

Digital Village Construction, Income Structure and Rural Income Growth: Evidence from Peking University Digital Village Index and China Household Finance Survey

Xiang Cao^{1, a}, Pengcheng Liang^{2, b}, Nan Jia^{1, c}, Jiayang Yu^{1, d}, and Chuanjiang Yu^{1, e, *}

¹ School of Economics, Sichuan University, Chengdu, China

² School of Statistics and Mathematics, Central University of Finance and Economics, Beijing, China

^acaox0409@scu.edu.cn, ^b1325208472@qq.com, ^cjianan@scu.edu.cn, ^d2207298418@qq.com, ^{e, *}yuchuanjiang@scu.edu.cn

Abstract

As one of the most economical and convenient ways to connect rural areas to better economic opportunities, this paper provides empirical evidence on digital village building to improve rural household incomes and its main pathways. Utilizing county-level digital village index data from Peking University paired with the 2018 and 2020 CHFS survey, this study evaluates the influence of digital village construction on rural household's income in China. The results confirm that digital village construction significantly improves household income, predominantly non-farm earnings, with wages being a prime contributor. Mechanism analysis reveals that digital village construction impacts household income via labor structure, land transfer, and working hours, stimulating both direct and indirect employment across various industries. Furthermore, it is found that digital village construction facilitates inclusive growth, amplifying incomes of marginalized groups such as low-income households, central-western regions, and lesser-educated populations. These findings can help in narrowing the income gap between urban and rural group.

Keywords

Digital Village Construction; Income Growth; Non-Farm Income; Rural Household.

1. Introduction

The economic development of developing countries is often marked by a crucial transition of labor from agriculture to industrial and service sectors. This shift, central to model, is propelled by the higher productivity and wages in the non-agricultural sectors. Expanding farmers' economic activities into these sectors, particularly urban employment, is widely recognized as an effective strategy for income enhancement in developing nations [1, 2, 3]. Improved connectivity to broader economic opportunities is essential for facilitating this transition. Traditional methods like rural road construction, though effective, are often costly [4]. In contrast, the digital age has seen the rise of digital villages as a cost-effective and convenient approach to integrating remote rural areas into the larger economy. This trend, observed in various developing countries including China, addresses the challenges of relative poverty in rural areas.

In developing countries, advancements in digital agricultural technology have revolutionized rural economies and income sources. This shift has introduced new economic models, such as in China, and has significantly enhanced non-agricultural earnings. The World Development Report 2016 suggests digital technology's potential to uplift the impoverished, noting mobile

phone access outpacing basic utilities in these regions. However, internet access remains limited for many, hindering full participation in the digital economy. Despite this, countries like India and China are making significant progress; India, following its digitization program, saw an 18% increase in internet users in 2018 [5], and over 90% of Chinese villages had internet access by 2015, showcasing substantial rural connectivity investments.

The impact of digital rural development on farmers' income growth has been the subject of extensive research, yet there remains a lack of consensus in the findings. However, several studies indicate that digitalization can positively influence farmers' income. For instance, Chen et al. [6] and Qin et al. [7] found that digital rural construction significantly boosts farmers' total household income, wage income, and property income, though it may constrain the growth of net agricultural income. Further supporting this perspective, research by Zhang et al. [8], Chao et al. [9], Liu and Zhou [10], Song et al. [11], X. Zhang et al. [12], Zeng et al. [13], Zhu et al. [14] suggests that internet access, e-commerce, digital literacy, and digital finance are instrumental in elevating farmers' income levels. Despite these positive indications, the diverse outcomes observed necessitate ongoing empirical examination to fully understand the impact of digitalization on rural economies. However, some studies suggest that the growth of the digital economy might adversely affect farmers' income. Additionally, there is no definitive evidence to establish a direct link between digital technology and a general increase in residents' income. For example, Liu and Zhou [15] observed that improvements in rural communication infrastructure did not lead to an increase in household income. Similarly, Aker et al. [16] noted that advancements in digital technology did not always result in the anticipated income rise. These observations highlight the need for more detailed research to understand the specific ways digitization influences farmers' income levels. Complementing this, Camacho and Conover [17] found that although farmers are willing to adopt new technologies, these technologies do not always translate into immediate welfare improvements.

This study explores the impact and pathways of digital economy development on rural household income in developing countries, using China as a case study to highlight broader trends and dynamics. It particularly focuses on how the concept of the digital village, a crucial component of China's digital economy, influences rural income. We combine Peking University's county-level digital rural index from 2018 and 2020 with data from the China Household Finance Survey (CHFS) for 2019 and 2021, creating a comprehensive rural household dataset with extensive temporal and geographical coverage. To address the potential endogeneity stemming from the inverse causality between digital rural construction and household income, we employ the instrumental variable two-stage least squares (IV-2SLS) method. Additionally, we conduct various heterogeneity analyses to provide nuanced insights into both agricultural and nonfarm incomes. Crucially, we explore the impact mechanisms of digital rural construction on household income through three channels: household labor structure, land transfer, and extended working time.

This paper makes three key contributions. First, it introduces the county-level Digital Village Index as a significant influencer on rural households' income, representing a more comprehensive approach than the single-dimensional metrics commonly used in previous studies. These earlier studies often relied on either macro-level indices, like digitalization rate, or micro-level indicators, such as Internet usage or the digital inclusive finance index, which do not fully capture the multifaceted nature of digital village development in rural settings. Second, we address the inverse causal relationship between rural digital village development and rural households' income, which could lead to biased estimations. In this study, we use the distances from each county to the provincial capital and Hangzhou as two instrumental variables to effectively mitigate this endogeneity issue. Third, by decomposing income sources, we aim to identify the effects of digital village construction on both agricultural income and non-farm income of rural households, including wage income and non-financial asset income. Our study

reveals that non-farm income, particularly wage income, has significant implications for the sustainable growth of rural households' income.

The structure of this paper is as follows: Section two reviews the relevant literature and formulates theoretical hypotheses. Section three outlines the data sources, criteria for variable selection, and the configuration of the model. In section four, we present the results of our empirical analysis, which includes benchmark regressions, robustness checks, heterogeneity analysis, and an analysis of the underlying mechanisms. The paper concludes with the final section, offering insights and policy recommendations based on our findings.

2. Literature Review and Hypotheses

Past research primarily examined the correlation between digital village construction and farmers' income, revealing a broad income-boosting impact of digital village development on rural residents. The digital economy can improve farmers' human capital level and improve the social environment [18], use of information tools to reduce farmers' information search costs [19, 20], expand employment and property income channels [21, 22], thereby comprehensively improving the diversified income growth of rural residents [23, 24]. Regarding income structure, current literature suggests that the labor utilization rate in the agricultural sector is typically lower than in non-agricultural sectors. Therefore, growth in non-agricultural sectors plays a crucial role in the sustained enhancement of rural household income [25, 26, 27, 28, 29]. Consequently, scholars have shifted their research focus to the impact of digital villages on non-farm income rather than agricultural income, finding that internet utilization generally fosters non-agricultural employment among the rural labor force [30], and ensure that farmers can earn decent wage incomes with the work they do [31, 32]. Furthermore, the development of digital village construction can promote rural entrepreneurial activities, off-farm employment [33], and enhance rural land transfer [34], so as to increase non-farm income [7].

Numerous studies have investigated the mechanisms by which digital village development influences farmers' non-farm income. The existing research can be summarized into the following three aspects. First, digital village construction affects labor structure in the household.

Digital village development generates a multitude of temporary job opportunities, optimizes the non-agricultural employment landscape, diminishes information acquisition costs, enhances information immediacy, and stimulates off-farm employment, thereby directly augmenting non-farm income [35, 36, 37]. Second, digital village construction has a significant influence on rural land transfer. Rural land transfer has become an essential part of rural development, increasing the relative income and living standards of rural residents [38, 39]. In addition, digital village construction also enlarges the scale effect of agricultural production. The centralized management of agriculture accelerates rural land transfer, and the remaining labor force in rural areas can be further transferred to the non-agricultural sector, so that rural households can earn more non-farm income. Third, digital village construction also empowers farmers by offering them the opportunity to work flexible hours. Traditional agriculture, with its seasonal ebbs and flows, can limit income potential, however, with digitalization, farmers are no longer bound by such constraints. It allows them to increase their productivity based on the demands of their work rather than the dictates of the seasons, which in turn can lead to a substantial increase in their income.

Additionally, digital village development can promote inclusive growth. Prior studies highlighted that the impacts of digital economy development vary among different household groups, with digital development more effectively stimulating inclusive growth of rural household income. Zhang et al. [40] pointed out that China's rural digital construction is

developing faster in backward areas, so it has significantly increased the household income of rural low-income groups. Ma et al. [41] concluded that the effect of digitalization on income is greater for the low-income households in rural areas than those middle- and high-income households, which is conducive to the realization of social equity.

Accordingly, three hypotheses to be tested in this study are proposed as follows:

H1: Digital village development significantly enhances rural household income by primarily boosting their non-farm earnings.

H2: Digital village development potentially elevates rural households' non-farm income through three channels: optimization of labor structure, facilitation of land transfer, and extension of working hours.

H3: Digital village development variably enhances non-farm income, notably benefiting rural households in central and western regions and less-educated households for inclusive growth.

3. Data Source, Variable Selection, and Model Setting

3.1. Data Sources

The data of digital village construction is obtained from the Digital Village Index (DVI) compiled by Peking University. This index uses the county as its primary unit of analysis and offers a comprehensive information across multiple dimensions including rural infrastructure development, economic growth in rural areas, living conditions in the countryside, and rural governance practices. The DVI dataset was initially released in 2018 and has since been updated annually.

The fundamental data of rural households come from the 2019 and 2021 China Household Finance Survey (CHFS) database. Conducted biennially since 2011, the CHFS questionnaire captures information pertaining to the year preceding the survey. The CHFS dataset spans 29 provinces (except Xinjiang, Tibet, Taiwan, Hong Kong and Macau) based on the available data, encompassing over 360 districts (counties) and in excess of 1,400 communities.

The DVI is matched with the CHFS dataset by the county identifier. After eliminating the missing values and obvious outliers, we obtain a two-year cross-sectional dataset with a total of 12,066 sampled households. We also winsorize the household income at the 0.5% tails and applied a $\ln(x + 1)$ transformation to address negative values.

3.2. Variable Selection

Dependent variable: Total income of rural households, comprised of agricultural income (from farming, forestry, animal husbandry, fishing) and non-farm income (a combination of wage income, transfer income, and income from both non-financial and financial assets). Wage income refers to earnings from off-farm employment. Transfer income is primarily government subsidies and intra-household gifts. Income from non-financial assets includes rents from assets like cars and houses, land transfers, and intellectual property sales. Financial asset income encompasses bank deposits, stock funds, commercial insurance, and business income, excluding industrial and commercial business income due to its rarity in the sample.

Core explanatory variable: DVI compiled by Peking University. The detailed composition and weights of the DVI are listed in Table A1 in the appendix.

Control variables: this paper uses three categories of control variables by referencing Cheng et al. [42]. The first control variable category includes the household head's characteristics (age, gender, educational level, marital status, health). The second category includes household attributes like household size and farmland size. The final category comprises county-level factors such as per capita county GDP, tertiary industry proportion and local fiscal budget expenditure.

Table 1. Descriptive statistics of main variables.

Variable	Mean	Std. Dev.	Min.	Max.
DVI	54.117	10.388	25.166	82.781
Distance to provincial capital (km)	140.752	65.223	21.749	345.281
Total income of household (yuan), take logarithm	10.238	1.234	2.710	16.120
Agricultural income of household (yuan), take logarithm	6.560	4.134	0.000	16.118
Non-farm income of household (yuan), take logarithm	9.257	2.379	0.000	15.436
Wage income of household (yuan), take logarithm	5.503	5.160	0.000	14.403
Income from financial assets of household (yuan), take logarithm	0.959	3.020	0.000	15.425
Income from non-financial assets of household (yuan), take logarithm	1.155	2.750	0.000	13.190
Transfer income of household (yuan), take logarithm	6.536	3.152	0.000	15.215
Age of head of household	53.713	10.560	18.000	70.000
Gender of head of household (male=1, female=0)	0.624	0.484	0.000	1.000
Marital status of head of household (married=1, others=0)	0.887	0.317	0.000	1.000
Health condition of head of household (better or above=1, others=0)	0.730	0.446	0.000	1.000
Education of head of household: preliminary school or below (yes=1, no=0)	0.518	0.500	0.000	1.000
Education of head of household: junior or high school (yes=1, no=0)	0.349	0.480	0.000	1.000
Education of head of household: college or above (yes=1, no=0)	0.141	0.333	0.000	1.000
Household size	6.980	9.176	1.000	39.000
Land size (acres)	1.105	1.256	0.000	4100
Per capita GDP in the county (yuan), take logarithm	10.379	0.630	9.010	12.497
Percentage of Tertiary sector in the county (%)	0.423	0.091	0.113	0.691
Local fiscal budget expenditure (ten thousand yuan), take logarithm	12.906	0.524	10.182	16.993
Household employment structure	0.183	0.200	0	1
Distance to Hangzhou (km)	1167.805	526.488	0	2429.936
Distance to the provincial capital (km)	142.183	73.725	22.019	342.407
Number of observations	12,066			

Note: Household employment structure is calculated as the proportion of non-agricultural employment.

3.3. Econometric Model Setting

3.3.1. Benchmark Regression

In order to verify the impact of digital village construction on rural households' income in China, we construct the following model:

$$Y_{ict} = \alpha_0 + \beta_0 DVI_{ct} + \theta_0 Controls_{it} + \mu_c + \varepsilon_{it} \quad (1)$$

where i is the rural household, c is the county where the household is located and t is the survey year. y_{it} is the indicator of rural households' income. Specifically, y_{it} denotes the income of the household, DVI_{it} represents the digital village index of the county where rural household i is located. $controls_{it}$ is a vector of the control variables also affecting y_{it} , μ_i represents the regional fixed effect of county and ε_{it} is random disturbance term.

3.3.2. Endogeneity

Endogeneity may bias the regression estimation in equation (1), due to two sources: potential inverse causality between rural income and digital village construction, as wealthier rural households may invest more in digitalization, enhancing the digital village level, and omitted variables like natural environment factors and personal attributes that may influence household income but remain unobserved.

To solve the problem of endogeneity of household behavior, this paper adopts instrumental variable (IV) estimation. Effective instrumental variables must meet two conditions: externality and relevance. The instrument variables selected are the spherical distances from the household's location to Hangzhou and the provincial capital as suggested by Zhang et al. (2019). Firstly, Hangzhou's digital growth influences nationwide development, with closer regions experiencing greater spillovers. After accounting for economic and regional effects, distances from a household to Hangzhou and the provincial capital should inversely correlate with digital village development. Secondly, the fixed spherical distances from a household's location to Hangzhou and the provincial capital, shaped by historical, cultural, and economic influences, satisfy the exogeneity assumption. Thirdly, despite proximity to neighboring provincial capitals, administrative barriers may limit economic spillovers. With controls for county-level GDP and the regional fixed effects, no direct relationship should exist between spherical distance to the provincial capital and rural income, satisfying exclusion restrictions.

4. Empirical Results

4.1. Digital Village and Income: Baseline Results

The estimation results of model (1) are summarized in Table 2. Columns (1), (3), and (5) present OLS estimation results, while columns (2), (4), and (6) provide IV-2SLS estimation outcomes. It is found that the coefficient estimates of the IV-2SLS regression model are significantly larger than those of OLS. The reasons for this are twofold. Firstly, reverse causality—where rural income impacts digital village development—could overestimate the results. Secondly, unobserved variables such as household abilities, cultural norms, or environmental factors might lead to underestimations. This dual bias could ultimately skew results downward. The IV-2SLS results indicate that the enhancement of digital village development significantly boosts both the total and non-farm income of rural households; however, it does not significantly affect their agricultural income. The validity of the two IVs is examined. First-stage results show the two instrumental variables selected both significantly and negatively affect digital village index, confirming the relevance condition. With a Cragg-Donald Wald F statistic of 348.466, the IVs pass the weak identification test. In addition, the Hansen J value indicate that we fail to reject the overidentification null hypothesis, confirming the exogeneity of both instrumental variables.

It's worth mentioning that despite foreign studies have found that rural digitalization positively impacts the adoption of advanced agricultural technology by rural households, thereby boosting agricultural income [43, 44], this is not supported by our findings in columns (3) and (4) of Table 2. The first reason is that the current stage of imperfect integration between information and agricultural technology, combined with the generally lower quality of rural labor and inadequate agricultural tech education, prevents Chinese rural households from fully

absorbing and implementing the advances from digitalization. As a result, informatization has yet to spur agricultural technological progress [45]. Additionally, agriculture has certain lagging characteristics and long cyclicity. Therefore, translating digital technology development into crop yield and quality improvements, and subsequently into increased agricultural income, takes considerable time. Hence, the positive effect of rural digitalization on agricultural income isn't yet observable.

Table 2. Results of OLS and IV-2SLS estimations.

Variable	Total income		Agricultural income		Non-farm income	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
DVI	0.016*** (0.003)	0.045** (0.023)	0.021 (0.018)	0.074 (0.069)	0.015*** (0.006)	0.064** (0.031)
Age	-0.011*** (0.002)	0.280*** (0.030)	-0.027*** (0.005)	-0.026*** (0.006)	0.006*** (0.002)	0.007*** (0.002)
Gender	0.039 (0.030)	0.038 (0.031)	0.658*** (0.114)	0.657*** (0.116)	-0.094* (0.060)	-0.094* (0.056)
Marital status	0.270*** (0.040)	0.260*** (0.042)	1.247*** (0.129)	1.229*** (0.131)	-0.013 (0.057)	-0.003 (0.057)
Health condition	0.330*** (0.028)	0.326*** (0.028)	0.411*** (0.094)	0.403*** (0.095)	0.281*** (0.047)	0.274*** (0.048)
Education: junior or high school	0.292*** (0.029)	0.280*** (0.030)	0.073 (0.099)	0.049 (0.107)	0.403*** (0.049)	0.382*** (0.052)
Education: college or above	0.810*** (0.086)	0.798*** (0.085)	-0.995*** (0.256)	-1.017 (0.254)	1.260*** (0.120)	1.260*** (0.121)
CPC party member	0.185*** (0.039)	0.193*** (0.040)	-0.140 (0.148)	-0.124 (0.069)	0.255*** (0.057)	0.269*** (0.061)
Household size	0.191*** (0.012)	0.193*** (0.012)	0.023 (0.033)	0.025(0.033)	0.260*** (0.023)	0.261*** (0.023)
Family assets	0.136*** (0.015)	0.139*** (0.015)	0.917*** (0.076)	0.922*** (0.075)	0.002 (0.019)	0.007 (0.020)
Land size	0.005 (0.044)	-0.177 (0.137)	-0.110 (0.193)	-0.447 (0.438)	-0.025 (0.077)	-0.330* (0.183)
Percentage of tertiary sector (%)	-0.074 (0.256)	-0.058 (0.276)	-0.034 (0.018)	-0.005 (1.220)	-0.113 (0.431)	-0.087 (0.500)
Regional FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FES	Yes	Yes	Yes	Yes	Yes	Yes
Coeff. of 1st IV		-0.002** (0.001)		-0.002** (0.001)		-0.002** (0.001)
Coeff. of 2nd IV		-0.010** (0.005)		-0.010** (0.005)		-0.010** (0.005)
Cragg-Donald Wald F		348.466		348.466		348.466
Hansen J p-value		0.149		0.070		0.769
N	12,066	12,066	12,066	12,066	12,066	12,066

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Figures in parentheses represent standard deviations. Standard errors are county-clustered. The same applies hereinafter.

4.2. Digital Village and Decomposed Non-farm Income

The results above suggest the most direct impact of digital villages on rural households is on non-farm income. To further investigate, we disaggregate non-farm income, exploring the effects of digital villages on different income sources, specifically wage and non-wage income. Column (1) provides OLS results for the impact on wage income, while column (2) shows the corresponding IV results. Columns (3) and (4) present OLS and IV results, respectively, for non-wage income. A positive, significant coefficient at the 1% level in column (2) indicates digital village development significantly promotes rural wage income. However, coefficients in columns (3) and (4) are not significant.

Table 3. Estimation results on decomposed non-wage income.

Variable	Wage income		Non-wage income	
	(1)	(2)	(3)	(4)
	OLS	IV-2SLS	OLS	IV-2SLS
DVI	0.358*** (0.093)	0.095*** (0.041)	0.009 (0.018)	0.071 (0.055)
Control variables	Yes	Yes	Yes	Yes
Regional FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
N	12,066	12,066	12,066	12,066

4.3. Decomposed Digital Village and Non-farm Income

To examine the structural effects of DVI, we analyze its influence on rural income across four dimensions (subindices): infrastructure, economy, governance, and lifestyle digitalization, as shown in Table 5. Both infrastructure and economic digitalization significantly increase rural income, whereas governance and lifestyle digitalization show no significant impact. These findings suggest digital village development can alleviate rural development gaps in areas like infrastructure and industrial structure, providing farmers with diverse income sources and fostering high-quality rural growth.

Table 4. Estimation results using subindices of DVI on non-wage income.

	(1)	(2)	(3)	(4)
infrastructure	0.040** (0.016)			
economy		0.046** (0.021)		
governance			-0.043 (0.035)	
lifestyle digitalization				0.042 (0.035)
Control variables	Yes	Yes	Yes	Yes
Regional FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
N	12,066	12,066	12,066	12,066

4.4. Robustness Checks

4.4.1. Using New Instrumental Variable

To verify the robustness the results shown above, we use the relief degree of land surface (RDLS) measured by Feng et al. [46] as an IV. Generally, areas with complex terrains, rich in mountains and rivers, are more likely to be divided into smaller, relatively isolated regions. This division can inhibit economic growth, disperse labor, complicate transportation, and increase costs of network communication and digital rural development, thus affecting farmers' use of digital technology. Table 5, employing the new instrumental variable, reports consistent coefficient signs as in Table 2, affirming our initial regression's robustness.

Table 5. The IV-2SLS estimation results using RDLS as an alternative IV.

	Total income	Agricultural income	Non-farm income
	(1)	(2)	(3)
DVI	0.053*** (0.022)	0.068 (0.065)	0.047** (0.024)
Control variables	Yes	Yes	Yes
Regional FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
N	12,066	12,066	12,066

4.4.2. Using DIFI as the Key Independent Variable

To mitigate measurement error bias, we replace DVI with the digital inclusive finance index (DIFI) also published by Peking University as our key independent variable. It is noted that digital village development bolsters digital inclusive finance through infrastructure support, which in turn propels economic growth and societal advancement in these digital villages. The updated IV-2SLS estimation results using DIFI, as presented in Table 6, reveal that the coefficients in columns (1) and (3) align with the baseline model shown in Table 2.

Table 6. The IV-2SLS estimation results using DIFI as key independent variable.

	Total income	Agricultural income	Non-farm income
	(1)	(2)	(3)
DIFI	0.022*** (0.008)	0.047 (0.049)	0.034*** (0.011)
Control variables	Yes	Yes	Yes
Regional FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
N	12,066	12,066	12,066

4.5. Mechanism Analysis

This paper explores the mechanisms of income effect of digital villages from three perspectives: household labor structure, land transfer and extended working hours. The evolution of digital village construction significantly bolsters rural economic growth and rural households' income in China. It directly offers more non-agricultural employment opportunities, promotes diverse income streams, and indirectly fosters job growth in related industries like digital agriculture, e-commerce, and logistics. It also facilitates flexible working hours for farmers, unrestricted by traditional agriculture's seasonality, enabling income increase as per work demands.

Specifically, using the non-agricultural-to-total labor ratio to measure labor structure (Table 7, Column 1), it reveals that digital villages foster labor transfer into non-agricultural sectors. Second, we use the question "Last year, did you transfer the management rights of your

farmland to others or institutions?" in the CHFS questionnaire to determine the situation of farmers transferring land. An IV-probit model is estimated and the result in column (2) in Table 7 shows digital village development encourage the households to transfer their lands. Lastly, we calculate individual working hours from the questionnaire question "Last year, how many months did you work in your main job, on average how many hours per day?" and sum it up by household. The result in column (3) demonstrates that digital village advancement extends non-agricultural work time, ensuring income growth for households.

Table 7. The IV-2SLS estimation results from the mechanism analysis.

	Labor structure	Land transfer	Working time
	(1)	(2)	(3)
DVI	0.007** (0.003)	0.024** (0.011)	29.741*** (10.459)
Control variables	Yes	Yes	Yes
Regional FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
N	12,066	12,066	12,066

4.6. Heterogeneity Analysis

4.6.1. Heterogeneity of Income Level

Income disparity, a focal point in studying the income effect of digital development, remains a persistent issue in China's economic growth [47]. Some researchers found an "inverted U-shaped" correlation between digital village development and income inequality [48]. While this paper cannot confirm the "inverted U-shape" over time due to data availability, heterogeneity analysis can discern if digital village construction notably benefits lower-income rural households, thereby assessing its efficiency in promoting inclusive economic growth. We categorize the sampled households into high and low-income groups based on the median income and re-run the model for each of these groups. Table 8 demonstrates significant positive coefficients in columns (2) and (4), indicating a prominent influence of digital villages on boosting and inclusively impacting low-income farmers' income level.

Table 8. The IV-2SLS estimation results by heterogeneous income level.

Dependent variable	Total income		Non-farm income	
	Low income	High income	Low income	High income
DVI	0.042** (0.017)	0.001 (0.008)	0.074*** (0.028)	0.004 (0.030)
Control variables	Yes	Yes	Yes	Yes
Regional FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
N	8,337	3,729	8,337	3,729

4.6.2. Heterogeneity of Educational Level

Based on the household head's education, we categorize households into 'low-education' (primary school or less) and 'high-education' (middle school or above, including junior and senior high school, junior college, undergraduate, and postgraduate). Table 9 presents subgroup regression estimations, with significant positive coefficients in columns (2) and (4). Thus, digital village construction has a more potent impact on the total and non-farm income of low-educated households.

Table 9. The IV-2SLS estimation results by heterogeneous educational level.

Dependent variable	Total income		Non-farm income	
	Low-educated	High-educated	Low-educated	High-educated
Group				
DVI	0.252*** (0.091)	0.034*** (0.010)	0.327*** (0.144)	0.058*** (0.015)
Control variables	Yes	Yes	Yes	Yes
Regional FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
N	7,509	4,557	7,509	4,557

4.6.3. Heterogeneity of Region

China is often divided into eastern and western regions due to the significant disparities between these areas in terms of economic development, resource distribution, and policy implementation. As illustrated in Table 10, digital village construction notably enhances total and non-farm income in central and western China, but not in the east, emphasizing its impactful role in comparatively underdeveloped areas. This aids in reducing regional income disparities, contributing to the promotion of “Common Prosperity”.

Table 10. The IV-2SLS estimation results by heterogeneous regions.

	Total income		Non-farm income	
	East	Center & West	East	Center & West
	(1)	(2)	(3)	(4)
DVI	0.015 (0.022)	0.062*** (0.018)	0.018 (0.037)	0.072*** (0.027)
Control variables	Yes	Yes	Yes	Yes
Regional FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
N	3,978	8,088	3,978	8,088

5. Conclusion and Policy Recommendations

5.1. Key Findings

Based on the combination of the county-level DVI data from Peking University and the CHFS survey data, this paper examines the impact of the development of digital village construction on the rural households' income in China. The key findings are summarized as follows: (1) Digital village development significantly increases household income, especially non-farm earnings, primarily driven by wage increases. (2) Mechanism analysis reveals that digital villages impact household income via labor structure, land transfer, and work hours, stimulating both direct and indirect employment across various industries. This leads to enhanced work time flexibility, especially in non-agricultural sectors. (3) Heterogeneity analysis indicates that digital villages promote inclusive growth, boosting both total and non-farm income for low-income, central and western region households, and those with lower education levels. Consequently, this helps in narrowing the income gap and advancing towards common prosperity.

5.2. Policy Implications

Recognizing the pivotal role non-agricultural income plays in boosting farmers' earnings is vital. As traditional agricultural income struggles to support modern lifestyles amid China's rapid economic development, new income-enhancing avenues need exploring to increase rural households' income and achieve common prosperity. Digital villages can effectively boost non-

agricultural employment and profitability, leveraging internet and ICT technologies to enhance efficiency throughout the agricultural production and sales process. Enhancing digital economy investments can foster more job opportunities, enabling urban and rural populations to secure quality employment, thus promoting social justice and sustainability. Investments in digital village construction should progress simultaneously to create a diversified rural income system, because it can further drive the development of rural non-agricultural sector.

The potential of digital villages to augment rural household wage income should be maximized. Digital village construction plays an essential role in enhancing the income structure of rural households by using digital technologies to boost agricultural productivity, broaden sales channels, and improve product quality and added value. Additionally, digital village construction can stimulate and bolster rural employment, assisting residents in diversifying their income through non-agricultural pursuits. Such strategies improve rural households' income levels and refine their income structure.

Policy implementation should account for regional differences, focusing on digital village growth in central and western China to effectively benefit rural communities. Digital village initiatives, using technology to enhance rural living and production, aim to raise rural households' income. Instead of simply mimicking urban models, solutions should address rural-specific challenges. Recognizing digital infrastructure deficits in central and western regions, efforts should be made to extend coverage to remote areas, maximizing digital benefits for rural residents. Viewing digital infrastructure as a sustainable investment, strategies should cater to regional variations and address issues like information asymmetry in these areas.

The government should enhance educational and training investments in rural areas, earnestly improving households' ability to access and utilize information. While focusing on the income growth effect brought about by digitalization, the policy makers also need to consider balanced income distribution, gradually resolving the "digital divide" and income disparity caused by the existence of conditions but a lack of capability.

References

- [1] Fan, S., and Jiang, K. (2016). Study on the Poverty Reduction Effect of Rural Household Labor Mobility in China -Micro Evidence Based on CFPS Data. *Chinese Journal of Population Science*(5), 26-34+126.
- [2] Jiang, K., and Liu, S. (2017). Income Structure, Income Inequality and Rural Family Poverty. *Chinese Rural Economy*(8), 75-90.
- [3] Xia, Q., Song, L., and Appleton, S. (2010). Economic Growth and Poverty Reduction in Rural China. *China Economic Quarterly*, 9(2), 851-870. 10.13821/j.cnki.ceq.2010.03.009.
- [4] Asher, S., and Novosad, P. (2020). Rural roads and local economic development. *American economic review*, 110(3), 797-823.
- [5] Bhatt, S. (2020). Digitalization of rural India: Digital village. *VISION: Journal of Indian Taxation*, 7(1), 83-93.
- [6] Chen, W., Wang, Q., and Zhou, H. (2022). Digital rural construction and farmers' income growth: Theoretical mechanism and micro experience based on data from China. *Sustainability*, 14(18), 11679.
- [7] Qin, F., Wang, J., and Xu, Q. (2022). How Does the Digital Economy Affect Farmer's Income? - Evidence from the Development of Rural E-commerce in China. *China Economic Quarterly*(2), 591-612. 10.13821/j.cnki.ceq.2022.02.12.
- [8] Zhang, G., Wu, X., and Wang, K. (2022). Research on the impact and mechanism of internet use on the poverty vulnerability of farmers in China. *Sustainability*, 14(9), 5216.

- [9] Chao, P., Biao, M., and Zhang, C. (2021). Poverty alleviation through e-commerce: Village involvement and demonstration policies in rural China. *Journal of Integrative Agriculture*, 20(4), 998-1011.
- [10] Liu, B., and Zhou, J. (2023). Digital Literacy, Farmers' Income Increase and Rural Internal Income Gap. *Sustainability*, 15(14), 11422.
- [11] Song, L., and He, Y. (2020). The impact of Internet use on the Employment Choice of China's Rural Labor Force. *Chinese Journal of Population Science*(3), 61-74+127.
- [12] Zhang, Q., Kuang, Z., and Wang, Y. (2021). Research on The Impact of Digital Inclusive Finance On Rural Youth's Non-Agricultural Employment. *Finance and Economy*(11), 34-45. 10.19622/j.cnki.cn36-1005/f.2021.11.004.
- [13] Zeng, Y., Guo, H., and Jin, S. (2018). Does E-commerce Increase Farmers' Income? Evidence from Shuyang County, Jiangsu Province, China. *Chinese Rural Economy*(2), 49-64.
- [14] Zhu, Q., Zhu, C., Bai, J., and Peng, C. (2022). Can Informatization Boost Farmers' Income and Narrow the Income Disparity Rural China? *China Economic Quarterly*, 22(01), 237-256. 10.13821/j.cnki.ceq.2022.01.12 %W CNKI.
- [15] Liu, S., and Zhou, S. (2011). Accessibility of Infrastructure and Income Growth of Rural Residents in China -- Based on the Regression Results of Static and Dynamic Unbalanced Panel Data. *China Rural Economy*(1), 27-36.
- [16] Aker, J. C., Ghosh, I., and Burrell, J. (2016). The promise (and pitfalls) of ICT for agriculture initiatives. *Agricultural Economics*, 47(S1), 35-48.
- [17] Camacho, A., and Conover, E. (2019). The impact of receiving SMS price and weather information on small scale farmers in Colombia. *World development*, 123, 104596.
- [18] Fang, F., and Tian, G. (2021). Does Digital Economy Promote Inclusive Growth -- A Quasi Natural Experiment Based on 'Broadband China. *Academics*(10), 55-74.
- [19] Kuhn, P., and Mansour, H. (2014). Is internet job search still ineffective? *The Economic Journal*, 124(581), 1213-1233.
- [20] Svensson, J., and Yanagizawa, D. (2009). Getting prices right: the impact of the market information service in Uganda. *Journal of the European Economic Association*, 7(2-3), 435-445.
- [21] DiMaggio, P., and Bonikowski, B. (2008). Make money surfing the web? The impact of Internet use on the earnings of US workers. *American Sociological Review*, 73(2), 227-250.
- [22] Han, C., and Zhang, L. (2017). The Impact Of Internet Popularization On Urban And Rural Income Distribution: A Systematic Gmm Analysis Based On China's Inter Provincial Panel Data. *Exploration Of Economic Issues*(8), 18-27.
- [23] Liu, M., Min, S., Ma, W., and Liu, T. (2021). The adoption and impact of E-commerce in rural China: Application of an endogenous switching regression model. *Journal of Rural Studies*, 83, 106-116.
- [24] Liu, X., and Han, Q. (2018). The Influence of Internet Usage of Rural Residents on Income and Its Mechanism ---Based on China Family Panel Studies (CFPS) Data. *Journal of Agrotechnical Economics*(9), 123-134. 10.13246/j.cnki.jae.2018.09.011.
- [25] Barrett, C. B., Reardon, T., and Webb, P. (2001). Non-farm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications. *Food Policy*, 26(4), 315-331.
- [26] Lewis, W. A. (1954). Economic development with unlimited supplies of labour. *The Manchester School*, 22(2), 139-191.
- [27] Schultz, T. W. (1966). Transforming traditional agriculture: Reply. *Journal of farm Economics*, 48(4), 1015-1018.
- [28] Sui, F. (2018). Market Development, Non-agricultural Employment and Rural Households' Choices: Evidence from Baoding's Countryside in the 1930s and 1940s. *Economic Research Journal*, 53(7), 167-181.
- [29] Wei, D., and Lu, M. (2021). The Returns to Early Migration to Cities: Rural Migrants' Life Experiences and the Labor Market Performances. *Economic Research Journal*, 56(12), 168-186.

- [30] Ma, J., and Ning, G. (2017). The Internet and Non-agricultural Employment of Rural Labor Force. *Finance & Economics*(7), 50-63.
- [31] Li, Y., and Xie, Q. (2017). The Impact of Internet on Wage and Wage Distribution—Based On CHNS Data. *Economic Theory and Business Management*(7), 87-100.
- [32] Mao, Y., Zeng, X., and Zhu, H. (2019). Internet Use, Employment Decision and Employment Quality: Empirical Evidence from CGSS Data. *Economic Theory and Business Management*(1), 72-85.
- [33] Lu, Y., Xie, H., and Xu, L. C. (2016). Telecommunication externality on migration: Evidence from Chinese villages. *China Economic Review*, 39, 77-90.
- [34] Bezu, S., and Barrett, C. (2012). Employment dynamics in the rural non-farm sector in Ethiopia: Do the poor have time on their side? *Journal of Development Studies*, 48(9), 1223-1240.
- [35] Cheng, M., Shi, Q., and Jin, Y. (2014). Incomes Level, Structure and Its Causes. *The Journal of Quantitative & Technical Economics*, 31(5), 3-19. 10.13653/j.cnki.jqte.2014.05.001.
- [36] Mao, X., and Liu, J. (2016). Local Non-Agricultural Employment, Migrant Workers and Rural Income Inequality in China. *Economic Theory and Business Management*(4), 100-112.
- [37] Zhang, X., Wan, G., and Wu, H. (2021). Narrowing the Digital Divide: The Development of Digital Finance with Chinese Characteristics. *Social Sciences in China*(08), 35-51+204-205.
- [38] Gai, Q., Zhu, X., and Shi, Q. (2014). Labor's Migration and Chinese Agricultural Production. *China Economic Quarterly*(2), 1147-1170. 10.13821/j.cnki.ceq.2014.03.015.
- [39] Zhou, J., Wang, W., Gong, M., and Huang, Z. (2020). Land Transfers, Occupational Stratification and Poverty Reduction. *Economic Research Journal*, 55(6), 155-171.
- [40] Zhang, X., Wan, G., Zhang, J., and He, Z. (2019). Digital Economy, Financial Inclusion and Inclusive Growth. *Economic Research Journal*, 54(8), 71-86.
- [41] Ma, B., Peng, C., Xue, Y., and Zhu, X. (2021). Does Rural E-commerce Affect the Income of China's Family Farms? *Statistical Research*, 38(9), 101-113. 10.19343/j.cnki.11-1302/c.2021.09.008.
- [42] Cheng, M., Shi, Q., Jin, Y., and Gai, Q. (2015). Farmers' income gap and its root causes: model and demonstration. *Journal of Management World*(7), 17-28. 10.19744/j.cnki.11-1235/f.2015.07.004.
- [43] Adegbola, P., and Gardebroke, C. (2007). The effect of information sources on technology adoption and modification decisions. *Agricultural Economics*, 37(1), 55-65.
- [44] Larochelle, C., Alwang, J., Travis, E., Barrera, V. H., and Dominguez Andrade, J. M. (2019). Did you really get the message? Using text reminders to stimulate adoption of agricultural technologies. *The Journal of Development Studies*, 55(4), 548-564.
- [45] Zhu, Q., Bai, J., Peng, C., and Zhu, C. (2019). Do Information Communication Technologies Improve Agricultural Productivity? *Chinese Rural Economy*(04), 22-40
- [46] Feng, Z., Tang, Y., Yang, Y., and Zhang, D. (2007). The Relief Degree of Land Surface In China and Its Correlation With Population Distribution. *ACTA GEOGRAPHICA SINICA*(10), 1073-1082.
- [47] Li, S., and Zhu, M. (2022). Promoting the Reform of Income Distribution System and the Realization of Common Prosperity. *Journal of Management World*(1), 52-61+76+62. 10.19744/j.cnki.11-1235/f.2022.0002.
- [48] Mu, H., and Wu, P. (2016). Urbanization, Industrial Structure Optimization and Urban-Rural Income Gap. *Economist*(5), 37-44. 10.16158/j.cnki.51-1312/f.2016.05.006.