ISSN: 2771-7763

Research Article

Journal of Economic Research & Reviews

Impact of Internet Use on The Income Gap Among Farmer: A Social Capital-Based Analysis of The Mediating Effect

Yun Zhu[1], **Xiaoyan Peng** [2*]

[1]Wuhan Universuty, School of Sociology, Wuhan, China

[2]Wuhan Universuty, School of Politics and Public Administration, Wuhan, China.

[*]**Corresponding author:**
Xiaoyan Peng, Wuhan Universuty, School of Politics and Public Administration, Wuhan, China.

Submitted: 07 Sep 2022; **Accepted**: 14 Sep 2022; **Published**: 22 Nov 2022

Citation: *Xiaoyan Peng (2022). Impact of Internet Use on The Income Gap Among Farmer: A Social Capital-Based Analysis of The Mediating Effect, J Eco Res & Rev, 2(4), 453-463.*

Abstract

Based on 2010, 2013 and 2015 CGSS data, the impact of Internet use and social capital on the income gap among farmers in the past five years is assessed at three time points using the OLS method and a quantile regression method. The study finds that the income gap among farmers increases continuously in the five-year period, while Internet use plays a positive impact on farmers' income growth in all five quartiles; the coefficient differences are all significantly negative, indicating that Internet use plays a positive role in alleviating the income gap between high-income and low-income farmer subgroups, and social capital plays a positive role in moderating the income gap among farmers and that Internet use by farmers expands the boundary of social capital, which in turn increases the income level of and alleviates the income gap among farmers.

Keywords: Internet use; social capital; income gap between farmers; mechanism

Problem statement

The report of the 19th National Congress of the Communist Party of China clearly noted that "the resolution of the issues relating to agriculture, rural areas and farmers should always be taken as the top priority of the Party's work in the implementation of the rural revitalization strategy." Increasing the income of rural residents, narrowing regional and urban-rural income gaps, and realizing the fairness of income distribution are the core strategies for addressing the issues relating to agriculture, rural areas and farmers. Over the past four decades of reform and opening up in China, the rapid economic growth and the continuous expansion of the scale of financial expenditure on basic public services have provided material guarantees for improving rural infrastructure construction and increasing farmers' income. As economic development enters a new normal, the rate of farmers' income growth has slowed sig-nificantly. According to data of the National Bureau of Statistics, the growth rates for farmers' per capita disposable income in the 2014-2016 period were 11.2%, 8.9% and 8.2%, respectively. Additionally, the gap between the highest income group and the lowest income group widened from 7.27× to 9.46× during the 2008-2017 decade, based on the income quintiles of China's rural residents. The growing rural income gap has become one of the urgent issues needing to be addressed during the economic and social trans-formation in China.

Since 2004, the Central Government has issued 14 consecutive No. 1 Central Documents involving strategic plans and institutional arrangements to promote farmers' income growth. The Opinions of the Central Committee of the Communist Party of China and the State Council on the Implementation of Rural Revitalization Strategy, a No. 1 Central Document issued in 2018, clearly noted the need to actively promote an increase in farmers' income, facilitate the "digital rural strategy" and accelerate the construction of broadband networks and mobile communication in rural areas. According to the 42nd Statistical Report on Internet Development in China, as of June 2018, there were a total of 802 million Internet users in China, an increase of 3.8% compared to the end of 2017; the Internet penetration rate was 57.7%, of which the number of rural Internet users was 211 million, accounting for 26.3% and representing an increase of 1% over 2017; the Internet penetration rate in rural areas was 36.5%; and residents spent an average of 27.7 hours online per week. The data indicate that the use of the Internet has become an important part of the life of rural residents in China. With the promotion of the "Internet +" national strategy, the Internet is exerting a profound impact on the human capital, social capital, and cultural capital of rural residents. Therefore, taking advantage of Internet development to actively explore the "Internet + farmers' income increase" model is an important means to alleviate the income gap among rural residents.

The Chinese rural society has a strong "local complex" and "human relationships," and hence, social capital networks established on the basis of social interaction and mutual trust can have a direct or indirect impact on the income of rural residents. The development of the Internet has provided technical support for the realization of free communication and information transfer among rural residents and the construction of information society life scenarios, which have promoted the transformation of the traditional concepts and behaviours of interpersonal communication and have important impacts on the social capital of rural residents. Therefore, in the context of Internet development and the slowdown in rural residents' income growth, the present study uses China General Social Survey (CGSS) data from 2010, 2013 and 2015 to incorporate Internet use and social capital into the same analytical framework to analyse the impact of Internet use and social capital on the income gap among rural residents and, on this basis, attempts to establish the mechanism of this impact path.

Literature review

As the Internet was being developed, Krueger, based on US census data, found that computer use significantly increased the wages of employees, with those who used computers at work earning 1.5× as much as those who did not indicating that the computer skills of employees have a significant wage premium effect. Subsequently, many researchers questioned this conclusion, arguing that computer use is not a main factor influencing increases in employee wages because of the lack of effective control over the occu-pational heterogeneity and tool preferences of employees [1-3]. After controlling for the individual characteristics of employees, Dunne et al. found that computer use has little effect on increases in employee wages [4]. A study by DiMaggio and Bonikowski revealed that Internet use significantly increases individual wages but has a clearly lower degree of impact on wage premiums than does computer use [5]. Sabrina and Zoghi argued that the promotion of human capital by Internet use and thus access to more employment options is an important cause of improvements in income levels [6]. Early research results focused on the effect of the use of computers and the Internet on the wage levels of employees. With improvements in Internet information technology and the construction of an Internet-based information and digital society, the impact of the Internet on the income of residents has attracted extensive attention in the academic community. Current research results generally agree that Internet use can increase the income of residents, but there are certain differences in the degree of such an impact due to the constraints of factors such as data and variables. Specifically, the research results can be summarized in the following three aspects.

First is the impact of Internet usage on the farm income of rural residents. In the 21st century, there are new ideas, new producers, new consumers, and new collaborations that can develop a global environment rapidly through coordination with the private sector [7]. Internet information technology improves agricultural productivity. The emerging media on the Internet act as a hub for dis-seminating information from the government and the public and can deliver economic information from government departments in a timely manner, significantly lower transaction costs and reduce transaction links [8]. Through the use of the Internet, farmers can quickly and conveniently access relevant agricultural information, having a positive impact on improvements in agricultural tech-nology, the sale of agricultural products, and the prevention and control of agricultural disasters, thereby reducing the cost of in-formation acquisition and promoting an increase in income. Through technological innovations related to traditional agricultural production methods, Internet information technology has promoted the scale, digitization and automation of agricultural production, improved production efficiency and increased the income of farmers. Furthermore, Internet use helps to improve the efficiency of farmers' decision-making [9]. For Internet informatization in rural areas, the information asymmetry between farmers and dealers increases the cost of acquiring additional information, thereby increasing the cost of agricultural production. The use and promotion of the Internet leads to the establishment of effective information exchange channels, which play a positive role in guiding farmers to make correct market choices and thus maximize agricultural production profits. However, scant studies have concentrated on the quantitative effects of internet use on agricultural production and household income. Other researchers have paid close consideration to the quantitative impacts of smartphone communication service, smartphone short message services, and on-farm households [10-13].

Second is the impact of Internet use on the off-farm income of rural residents. Many studies have investigated the potential con-tributions of mobile ICTs to agricultural production and poverty reduction, but have failed to consider the wider income effects of the use of updated ICTs, such as the use of Internet [14]. First, Internet use promotes the transfer of surplus rural labour. Currently, there is a large labour surplus and an inefficient allocation of labour resources in rural areas. Realizing the effective mobility of rural labour and obtaining wage income through off-farm employment is an important way to increase farmers' income [15]. By using the Internet, rural residents can collect a large amount of off-farm employment information in a timely and accurate manner, which promotes the effective allocation of surplus rural labour resources. A study by Ma and Ning indicated that the Internet use by rural residents increases the employment rate and off-farm employment income and that this effect has a stronger impact on remote and poor areas [16]. than Compared with those who do not use the Internet, rural residents who are proficient in using the Internet have a higher employment rate and shorter unemployment time. Furthermore, Internet use promotes the entrepreneurial behaviour of rural households. The Internet technology-based informatization strategy for poverty alleviation has promoted rural e-commerce development, effectively improved the motivation of rural households to start their own business and increased the income of rural households. In addition, the development of Internet finance breaks the geographical constraints and realizes the precise placement of funds, which effectively solve financing problems in the entrepreneurship of rural residents and promote the healthy operation of family entrepreneurship, thereby increasing the income level [17].

Third is the impact of Internet use on the income gap. Yanyan Gao used to explore the constraints of the income-increase effect of rural computer penetration shows that the effect is at least doubled over the average effect estimated from instrument variables method, once the digital divide causes are removed [18]. Using data from the China Family Panel Studies (CFPS) and controlling for individual heterogeneity variables, Ma and Kong found that regional differences in Internet use widened the income gap between urban and rural residents [19]. The imbalance in the allocation of Internet resources in different regions further widens the "digital divide" between the rich and the poor in terms of information resources, thereby exacerbating the income gap. The information dividend brought by the Internet can only be enjoyed by wealthy groups with a high socioeconomic status, and poor people with low socioeconomic status are excluded, which further increases the gap between the rich and the poor in society. The heterogeneity of Internet usage groups also further widens the income gap. Specifically, according to Bound and Johnson's "skill bias theory," highly skilled workers are able to quickly adapt to new Internet technologies, and Internet use has a greater impact on the wages of high-skilled workers than on those of ordinary workers, thereby creating income inequality among workers [20]. Based on a study of the data from counties in Spain, Whitacre et al. found that the impact of Internet use on the income of the middle class is significantly greater than that of the lower class [21].

In addition, Xu et a. noted that the emergence of the "secondary digital divide" leads to the differences in the ability to identify, utilize and appreciate information, further widening the income gap within the Internet user groups [22]. In contrast, Song argued that Internet information technology significantly improves regional economic development and plays an effective role in alleviating the imbalance between urban and rural economic development; a study of panel data from 31 provinces in China found that the effective integration of Internet information technology and inclusive finance has provided more development opportunities for low-income groups in rural areas and played a positive role in alleviating the income gap between urban and rural residents [23]. In addition, Zhou and Hua found that Internet use alleviates the income gap only for economically developed areas but does not have a significant impact on the income gap for economically backward areas and that Internet use promotes rural entrepreneurship but does not increase the household income of farmers [24].

In recent years, social capital theory has been increasingly applied to address the issue of the income gap among farmers, reaching different conclusions. One viewpoint is that the difference in social capital further widens the income gap among rural residents due to the constraints of traditional concepts and modes of communication. In the context of China, the use of renqing guanxi (the favoured human relations) can reduce the cost of searching for job information and increase off-farm employment opportunities, while the off-farm employment rate is relatively low for farmers with poor social capital. Due to the imbalance in regional economic development, the quality of social capital of farmers in economically underdeveloped areas is low, while both the quality and quantity of social capital of farmers in economically developed areas are relatively high, further promoting labour mobility and thereby increasing income and widening the income gap among farmers [25].

In the absence of a sound credit network system, farmers with more social capital can be provided with more financing for their own household businesses, while farmers with a lack of social capital give up entrepreneurial opportunities due to financing difficulties, likely further increasing the income gap. In contrast, Westlund and Adam maintained that social capital, as the "capital of the poor", can effectively regulate the income distribution among farmers and thus reduce the income gap among farmers [26]. A study of Tang and Zhou also confirmed that social capital can increase farmers' off-farm employment income and thus narrows the income gap among farmers [27]. In summary, although the current research findings generally agree that "Internet use" can increase the income of residents, the impact of heterogeneity of Internet user groups and the difference in use time on the income of farmers as well as the mechanism of this impact have not been investigated in depth, and there is even less literature analysing the impact of Internet use on the income gap among farmers. Therefore, in this study, CGSS data for 2010, 2013 and 2015 are selected, and Internet use is divided into two dimensions, "Internet use or not" and "Internet use frequency," to analyse the impact of Internet use and social capital on the income gap among farmers as well as the mechanism of this impact.

Study design

Data sources

The data for the present study are CGSS survey data from 2010, 2013 and 2015. The CGSS started in 2003 and is the earliest national, comprehensive and continuous academic survey project in China. The data for these three years are selected because they cover a 5-year time span and the variable measurements are consistent. The present study examines the impact of Internet use and social capital on the income gap among rural residents. To this end, samples are screened to eliminate those with missing values, ultimately obtaining a total of 14015 effective samples, of which 4524, 4845 and 4646 samples are for 2010, 2013 and 2015, respectively.

Variable selection

Dependent variable: farmers' income gap.

The dependent variable of interest in this paper is the total annual income of individual farmers in 2009, 2012 and 2014, and the income is transformed into logarithmic form in the regression model. The Gini coefficient for farmers in the sample set is calculated using Stata14.0. The mean value of the Gini coefficient for farmers in the full sample set is 0.511, implying a severe income gap among farmers, and the Gini coefficients for farmers in 2009, 2012 and 2014 are 0.498, 0.502 and 0.532, respectively, indicating that the income gap among farmers increases year by year. The income gap is even more pronounced after the farmers in the full sample set are grouped in terms of Internet use. The Gini coefficients for farmers who use (do not use) the Internet are 0.501 (0.497), 0.482 (0.511) and 0.520 (0.538) in 2009, 2013 and 2014, respectively. Next, the farmers in the full sample set are grouped based on region. The Gini coefficients for farmers in the eastern, central and western regions are 0.507, 0.506 and 0.519, respectively, indicating that the income gap among farmers in the western region is greater than that in the eastern and central regions.

3.2.2 Independent variables: Internet use and social capital

• First bullet; Internet usage

Internet use, i.e. "whether you use the Internet" is a dummy variable, and the question "a285. In the past year, your use of the

Internet: answer yes, assign a value of 1, answer no, assign a value of 0" was selected, accounting for 37.26% and 72.74% respectively. “Internet use or not” is treated as a dummy variable, with data obtained using the following question: “a285. At any time last year, did you use the Internet? Assign a value of 1 if the answer is yes and 0 if no.” Among the responses provided, “yes” and “no” account for 27.26% and 72.74%, respectively. In addition, the variable “Internet use frequency” is selected as a variable to further examine the impact of Internet use time on the income gap among farmers.

• Second bullet; Social capital

According to the definition of social capital by Xie and Wang and Huang and Sheng the measure of farmers’ social capital is constructed from the perspectives of social communication and social interaction, respectively, with data obtained using the following questions: “a3006. Last year, in your free time, did you often get together with relatives who did not live with you?”, “a3007 [28, 29]. Last year, in your free time, did you often get together with friends?” and “a311. Last year, in your free time, did you often engage in social activities?”. Then, the average value of the three is taken as the value of the social capital variable in the present study.

• Third bullet; Control variables

Variables related to farmers’ demographic characteristics, family characteristics and social characteristics are selected as control variables. The demographic variables include gender, age, education, ethnic group, marital status, health level, and job type; the family variables include the number of children, whether there is household investment, and household economic level; and the social variables include region type and year dummy variables. The descriptive statistics of each variable are shown in Table 1.

Table 1: Definition and descriptive statistics of variables

Variable name	Definition and description	Mean	Standard deviation
Farmers’ income	Log of farmers' total income in the previous year	9.044	1.244
Internet use	Use = 1, no use = 0	0.272	0.445
Internet use frequency	Never = 1, several times a year = 2, several times a month = 4, several times a week = 4, every day = 5	1.783	1.439
Social capital	Never = 1, several times a year = 2, several times a month = 4, several times a week = 4, every day = 5	2.235	0.963
Gender	Male=1, Female=0	0.537	0.499
Age	Continuous variables	40.412	15.118
Age squared	Continuous variables	2572.3	1526.5
Ethnic group	Han Chinese = 1, other nationalities = 0	0.893	0.309
Education level	Elementary school and below = 1, middle school = 2, high school = 3, college and above = 4	1.667	0.807
Marital status	Married = 1, unmarried = 0	0.929	0.255
Health level	Very unhealthy=1, relatively unhealthy=2, average=3, relatively healthy=4, very healthy=5	3.625	1.126
Job type	Non-farm payrolls = 1, otherwise = 0	0.347	0.476
Household investment	With investment = 1, without = 0	0.025	0.154
Number of children	Continuous Variables	2.759	1.563
Household economic level	Below average = 1, average = 2, above average = 3	1.641	0.593
Region type	West = 1, Central = 2, East = 3	1.932	0.764
Year dummy variable 1	2013=1, other=0	0.346	0.475
Year dummy variable 2	2015=1, other=0	0.332	0.471
Information source channel	Internet, mobile = 1, others = 0	0.116	0.320

Model construction

In the present study, Internet use and social capital are added as variables into the Mincer equation to test their impact on farmers' income level. The baseline model is as follows:

$$\boldsymbol{lnIncome_i = \alpha + \beta Internet_i + \gamma SC_i + \delta X_i + \mu_i} \quad (1)$$

In Equation (1), $\boldsymbol{lnIncome_i}$ is the logarithm of farmers' income (dependent variable), $\boldsymbol{Internet_i}$ and $\boldsymbol{SC_i}$ are Internet use and social capital, respectively (independent variables), $\boldsymbol{X_i}$ represents other control variables, $\boldsymbol{\mu_i}$ is a random disturbance term, α is a constant term, and $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ and $\boldsymbol{\delta}$ are the coefficients of different variables. To further estimate and compare the differences in the marginal contributions of independent variables to different income groups, with reference to Cheng's study model, he following quantile regression model is established in the present study based on Equation (1) and the quantile regression method of Koenker and Bassett and Buchinsky [30-32].

$$\boldsymbol{Q_t [lnIncome|X] = \alpha_t + \beta_1 Internet_t + \beta_2 SC_t + \beta_3 X_t + \mu_t} \quad (2)$$

In Equation (2), $\boldsymbol{Q_t}$ [lnIncome|X] is the conditional distribution of the logarithm of income at the th tth, quantile, $\boldsymbol{\alpha_t}$ is a constant term, $\boldsymbol{\beta_1}$ to $\boldsymbol{\beta_3}$ are the coefficients of different variables, and $\boldsymbol{\mu_t}$ is a random disturbance term. To obtain the differences in the impact of the independent and control variables on different income subgroups, the quantile regression coefficient differences are used to test the differences in the marginal impacts of different variables on different income subgroups, and thus, the impact on the income gap among farmers is obtained.

Empirical analysis of the impact of Internet use and social capital on the income gap among farmers

Impact of Internet use on income gap among farmers Baseline regression

Table 2 provides data regarding the impact of Internet use on farmers' income. Model 1 uses the ordinary least squares (OLS) regression model, with an R2 of 0.497, indicating a high explanatory power. When other variables are controlled for, Internet use positively impacts farmers' income at the 1% significance level, indicating that farmers' use of the Internet can significantly increase their income levels, with farmers who use the Internet earning 32.7% more than those who do not and an income premium of 38.67% (e0.327-1) for farmers who use the Internet.

Other control variables also have varying degrees of impact on farmers' income. Regarding individual-level variables, the income of male farmers is 47.4% higher than that of female farmers. Additionally, the age coefficient is positive at the 1% significance level, and the age-squared coefficient is negative at the 1% significance level, indicating that age has an inverted U-shaped impact on farmers' income. The higher the level of education, the higher is farmers' income. A higher level of education represents a higher level of human capital and faster acquisition and application of new knowledge and skills, which in turn leads to better employment opportunities and higher income returns. The income of married farmers is significantly higher than that of unmarried farmers. Influenced by the traditional concept of "get married and start a career," marriage can improve entrepreneurship and sense of responsibility, which in turn increase farmer motivation. Health status positively impacts farmers' income at the 1% significance level. The healthier farmers are, the higher is their income. The income of Han Chinese farmers is significantly higher than that of ethnic minority farmers. The income of farmers with off-farm employment is significantly higher than that of farmers solely engaged in agricultural production. Off-farm employment channels can effectively transfer surplus rural labour, and urban employment as migrant workers and household entrepreneurship can create additional income, which in turn increases income levels. Regarding household-level variables, the income of farmers with additional household investments is significantly higher than that of farmers without additional investments. The higher is the household economic level, the higher is the income. The number of children negatively impacts farmers' income at the 1% significance level, probably because the more children there are, the higher are the costs of raising children, thus exerting a strong inhibiting effect on farmers' income. Finally, regarding social-level variables, the coefficient of the year dummy variable is positive at the 1% significance level, indicating that farmers' income tends to increase as the year progresses. The region variable indicates that the income of farmers in the eastern region is significantly higher than that of farmers in the central and western regions, probably because the eastern region is economically developed, which plays a positive role in facilitating the agricultural trade and farmers' labour transfer, thus promoting the increase in farmers' income.

Quantile regression

The quantile regression results of models 2 to 6 show that the coefficients of Internet use are all positive at the 1% significance level, indicating that Internet use has a significant income-increasing effect on farmers in different income subgroups; however, there are also some differences. As the quantile increases (10% to 90%), the regression coefficients of the quantile of Internet use first decrease and then increase (34% → 30.9% → 28.1% → 29.85% → 33.6%), indicating that the impact of Internet use on low- and high-income farmers is greater than that on middle-income farmers and that low-income farmers are the largest beneficiaries of Internet use. As seen from the "quantile coefficient differences" in Table 3, the differences in coefficients of the four quantile intervals are negative at both the 1% and 10% significance levels, indicating that Internet use can significantly reduce the income gap among farmers. Specifically, Internet use effectively alleviates the income gap between the low-income and middle-high-income subgroups (Q75-Q25), between the low-income and high-income subgroups (Q90-Q25), between the middle-high-income and low-income subgroups (Q75-Q10) and between the high-income and low-income subgroups (Q90-Q10). A comparison of coefficient differences indicates that Internet use has a more pronounced effect on alleviating the income gap between the middle-high-income and middle-low-income subgroups and between the middle-high-income and low-income subgroups.

Treatment of endogeneity problem

Although a series of variables that may affect farmers' income are controlled for in the regression model, there may still be missing variables. Additionally, there may also be a bidirectional causal relationship between Internet use and farmers' income, as increasing farmers' income and improving living standards can further boost Internet consumption and increase the Internet access for rural households. In addition, the increase in income can also further motivate farmers to participate in vocational training, which will increase their knowledge of new Internet skills and expand the scope of their Internet use by improving their human capital. Regarding the verification of the endogeneity of "Internet use," the Hausman test results indicate that Prob > chi2 = 0.0389; therefore, the null hypothesis that "all variables are exogenous" is rejected at the 5% significance level. Therefore, the Internet use variable is endogenous. To reduce the bias caused by the endogeneity problem on the regression results, the two-stage least squares method is used and, by referring to Chen's research method, "electronic product use preference" is added as an instrumental variable of farmers' income. In general, farmers who prefer to use electronic products such as computers and mobile phones are more likely to use the Internet or mobile phones to access the Internet, thus establishing a correlation; the preference of using electronic products is a heterogeneity of the individual consumption of farmers and is not directly related to their income growth, thereby satisfying exogeneity [33]. In the present study, the electronic product use preference is operationalized as an "information source channel," and a value of 1 is assigned for the response "mobile phone, Internet" and 0 otherwise. The first-stage regression results indicate that the information source channel has a positive impact on Internet use at the 1% significance level and that the F-statistic for testing the joint significance of instrumental variable coefficients is 1487.86, i.e. much greater than 10. Therefore, there is no weak instrumental variable. The two-stage least squares regression results of model 7 show that Internet use positively impacts farmers' income at the 1% significance level and that the income of farmers who use the Internet is 47.6% higher than that of farmers who do not, consistent with the baseline regression results of model 1. The significance and signs of other variables are completely consistent with the regression results of model 1, indicating the robustness of the results.

Table 2: Parameter estimation of the impact of Internet use on the income gap among farmers

Variable name	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	OLS	Q(10)	Q(25)	Q(50)	Q(75)	Q(90)	2SLS
Internet use	0.327***	0.341***	0.309***	0.281***	0.298***	0.336***	0.476***
	(0.0236)	(0.0419)	(0.0326)	(0.0285)	(0.0288)	(0.0347)	(0.0759)
Gender	0.474***	0.458***	0.502***	0.493***	0.441***	0.412***	0.471***
	(0.0155)	(0.0276)	(0.0214)	(0.0187)	(0.0189)	(0.0228)	(0.0156)
Age	0.0417***	0.0511***	0.0496***	0.0445***	0.0382***	0.0298***	0.0485***
	(0.00338)	(0.00601)	(0.00466)	(0.00408)	(0.00412)	(0.00498)	(0.00471)
Age squared	-0.0006***	-0.0007***	-0.0007***	-0.0007***	-0.0006***	-0.0005***	-0.0007***
	(0.000032)	(0.000056)	(0.000044)	(0.000038)	(0.000039)	(0.000047)	(0.00004)
Education level	0.107***	0.124***	0.108***	0.105***	0.0985***	0.117***	0.0901***
	(0.0115)	(0.0205)	(0.0159)	(0.0139)	(0.0141)	(0.0170)	(0.0142)
Marital status	0.320***	0.429***	0.347***	0.235***	0.240***	0.278***	0.323***
	(0.0349)	(0.0620)	(0.0481)	(0.0421)	(0.0425)	(0.0513)	(0.0349)
Health level	0.0781***	0.0948***	0.0972***	0.0724***	0.0576***	0.0546***	0.0782***
	(0.00752)	(0.0134)	(0.0104)	(0.00908)	(0.00917)	(0.0111)	(0.00752)
Ethnic group	0.138***	0.182***	0.123***	0.193***	0.125***	0.0631*	0.134***
	(0.0249)	(0.0443)	(0.0344)	(0.0301)	(0.0304)	(0.0367)	(0.0250)
Job type	0.647***	0.924***	0.761***	0.616***	0.471***	0.430***	0.626***
	(0.0188)	(0.0334)	(0.0259)	(0.0227)	(0.0229)	(0.0276)	(0.0212)
Household investment	0.383***	0.208**	0.338***	0.396***	0.482***	0.409***	0.363***
	(0.0494)	(0.0879)	(0.0682)	(0.0597)	(0.0603)	(0.0728)	(0.0503)
Number of children	-0.0204***	-0.0154*	-0.0136*	-0.00953	-0.0205***	-0.0264***	-0.0221***
	(0.00515)	(0.00916)	(0.00711)	(0.00622)	(0.00628)	(0.00759)	(0.00522)
Family economic level	0.271***	0.222***	0.244***	0.261***	0.299***	0.302***	0.266***
	(0.0111)	(0.0197)	(0.0153)	(0.0133)	(0.0135)	(0.0163)	(0.0113)
Region type	0.101***	0.102***	0.134***	0.121***	0.117***	0.0777***	0.0964***
	(0.0105)	(0.0187)	(0.0145)	(0.0127)	(0.0128)	(0.0155)	(0.0108)

Year 2013 = 1	0.391***	0.349***	0.369***	0.400***	0.469***	0.439***	0.375***
	(0.0196)	(0.0349)	(0.0271)	(0.0237)	(0.0239)	(0.0289)	(0.0212)
Year 2015 = 1	0.556***	0.388***	0.501***	0.583***	0.656***	0.672***	0.529***
	(0.0199)	(0.0353)	(0.0274)	(0.0240)	(0.0242)	(0.0293)	(0.0238)
Constant term	6.018***	4.630***	5.262***	6.048***	6.736***	7.412***	5.861***
	(0.0925)	(0.164)	(0.128)	(0.112)	(0.113)	(0.136)	(0.120)
Sample size	13917	13917	13917	13917	13917	13917	13917
Note: ***, ** and * represent the 1%, 5% and 10% significance levels, respectively (same below).							

Table 3: Results of the quantile difference test

Variable name	Q75-Q25	Q75-Q10	Q90-Q25	Q90-Q10	Q75-Q25	Q75-Q10
Internet use	-0.181***	-0.162***	-0.157***	-0.137*		
	(0.0307)	(0.0596)	(0.0421)	(0.0749)		
Internet use frequency					-0.0647***	-0.0543**
					(0.0111)	(0.0230)
Other variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant term	1.763***	2.321***	2.221***	2.780***	1.767***	2.249***
	(0.138)	(0.0469)	(0.146)	(0.267)	(0.146)	(0.245)
Sample size	13982	13982	13982	13982	13968	13968
Robustness test based on propensity score matching (PSM)						

It is difficult for the aforementioned OLS regression to circumvent issues such as confounding variables and selection bias. To obtain the net effect of Internet use on improving the income level of farmers, PSM is selected to test the robustness of the aforementioned OLS regression results. The core of the PSM method, which was proposed by Rubin and Rosenbaum, is to make the observed data as close as possible to the randomized experimental data by matched resampling to achieve a robust inference on the causal relationship between Internet use and farmers' income. Using PSM, we test whether there is a systematic difference in farmers' income between the treated group (i.e., farmers who use the Internet) and the control group (i.e., farmers who do not use the Internet) [34]. In accordance with PSM design, let $lnIncome_i$ be the outcome variable for farmers' income, $lnincome_i^1$ be the income of farmers who use the Internet, and $lnincome_i^0$ be the income of farmers who do not use the Internet. The treated group and the control group are matched by different matching methods, and the differences in farmers' income between the two groups are compared based on the characteristics of the matched samples to obtain the impact coefficient of the causal relationship between Internet use and farmers' income, i.e., the average treatment effect on the treated (ATT), which is defined as follows:

$$ATT=E(\ln Income_i^1|Internet_i=1)-E(\ln Income_i^0\ |Internet_i=1)$$

First, we perform one-to-one matching with replacement and allow for ties. A comparison of pre-matching and post-matching results indicates that the standardized mean bias before matching is 58.9%, which is reduced to 5% after matching. After matching, the standardized biases of all variables are less than 10%, except for that for "number of children", which is greater than 10%, indicating a good matching effect. In addition, the post-matching t-test results do not reject the null hypothesis that "there is no systematic difference between the treated and control groups." Second, the average treatment effect of the impact of Internet use on farmers' income is estimated using k-nearest neighbour matching, radius matching, kernel matching, local linear regression matching and spline matching.

The analysis results in Table 4 indicate that Internet use significantly increases farmers' income levels both before and after matching and that, after matching, Internet use generates a 34.9% income premium, a finding that is basically consistent with the aforementioned OLS regression results, which therefore have a certain degree of robustness.

Table 4: Average treatment effect of the impact of Internet use on farmers' income

Variable	Sample	Internet use	No Internet use	ATT difference	Standard deviation	t value
		(1)	(2)	(1)-(2)		
k-nearest neighbour matching (k=4)	Before matching	9.956	8.703	1.253	0.0212	59.14***
	After matching	9.945	9.616	0.329	0.0702	4.68***
Radius matching	Before matching	9.956	8.703	1.253	0.0212	59.14***
	After matching	9.945	9.621	0.324	0.0728	4.44***
Kernel matching	Before matching	9.956	8.703	1.253	0.0212	59.14***
	After matching	9.945	9.627	0.318	0.0609	5.22***
Local linear regression matching	Before matching	9.956	8.703	1.253	0.0212	59.14***
	After matching	9.945	9.631	0.314	0.0729	4.30***
Spline matching	Before matching	9.956	8.703	1.253	0.0212	59.14***
	After matching	9.956	9.564	0.392	0.0316	12.41***

Impact of Internet use frequency on the income gap among farmers

In view of the significant differences in the amount of time spent on the Internet by different farmers, the impact of Internet use frequency on the income gap among farmers is further analysed. Table 5 reports the OLS regression and quantile regression results of the impact of Internet use frequency on farmers' income. The regression results of model 1a show that Internet use frequency has a significant positive impact on farmers' income and that the return on wages of Internet use frequency is 9.65%. The two-stage least squares regression results of model 7a, which includes the instrumental variable, still show a positive effect of Internet use frequency on farmers' income. The quantile regression results of models 2a-6a show that the coefficients of Internet use frequency are all positive at the 1% significance level, indicating that Internet use frequency has a positive effect on the income of farmers at different income levels but that there also exist some internal differences. As the quantile increases, the quantile regression coefficient of Internet use frequency first decreases and then increases, indicating that the impact of Internet use frequency on both ends is greater than that on the middle, i.e., the higher the Internet use frequency, the greater is the impact on low-income and high-income farmer subgroups. The quantile coefficient differences (Table 3) of the four quantile intervals are all negative and statistically significant, indicating that Internet use frequency can significantly reduce the income gap among farmers.

Table 5: Parameter estimation of the impact of Internet use frequency on the income gap among farmersa

Variable name	Model 1a	Model 2a	Model 3a	Model 4a	Model 5a	Model 6a	Model 7a
	OLS	Q(10)	Q(25)	Q(50)	Q(75)	Q(90)	2SLS
Internet use frequency	0.0965***	0.103***	0.0948***	0.0927***	0.0827***	0.0914***	0.0935***
	(0.00764)	(0.0135)	(0.0104)	(0.00875)	(0.00941)	(0.0115)	(0.0148)
Other variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant term	5.897***	4.468***	5.102***	5.840***	6.700***	7.384***	5.912***
	(0.0967)	(0.171)	(0.132)	(0.111)	(0.119)	(0.146)	(0.115)
Sample size	13903	13903	13903	13903	13903	13903	13903

Analysis of the mechanism of the impact of Internet use on the income gap among farmers

The aforementioned analysis demonstrates that Internet use can increase the income of farmers in different income subgroups and hence effectively close the income gap among farmers. Based on a theoretical analysis of the "Social compensation effect ," McKenna et al. argue that Internet use by residents has a positive impact on the accumulation of social capital through social communication and social interaction in cyberspace [35]. Huang et al. found that residents are better at expressing their inner thoughts in cyberspace, facilitating interpersonal communication and interaction in real life and thereby promoting residents' participation in social governance and expanding their social capital [36]. Based on the "uses and gratifications theory," Zeng suggests that an obvious motive for residents to use the Internet is to expand their social capital and responds to the "time replacement hypothesis" by arguing that residents' use of the Internet can expand social capital [37]. As social capital is one of the important factors that affect farmers' income, Internet use may have an impact on the income gap among farmers through a social capital mechanism.On this basis, we first test whether social capital plays a mediating role in the impact of Internet use on farmers' income and then analyse how Internet use impacts farmers' income through social capital.

Table 6 provides the regression results for the mediating effect of social capital on the impact of Internet use on farmers' income. As social capital increases, the impact of Internet use on farmers' income becomes greater, and the difference in social capital further increases the income gap among farmers. Table 7 Mechanism of action model regression results show that the regression results of model 1 indicate that Internet use can significantly increase farmers' social capital. The regression results of models 2 and 3, which include the interaction terms Internet use and social capital, indicate that the coefficients of social capital and the interaction term are both positive at the 1% significance level, implying that social capital significantly increases farmers' income and that Internet use has a positive impact on farmers' income growth by increasing social capital, suggesting that social capital is one of the important mechanisms by which Internet use impacts farmers' income. The quantile regression results of models 4 to 7 show that the coefficient of the interaction term first decreases and then increases as the quantile increases, indicating that Internet use has the greatest impact on low-income farmers and high-income farmers s through social capital; furthermore, the difference between the coefficients of the interaction term for the 90% and 10% quantiles and the difference between that for the 90% and 25% quantiles are both negative, indicating that Internet use effectively alleviates the income gap among the high-income, low-middle-income and low-income farmer subgroups through social capital.

Table 6: The mediating effect of social capital

Variable name	Farmers' income level				
	Never	Several times a year	Several times a month	Several times a week	Every day
Internet use	0.289***	0.463***	0.536***	0.491***	0.617***
	(0.0748)	(0.0332)	(0.0432)	(0.0820)	(0.191)
Other variables	Yes	Yes	Yes	Yes	Yes
Constant term	6.549***	5.946***	6.005***	5.525***	9.150***
	(0.251)	(0.145)	(0.186)	(0.324)	(0.332)
Sample size	3069	6306	3004	1193	312
R^2	0.340	0.423	0.452	0.506	0.431

Table 7: Mechanism of the impact of Internet use on the income gap among farmers

Variable name	OL regression							
	Model(1)	Model(2)	Model(3)	Model(4)	Model(5)	Model(5)	Model(6)	Model(7)
Internet use	0.234***	1.027***	0.181***	0.456***	0.512***	0.464***	0.340***	0.285***
	(0.0244)	(0.0637)	(0.0528)	(0.113)	(0.0810)	(0.0677)	(0.0674)	(0.0840)
Social capital		0.162***	0.0586***	0.0944***	0.0869***	0.0903***	0.115***	0.123***
		(0.0113)	(0.00922)	(0.0198)	(0.0141)	(0.0118)	(0.0118)	(0.0147)
Internet use ×		0.0537**	0.0540***	0.0871**	0.0567**	0.00658	0.0176	0.0649**
Social capital		(0.0239)	(0.0194)	(0.0417)	(0.0266)	(0.0250)	(0.0248)	(0.0309)
Other variables	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Constant term	1.990***	8.365***	5.880***	5.078***	5.732***	6.679***	7.357***	7.960***
	(0.0958)	(0.0261)	(0.0937)	(0.186)	(0.133)	(0.111)	(0.111)	(0.138)
Sample size	13883	13953	13883	13883	13883	13883	13883	13883

Policy recommendations for increasing farmers' income from the perspective of "Internet+"

The report of the 19th National Congress of the Communist Party of China clearly put forward "narrowing the income gap." Therefore, increasing farmers' income and narrowing the income gap among farmers is key to the success of the rural revitalization strategy in the new era. The "Internet+" strategy has been fully implemented; in particular, the "Internet+ farmers' income growth" model provides a new strategy for regulating farmers' income distribution. Based on the 2010, 2013, and 2015 CGSS data, the present study examines the impact of Internet use and social capital on the income gap among farmers using OLS regression and the quantile regression.

The results from the study indicate that (1) in general, the two dimensions of Internet use can significantly increase farmers' income levels and that the role of Internet use in promoting farmers' income still holds after adding "information source channel" as an instrumental variable of farmers' income, to solve the endogeneity problem, and using the PSM method, to test robustness. The quantile regression results show that Internet use can significantly reduce income gap between high-income, upper-middle-income and low-income, lower-middle-income farmer groups and that Internet use plays a positive role in narrowing the income gap among farmers. (2) Social capital plays a positive role in promoting the growth of individual farmers' income, and social capital can sig-nificantly reduce the income gap between the high-income and low-income farmer subgroups. (3) Social capital is an important mechanism by which Internet use affects the income gap between farmers, and Internet use increases farmers' social capital, which in turn increases farmers' income and narrows the income gap among farmers.

The findings of the present study also offer useful insights. First, we should actively promote the equalization of basic public services, improve the structure of the government's public service financial expenditures, enhance the efficiency of the government's public service financial supply, and then promote the balanced and high-quality development of urban and rural Internet construction, comprehensively implement "increased speed and decreased fees" for the Internet, and eliminate the "digital divide" to ensure that farmers in rural areas, especially in remote and impoverished areas, have access to the Internet and can afford it. Second, we should actively promote Internet skills training, improve the ability of farmers in rural areas to use the Internet, ensure correct Internet use, actively utilize social communication, social exchange, and social interaction functions on the Internet, and establish a platform for information exchange among farmers, the government and social organizations, thereby increasing farmers' income. Third, the "informal" function of social capital should be fully utilized to promote an increase in human capital through the accumulation of social capital, so as to achieve income growth for farmers and close the income gap. Finally, the "Internet + social capital" mechanism for increasing farmers' income should be developed, and Internet information technology should be used as a driver to improve Internet financing systems based on mutual trust and reciprocity to broaden the employment channels of farmers, thereby narrowing the income gap among farmers and achieving a fair income distribution.

This study has certain limitations. Because the questionnaire did not ask specific questions regarding Internet browsing content and spending on gifts, for example, the measurement of Internet use and social capital is still biased to some extent. In addition, there may still be a problem related to variable omission although a series of variables has been controlled for. Therefore, to compre-hensively examine the impact of Internet use and social capital on the income gap among farmers, further verification of the results reported herein, using more scientific research methods and data, are needed.

References

1. Krueger, A. B. (1993). How computers have changed the wage structure: evidence from microdata, 1984–1989. The Quarterly Journal of Economics, 108(1), 33-60.
2. Goss, E. P., & Phillips, J. M. (2002). How information technology affects wages: Evidence using internet usage as a proxy for IT skills. Journal of labor Research, 23(3), 463-474.
3. Siaw, A., Jiang, Y., Twumasi, M. A., & Agbenyo, W. (2020). The impact of Internet use on income: the case of rural Ghana. Sustainability, 12(8), 3255.
4. Miremberg, H., Ben-Ari, T., Betzer, T., Raphaeli, H., Gasnier, R., Barda, G., ... & Weiner, E. (2018). The impact of a daily smartphone-based feedback system among women with gestational diabetes on compliance, glycemic con-trol, satisfaction, and pregnancy outcome: a randomized controlled trial. American journal of obstetrics and gyne-cology, 218(4), 453-e1.
5. Lu, K., Marino, N. E., Russell, D., Singareddy, A., Zhang, D., Hardi, A., ... & Puri, V. (2018). Use of short message service and smartphone applications in the management of surgical patients: a systematic review. Telemedicine and e-Health, 24(6), 406-414.
6. Fafchamps, M., & Minten, B. (2012). Impact of SMS-based agricultural information on Indian farmers. The World Bank Economic Review, 26(3), 383-414.
7. Davis, B., Di Giuseppe, S., & Zezza, A. (2017). Are African households (not) leaving agriculture? Patterns of households' income sources in rural Sub-Saharan Africa. Food policy, 67, 153-174.
8. Card, D., & DiNardo, J. E. (2002). Skill-biased technological change and rising wage inequality: Some problems and puzzles. Journal of labor economics, 20(4), 733-783.
9. Ma, W., Grafton, R. Q., & Renwick, A. (2020). Smartphone use and income growth in rural China: Empirical results and policy implications. Electronic Commerce Research, 20(4), 713-736.
10. Sai, T., Yulian, W., & Xiaofeng, H. (2010). An empirical study of agricultural insurance—Evidence from Chi-na. Agriculture and Agricultural Science Procedia, 1, 62-66.
11. Dunne, T., Foster, L., Haltiwanger, J., & Troske, K. R. (2004). Wage and productivity dispersion in United States manufacturing: The role of computer investment. Journal of Labor Economics, 22(2), 397-429.
12. DiMaggio, P., & Bonikowski, B. (2008). Make money surf-

ing the web? The impact of Internet use on the earnings of US workers. American Sociological Review, 73(2), 227-250.
13. Pabilonia, S. W., & Zoghi, C. (2005). Returning to the returns to computer use. American Economic Review, 95(2), 314-317.
14. Liu, X., & Han, Q. (2018). The influence of Internet usage of rural residents on income and its mechanism: based on China family panel studies (CFPS) data. J. Agr. Econ., 9, 124-134.
15. Kumar, J. (2012). Information and Communication Technology in agriculture and rural development. Asia Pacific Journal of Management & Entrepreneurship Research, 1(2), 193.
16. Zhou, D. (2016). Research on the Effect of Internet Coverage in Driving Rural Employment. World Econ. Pap, 3, 76-90.
17. Ma Junlong, Ning Guangjie.The Internet and Non-agricultural Employment of Rural Labor Force[J]. Finance & Econom-ics, 2017, (07).
18. Han, C., & Zhang, L. (2017). The Influence of Internet Popularization on Urban and Rural Income Distribution: GMM Analysis Based on the Data of Provincial Panel in China. Inquiry into Economic Issues (Jingji Wenti Tansuo), 8, 18-27.
19. Ma, J. Q., & Kong, T. T. (2019). Agricultural Technology Progress, Labor Force Transfer and Regional Rural Income Gap. Journal of South China Agricultural University (Social Science Edition), 18(6), 35-44.
20. Bound, J., & Johnson, G. (1992). Changes in the structure of wages in th 1980's: An evaluation in means-tested entitlement programs. American Economic Review, 82, 371-392.
21. Whitacre, B., Gallardo, R., & Strover, S. (2014). Broadband' s contribution to economic growth in rural areas: Moving towards a causal relationship. Telecommunications Policy, 38(11), 1011-1023.
22. Xu, Z., Zheng, F., & Chen, J. (2013). Digital divided or digital provided? The effective supply of information and the farm-gate price: an empirical study from micro-level. China Economic Quarterly, 12(4), 1513-1536.
23. Song, X. (2017). Empirical analysis of digital inclusive finance bridging the urban-rural residents' income gap. Finance & Economics, 6, 20-31.
24. Zhou Yang, Hua Yuyin. Internet and rural household entrepreneurship: An empirical analysis based on CFPS data[J]. Journal of Agrotechnical Economics,2017, (05).
25. Wu Yan, Hu Biliang. Social Capital and Income Gap of China' Peasant Workers[J]. Chinese Journal of Population Science, 2014(06).
26. Westlund, H., & Adam, F. (2010). Social capital and economic performance: A meta-analysis of 65 stud-ies. European planning studies, 18(6), 893-919.
27. Tang Liqiang, Zhou Jing. Social capital, employment status and rural residents' non-farm income: An empirical analysis based on CGSS2013 survey data[J]. Rural Economy, 2017, (05).
28. Xie Jiazhi, Wang Wentao. Social Structure Change, Social Capital Transition, and Income Inequality in Rural China[J]. China Soft Science,2016(10).
29. Huang Lina, Sheng Lan. Internet Use, Social Capital and Citizenship: An Empirical Study Based on CGSS2013 Data[J]. Press Circles, 2017, (07).
30. CHENG, M., GAI, Q. E., JIN, Y., & Shi, Q. (2016). Focusing on human capital improvement and income growth. Econ Res J, 51(1), 168-181.
31. Koenker, R., & Bassett Jr, G. (1978). Regression quantiles. Econometrica: journal of the Econometric Society, 33-50.
32. Buchinsky, M. (1994). Changes in the US wage structure 1963-1987: Application of quantile regres-sion. Econometrica: Journal of the Econometric Society, 405-458.
33. Yunsong, C. H. E. N. (2013). Does Internet Use Encourage Non-Institutional Political Participation? An Instrumental Variable Analysis of the Data from CGSS2006. Society: Chinese Journal of Sociology/Shehui, 33(5).
34. Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. Journal of educational Psychology, 66(5), 688.
35. Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. The American Statistician, 39(1), 33-38.
36. McKenna□Green & Gleason. "Relation Formation on the Internet: What 's the Big Attraction?" Journal of Social Issues, 2002,58(1)
37. Huang, R., Tianjue, L., & Yong, G. (2013). The Impact of the Internet on Social Capital: An Empirical Study Based on Internet Activity. 互联网对社会资本的影响: 一项基于上网活动的实证研究). Jianghai Academic Journal.
38. Zheng Fanbin. Relationship between Internet Usage and Social Capital: Analyzing the Role of Computer-mediated Commu-nication Competence[J]. Journal of Social Science of Hunan Normal University, 2014,43(04).