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Internet use and rural income inequality: evidence from China

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ABSTRACT
The integration of the digital transformation of agriculture and China's 'dual-carbon' strategy for agriculture is new momentum for developing agriculture, reducing rural income inequality, and improving the subjective well-being of farm households. This paper uses data from the China Family Panel Studies (CFPS) in 2014, 2016, and 2018 to examine the impact of internet use on rural income inequality at the household level. The results show that internet use can significantly reduce rural income inequality by enhancing information availability and farm households' nonfarm employment level. The results of a heterogeneity analysis reveal that the internet is more conducive to improving the income inequality of rural burdened families and families in Western China. Further analysis shows that improving income inequality can enhance the subjective well-being of farmer households. Accelerating the construction of digital villages, building internet skills cultivation systems, and focusing on the utility of internet use among vulnerable rural groups can reduce rural income inequality.

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1. Introduction

Rapid economic growth is accompanied by income gap expansion and environmental degradation (Golley & Meng, 2012; Qin et al., 2023a; Rojas-Vallejos & Lastuka, 2020). To meet the Sustainable Development Goals' (SDGs'[1]) target of reducing income inequality and protecting the environment, it is critical to monitor progress made towards income inequality reduction and decarbonization, including among rural areas (Qin et al., 2022, 2023b; Škare, & Porada-Rochoń, 2023; Stjepanovic et al., 2022; Su et al., 2023a). The low-income group has higher pollution emissions because the majority of direct energy consumption of the low-income group is coal consumption, which has higher pollution emissions than other energy consumption (Golley & Meng, 2012; Liu et al., 2019). Therefore, reducing the income inequality of the low-income group may change the

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structure of energy consumption and thus reduce the intensity of pollution emissions. As the most populous and largest developing country in the world, China has experienced high-speed economic growth in the past 40 years of reform and opening up, which has promoted rural household income growth and widened household income inequality (Qin et al., 2023c). With the traditional momentum supporting rural income growth gradually weakening[2], the rural income gap in China is expanding. By 2021, the income gap between high-income and low-income groups reached 6.12[3] in urban China. The income gap multiplier between high-income and low-income groups in rural China is 8.87, much higher than in urban China.

Meanwhile, the average annual income growth rate of the rural low-income group is always lower than that of the rural high-income group. Based on current prices, the low-income group's average annual income growth rate is 6.76%. In comparison, the high-income group's average annual income growth rate was as high as 9.19% from 2013 to 2021[4], indicating that the absolute income gap between the rural low-income and high-income groups is still widening. Rural income inequality in China is severe and may negatively affect decarbonization and subjective well-being (SWB). Reducing the widening rural income inequality has thus attracted growing interest (Luo et al., 2020; Pu et al., 2022; Xu et al., 2021, 2023).

Technological change is acknowledged as a critical element in solving this problem (Qiu et al., 2021). China has achieved complete access to the internet. Digital technologies are rapidly extending and penetrating rural agriculture, which provides opportunities to promote the digitization of rural industries (Kaila & Tarp, 2019; Leng, 2022; Liao et al., 2023; Lu et al., 2016; Škare et al., 2021, 2022) and provide technical support for carbon emissions (Lin & Zhou, 2021; Wang et al., 2022; Zhong et al., 2022). Enhancing information accessibility plays a crucial role in activating rural subjects, factors and markets. It can enhance farmers' endogenous rural development momentum and capacity. Training in information and communication technologies is a priority in providing job opportunities and adequate access to relevant information for relatively disadvantaged groups (Akerman et al., 2015; Lu & Wang, 2020; Tack & Aker, 2014). Currently, China is still in the early stage of digital village construction[5]. One of the most notable social concerns in academia and government is the following: How can internet use help narrow rural income inequality in China, and what is its mechanism? It is one of the most notable social concerns in academia and government.

Based on sizeable micro survey data drawn from the CFPS, this paper measures household-level income inequality in rural China using the Kakwani index (Kakwani, 1984; Ren & Pan, 2016) in the framework of the relative deprivation theory. Then, we quantitatively evaluate the impact of internet use on rural households' income inequality and its mechanism. Regression results show that internet use significantly reduces rural households' intra-rural income inequality. Regarding transmission mechanisms, rural internet users could resolve development dilemmas and alleviate rural income inequality by improving non-farm employment and information accessibility. Moreover, the results of a heterogeneity analysis show that internet users are more likely to promote burdened farm households and families in the western area. Finally, further analysis suggests that reducing the income inequality of farm households at the objective level can enhance their subjective well-being at the subjective level. Therefore, it provides a reference for the government to improve the

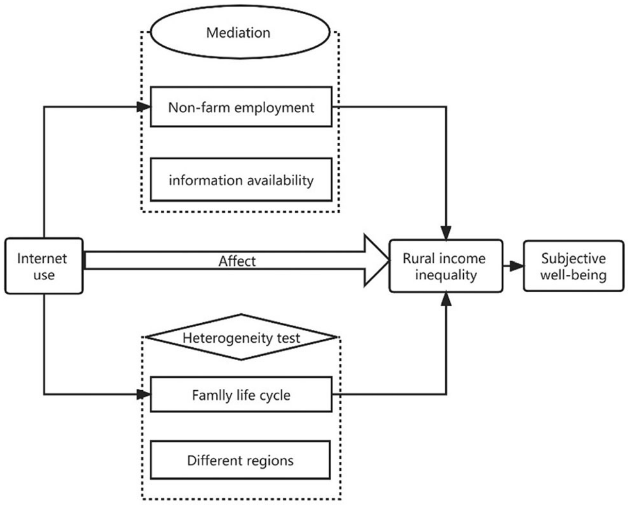

Figure 1. Concept framework.
Source: Author's design

specific implementation path of the digital countryside and alleviation of rural income inequality. Moreover, it also provides a reference for the government to implement accurate policies according to the particularity of farm households with different characteristics (Figure 1). The conceptual framework of this study is shown in Figure 1.

Compared with the existing studies, this paper makes three marginal contributions. First, this paper introduces the framework of relative deprivation analysis and explores the degree of rural income inequality from a micro perspective. Existing studies are concerned with growing income inequality in urban–rural areas and interregional areas using the provincial-level Gini coefficient (Komatsu & Suzuki, 2023; Luo et al., 2020; Yan & Wen, 2020). Only a few studies focus on household-level income inequality (Ren & Pan, 2016). We examine the impact of internet use on rural income inequality using the relative deprivation index at the household level. Second, this paper enriches the heterogeneous perspective of internet use research. Most studies distinguish the heterogeneous effects of internet use on income inequality from individual characteristics and regional heterogeneity (Kaila & Tarp, 2019; Lin & Zhou, 2021; Qiu et al., 2021). This study considers the influence of family structure on farmer households' decisions on production and management. It analyses the heterogeneity of farmer households' income inequality based on the family life cycle. Third, previous studies have analyzed the relationship between income inequality and SWB (Ding et al., 2021; Yan & Wen, 2020) and the causality between the internet and income growth (Kurantin & Osei-Hwedie, 2019; Leng, 2022). The relationship among internet use, rural income inequality and SWB are explored, which provides policy implications that internet use can be used to reduce rural income inequality and increase the level of SWB.

2. Theoretical analysis and hypothesis

There are two main strands of literature related to the topic of this paper. The first focuses on rural income inequality. Scholars have introduced various indicators and methods for identifying and decomposing farm households' inequality and portraying the degree and characteristics of income inequality in different regions and groups (Luo et al., 2020; Ren & Pan, 2016; Wang et al., 2022; Wan & Zhou, 2005). The second is the impact of internet use on rural income inequality. It is widely accepted that internet use is able to increase income (Ding et al., 2021; Leng, 2022). Based on search theory, the lower the information search cost is, the more adequate the information search is and thus, the greater the possibility of optimizing resource allocation and improving income levels is.

Informatization construction can reduce the cost of information search and thus promote farmers' income. However, the impact of the internet on rural income inequality is still controversial. Some scholars believe that internet penetration can narrow the digital divide, energize rural residents, reduce information asymmetry, promote nonfarm employment and entrepreneurship, facilitate the participation of low-income groups in the market, and stimulate the endogenous development motivation of farm households (Zhang, 2013; Martínez-Domínguez, & Mora-Rivera, 2020; Su et al., 2022a, 2022b, 2023b). Against this controversial background, this paper attempts to study the causality between internet use and rural income disparity at the household level under the 'relative deprivation' analysis framework.

Chatman's small world theory highlights marginalized and underprivileged people's information needs and behaviours (Burnett et al., 2001). Rural low-income people are seen as members of the 'small world'. Factors such as geographical restrictions, poor access to information devices, and policy differences hinder rural low-income people's access and use of information. With the implementation of Broadband China and the digital village movement, internet technology has gradually become popular, which cracks the information islands in rural areas. Internet use breaks through the information wall between the 'small world' and the outside world and establishes a perfect information resource channel for farmers. In the era of the information economy, rural internet information resources have gradually become the core element in the development of modern rural areas.

Internet use can also promote nonfarm employment, while nonfarm employment can reduce poverty and income inequality. First of all, Internet use can provide low-income rural households with more nonfarm employment information and training, improve human capital, and reduce job research costs. Due to the resource constraints (such as land), rural low-income groups have a higher incentive to choose nonfarm employment than wealthier farmers. In contrast, the initially wealthier groups will remain in agriculture, which will help reduce overall income inequality when the proportion of nonfarm income in total income increases (Al-Amin & Hossain, 2019; Reardon et al., 2008; Su et al., 2023c, 2023d).

Therefore, internet use improves nonfarm employment levels and information availability. On one hand, farmers can obtain valuable agricultural production information through participation in market activities and make effective agricultural decisions. They can also obtain market information related to employment and entrepreneurship to significantly increase the probability of nonfarm employment and entrepreneurship, increasing farmers' income. On the other hand, nonfarm employment not only has income increase effects but can also effectively reduce the risks of agricultural production incomes, which can stabilize the income of the middle-income group and narrow the income gap (Al-Amin & Hossain, 2019; Reardon et al., 2008). The information and nonfarm employment effects generated by internet applications can bring a backward advantage to rural low-income people and suppress income inequality. In summary, this paper proposes the following hypothesis.

Hypothesis 1: *Internet use can significantly reduce rural income inequality by increasing information availability and nonfarm employment.*

The family life cycle theory was proposed by Glick (1947). Families at different life cycle stages differ significantly in their labour supply and consumption structure. Family life cycle changes can effectively portray the process of family resource allocation and utility changes (McAuley & Nutty, 1982). Domestic and international studies have shown that with the continuous evolution of the family life cycle, farm households will continue to change regarding dependency burden, household labour quantity, and production and livelihood needs. Thus, the family life cycle can affect farm households' livelihood strategies, consumption decisions, and behaviours (Li et al., 2022; Lugauer et al., 2019; Pu et al., 2022). There is heterogeneity in the internet use of farmers in different family life cycles on farm income supplements.

Compared with the high level of internet technology development in the developed eastern regions, the central and western regions, especially the rural areas, are relatively backward concerning internet technology development and unattractive to internet technology talent. Therefore, the following hypothesis is proposed:

Hypothesis 2: *Internet use to alleviate rural income inequality is differentiated in family life cycles and regions.*

According to Diener et al. (1999), SWB is an overall assessment of people's emotional and cognitive perceptions of their quality of life. Increased objective income inequality is believed to undermine residents' subjective well-being (Ding et al., 2021; Komatsu & Suzuki, 2023; Lei et al., 2018; Tack & Aker, 2014; Yan & Wen, 2020). Income inequality negatively affects subjective well-being through the relative deprivation effect (Zhang & Churchill, 2020). The comparison with others in higher quintiles would create a sense of unhappiness and dissatisfaction (Yitzhaki, 1979). Assuming that internet use can significantly improve the income inequality of farm households and incorporate income inequality into the happiness model, what is the impact of income inequality on the quality of rural residents' lives? Can this impact affect the subjective well-being of residents? Therefore, the following hypothesis is proposed:

Hypothesis 3: *Internet use reduces rural income inequality and improves rural households' subjective well-being.*

3. Methods and data

3.1. Data

The CFPS began as a baseline survey in 2010. The tracking survey is updated every two years; it has maintained continuous questions about internet use since 2014, including family members' economic and social information. This paper uses the three-year CFPS rural household and individual micro database[6] for 2014, 2016, and 2018. Households with at least one family member with an agricultural household registration and the right to contract rural land are identified as rural households. The primary respondent to the household finances is designated as the head of the household. According to the research needs of the current paper, the data is comprehensively examined and organized; finally, 11472[7] valid sample households are obtained across the three-year study period.

3.2. Model design and definition of variables

This study mainly investigates the influencing mechanism of internet use on rural income inequality. Based on Hypothesis 1, Tobit is used to build the model in the first step. The second step is to consider endogeneity. The instrumental variables of explained variables are used to test the possible endogeneity problems. Third, there is a two-way causal relationship between internet use and the rural income inequality of rural households and between rural income inequality and the subjective well-being of rural households. A mediating effects model tests Hypothesis 1, referring to Yang et al. (2022). Models (1)-(3) are constructed as follows:

$$RD_{it} = \alpha_0 + \alpha_1 internet_{it} + \sum_{j=1}^{n} \partial_j X_{jit} + \sigma_i + \tau_t + \omega_{it} \tag{1}$$

$$MED_{it} = \lambda_0 + \lambda_1 internet_{it} + \sum_{j=1}^{n} \partial_j X_{jit} + \sigma_i + \tau_t + \mu_{it} \tag{2}$$

$$RD_{it} = \beta_0 + \beta_1 internet_{it} + \beta_2 MED_{it} + \sum_{j=1}^{n} \partial_j X_{jit} + \sigma_\mathrm{i} + \tau_t + \upsilon_{it} \tag{3}$$

In Equation (1), RD_{it} denotes the income inequality status of farm households i in the current period, and $internet_{it}$ denotes a binary dummy variable for whether farmers apply for the internet.

Most studies adopt the stepwise causal test proposed by Baron and Kenny (1986). In Equations (2)–(3), we use a stepwise causal test to analyse the mediation effect. MED_{it} represents the mediating variable, and X_{jit} is the control variable. σ_{it} and τ_{it} are the province control variable and year control variable. ω_{it}, υ_{it}, μ_{it} represent the random error difference, subscript i and t tabulate the household and year. Subscript j represents the j th control variable.

3.2.1. Dependent variables

The explained variable of this paper is farm household income inequality. Referring to Ren and Pan (2016), this paper uses the relative deprivation index to measure farm households' income inequality. Many extant studies (Ding et al., 2021; Wang et al., 2022) have often used the Gini coefficient or the Theil index to measure inequality; however, the Gini coefficient and the Theil index have limitations in that they can only describe the degree of inequality at the general level and cannot portray the characteristics of inequality at the household level (Pu et al., 2022; Ren & Pan, 2016). Therefore, this paper measures rural income inequality under 'relative deprivation' analysis and uses the relative deprivation index to reflect the state of income inequality at the household level. Ren and Pan (2016) redesigned the Kakwani index, which compares each household with other samples with higher income. This index can fit the income inequality behind the relative income differences more clearly and precisely. It can overcome the Gini coefficient's disadvantages, which do not satisfy the summation decomposability. This is done as follows.

Assuming that Cluster X contains n farm households, the distribution of household per capita net income $X = (x_1, x_2, \ \ldots, \ x_n)$ is obtained for all farm households as a whole $(x_1 \le x_2 \ldots \ \le x_n)$. According to the definition of the relative deprivation index, comparing each farm household with other reference households, the relative deprivation of farm household j to farmer i can be expressed as follows:

$$RD(x_j, x_i) = \begin{cases} x_j - x_i, & if \ x_j > x_i \\ 0, & if \ x_j > x_i \end{cases} \tag{4}$$

To obtain the average relative deprivation of farm household i in the group, $RD(x_j, x_i)$ obtains a sum over j.

$$D(x_i) = \sum_{j=1}^{n} RD(x_j - x_i) = \frac{1}{n\mu_x}\left(\sum_{x_j > x_i x_i \in X,} x_j - \sum_{x_j > x_i x_i \in X,} x_i \right) \tag{5}$$

The following solution can be obtained:

$$RD(x_i) = \ \frac{1}{n\mu_x}\left(n_{x_i}^{+} \times \mu_{x_i}^{+} - n_{x_i}^{+} \times x_i\right) = \frac{1}{\mu_x}\gamma_{x_i}^{+}\left(\mu_{x_i}^{+} - x_i\right) \tag{6}$$

μ_x is the mean of the per capita net income of all farm households, $\mu_{x_i}^{+}$ is the mean value of income of all farm households whose income exceeds household i in rural cluster X, and $\gamma_{x_i}^{+}$ is the percentage of farm households whose income exceeds household i in rural cluster X in the total number of farm households. $RD(x_i)$ is a strictly decreasing function that takes values in the range [0,1].

3.2.2. Independent variables

The core variable of this study, namely, the internet, is a dummy variable. This variable is assigned a value of 1 if the resident has mastered and applied the internet in the current period; otherwise, the value is 0. Referring to Zhang et al. (2021), the core variable values are collated by the survey's following related question: 'How often do you use the internet to study (work, play, socialize, and do business)?' For farmers with relatively low internet penetration and heavy farming workload, if the frequency of internet activities exceeds 'once a month', using the internet once a month for learning, work, entertainment, social, and business activities is consistent with real experience. It can identify farmers who use the internet. If the frequency of internet activities exceeds 'once a month', the farmer has appropriate internet access, and the variable is assigned a value of 1; otherwise, the value is 0.

3.2.3. Mediator

Information availability. Internet use can widen residents' access to information and enhance their ability to market participation and access to social services. Referring to Leng (2022), this paper chooses the 'importance of the internet as an information channel' scale as a proxy for information availability variables. The importance of information is expressed in numbers that range from 1 to 5. A high value means that farmers consider the importance of 'the internet as an information channel'. If an individual feels that a particular information channel is more critical, then consumers mainly obtain their information from that channel. Suppose farmers think that the internet is a highly important information channel. In that case, the availability of information is enhanced through the internet, and farmers will more actively use the internet to obtain information, thus eventually influencing individual decisions and behaviours.

Nonfarm employment. According to previous literature (Al-Amin & Hossain, 2019; Leng 2022; Reardon et al., 2008), nonfarm employment positively affects the capability and income of rural low-income households. Nonfarm employment provides relief from the adverse effects of income uncertainty and increases the resilience of farmers themselves during the distress situations of low or fluctuating seasonal in agriculture. In this paper, the logarithm of nonfarm employment income is used as a proxy variable for the nonfarm employment status of rural households. The higher the value is, the higher the nonfarm employment income is. If the farm household has never engaged in nonfarm employment, the income is 0.

3.2.4. Instrumental variables

Drawing on the literature (Ding et al., 2021; Pu et al., 2022), the authors use the 'monthly postal and telecommunications expenses' of the historical year of the farm households and the mean value of 'spare time on the internet in the current year' of the village in which the sample lived (except themselves) as the instrumental variables for internet application. We use logarithmic variables of both instrumental variables. On the one hand, the cost of posting and telecommunications includes internet consumption expenditure, a kind of consumption behaviour. The ratchet effect holds that consumption habit is irreversible. The average leisure time of a village reflects the current situation of the local internet infrastructure. The average leisure time of a village reflects the current situation of the local internet infrastructure. The local internet infrastructure can affect the internet application of local farmers through the peer effect, which satisfies the premise of the correlation of instrumental variables. On the other hand, in historical years, village residents' average value of post and telecommunications communication behaviour and spare time (except for oneself) will not directly affect the later rural income gap. There is no reverse causality problem; the two instrumental variables are unrelated to the error term.

3.2.5. Control variables

Referring to the literature (Zhang & Churchill, 2020; Zhang et al., 2021), the control variables in this paper include personal characteristics and household characteristics, and the values of the variables are drawn from the CFPS questionnaire. Householder characteristics include marital status, age, gender, employment status, nonfarm employment income, education level, and health status. For household characteristics, social capital, dependency ratio, household labour force share, and household size are also introduced as household-level control variables. Variables such as social capital, nonfarm employment income, monthly postal and telecommunication expenses, and the mean value of spare time for internet access (except for oneself) in the village are also subjected to logarithmic correction. In this paper, the fixed effect of the year and the fixed effect of the province are controlled in all regression models.

4. Empirical results and discussion

4.1. Descriptive statistics and variance test

Table 2 reports the statistical descriptions and mean differences of the main variables covered in the paper. A total of 11472 farm households are involved in this study, of which 3100 use the internet, approximately 27.02% of the full sample. Approximately 72.55% of farm households do not use the internet, amounting to 8324. These data show that internet application is not widespread enough in rural areas. The urban-rural digital divide is gradually bridged when digital construction is gradually promoted in the countryside. From the mean difference test results, the proportion of young farmers who use the internet is significantly higher than that of older farmers. The proportion of

Table 1. The specific definitions of variables.

Variable type	Variable name	Variable symbol	Definition
Dependent variable	Rural income inequality	RD	The rural income inequality of household
Explanatory variable	Internet use	Internet	If the householders use the internet, the value is 1; otherwise, it is 0.
	work and study skills	Work&study	If the householders use the internet to study or work once a month, the value is 1; otherwise, it is 0.
	Business skills	Business	If the householders use the internet for business once a month, the value is 1; otherwise, it is 0.
	Entertainment and social	Entertain&social	If the householders use the internet for Entertainment or social activities once a month, the value is 1; otherwise, it is 0.
Mediation variable	Information avaibality	Infor	The importance of the internet as an information channel
	Nonfarm income	Nonfarm	The logarithmic value of household nonfarm income.
Householder characteristics	Age of householder	Age	Age of householder.
	Age squared / 100	Age2	Age squared of householder / 100
	Gender	Gender	Gender of the householder.
	Marital status	Marriage	Marital status of the householder.
	Work status	Employment	Work status of the householder.
	Health status	Health	Health status of the householder.
	Education	Education	Years of education of householder
Household characteristics	Family size	hhsize	The number of family members
	Dependency ratio	Dependency_r	Dependency ratio of household
	Farm machinery value	Machine	The logarithmic value of household farm machine.
	Land value	Land	The logarithmic value of household land
	Number of medical insurance	medsure_num	The number of medical insurance of household.
	Happiness	Happiness	Subjective well-being indicator.

Source: Author's design.

Table 2. Main variables descriptive statistics and variance test.

	Full sample		Internet = 0		Internet = 1		
Variable	Observations	Mean	Observations	Mean	Observations	Mean	Mean difference test
RD	11472	0.552	8324	0.567	3100	0.508	0.060***
Internet	11424	0.271	8324	0	3100	1	−1
Work&study	8586	0.159	5486	0	3100	0.440	−0.440***
Business	8586	0.116	5486	0	3100	0.322	−0.322***
Entertain&social	8586	0.335	5486	0	3100	0.928	−0.928***
Householder							
Age	11472	48.14	8324	50.58	3100	41.65	8.921***
Age2	11472	24.09	8324	26.26	3100	18.29	7.969***
Gender	11472	1.467	8324	1.477	3100	1.445	0.031***
Marriage	11153	0.929	8074	0.943	3037	0.893	0.050***
Employment	11370	0.895	8322	0.891	3030	0.906	−0.015**
Health	11449	0.806	8319	0.781	3096	0.872	−0.090***
education	11308	6.151	8163	5.371	3099	8.225	−2.854***
Household characteristics							
hhsize	11472	3.434	8324	3.416	3100	3.481	−0.065**
Dependency_r	11472	0.362	8324	0.334	3100	0.437	−0.103***
machine	11462	3.502	8315	3.618	3099	3.192	0.426***
Land	11465	8.175	8321	8.434	3096	7.472	0.963***
medsure_num	11472	3.290	8324	3.038	3100	3.985	−0.947***
Infor	11424	1.691	8324	1	3100	3.546	−2.546***
Nonfarm income	11472	0.462	8324	0.444	3100	0.510	−0.066***
Happiness	7604	7.198	5481	7.140	2123	7.350	−0.210***

Note: Nonfarm employment, farm machinery value, and land value are all taken as a logarithm. ***, **, * represent the significance level of 1%, 5% and 10% respectively.
Source: CFPS.

unmarried farmers who use the internet is significantly higher than that of married farmers. The more educated the householder is, the more likely he or she is to use the internet. The proportion of female householders who use the internet is significantly higher than that of male householders, which is roughly consistent with the empirical facts.

4.2. Baseline regression results

4.2.1. The impact of internet adoption on rural income inequality

Table 3 shows the baseline regression results for internet use and income inequality. Column (1) shows that the estimated coefficient of the internet is significantly −0.0668 at 1%. Columns (2)-(3) show that the symbol and significance of the results remain stable after introducing control variables gradually, suggesting that households could significantly reduce their household inequality index through internet use. In Column (3), the estimated coefficient of internet use is −0.0609, indicating that farm households using the internet can reduce their inequality index by 6.09 percent more than those not using it.

4.2.2. The impact of different internet skills on income inequality

Table 4 reports estimates of the impact of different types of internet skills on rural income inequality. Column (1) shows that the estimated coefficients of entertainment and social activities skill and business skill are significantly negative at 1%, but work skill is negative at 10%. When controlling variables of householder characteristics are added, the result in Column (2) remains robust, and the coefficient of entertainment and social activities skills is greater than other internet skills. When we add controlling variables of household characteristics, the coefficient of internet business skills becomes

Table 3. Baseline regression: impact of Internet use on rural income inequality.

Variable	(1) Rural income inequality	(2) Rural income inequality	(3) Rural income inequality
Internet	−0.0668***	−0.0634***	−0.0609***
	(0.0056)	(0.0063)	(0.0062)
Age		−0.0186***	−0.0152***
		(0.0023)	(0.0023)
Age2		0.0184***	0.0161***
		(0.0024)	(0.0024)
Gender		−0.0294***	−0.0300***
		(0.0053)	(0.0052)
Marriage		0.0046	0.0121
		(0.0107)	(0.0107)
Employment		−0.0025	0.0008
		(0.0079)	(0.0080)
Health		−0.0336***	−0.0354***
		(0.0063)	(0.0061)
Education		−0.0071***	−0.0064***
		(0.0007)	(0.0007)
Hhsize			0.0008
			(0.0020)
Dependency_r			0.0766***
			(0.0048)
machine			−0.0002
			(0.0007)
Land			−0.0004
			(0.0007)
medsure_num			−0.0373***
			(0.0111)
Provincial FE	Y	Y	Y
Year FE	Y	Y	Y
R2	0.1219	0.1466	0.1719
Observations	11416	10894	10877

Note: All regressions are clustered at the household level. The control variable in all regressions includes the householder characteristic (age, age2, marriage, employment, health and education and family characteristic (dependency ratio, farm machinery value, land value and the number of health insurance). Farm machinery value and land value are both taken as logarithms. ***, **, * represent the significance level of 1%, 5% and 10% respectively. Robust standard errors are in parentheses.
Source: Author's calculations.

greater than that of other skills, followed by entertainment and social activities skills. The main effect of the internet on rural income inequality comes from the business function and entertainment and social activities. Internet business skills can increase household income rapidly, optimize their income structure, and ease the relative deprivation of family income. Entertainment and social activities skills can break through the barriers of information transmission, not only maintaining rural social networks to increase farmers' social capital but also relieving the pressure of the positive effects for individual work. The coefficient of online learning skills is significantly negative at the 10% level, which is lower than that of other skills. This indicates that internet learning and work can improve rural households' human capital accumulation, increase their wage income, and improve income inequality among rural households.

The results indicate that the structure of internet skills cultivation in rural households needs to be urgently improved. This suggests that rural digital construction and internet skills training systems for farmers should be focused on alleviating the income inequality of rural households. In particular, rural residents need to focus on internet business and work-learning skills for rural low-income families to accumulate livelihood capital.

Table 4. Impact of different Internet skills on rural income inequality.

Variable	(1) Rural income inequality	(2) Rural income inequality	(3) Rural income inequality
Work&Study	−0.0191**	−0.0176*	−0.0173*
	(0.0089)	(0.0091)	(0.0091)
Business	−0.0306***	−0.0463***	−0.0508***
	(0.0093)	(0.0097)	(0.0096)
Entertain&Social	−0.0605***	−0.0543***	−0.0495***
	(0.0075)	(0.0078)	(0.0077)
Age		−0.0201***	−0.0180***
		(0.0024)	(0.0023)
Age2		0.0198***	0.0190***
		(0.0026)	(0.0025)
Gender		−0.0331***	−0.0340***
		(0.0059)	(0.0058)
Marriage		0.0024	0.0068
		(0.0122)	(0.0122)
Employment		−0.0022	0.0026
		(0.0090)	(0.0091)
Health		−0.0308***	−0.0340***
		(0.0072)	(0.0071)
Education		−0.0073***	−0.0068***
		(0.0008)	(0.0008)
hhsize			0.0036
			(0.0022)
Dependency_r			0.0722***
			(0.0050)
machine			−0.0005
			(0.0008)
Land			−0.0006
			(0.0008)
medsure_num			−0.0255**
			(0.0129)
Provincial FE	Y	Y	Y
Year FE	Y	Y	Y
R2	0.1280	0.1558	0.1817
Observations	8578	8058	8047

Note: All regressions are clustered at the household level. The control variable in all regressions includes the householder characteristic (age, age2, marriage, employment, health and education) and family characteristic (dependency ratio, farm machinery value, land value and the number of health insurance). Farm machinery value and land value are both taken as logarithms. ***, **, * represent the significance level of 1%, 5% and 10% respectively. Robust standard errors are in parentheses.
Source: Author's calculations.

4.3. Endogeneity test and robustness test

4.3.1. Endogeneity test

Since there may be a two-way causal issue between internet adoption and rural income disparity, this paper adopts an instrumental variable approach to test the endogeneity issue. Table 5 reports the results of instrumental variable regression. Columns (1) and (2) use the mean values of 'monthly communication and postage costs' and spare time for the internet within the village as instrumental variables, respectively. Column (3) uses two instrumental variables at the same time. The regression results show that the internet negatively affects farm households' income inequality at the 1% significance level. This proves internet use can significantly reduce rural income inequality after accounting for endogeneity. The LM statistic in the test results reported in Table 5 is significant at the 1% level, thus rejecting the original hypothesis that the instrumental variable is not identifiable. In the overidentification test, the Hansen-J test results do not reject the original hypothesis, indicating that the IV is jointly valid; i.e. both

Table 5. Instrumental variables regression: impact of the Internet on rural income inequality.

Explained variables: Rural income inequality	(1) IV1 = Historical year postage expense	(2) IV2 = spare time of village residence	(3) Use two Instrumental variables at the same time
Internet	−0.4777***	−0.7473***	−0.6746***
	(0.0692)	(0.0931)	(0.0638)
Control variables	Y	Y	Y
Year FE	Y	Y	Y
Provincial FE	Y	Y	Y
Kleibergen-Paap rk LM statistic	123.232***	88.901***	187.835***
Kleibergen-Paap rk Wald F statistic	125.767***	94.104***	100.102***
Hansen -J P-value	–	–	0.2430
R^2	−0.3659	−0.9862	−0.7740
Observations	10664	8042	7996

Note: All regressions are clustered at the household level. The control variable in all regressions includes the householder characteristic (age, age, age2, marriage, employment, health and education) and family characteristic (dependency ratio, farm machinery value, land value and the number of health insurance). Farm machinery value and land value are both taken as logarithms. ***, **, * represent the significance level of 1%, 5% and 10% respectively. Robust standard errors are in parentheses.
Source: Author's calculations.

instrumental variables are exogenous, independent of the nuisance term, and meet the requirements for instrumental variable selection. Furthermore, the F values of the weak instrumental variable tests are all greater than 10.

4.3.2. Robustness test

Although the abovementioned process fully considers the endogeneity problem, the instrumental variables are regressed. However, some nonrandom selection problems and observation errors exist between internet USE and the rural internal income gap. To ensure the reliability of the previously stated conclusions, this paper uses the recentred influence function (RIF) to measure Gini coefficients, the 90-10th percentile distance and the 90-10th percentile ratio. Then it explores internet use and these RIF statistics of rural income inequality. In RIF regression, the effect of study grouping is used to explore the difference in income inequality among the groups of farmers who used the internet or not. The explained variables are synthesized from the Rif of two groups and are subjected to OLS regression. Take the unconditional expectation for the two sides of the equation, and the coefficient is the difference between the statistics of the two groups. The benefit of using RIF regression is that we can obtain results 'ceteris paribus' (Rios-Avila, 2020).

Columns (1)-(3) of Table 6 report the Gini coefficients, RIF statistics such as 90-10th percentile distance, and RIF regression coefficients for net per capita income of farm households. The Gini coefficient of net income per farm household in Column (1) is 0.45801. The coefficient of the internet is −0.0196 and significant at the 5% level, which indicates that the Gini coefficient per farm household will be 1.96% smaller when all farm households in the sample use the internet than when they do not use the internet. In Column (2), the value of the 90-10 quantile distance is 2.6795, and the coefficient of the internet is −0.2125 and significant at 5%, which indicates that the 90-10 quantile distance of the per capita net income of farm households will be reduced by 21.23% when all farmers in the sample use the internet than when they do not use the internet. In Column (3), the 90-10 quantile ratio of the log of net income per household is 14.644, and the coefficient of the internet is −2.9123 and significant at 5%, indicating

Table 6. Results of robustness regression tests.

Explained variables: Rural income inequality	(1) Gini coefficient	(2) 90-10th percentile distance	(3) 90-10th percentile ratio
Internet	−0.0196**	−0.2125**	−2.9123**
	(0.009)	(0.091)	(1.324)
RIF value	0.45801	2.6795	14.644
Control variables	Y	Y	Y
Provincial FE	Y	Y	Y
Year FE	Y	Y	Y
R^2	0.0249	0.0179	0.0172
Observations	10,877	10,877	10,877

Note: All regressions are clustered to the household level. In this section, Gini coefficient and 90-10 percentile distance are measured on rural households' per capita net income. In contrast, the 90-10th percentile ratio is measured on the logarithm of rural household net income per capita. The control variable in all regressions includes the householder characteristic (age, age2, marriage, employment, health and education) and family characteristic (dependency ratio, farm machinery value, land value and the number of health insurance). Farm machinery value and land value are both taken as a logarithm. ***, **, * represent the significance level of 1%, 5% and 10% respectively. Robust standard errors are in parentheses.
Source: Author's calculations.

that the 90-10 quantile distance of the log of net income per household is 291.23% smaller for all households in the sample when they use the internet than when they do not use the internet. This suggests that internet applications will reduce inequality in income distribution in rural areas when other factors are controlled.

4.4. Mechanism analysis

As mentioned previously, internet use affects farm households' income inequality mainly through the following paths: information availability and nonfarm employment.

4.4.1. The mediating effect of information availability

The popularization of internet use improves the accessibility of information for rural households. The internet gradually dismantles the information wall for household entrepreneurship, financing, and social services for rural households in poor areas. Thus, farm households can use information technology tools to obtain equal economic opportunities to participate in the market and access public social services. Internet application guides the rural low-income crowd to integrate into the market, increasing income and alleviating rural income inequality.

To test the above conjecture, the importance of the internet as an information channel is selected as the proxy variable of information availability. The mediating effect and its micro mechanism are analysed. The results are shown in Table 7. According to the step-by-step test, Column (1) shows the results of the benchmark regression of the rural internal income gap as the explained variable. Column (2) validates whether internet application significantly affects the importance of the intermediary variable internet information. In Column (3), after adding the importance of internet information channels, the coefficient of the internet is shown to be decreased compared with the baseline regression. In summary, the availability of information is a virtual channel for internet users to alleviate the internal income gap in rural areas. Through internet applications, farmer households can widen information channels, reduce market friction, promote knowledge sharing to resolve their development difficulties and alleviate their relative income deprivation.

Table 7. Mediation mechanism of information availability.

Variables	(1) Rural income inequality	(2) Information availability	(3) Rural income inequality
Internet	−0.0609***	2.3675***	−0.0270***
	(0.0062)	(0.0278)	(0.0098)
Infor			−0.0143***
			(0.0033)
Control variables	Y	Y	Y
Provincial FE	Y	Y	Y
Year FE	Y	Y	Y
R^2	0.1719	0.7500	0.1734
Observations	10877	10877	10877

Note: All regressions are clustered at the household level. The control variable in all regressions includes the householder characteristic (age, age2, marriage, employment, health and education) and family characteristic (dependency ratio, farm machinery value, land value and the number of health insurance). Farm machinery value and land value are both taken as logarithms. ***, **, * represent the significance level of 1%, 5% and 10% respectively. Robust standard errors are in parentheses.
Source: Author's calculations.

Table 8. Intermediation mechanism of nonfarm employment.

Variables	(1) Rural income inequality	(2) Information availability	(3) Rural income inequality
Internet	−0.0609***	0.0227***	−0.0511***
	(0.0062)	(0.0068)	(0.0055)
Nonfarm			−0.4278***
			(0.0095)
Control variables	Y	Y	Y
Provincial FE	Y	Y	Y
Year FE	Y	Y	Y
R^2	0.1719	0.1595	0.3468
Observations	10877	10877	10877

Note: All regressions are clustered at the household level. The control variable in all regressions includes the householder characteristic (age, age2, marriage, employment, health and education) and family characteristic (dependency ratio, farm machinery value, land value and the number of health insurance). Farm machinery value and land value are both taken as logarithms. ***, **, * represent the significance level of 1%, 5% and 10% respectively. Robust standard errors are in parentheses.
Source: Author's calculations.

4.4.2. The mediating effect of nonfarm employment

The log of household nonfarm income is selected as a proxy variable for nonfarm employment and tested for mediating effects; the results are shown in Table 8. According to the idea of a step-by-step test, in Column (1), the income inequality of rural households is taken as the result of the baseline regression of the explained variable. Column (2) verifies whether internet use has a significant impact on the transformation of nonfarm employment. In Column (3), after adding nonfarm employment, the internet coefficient decreases compared with the baseline regression. In conclusion, the availability of information is an essential channel through which to use the internet to alleviate the internal income gap in rural areas. By promoting nonfarm employment and increasing family income, farmers can alleviate their relative deprivation of income.

4.5. Further analysis

4.5.1. Heterogeneity analysis

4.5.1.1. Heterogeneity analysis of family life cycles. To test Hypothesis 2, referring to the literature, according to family life cycle theory, the households, as shown in Table 9, are classified into four types: households with unburdened families, child-rearing households, burdened households, and aging-cared households.

Table 9. Classification of different family life cycles.

Family Life Cycle	Classification criteria
Unburdened Families	If there are neither older people (over 65 years old) nor children under 16 years old, the value is 1. Otherwise, it is 0
Child-rearing Families	If there are no older people over 65 but only children under 16, the value is 1. Otherwise, it is 0.
Burdened Families	If there are older people over 65 and children under 16, the value is 1. Otherwise, it is 0.
Aging-cared Families	If there are only older people over 65 but no children under 16, the value is 1. Otherwise, it is 0

Source: Author's design.

Table 10. Heterogeneity analysis of family life cycle.

Explained variables: Rural income Inequality	(1) Unburdened Families	(2) Child-rearing Families	(3) Burdened Families	(4) Aging-cared Families
Internet	−0.0457***	−0.0315***	−0.0622***	−0.0358**
	(0.0091)	(0.0107)	(0.0168)	(0.0165)
Control variables	Y	Y	Y	Y
Provincial FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
R^2	0.2395	0.2353	0.3264	0.3732
Observations	5383	3044	1036	1325

Note: All regressions are clustered at the household level. The control variable in all regressions includes the householder characteristic (age, age2, marriage, employment, health and education) and family characteristic (dependency ratio, farm machinery value, land value and the number of health insurance). Farm machinery value and land value are both taken as logarithms. ***, **, * represent the significance level of 1%, 5% and 10% respectively. Robust standard errors are in parentheses.
Source: Author's calculations.

Columns (1)-(3) of Table 10 report the coefficients of internet use in unburdened families, childcare-rearing families, and burdened families, which are −0.0457, −0.0315, and −0.0622, respectively, which are significantly negative at the 1% level, indicating that internet use is most effective in reducing the income inequality of burdened families, followed by unburdened and child-rearing families. Column (4) reports that the coefficient for the aging-care family group is significantly negative at the 5% level, and the coefficient value is −0.0358. For the rural elderly population, both their income and level of education are generally low. Even if they can bear the cost of information, they may not be able to use it. They cannot use the internet to obtain information, absorb knowledge, and improve their self-development to narrow the income gap.

4.5.1.2. Heterogeneity analysis of regions. Table 11 shows the effect of internet use in different regions. The coefficients of internet use are −0.0445. −0.0344 and −0.056, all of which are significantly negative at a level of 1%. This finding indicates a significantly negative effect on rural income inequality, and the reduction effect is more significant than in the eastern and central regions. This result may have occurred because of the greater lack of talent in internet technology. Farmers who can apply internet technology will have more information advantages and competitiveness, thus significantly increasing their income.

4.5.2. Further analysis based on subjective well-being

To test Hypothesis 3, the relationships among internet use, rural income inequality and subjective well-being are analysed. After finding that internet application reduces

Table 11. Heterogeneity analysis of regions.

Explained variables: Rural income Inequality	(1) Eastern	(2) Central	(3) Western
Internet	−0.0445***	−0.0344***	−0.0560***
	(0.0098)	(0.0113)	(0.0104)
Control variables	Y	Y	Y
Provincial FE	Y	Y	Y
Year FE	Y	Y	Y
R2	0.2928	0.1609	0.1579
Observations	3890	3152	3777

Note: All regressions are clustered at the household level. The control variable in all regressions includes the householder characteristic (age, age2, marriage, employment, health and education) and family characteristic (dependency ratio, farm machinery value, land value and the number of health insurance). Farm machinery value and land value are both taken as logarithms. ***, **, * represent the significance level of 1%, 5% and 10% respectively. Robust standard errors are in parentheses.
Source: Author's calculations.

Table 12. Effect of income inequality on SWB of farm households.

Variables	(1) Happiness	(2) Happiness	(3) Satisfaction	(4) Satisfaction
Rural Income Inequality	−0.0699***	−0.0616***	−0.0472***	−0.0491***
	(0.0119)	(0.0122)	(0.0092)	(0.0094)
Control variables		Y		Y
Provincial FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
R^2	0.0377	0.0702	0.0579	0.0914
Observations	7598	7099	11386	10853

Note: All regressions are clustered at the household level. The control variable in all regressions includes the householder characteristic (age, age2, marriage, employment, health and education) and family characteristic (dependency ratio, farm machinery value, land value and the number of health insurance). Farm machinery value and land value are both taken as logarithms. ***, **, * represent the significance level of 1%, 5% and 10% respectively. Robust standard errors are in parentheses.
Source: Author's calculations.

the income inequality of farmers, the objective level of the income inequality of farmers is examined concerning the subjective level of farmers, i.e. whether the subjective well-being of farmers can be improved. The model is constructed as shown in Equation (7):

$$happiness_{it} = \alpha_0 + \alpha_1 RD_{it} + + \sum\nolimits_{j=1}^{n} \partial_j X_{jit} + \sigma_i + \tau_t + \varepsilon_{it} \tag{7}$$

In Formula (7), $happiness_{it}$ denotes the subjective well-being of current farmers. Using Zhang and Churchill (2020) as a reference, scores from the CFPS questionnaire questions of 'How happy are you?' and 'How satisfied are you with your life?' are used as proxy variables. 'How happy are you?' is scored ranging from 1 to 10. The higher the score is, the higher the degree of happiness is. 'How satisfied are you with your life?' is scored with numbers ranging from 1 to 5. The higher the score is, the more satisfied the farm householders are with their lives. ε_{it} stands for random standard error, and RD_{it} and X_{jit} are defined as described previously. To facilitate a comparison of the results, we have dimensionlessed satisfaction and happiness. Normalize the values of satisfaction and happiness to be between 0 and 1.

Table 12 Columns (1) and (3) report that the regression coefficients of income inequality on well-being and life satisfaction are significantly negative at 1%. After adding the control variables, the sign orientation and significance remain robust. This shows that the higher the farmers' income inequality is, the more significant the damage to the subjective well-being of farmers is. Reducing farmers' income inequality can objectively improve residents' happiness and life satisfaction subjectively. This confirms the abovementioned reasoning and shows that the government can reduce farm households' income inequality and improve farmers' well-being by promoting the construction of digital villages.

5. Conclusions and implications

This paper measures rural income inequality in our country under the relative deprivation theory. Through the empirical results, farmers can significantly reduce their income inequality through internet use and improve subjective well-being furtherly. Acquiring three digital skills- internet work and study, business and entertainment and social interaction- can negatively impact rural income inequality. The negative effect of business and entertainment and social interaction is more significant. The results of a heterogeneity analysis show that the negative impact of internet application on farm households' income inequality is more effective for burdened families and families in the western China. Our findings have significant policy implications for design of internet projects in China and beyond.

Based on the above findings, the following recommendations are made. First, the government should vigorously promote the overall construction of digital villages and enhance internet construction in rural areas, farmers and agriculture. Digital rural construction provides a solid information-based guarantee for alleviating the rural internal income gap. Our country is still in the primary stage of digital rural construction. Thus, it is necessary to promote multiple subjects to increase investment in rural digital infrastructure construction, tamp down on the new rural infrastructure, and build a system for fostering and popularizing the internet for all, covering both urban and rural areas. Therefore, farmer households, especially low-income groups, should have fair access to development opportunities to achieve the effectiveness of rural resource allocation.

Second, the internet skills development system should be improved to provide a systematic focus on business, education and work. This paper shows that the distribution of rural internet skills is only at the entertainment and social skills level. The entertainment and social interaction available to farmers to increase their income has accumulated enough social capital. In the context of the development opportunity of the digital economy, we cannot reduce income inequality without cultivating farmers' internet business skills and work skills. Rural areas still lack enough digital talent to put to work. Specifically, one goal is to train local digital rural leaders so that more low-income groups in rural areas can share the digital economy development dividend, raise income levels, and alleviate the wealth gap. The second goal is to consolidate agricultural resources within the government. Efforts to implement preferential agricultural policies such as the 'number of merchants to boost agriculture' project can reduce circulation costs for farmer households, especially small-scale farmer households. Internet use can break the development barrier by regional disadvantages and dock into the national unified large market.

The effectiveness of the internet for vulnerable rural groups should be noted. Differential internet training and promotion policies should be implemented. The effect of internet use on alleviating farm households' income inequality in the different family life cycles is heterogeneous. Therefore, the formulation and implementation of rural internet application development policy should pay attention to the vulnerable groups with a limited household labour force and the heavy burden of raising the elderly and children. The implementation of policies for households and measures for local conditions should be carried out.

Third, western provinces are suggested to seize the digital opportunity to fully coordinate the development and use various policy tools to make up for the lack of development and construction of digital villages in western China. We should maximize the advantages of talents and capital in the east and the potential market in the west. For example, we should build a communication system for digital economic talents in the east and underdeveloped areas in the western regions. We can cultivate localized digital rural leaders and create opportunities and conditions for more low-income groups in the western rural areas to share the dividend economic development and alleviate income inequality brought by digitalization.

The limitations and prospects of this study are as follows. As for the selection of sample time, due to the continuous data generation limitation, this study only selects the farm household samples from 2014 to 2018. It does not test the various research hypotheses proposed with the latest data. The sample started in 2014 because CFPS disclosed the Internet use data in 2012, and the 2010 questionnaire did not address specific internet skills. In addition, the deadline was not the latest year in 2020 because CFPS disclosed the family income data in 2020. In future research, the effect of internet access after 2020 on rural income inequality can be considered. Other policy tools to alleviate rural income inequality could be complemented and expanded to explore more comprehensively the pathways to alleviate rural income inequality and enhance subjective well-being. This study highlights the importance of using income indicators of inequality in tracking the SDGs and other development goals. Multidimensions of inequality should be considered in further research, such as wealth, health and education, to meet the goals of SDGs.

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. The SDGs, or the Global Goals, are the primary means for the United Nations to satisfy that demand, which is both emotional and existential.
2. General Office of the State Council "Several Opinions of the General Office of the State Council on Improving Support Policies to Promote Sustained Income of Farmers" [EB/OL] http://www.gov.cn/zhengce/content/2016-12/06/content_5143969.htm
3. The incomes gap multiplier is 6.12 means that the income of high-income group in urban China is 6.12 times higher than that of low-income group.
4. Calculations result from Statistical Yearbook.
5. Ministry of Agriculture and Rural Affairs Press Office. Two departments issued "Digital Agriculture Rural Development Plan (2019-2025)" [EB/OL] http://www.moa.gov.cn/xw/zwdt/202001/t20200120_6336380.htm.
6. CFPS started to ask questions about internet use starting in 2014; thus, this paper takes data from 2014, 2016 and 2018.
7. A total of 11,472 is the sample data size at the time of the multidimensional relative poverty measure; the subsequent regression and mechanism tests may have less than 11472 observations entering the regression due to the presence of some missing values for the newly added variables.

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