas, it is suggested to build public internet bars to improve internet access for the low-income areas. In addition, the government should conduct public education to popularize internet knowledge and reduce the ‘internet illiteracy rate’. Finally, although ICT development can help reduce the negative effects of GINI coefficient on health service performance, the important role of the absolute income level should not be ignored. Reducing the relative income inequality by promoting the overall income level and ICT application is the best alternative to realize public health promotion in developing countries.

**References**

Abbott P.A. and Coenen A., 2008. Globalization and advances in information and communication technologies: The impact on nursing and health. Nursing Outlook, 56(5), 238-246.

Adams S. and Akobeng E., 2021. ICT, governance, and inequality in Africa. Telecommunications Policy, 45(10), 102198.

Ahadzadeh A.S., Pahlevan Sharif S., Ong F.S. and Khong K.W., 2015. Integrating health belief model and technology acceptance model: an investigation of health-related internet use. Journal of Medical Internet Research, 17(2), e45.

Ali M.A., Alam K., Taylor B. and Rafiq S., 2019. Do income distribution and socio-economic inequality affect ICT affordability? Evidence from Australian household panel data. Economic Analysis and Policy, 64, 317-328.

Apouey B.H. and Geoffard P. Y., 2014. Child health and access to health care in France: Evidence on the role of family income. Revue d'Epidemiologie et de Santé Publique, 62(3), 179-190.

Arellano M. and Bover O., 1995. Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68 (1), 29–51.

Arestis, P., Lai, M. and Hou, J. (2023), "The Effects of Reference Pricing on Housing Market: Evidence from Shenzhen China", *Panoeconomicus*, 70(1), 1-27.

Asongu S.A. and Odhiambo N.M., 2020. Inequality and Gender Inclusion: Minimum ICT Policy Thresholds for Promoting Female Employment in Sub-Saharan Africa. Telecommunications Policy, 44(4), 101900.

Asongu S.A., Orim S.I. and Nting R.T., 2019. Inequality, information technology and inclusive education in sub-Saharan Africa. Technological Forecasting & Social Change, 146, 380-389.

Beck T., Demirgüç-Kunt A. and Levine R., 2003. Law and finance: why does legal origin matter? Journal of Comparative Economics, 31 (4), 653–675.

Caves D.W., Christensen L. R. and Diewert W., 1982. The Economic Theory of Index Numbers and the Measurement of Input, Output, and Productivity. Econometrica,50(6),1393-1414.

Celeste R.K. and Nadanovsky P., 2009. Income and oral health relationship in Brazil: is there a threshold?. Community dentistry and oral epidemiology, 37(4), 285-293.

Cook G.A., Bailey C. and Moyle W., 2013. The impact of ICT-based telecare technology on quality of life of people with dementia: Review of the literature. 2013 6th International Conference on Human System Interactions (HSI), 614-619.

CPC Central Committee and State Council, 2015. "Healthy China 2030" plan outline. Retrived from: http://www.gov.cn/zhengce/2016-10/25/content_5124174.htm (accessed 2022.06.22)

Davis F.D., 1989. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. Mis Quarterly, 13(3), 319-340.

Do H.N., Onyango B., Prakash R., Tran B.X., Nguyen Q.N., Nguyen L.H., Nguyen H.Q.T., Nguyen A.T., Nguyen H.D., Bui T.P., Vu T.B.T., Le K.T., Nguyen D.T., Dang A.K., Nguyen N.B., Latkin C.A., Ho C.S.H. and Ho R.C.M., 2020. Susceptibility and perceptions of excessive internet use impact on health among Vietnamese youths. Addictive Behaviors, 101, 105898.

Driscoll, J.C. and Kraay, A.C., 1998. Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. Review of Economics and Statistics, 80, 549–560.

Fareed N., Swoboda C.M., Jonnalagadda P. and Huerta T.R., 2021. Persistent digital divide in health-related internet use among cancer survivors: findings from the Health Information National Trends Survey, 2003-2018. Journal of Cancer Survivorship, 15(1), 87-98.

Feng J. and Yu Y.Y., 2007. Income Inequality and Health in Rural China. Economic Research Journal, 01, 79-88. (in Chinese)

Hansen L.P., 1982. Large Sample Properties of Generalized Method of Moments Estimators. Econometrica. 50 (4): 1029 – 1054.

Hansen B.E., 1999. Threshold effects in non-dynamic panels: estimation, testing, and inference. J. Econometrica, 93, 345–368.

Hansen B.E., 2000. Sample splitting and threshold estimation. Econometrica, 68, 575–603.

He X., Liang Q. and Wang S., 2019. ICT, labor structure and enterprise productivity. Management World, 2019(9), 65-80 (in Chinese).

Huang Y., Ren G., Zhou Y., 2019. The Impact of Income Inequality on the Physical and Mental Health of the Rural Residents: Empirical Analysis Based on CGSS2015. Journal of Agrotechnical Economics, 03, 25-37 (in Chinese).

International Labour Organization, 2022. Health services sector. Available at: https://www.ilo.org/global/industries-and-sectors/health-services/lang--en/index.htm

Kouton J., Bétila R.R. and Lawin M., 2021. The Impact of ICT Development on Health Outcomes in Africa: Does Economic Freedom Matter? Journal of the Knowledge Economy, 12(4), 1830-1869.

Lee M.H., Liu P.Y. and Lio M.C., 2016. The Impact of the Diffusion of Information and Communication Technology on Health: A Cross-Country Study. Applied Research in Quality of Life, 11 (2), 471-491.

Li H. and Zhu Y., 2006. Income, income inequality, and health: Evidence from China. Journal of Comparative Economics, 34(4), 668-693.

Love I. and Zicchino L., 2006. Financial development and dynamic investment behavior: Evidence from panel VAR. Q. Rev. Econ. Finance, 46 (2), 190–21.

Lu C. and Wu A.L., 2019. Income gap, social support and mental health of the new generation of migrant workers. Population and Development, 25(04), 65-77 (in Chinese).

Lu H.J. and Wang B., 2020. Research on the mechanism of Internet use on residents' self-rated health: Based on data from the 2016 Chinese Household Tracking Survey. Journal of Sun Yat-sen University (Social Science Edition), 60 (03), 117-127 (in Chinese).

Luo C., Li S. and Sicular T., 2020. The long-term evolution of national income inequality and rural poverty in China. China Economic Review, 2020(62), 101465.

Ma J.K.H., Vachon T.E. and Cheng S., 2019. National Income, Political Freedom, and Investments in R&D and Education: A Comparative Analysis of the Second Digital Divide Among 15-Year-Old Students. Social Indicators Research, 144(1), 133-166.

Malmquist S., 1953. Index numbers and indifference surfaces. Trabajos De Estadistica 4.2(1953):209-242.

Marques A., Calmeiro L., Loureiro N., Frasquilho D. and de Matos M.G., 2015. Health complaints among adolescents: Associations with more screen-based behaviours and less physical activity. Journal of Adolescence, 44, 150-157.

National Bureau of Statistics of China, 2020. China Statistical Yearbook. National Bureau of Statistics of China, Beijing.

Newby J.M. and McElroy E., 2020. The impact of internet-delivered cognitive behavioural therapy for health anxiety on cyberchondria. Journal of Anxiety Disorders, 69, 102150.

Pesaran M.H., 2004. General diagnostic tests for cross section dependence in panels. Cambridge Working Papers in Economics, 69(7), 1240

Pesaran M. H., 2007. A simple panel unit root test in the presence of cross section dependence. Journal of Applied Econometrics, 22(2), 265-312.

Pettigrew L.M., De Maeseneer J., Anderson M.I.P., Essuman A., Kidd M.R. and Haines A., 2015. Primary health care and the Sustainable Development Goals. The LANCET, 386(10009), 2119-2121.

Preston S.H., 1975. The Changing Relation between Mortality and Level of Economic Development. Population Studies, 29(2), 231-248.

Putnam, R.D., Leonardi, R. and Nanetti, R.Y., 1993. Making Democracy Work, Princeton: Princeton University Press.

Qi Y. and Lu H.Y., 2015. Pollution, Health and Inequality -- Overcoming the environmental health Poverty trap. Management World, 09, 32-51 (in Chinese).

Rogers G.B., 1979. Income and Inequality as Determinants of Mortality: An International Cross-Section Analysis." Population Studies, 33(2), 343-351.

Rogers, W.H., 1993. Regression standard errors in clustered samples. Stata Technical Bulletin, 13, 19–23.

Roodman D., 2009a. How to do xtabond2: An introduction to difference and system GMM in Stata. Stata J, 9 (1), 86–136.

Roodman D., 2009b. A note on the theme of too many instruments. Oxford Bull. Econ. Stat, 71 (1), 135–158.

Sargan, J. D., 1975. Testing for misspecification after estimating using instrumental variables. Mimeo. London School of Economics.

Simpson J., Albani V., Bell Z., Bambra C. and Brown H., 2021. Effects of social security policy reforms on mental health and inequalities: A systematic review of observational studies in high-income countries. Social Science & Medicine, 272, 113717.

Song Z.Y., Wang C. and Bergmann L., 2020. China's prefectural digital divide: Spatial analysis and multivariate determinants of ICT diffusion. International Journal of Information Management, 52, 102072.

Tchamyou V.S., Asongu S.A. and Odhiambo N.M., 2019. The Role of ICT in Modulating the Effect of Education and Lifelong Learning on Income Inequality and Economic Growth in Africa. African Development Review, 31(3), 261-274.

Tchamyou V.S., Erreygers G. and Cassimon D., 2019. Inequality, ICT and financial access in Africa.

Technological Forecasting and Social Change, 139, 169-184.

Ueckert F., Goerz M., Ataian M., Tessmann S. and Prokosch H.U., 2003. Empowerment of patients and communication with health care professionals through an electronic health record. Int. J. Med. Inform, 70, 99–108.

Văidean V. L. and Achim M.V., 2022. When more is less: Do information and communication technologies (ICTs) improve health outcomes? An empirical investigation in a non-linear framework. Socio-Economic Planning Sciences, 80, 101218.

Wang, H., and S. Ma., 2022. Preventing Crimes Against Public Health with Artificial Intelligence and Machine Learning Capabilities. Socio-Economic Planning Sciences, 6301(2021):101043.

Wang, Q.Y. ,2015. Fixed-effect panel threshold model using Stata. Stata Journal (2015), 121-134.

White H., 1980. A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity. Econometrics, 48 (4), 817–838.

WHO, 2015. Health in 2015: from MDGs, Millennium Development Goals to SDGs, Sustainable Development Goals. The World Health Organization, Geneva.

WHO, 2019. World health statistics 2019: monitoring health for the SDGs, sustainable development goals. The World Health Organization, Geneva.

Wilkinson R.G. and Pickett K.E., 2006. Income inequality and population health: a review and explanation of the evidence. Social Science Med, 62 (7), 1768-1784.

Wooldridge J.M, 2003. Solutions manual and supplementary materials for econometric analysis of cross section and panel data. MIT Press Books, 1.

Yip W. and Hsiao W.C., 2008. The Chinese health system at a crossroads. Health Affairs, 27(2), 460-468.

Zhang C.G. and Zhao W., 2014. Panel estimation for income inequality and CO2 emissions: a regional analysis in China. Appl. Energy, 136, 382–392.

Zhang J.P., Gong X.M. and Zhang H., 2022. ICT diffusion and health outcome: Effects and transmission channels. Telematics and Informatics, 67,101755.

Zhao Y.Z. and Li X.Y., 2020. The impact of Internet use on individual health: an empirical analysis based on Chinese family tracking survey data. Jianghan Tribune, 05, 139-144 (in Chinese).

Zhu F., Li Q., Yang S. and Balezentis T., 2021. How ICT and R&D affect productivity? Firm level evidence for China. Economic Research-Ekonomska Istraživanja (published in 2021).

**Appendix**

Table A.1: Cross-sectional dependence test

| Variables | CD-tests |
|---|---|
| TFP | 10.61*** |
| Mob | 69.85*** |
| Internet | 67.42*** |
| GINI | 62.58*** |
| Internet * GINI | 70.35*** |
| Mob * GINI | 67.07*** |
| ur | 64.28*** |
| edu | 66.07*** |
| proportion | 38.94*** |
| coverage | 55.34*** |

**Source: Own estimations**

Table A.2: CIPS tests

| | Variables | Intercept | Trend |
|---|---|---|---|
| Level | TFP | –2.33* | –2.70* |
| | Mob | –1.98 | –2.12 |
| | Internet | –2.68*** | –2.93** |
| | GINI | –2.05 | –2.52 |
| | Internet * GINI | –2.67*** | –2.66* |
| | Mob * GINI | –2.01 | –2.00 |
| | ur | –1.33 | –1.79 |
| | edu | –2.26 | –2.38 |
| | proportion | –2.39** | –2.67* |
| | coverage | –1.95 | –2.50 |
| First difference | TFP | –3.60*** | –3.62*** |
| | Mob | –2.59*** | –3.15*** |
| | Internet | –3.07*** | –3.54*** |
| | GINI | –3.39*** | –3.25*** |
| | Internet * GINI | –3.18*** | –3.16*** |
| | Mob * GINI | –2.73*** | –3.08*** |
| | ur | –2.45*** | –3.02*** |
| | edu | –3.59*** | –3.63*** |

| | | |
|---|---|---|
| proportion | $-3.61^{***}$ | $-3.48^{***}$ |
| coverage | $-3.07^{***}$ | $-2.78^{**}$ |

**Source: Own estimations**