

The Multidimensional Poverty-Reduction Effects of Digital Infrastructure^{*}

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Digital infrastructure is foundational to the digital economy and key to reducing multidimensional poverty. Based on 2010-2020 CFPS data, this study constructs an A-F multidimensional poverty index and uses 4G base stations to proxy digital infrastructure. The main findings are as follows. First, digital infrastructure significantly reduces multidimensional poverty. Second, mechanism analysis identifies innovation, entrepreneurship, and public service efficiency as key channels. Third, heterogeneity analysis reveals varying poverty-reduction effects across dimensions. Finally, extended analysis shows these benefits primarily accrue to less affluent households, indicating digital infrastructure helps narrow social disparities. Overall, the findings provide empirical evidence to guide targeted policies and promote inclusive growth.

Key Words: Digital infrastructure; Multidimensional poverty; Innovation and entrepreneurship; Public service provision efficiency.

JEL Classification Numbers: I32, O18, O33.

1. INTRODUCTION

At present, China has entered a new stage of comprehensive strategic planning for digital transformation. The 14th Five-Year Plan for the Development of the Digital Economy, issued by the State Council of the People's Republic of China, explicitly proposes to “enhance the inclusiveness of digitalized social services and build a new form of intelligent and shared digital life”. As the underlying architecture of the digital economy, digi-

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tal infrastructure is profoundly reshaping the landscape of economic and social development. By 2024, the value added of China's core digital economy industries accounted for nearly 10% of GDP. In addition, a total of 62 "Lighthouse Factories" have been established, representing about 40% of the global total. Meanwhile, online retail sales reached RMB 15.42 trillion, and China has remained the world's largest online retail market for 11 consecutive years.¹ At the same time, the implementation of policy initiatives such as the "Broadband China" strategy, the Digital Rural Development initiative, and the Information Accessibility Action Plan has laid a solid foundation for addressing issues of inclusiveness and equity in the development of digital infrastructure. Against this background, an in-depth examination of the poverty-reduction effects of digital infrastructure development is of significant theoretical and practical importance for understanding how digital technologies can empower inclusive growth.

Poverty has long been a central issue in development economics. Traditional studies have primarily focused on poverty measurement based on a single dimension, such as income or consumption (Li Yongyou and Shen Kunrong, 2007; Fang Fuqian et al., 2023; Liang et al., 2025). However, the essence of poverty is inherently multidimensional — it not only refers to low income but also manifests in the deprivation of basic capabilities, including limited educational opportunities, poor health conditions, and a generally low quality of life. In recent years, international organizations have widely adopted the Multidimensional Poverty Index (MPI) as a new standard for poverty identification and poverty assessment. In China's anti-poverty practice, policy interventions have long moved beyond simple income support and gradually evolved into a comprehensive poverty-reduction policy system covering multiple dimensions such as education, healthcare, housing, and social security. For instance, in the field of basic education, the connectivity rate of compulsory education schools in China has reached 100%, and schools at all levels in rural areas are now generally equipped with information-based teaching environments. In terms of healthcare services, all tertiary hospitals (Class III hospitals) nationwide have implemented telemedicine services. In rural areas, internet-based healthcare users account for 21.5% of rural internet users, with the total number of online healthcare users reaching 414 million.² Therefore, examining the poverty-reduction effects of digital infrastructure from the perspective of

¹Data are derived from the report Research Report on the Digital Infrastructure Evaluation System for the Future New Base of the Digital Artery (2024) released by the China Academy of Information and Communications Technology (CAICT). Available at: https://www.caict.ac.cn/english/research/whitepapers/202404/t20240430_476683.html

²Data are derived from the report Research Report on Digital Inclusive Development in China (2024) released by the China Academy of Information and Communications Technology (CAICT). Available at: https://www.caict.ac.cn/english/research/whitepapers/202404/t20240430_476680.html

multidimensional poverty helps ensure that more households benefit from the process of digital development, thereby promoting a more inclusive and equitable pattern of socio-economic development.

Whether the development of digital infrastructure can effectively alleviate poverty has attracted substantial scholarly attention. At the theoretical level, digital infrastructure exhibits significant positive externalities (Liu Shenglong and Hu Angang, 2010), and can generate poverty-reduction effects through multiple channels, such as reducing information asymmetry, expanding market access, and promoting employment and entrepreneurship (Xie Shenxiang et al., 2018). At the empirical level, many studies have treated the pilot cities of the “Broadband China” strategy as a quasi-natural experiment, and have demonstrated that digital infrastructure can significantly reduce poverty vulnerability, increase rural household income, and narrow the income gap (Fang Fuqian et al., 2023; Wei Xiaohai and Wei Qingfang, 2023; Liang et al., 2025). However, the existing literature still leaves several important avenues for further exploration. First, regarding the measurement of digital infrastructure, most studies rely on policy dummy variables such as the “Broadband China” pilot program or macro indicators such as the internet penetration rate, which lack precise micro-level measures of infrastructure development. Second, in terms of poverty measurement, the current literature mainly focuses on single dimensions such as income or consumption, and thus fails to fully capture the multidimensional deprivation characteristics of poverty. Third, regarding the underlying mechanisms, most existing studies examine the issue from perspectives such as the digital divide and the development of e-commerce (He Zongyue et al., 2020; Tian Ge and Zhang Xun, 2022). By contrast, the internal mechanisms through which digital infrastructure may alleviate multidimensional poverty — for example, by enhancing innovation and entrepreneurship activity and improving the efficiency of public service provision — have not yet been systematically investigated.

This study seeks to address the aforementioned research gaps. Using panel data from the China Family Panel Studies (CFPS) covering the period 2010-2020, and drawing on the Alkire-Foster (AF) methodology proposed by Alkire and Foster (2007, 2011), this paper constructs a multidimensional poverty index system encompassing five dimensions: household income, financial assets, quality of life, basic education, and healthcare. At the same time, by compiling the geolocation information of 4G base stations from the OpenCellID database, the study provides a precise measure of the level of digital infrastructure development across prefecture-level cities in China. On this basis, the paper systematically examines the impact of digital infrastructure development on both the intensity of multidimensional poverty and multidimensional poverty status at the household level, as well as the underlying mechanisms through which such effects operate.

The empirical results show that the development of digital infrastructure significantly reduces both the intensity of multidimensional poverty and the probability of households being multidimensionally poor. This conclusion remains robust after a series of robustness checks and endogeneity treatments, including changes in estimation methods, variable substitutions, winsorization, the instrumental variables (IV) approach, and lagged variable specifications. Further mechanism analysis indicates that digital infrastructure alleviates multidimensional poverty through two main channels: by enhancing regional innovation and entrepreneurship activity, thereby encouraging households to engage more actively in entrepreneurial activities, and by improving the efficiency of government public service provision. Moreover, these two channels exhibit stronger poverty-reduction effects among less affluent households.

The contributions of this study are reflected in three main aspects. First, it introduces an innovation in measurement methodology. Unlike existing studies that mainly rely on policy dummy variables or macro-level proxy indicators, this paper utilizes geospatial data on 4G base stations to obtain a micro-level and precise measure of the scale of digital infrastructure development, thereby providing a useful methodological reference for future research. Second, the study expands the analytical framework of poverty research. Moving beyond the traditional single-dimensional income perspective, this paper adopts a multidimensional perspective encompassing income, financial assets, quality of life, education, and health. By systematically examining the impact of digital infrastructure on multidimensional poverty, the study enriches the empirical evidence on the poverty-reduction effects of digital technologies. Third, the study sheds light on the previously unexplored “black box” of the poverty-reduction mechanism. Specifically, it identifies two key transmission channels — entrepreneurship and public service efficiency — and reveals the internal logic through which digital infrastructure contributes to poverty alleviation, namely the transition from resource provision, to capability enhancement, and ultimately to poverty reduction. These findings provide micro-level theoretical support for the formulation of targeted poverty alleviation policies.

The remainder of this paper is organized as follows. Section 2 presents the theoretical framework and research hypotheses; Section 3 describes the model specification and variable definitions; Section 4 reports the empirical results; and Section 5 concludes with the main findings and policy implications.

2. THEORETICAL ANALYSIS AND RESEARCH HYPOTHESES

2.1. The Impact of Digital Infrastructure Development on Multidimensional Poverty

Digital infrastructure refers to a form of infrastructure that is communication-network-based, data-computing-centered, and driven by data and digital technologies.³ It encompasses several interrelated components: network infrastructure consisting of technologies such as 5G networks, fiber-optic communication, and satellite internet; computing infrastructure including cloud computing centers and intelligent computing clusters; data infrastructure such as blockchain platforms and privacy-preserving computing systems; and large-model infrastructure designed to enable artificial intelligence applications.⁴ This integrated and multi-layered system constitutes the foundational architecture of the digital economy, profoundly reshaping patterns of socio-economic development and increasingly becoming an essential component of modern anti-poverty policy frameworks. In China, the rapid expansion of digital infrastructure development has created new pathways through which digital technologies can support inclusive growth and mitigate multidimensional poverty. This process is not merely a matter of technological accumulation. Rather, it directly expands the basic capabilities of disadvantaged groups, generating systematic improvements across multiple dimensions of poverty, including income, health, and education.

First, in the household income dimension, digital infrastructure directly expands income-generating opportunities for poor households. Digital platforms built upon broadband networks and mobile payment systems enable farmers in remote regions to bypass traditional intermediaries and directly access national and even global markets. The emergence of new economic forms such as rural e-commerce and live-streaming commerce represents a typical example of how digital infrastructure can be transformed into tangible income growth.

Second, in terms of financial assets and quality of life, digital infrastructure improves household welfare by enhancing basic living conditions and

³Definition adapted from the International Organization for Standardization (ISO) standard documentation. Available at: <https://www.iso.org/obp/ui/en/#iso:std:iso:25556:ed-1:v1:en>

⁴See the report Promoting Global Digital Infrastructure Development and Bridging the Digital Divide (2025) released by the China Academy of Information and Communications Technology (CAICT). Available at: <https://cn.wicinternet.org/static/pdf/%EF%BC%88%E4%B8%AD%E6%96%87%E7%89%88%E7%BC%89%E4%BF%83%E8%BF%9B%E5%85%A8%E7%90%83%E6%95%B0%E5%AD%97%E5%9F%BA%E7%A1%80%E8%AE%BE%E6%96%BD%E5%BB%BA%E8%AE%BE%E3%80%81%E5%BC%A5%E5%90%88%E6%95%B0%E5%AD%97%E9%B8%BF%E6%B2%9F.pdf>

expanding access to financial services. The development of digital financial infrastructure allows disadvantaged groups to obtain payment, savings, credit, and insurance services at relatively low cost. This strengthens their ability to manage risks and accumulate assets, while also improving living conditions such as access to clean water and clean energy sources.

Third, in the dimension of basic education, digital infrastructure breaks the spatial and temporal barriers that traditionally limit access to high-quality educational resources. A study by the World Bank (2021) shows that digital education can increase rural students' mathematics scores by approximately 0.3 standard deviations. In China, digital education platforms — such as Massive Open Online Courses (MOOCs), AI-assisted teaching systems, and smart classroom technologies — rely on high-speed broadband networks to deliver high-quality educational resources to rural and remote areas, thereby compensating for the long-standing shortage of qualified teachers in rural schools. As a result, children from poor households are able to access educational resources comparable to those available in urban areas, fundamentally enhancing their long-term ability to escape poverty.

Fourth, in the dimension of healthcare, digital infrastructure reduces the risk of poverty caused by illness by transforming the mode of health service delivery. The World Health Organization (WHO) reports that digital health technologies can increase the efficiency of primary healthcare services by more than 30 percent. Supported by 5G networks, Internet of Things (IoT) devices, and medical big-data platforms, telemedicine systems enable patients in impoverished regions to access high-quality medical services without traveling long distances. Applications such as electronic medical record sharing, AI-assisted diagnosis, and remote surgical guidance significantly improve the service capacity of primary healthcare institutions, thereby effectively alleviating poverty in the health dimension.

Based on the above analysis, the following hypothesis is proposed:

H1: Digital infrastructure development contributes to the alleviation of multidimensional poverty.

2.2. The Mediating Mechanism of the Innovation and Entrepreneurship Effect

Digital infrastructure provides the tools and systems that enable communication, collaboration, and computational capacity for innovation and entrepreneurship (Nambisan, 2017; Briel et al., 2018; Nambisan et al., 2019). Improvements in information and communication technologies (ICT) — particularly the expansion of broadband networks and increased data traffic capacity — have been shown to exert a significantly positive impact on entrepreneurial activity (Audretsch et al., 2015; Alderete, 2015). Both theoretical and empirical studies indicate that the diffusion of digital technolo-

gies can substantially stimulate entrepreneurship, especially among groups with relatively limited resource endowments (Nambisan, 2017). From a regional perspective, the development of digital infrastructure can reduce information asymmetry and entrepreneurial entry barriers, promote the agglomeration of technology and resources, and enhance the overall innovation and entrepreneurship dynamism within a region.

First, broadband networks and e-commerce platforms enable entrepreneurs to rapidly obtain market information and overcome geographical constraints, thereby providing communication, collaboration, and computing capabilities for entrepreneurs and related actors while reducing barriers to information transmission (Sun Weizeng and Guo Dongmei, 2021). For example, since the implementation of the “E-commerce into Rural Areas” initiative in China, rural e-commerce platforms have enabled the circulation of industrial products to rural areas and agricultural products to urban markets, directly connecting supply and demand while reducing intermediary transaction costs.

Second, digital tools can substitute for traditionally high-cost resources, enabling small and micro enterprises and self-employed individuals to initiate business activities more easily and reducing the financial pressure associated with entrepreneurship. Technologies such as cloud computing and big data analytics provide start-ups with low-cost tools for data storage and analysis, thereby lowering initial investment thresholds.

Third, through technology spillover effects and resource sharing, regional innovation and entrepreneurship can generate a large number of employment opportunities, reduce information constraints in labor markets, and enable households to obtain timely information about job opportunities. Large-scale employment creation also produces multiplier and accelerator effects on the broader economy (Sato et al., 2012).

Finally, the expansion of digital infrastructure can alleviate financing constraints, thereby improving the survival and growth prospects of entrepreneurial projects. The development of digital finance can further encourage innovation and entrepreneurship by easing credit constraints, thereby contributing to poverty alleviation (Wang and Fu, 2022). Technologies such as digital payments and blockchain systems help optimize financial services and facilitate access to microloans and venture capital for entrepreneurs from disadvantaged backgrounds.

From a micro-level perspective, the development of digital infrastructure also exerts a strong incentive effect on household entrepreneurial behavior.

First, digital platforms have fostered new forms of flexible employment, such as the gig economy and content creation, providing low-skilled workers with accessible income-generating opportunities (Kuhn, 2016).

Second, mobile internet technologies and e-commerce platforms allow households to connect directly with national markets, transforming lo-

cal resources into marketable products and thereby stimulating a wave of household entrepreneurship. This form of digital empowerment has been shown to significantly increase household income and contribute to poverty reduction (Guo Feng et al., 2020; Han Xianfeng et al., 2025).

Third, the benefits of successful entrepreneurship extend beyond direct income gains. More importantly, entrepreneurial success can enhance household social capital, strengthen individual agency, and improve risk resilience, generating spillover effects on multiple dimensions of welfare, including education and health (Schoar, 2010).

Therefore, by activating entrepreneurship as a key micro-level mechanism, digital infrastructure effectively empowers disadvantaged groups and facilitates a sustainable transition in poverty alleviation from external assistance (“blood transfusion”) to self-sustained development (“blood generation”).

Based on this analysis, the following hypothesis is proposed:

H2: Digital infrastructure development stimulates regional and household innovation and entrepreneurship, thereby alleviating multidimensional poverty.

2.3. The Mediating Mechanism of the Public Service Provision Efficiency Effect

The development of digital infrastructure provides crucial support for governments to enhance the efficiency of public service provision, thereby strengthening the government’s foundational and leading role in poverty alleviation policies.

On the one hand, extensive infrastructure coverage constitutes the prerequisite for the digitalization of public services. According to the Digital China Development Report (2024) released by the China Academy of Information and Communications Technology (CAICT), by the end of 2023, the broadband coverage rate in administrative villages and formerly impoverished villages in China had reached 100%, while the proportions of villages connected to optical fiber networks and 4G networks both exceeded 99%. China has thus historically achieved nationwide connectivity in which “every village has broadband access and every county has access to 5G services”. This extensive infrastructure coverage has laid a solid foundational basis for the comprehensive digital transformation of public services.

On the other hand, the effective provision of public services itself represents a key mechanism for poverty reduction. In his study of Chile, Weyland (1999) found that even in periods of economic slowdown, sustained growth in government public expenditure could still lead to a decline in the poverty rate, demonstrating the irreplaceable role of public services in poverty alleviation.

The channel through which public service provision efficiency operates can be understood at three main levels.

First, digital infrastructure helps establish standardized governance systems, which can effectively regulate administrative behavior and improve administrative efficiency, thereby ensuring the accurate implementation of public service objectives (Hu Yefei and Xiang Miao, 2023). For instance, disadvantaged households can submit applications for minimum livelihood guarantees, student financial aid loans, and medical insurance through a single digital platform. This not only substantially reduces administrative costs but also significantly improves policy accessibility.

Second, digital infrastructure helps overcome spatial and temporal constraints, facilitating government information flows and resource sharing while narrowing the digital divide between urban and rural areas. The widespread deployment of broadband networks and 5G technologies allows residents in remote and impoverished regions to access high-quality public services previously concentrated in urban areas. As Zhang Xun et al. (2021) demonstrate, by promoting household internet access, digital infrastructure effectively removes spatial and temporal barriers to basic public services, thereby significantly alleviating multidimensional poverty.

Third, digital government platforms integrate services across multiple departments and can reshape administrative processes, enabling integrated online public service delivery. Xie Kang et al. (2020) argue that big data technologies empower governments by enabling the integration, sharing, and utilization of information resources. When combined with traditional production factors such as labor and capital, these data resources generate knowledge that can be applied to public administration and decision-making, thereby improving government governance capacity and public service delivery capabilities. For example, the “Zheli Ban” digital government platform in Zhejiang Province integrates more than 2,000 public services, significantly reducing administrative processing time for disadvantaged households and substantially improving citizens’ sense of access to services and public satisfaction.

Based on the above analysis, the following hypothesis is proposed:

H3: The development of digital infrastructure improves the efficiency of government public service provision, thereby alleviating multidimensional poverty.

3. MODEL SPECIFICATION AND VARIABLE DESCRIPTION

3.1. Model Specification

This study examines multidimensional relative poverty from two perspectives: the degree of multidimensional relative poverty at the household

level and whether a household is in a state of multidimensional relative poverty.

We first investigate the impact of digital infrastructure development on the degree of multidimensional relative poverty. The baseline econometric model is specified as follows:

$$\text{Poverty}_{ijt} = \gamma_0 + \gamma_1 \text{DI}_{jt} + \gamma_2 \text{Control}_{ijt} + \varphi_i + \delta_t + \varepsilon_{ijt} \quad (1)$$

In this specification, Poverty_{ijt} denotes the degree of multidimensional relative poverty of household i in city j in year t . The key explanatory variable DI_{jt} represents the level of digital infrastructure development in the prefecture-level city where the household is located, measured by the number of local 4G base stations.

The coefficient γ_1 captures the effect of digital infrastructure development on the degree of multidimensional poverty and is the primary parameter of interest in this study. If this coefficient is negative and statistically significant, it indicates that digital infrastructure development exerts a multidimensional poverty-reduction effect on households; otherwise, such an effect is not supported.

Control_{ijt} denotes a set of control variables. γ_0 represents the constant term. φ_i denotes household fixed effects, which control for household characteristics that do not change over time but may influence the degree of multidimensional relative poverty. δ_t represents time fixed effects, which remove the influence of time-varying factors that may affect multidimensional relative poverty. ε_{ijt} is the random error term.

After examining the degree of multidimensional poverty, the analysis further investigates whether households are in a state of multidimensional relative poverty. This variable is a binary indicator taking the value of 0 or 1. Following the approaches of Borgia and D'Ambrosio (2021) and Sun and Guo (2021), this study constructs a Probit model to analyze the impact of digital infrastructure development on multidimensional poverty status. The model is specified as follows:

$$M_{ijt}^* = \beta_0 + \beta_1 \text{DI}_{jt} + \beta_2 \text{Control}_{ijt} + \varphi_i + \delta_t + \varepsilon_{ijt} \quad (2)$$

$$\text{Prob}(M_{ijt=1}) = \phi(\beta_0 + \beta_1 \text{DI}_{jt} + \beta_2 \text{Control}_{ijt} + \varphi_i + \delta_t) \quad (3)$$

Here, the dependent variable M_{ijt} is a binary variable indicating whether household i in city j in year t is in a state of multidimensional poverty. The latent variable M_{ijt}^* represents the underlying continuous variable behind M_{ijt} . When the latent variable exceeds 0, the observed variable takes the value 1, indicating that the household is in a state of multidimensional poverty; otherwise, it takes the value 0.

3.2. Variable Selection

3.2.1. Dependent Variable

At present, scholars widely employ the Alkire-Foster (A-F) method to measure the multidimensional relative poverty index. This approach can accurately reflect the nature and causes of poverty by capturing the deprivation of households' basic capabilities across multiple dimensions at the micro level, thereby helping reveal the objective conditions of poverty in different dimensions. In practical applications, different scholars also adopt flexible dimensions and indicators to reflect multidimensional poverty at the regional or household level, which facilitates comparison across studies. Therefore, this paper constructs a multidimensional relative poverty index system based on the A-F method (as shown in Table 1). The construction process is as follows:

$$C_{i,j}^{(t)}(k) = \begin{cases} \sum_{j=1}^d g_{i,j}^{(t)} * w_j, & \sum_{j=1}^d g_{i,j}^{(t)} * w_j \geq k \\ 0, & \text{others} \end{cases} \quad (4)$$

$$\sum_{j=1}^d w_j = 1, \quad j = 1, 2, \dots, d$$

Here, $g_{i,j}^{(t)}$ denotes the deprivation matrix, in which any element represents whether household i experiences welfare deprivation in dimension j . $Y_{i,j}^{(t)}$ denotes the observed value of household i in dimension j for a given sample. When $Y_{i,j}^{(t)} < C_{i,j}^{(t)}(k)$, then $g_{i,j}^{(t)} = 1$, indicating that the household is deprived in dimension j . $C_{i,j}^{(t)}(k)$ represents the poverty threshold for dimension j . When a household falls below the poverty line in k or more dimensions, $C_{i,j}^{(t)}(k)$ represents the weighted deprivation score aggregated across all dimensions for household i .

w_j denotes the weight assigned to dimension j . There is no unified standard for determining weights in multidimensional poverty indices. Alkire and Santos (2014) find that multidimensional poverty indices are relatively robust under different weighting schemes. Therefore, this study adopts equal weights across dimensions and equal weights for indicators within each dimension when designing the index weights.

For each indicator within a dimension, a deprivation threshold must be specified. In other words, the size of the poverty line $C_{i,j}^{(t)}(k)$ for each indicator is crucial, as it directly determines whether residents are considered poor and the depth of their poverty. $C_{i,j}^{(t)}(k)$ exceeds the overall multidimensional poverty cutoff K , the household is identified as being in a state of multidimensional poverty. Referring to the poverty threshold settings

TABLE 1.

Multidimensional Poverty Indicator Variables			
Poverty Dimension	Indicator	Indicator Definition and Assignment Rule	Weight
Household Income	Per Capita Household Income	Households with per capita income (2010 constant prices) below RMB 2300 are classified as income-poor and assigned a value of 1; otherwise 0.	1/5
	Financial Assets	If the household does not possess any type of financial asset, the variable is assigned 1; otherwise 0.	1/5
Quality of Life	Cooking Water Source	In the CFPS, the relevant question asks: "What is the main source of water used for cooking in your household?" Options include river/lake water, well water, tap water, bottled/purified/filtered water, rainwater, cellar water, pond/spring water, or other sources. Households using non-clean water sources (i.e., not tap water, bottled water, purified water, or filtered water) are assigned 1; otherwise 0.	1/10
	Cooking Fuel	In the CFPS, the relevant question asks: "What is the primary type of fuel used for cooking in your household?" Options include firewood, coal, liquefied gas, natural gas/piped gas, solar energy/biogas, electricity, or other fuels. Households using non-clean fuels (firewood or coal) are assigned 1; otherwise 0.	1/10
Basic Education	Educational Attainment	If any household member has ≤ 9 years of schooling, the indicator is assigned 1; otherwise 0.	1/10
	Education Expenditure	If household spending on education or training is zero, the indicator is assigned 1; otherwise 0.	1/10
Health Care	Health Status	In the CFPS, respondents are asked: "How would you evaluate your health status?" Responses range from 1 (very healthy) to 5 (unhealthy). If any household member reports being unhealthy, the indicator is assigned 1; otherwise 0.	1/15
	Medical Insurance	If any household member does not have any form of medical insurance, the indicator is assigned 1; otherwise 0.	1/15
	Medical Expenditure	If household medical expenditure exceeds 50% of total household income, the indicator is assigned 1; otherwise 0.	1/15

used in the United Nations multidimensional poverty framework, this paper sets the poverty cutoff at $K = 0.4$, and further conducts robustness tests using $K = 0.3$ and $K = 0.5$.

3.2.2. Explanatory Variable

Following the approach of Chao Xiaojing et al. (2024), this study uses the number of 4G base stations in each prefecture-level city to measure the level of digital infrastructure development.

First, base station data are obtained from OpenCellID⁵, which is the largest open global database of cellular base station identifiers and their corresponding geographic locations. The database collects information through crowdsourcing, relying on users to upload base station measurement data, including base station IDs, geographic coordinates, and signal strength.

From this database, we extract base station records with a Mobile Country Code (MCC) of 460, which corresponds to China, and with the broadband cellular network technology standard identified as LTE (4G).

Next, timestamps recorded in UNIX time format are converted into Beijing Standard Time. The year in which each base station observation is first added to the database is used as a proxy for the year the base station was put into operation.

Subsequently, the base station observations are spatially matched with the geographic boundaries of prefecture-level cities in China using ArcGIS software. Through this process, we obtain the annual number of 4G base stations at the prefecture-level city level for the period 2010-2022.

It is important to note that 4G base stations in China were deployed only after 2014. Consequently, the number of 4G base stations in all prefecture-level cities is zero in 2010 and 2012, which forms a perfect pre-treatment comparison period. This feature is particularly advantageous for identifying the impact of 4G network expansion, as the effective identifying variation originates solely from the post-2014 period. There is no cross-sectional variation in the pre-treatment years, since all values are zero. Therefore, any apparent variation that might be mistaken for early period differentiation is in fact entirely driven by the post-2014 period, specifically by the differential rollout of 4G infrastructure across cities after 2014. A

⁵A free global database of mobile base station IDs and their corresponding locations. The database is built through crowdsourcing and relies on user-submitted base station measurement data — such as base station IDs, geographic coordinates (latitude and longitude), and signal strength — to construct and continuously update the dataset.

brief clarification of this point would help readers better understand the identification strategy.

3.2.3. *Mediating Variables*

To open the “black box” through which digital infrastructure development affects multidimensional poverty, this study introduces two categories of mediating variables. First, considering that the regional innovation environment constitutes an important macro-level foundation for poverty reduction, this study matches the Peking University Regional Innovation and Entrepreneurship Index with household-level data to construct the first mediating variable, which captures improvements in the overall regional level of innovation and entrepreneurship.

At the same time, focusing on micro-level household decision-making, this study draws on the approaches of Zhou Guangsu et al. (2015) and Yang Ziyang and Wen Feng (2020) to construct a household entrepreneurship variable using the CFPS database. This variable is used to examine whether digital infrastructure development can alleviate multidimensional poverty by empowering household entrepreneurship and increasing household income.

Second, a variable measuring public service provision efficiency is introduced to test whether digital infrastructure reduces household multidimensional poverty by improving the accessibility and efficiency of public services from the perspective of the external institutional environment.

The measurement of the efficiency of basic public service provision across regions originates from the Data Envelopment Analysis (DEA) method proposed by A. Charnes, W. W. Cooper, and E. Rhodes (1978). The basic principle of this method is to evaluate the relative efficiency of decision-making units (DMUs) based on multiple indicators of inputs and outputs.

Compared with DEA, the Malmquist productivity index method incorporates the influence of technological change on efficiency and examines the dynamic evolution of technical efficiency by calculating total factor productivity (Caves et al., 1982; Ray and Desli, 1997).

In the empirical calculation, local government fiscal expenditure on public services is treated as the input, while the actual provision of public services is treated as the output.

The specific expression of the Malmquist index is as follows:

$$M(x_{t+1}, y_{t+1}, x_t, y_t) = \left[\frac{D_t(x_{t+1}, y_{t+1})}{D_t(x_t, y_t)} \times \frac{D_{t+1}(x_{t+1}, y_{t+1})}{D_{t+1}(x_t, y_t)} \right]^{\frac{1}{2}} \quad (5)$$

In the formula, (x_{t+1}, y_{t+1}) and (x_t, y_t) denote the input-output vectors in periods $t+1$ and t , respectively. $D_{t+1}(x_{t+1}, y_{t+1})$ and $D_t(x_t, y_t)$ represent the input distance functions measured relative to the frontier technology in period t , while $D_t(x_{t+1}, y_{t+1})$ and $D_{t+1}(x_t, y_t)$ denote the input distance functions measured relative to the frontier technology in period $t+1$.

If the Malmquist index is greater than 1, it indicates that the efficiency of public service provision has improved. If the Malmquist index is less than 1, it indicates that the efficiency of public service provision has declined.

In this study, local government general budgetary expenditure is used to reflect the extent of fiscal support for public service provision. The output indicators mainly capture the actual outcomes of public service provision. Effective provision of basic public services is reflected in several dimensions, including improvements in the living environment, broader access to scientific and educational resources, more convenient healthcare services, and strengthened social welfare protection. These improvements can substantially alleviate economic and social disparities across regions.

Based on the principles of measurability, independence, and data availability, the following variables are selected as output indicators:

- number of general secondary schools
- number of primary schools
- total collection of books in public libraries
- number of hospital beds in township health centers
- total postal service volume
- harmless treatment rate of household waste
- number of participants in the urban employee basic pension insurance system

These indicators broadly cover several key dimensions of basic public services, including basic education, healthcare, quality of life, living environment, and social security. Among all variables, logarithmic transformation is applied to all indicators except the harmless household waste treatment rate. After matching household data with city-level data using the regional administrative codes corresponding to households' locations, the final dataset retains household observations from 126 cities. Descriptive statistics for the input and output variables are reported in Table 2 below.

3.2.4. Control Variables

The control variables are divided into three categories based on household, household head, and regional characteristics. Household-level control

TABLE 2.

Descriptive Statistics of Input and Output Variables

Variable Category	Indicator	Unit	Mean	Std. Dev.	Min	Max
Input Variable	Local Government General Budgetary Expenditure	10,000 RMB	14.816	0.787	11.711	18.241
Output Variables	Number of General Secondary Schools	units	5.145	0.697	2.398	7.194
	Number of Primary Schools	units	6.044	0.980	0	8.620
	Total Collection of Books in Public Libraries	volumes	7.317	1.035	2.996	11.301
	Number of Beds in Township Health Centers	beds	4.886	0.838	1.946	7.682
	Total Postal Service Volume	10,000 RMB	10.434	1.243	2.303	15.461
	Harmless Treatment Rate of Household Waste	%	85.249	28.714	0	100
	Number of Participants in Urban Employee Basic Pension Insurance	persons	13.466	1.090	5.697	17.299

variables include expenditure on social gifts, credit constraints, urban-rural residence, government subsidies, household size, net household real estate assets, and cash and deposits. Household head-level control variables include age, gender, marital status, social status, life satisfaction, confidence in the future, and membership in the Communist Party of China (CPC). Regional-level control variables include GDP per capita, industrial structure index, and foreign direct investment (FDI).

3.3. Data Sources

The empirical analysis in this study draws on four main data sources. First, household-level data are primarily obtained from the China Family Panel Studies (CFPS) for the period 2010-2020. The CFPS is a nationally representative survey conducted by the Institute of Social Science Survey (ISSS), Peking University. Second, data on 4G base stations are obtained from the OpenCellID database. Third, regional innovation data are drawn from the China Regional Innovation and Entrepreneurship Index, compiled by the Center for Enterprise Research of Peking University. Fourth, addi-

tional prefecture-level city data are collected to construct regional control variables as well as the input and output indicators used in the public service provision efficiency analysis.

During the data processing stage, household observations from the micro-level database are matched with geographic variables based on the regional administrative codes corresponding to household locations. Because the 2022 data contain substantial missing values, observations for that year are excluded. As a result, the time dimension includes six survey waves: 2010, 2012, 2014, 2016, 2018, and 2020. Using the city in which each household is located as the reference unit, observations with missing information at either the city or household level are removed. Samples with missing key variables — including income, expenditure, and assets — as well as observations with extreme outlier values are also excluded. After data cleaning, the final dataset consists of 21,690 valid observations across six years. Detailed descriptions of all variables and their descriptive statistics are reported in Table 3 below.

TABLE 3.

Definitions and Descriptive Statistics of All Variables

Variable Category	Variable	Definition	N	Mean	Std. Dev.	Min	Max
Dependent Variables	Degree of Multidimensional Poverty	Calculated based on the multidimensional poverty formula, reflecting the extent of average household welfare deprivation	21690	0.377	0.151	0	1
	Multidimensional Poverty Status ($k \geq 0.4$)	Household is classified as multidimensionally poor when $k \geq 0.4$, assigned value 1; otherwise 0	21690	0.305	0.461	0	1
	Multidimensional Poverty Status ($k \geq 0.3$)	Household is classified as multidimensionally poor when $k \geq 0.3$	21690	0.549	0.498	0	1
	Multidimensional Poverty Status ($k \geq 0.5$)	Household is classified as multidimensionally poor when $k \geq 0.5$	21690	0.139	0.346	0	1
Explanatory Variables	Digital Infrastructure	Logarithm of the number of 4G base stations in prefecture-level cities	19596	14.687	13.629	0	70

TABLE 3—*Continued*

Variable Category	Variable	Definition	N	Mean	Std. Dev.	Min	Max
Household Control Variables	Mobile Phone Users	Number of mobile phone users in the city (10,000 households)	20568	1.108	0.854	0.140	9.380
	Social Gift Expenditure	Household expenditure on social gifts (RMB), logarithmic form	21690	7.262	2.552	0	12.206
	Credit Constraint	Equals 1 if the household faces credit constraints, otherwise 0	21690	0.544	0.486	0	1
	Urban-Rural Residence	Urban household = 1; rural household = 0	21690	0.738	0.440	0	1
	Government Subsidy	Receives government subsidy = 1; otherwise 0	21690	0.458	0.498	0	1
	Household Size	Number of household members	21690	3.858	1.795	1	15
	Net Household Real Estate	Net household real estate assets (RMB), logarithmic form	21690	11.121	3.72	0	18.198
	Cash and Deposits	Household cash and deposits (RMB), logarithmic form	21690	6.449	4.826	0	15.425
	Age	Actual age of household head (years)	21690	50.689	12.837	14	93
	Gender	Male = 1; Female = 0	21690	0.587	0.492	0	1
Household Control Variables	Marital Status	Married = 1; otherwise 0	21690	0.895	0.306	0	1
	Social Status	Self-evaluated social status (1 = very low, 5 = very high)	21690	3.699	1.048	0	5
	Life Satisfaction	Self-evaluated life satisfaction (1 = very dissatisfied, 5 = very satisfied)	21690	3.909	1.067	0	5
	Confidence in the Future	Confidence in the future (1 = no confidence, 5 = strong confidence)	21690	0.107	0.297	0	1
	CPC Membership	Member of the Communist Party of China = 1; otherwise 0	21690	0.377	0.151	0	1
Regional Control Variables	GDP per Capita	Regional GDP per capita, logarithmic form	21690	10.649	0.472	9.464	12.009
	Industrial Structure Index	Rationalization index of industrial structure calculated based on the Theil index	21690	1.179	0.495	0.569	5.244

TABLE 3—*Continued*

Variable Category	Variable	Definition	N	Mean	Std. Dev.	Min	Max
Mechanism Variables	Foreign Direct Investment	Ratio of actually utilized foreign capital to GDP	19150	0.003	0.003	0	0.019
	Innovation and Entrepreneurship Index	Peking University Regional Innovation and Entrepreneurship Index	21432	52.613	176.906	0.017	2383.561
	Household Entrepreneurship	In the CFPS questionnaire respondents are asked whether any household member engaged in self-employment or operated a private business in the past 12 months. Households with such activity are coded as 1; otherwise 0	21690	0.091	0.288	0	1
	Public Service Provision Efficiency	Calculated using the Malmquist productivity index method	20070	0.993	0.116	0.434	1.606

4. EMPIRICAL ANALYSIS

4.1. Baseline Regression Results

Table 4 reports the impact of digital infrastructure development on the degree of multidimensional poverty. In Table 4, Column (1) presents the regression results without fixed effects and without control variables. Column (2) reports the regression results without fixed effects but including all control variables. Column (3) presents the regression results with both household and time fixed effects while including all control variables. Column (1) shows that the estimated coefficient of digital infrastructure development is -0.0131 , which is statistically significant at the 1% level. In Column (2), after including all control variables based on Column (1), the estimated coefficient of digital infrastructure decreases to -0.0086 , while remaining statistically significant at the 1% level. This result indicates that digital infrastructure development continues to exert a significantly negative effect on the degree of multidimensional poverty. Column (3) further controls for household fixed effects and time fixed effects on the basis of Column (2). The regression results show that the estimated coefficient of digital infras-

tructure development is -0.0109 , which remains statistically significant at the 1% level. Overall, the regression results reported in Table 4 demonstrate that digital infrastructure development significantly contributes to reducing households' multidimensional poverty, which is consistent with the theoretical analysis presented in this study.

TABLE 4.
Impact of Digital Infrastructure Development on the Degree of Multidimensional Poverty

Variables	Degree of Multidimensional Poverty		
	(1)	(2)	(3)
Digital Infrastructure	-0.0131^{***} (0.0002)	-0.0086^{***} (0.0004)	-0.0109^{***} (0.0005)
Observations	20,754	18,214	18,214
Control Variables	No	Yes	Yes
Fixed Effects	No	No	Yes
R-squared	0.137	0.162	0.903

Notes: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are reported in parentheses.

Table 5 reports the impact of digital infrastructure development on the multidimensional poverty status when $k \geq 0.4$. Column (1) presents the regression results without fixed effects and without including any control variables. The coefficient of digital infrastructure development is -0.1434 , which is statistically significant at the 1% level. Column (2) adds all control variables based on column (1). The results show that digital infrastructure development still has a significant negative impact on household multidimensional poverty status, with a coefficient of -0.1102 , significant at the 1% level. Column (3) further controls for household and time fixed effects based on column (2). The regression coefficient of digital infrastructure development is -0.0919 , which remains statistically significant at the 1% level. These results confirm the hypothesis that digital infrastructure development has a significant multidimensional poverty-reduction effect.

4.2. Robustness Analysis

4.2.1. Quantile Regression

To more comprehensively reflect the conditional distribution of the relationship between digital infrastructure and multidimensional poverty, and to eliminate the influence of extreme values, this study employs panel quantile regression in the robustness analysis to examine whether the poverty-reduction effect of digital infrastructure varies across different quantiles.

TABLE 5.

Impact of Digital Infrastructure Development on Multidimensional Poverty Status

Variables	Multidimensional Poverty Status ($k \geq 0.4$)		
	(1)	(2)	(3)
Digital Infrastructure	-0.1434*** (0.0039)	-0.1102*** (0.0060)	-0.0919*** (0.0085)
Observations	20,754	18,214	18,214
Control Variables	No	Yes	Yes
Fixed Effects	No	No	Yes

The econometric model is specified as follows:

$$\text{Poverty}_{ijt} = \rho_0 + \rho_1(q)\text{DI}_{jt} + \rho_2\text{control}_{ijt} + \varphi_i + \delta_t + \varepsilon_{ijt} \quad (6)$$

where q represents different quantiles of the conditional distribution, ranging from 0 to 1. In this study, the selected quantiles are $q = 0.25, 0.5$, and 0.75 .

Table 6 reports the relationship between digital infrastructure and the degree of multidimensional poverty at the three quantiles. Columns (1), (4), and (7) present the regression results without fixed effects and without any control variables. Columns (2), (5), and (8) present the results without fixed effects but including all control variables. Columns (3), (6), and (9) report the results with both fixed effects and all control variables included. The regression coefficients at the three quantiles are -0.0064 , -0.0064 , and -0.0072 , respectively.

TABLE 6.

Impact of Digital Infrastructure Development on the Degree of Multidimensional Poverty

Variables	25% Quantile			50% Quantile			75% Quantile		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Digital Infrastructure	-0.0050*** (0.0005)	-0.0062*** (0.0004)	-0.0064*** (0.0006)	-0.0129*** (0.0001)	-0.0083*** (0.0005)	-0.0064*** (0.0006)	-0.0159*** (0.0001)	-0.0102*** (0.0006)	-0.0072*** (0.0008)
Observations	20,754	18,214	18,214	20,754	18,214	18,214	20,754	18,214	18,214
Control Variables	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes
Pseudo R^2	0.005	0.128	0.137	0.056	0.169	0.179	0.077	0.183	0.196

The results in Table 6 indicate that at different quantiles, digital infrastructure consistently exhibits a significant mitigating effect on the degree of multidimensional poverty. Moreover, as the quantile increases, the poverty-

reducing effect of digital infrastructure becomes more pronounced. Therefore, strengthening the development of digital infrastructure, promoting the expansion of digital services, and broadening the application of information technologies will help fully realize the poverty-alleviation potential of digital infrastructure in reducing multidimensional poverty.

4.2.2. Alternative Variable Regression

To eliminate potential estimation bias arising from the selection of explanatory and dependent variables, this study employs alternative measurement methods for household multidimensional poverty in order to further test the robustness of the empirical results. Specifically, the number of mobile phone users (in logarithmic form) is first used to replace the explanatory variable. In addition, the multidimensional poverty status under thresholds of $k \geq 0.3$ and $k \geq 0.5$ is used as alternative measures of the dependent variable.

Table 7 reports the regression results for multidimensional poverty after replacing the explanatory variable. In column (3), after including household and time fixed effects as well as all control variables, the coefficient of the alternative explanatory variable on the degree of multidimensional poverty is -0.0138 , which is statistically significant at the 1% level. This result indicates that the findings of this study are relatively robust.

TABLE 7.
Regression Results of Multidimensional Poverty Degree after Replacing
the Explanatory Variable

Variables	Degree of Multidimensional Poverty		
	(1)	(2)	(3)
Mobile Phone Users	-0.0640^{***} (0.0018)	-0.0128^{***} (0.0018)	-0.0138^{***} (0.0012)
Observations	20,568	19,150	19,150
Control Variables	No	Yes	Yes
Fixed Effects	No	No	Yes
R-squared	0.083	0.145	0.907

In the robustness analysis of multidimensional poverty status, this study simultaneously replaces both the explanatory variable and the dependent variable. Specifically, columns (3)-(7) of Table 8 report the regression results after including fixed effects and all control variables. Column (3) shows that the coefficient of the alternative explanatory variable on the multidimensional poverty status when $k \geq 0.4$ is -0.1547 , and the estimated coefficient is statistically significant at the 1% level.

Columns (4) and (6) of Table 8 indicate that digital infrastructure development has a significant poverty-reducing effect on multidimensional poverty status when $k \geq 0.3$ and $k \geq 0.5$, respectively. Columns (5) and (7) present the regression results when both the explanatory variable and the dependent variable are replaced. The results verify that the number of mobile phone users has a significantly negative effect on the multidimensional poverty status when $k \geq 0.3$ and $k \geq 0.5$, with significance at the 1% level, further indicating that the empirical findings remain robust.

TABLE 8.
Regression Results of Multidimensional Poverty Status after Replacing
Both Explanatory and Dependent Variables

Variables	Multidimensional Poverty Status ($k \geq 0.4$)			Multidimensional Poverty Status ($k \geq 0.3$)		Multidimensional Poverty Status ($k \geq 0.5$)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Digital Infrastructure				-0.0639*** (0.0075)		-0.0098*** (0.0015)	
Mobile Phone Users	-0.6383*** (0.0284)	-0.1020*** (0.0257)	-0.1547*** (0.0268)		-0.1252*** (0.0221)		-0.0098*** (0.0015)
Observations	20,568	19,150	19,150	18,214	19,150	18,214	19,150
Control Variables	No	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes

Overall, the results in Table 8 show that regardless of whether the number of 4G base stations or the number of mobile phone users is used as the explanatory variable, and regardless of whether the multidimensional poverty status under $k \geq 0.4$, $k \geq 0.3$, or $k \geq 0.5$ is adopted as the dependent variable, the development of digital infrastructure significantly reduces the probability that households fall into multidimensional poverty. These findings are consistent with the theoretical analysis of this study and further confirm the robustness of the results.

4.2.3. Winsorization

To reduce the influence of extreme values on the statistical results while retaining as much information from the original data as possible, this study applies 1% winsorization to all variables. This approach preserves the completeness of the sample size while reducing the model's dependence on distributional assumptions and improving the reliability of the estimation results. The results reported in columns (1)-(4) of Table 9 show that after winsorization, digital infrastructure still has a significant inhibitory

effect on both the degree and status of multidimensional poverty, further confirming the robustness of the empirical findings in this study.

TABLE 9.

Regression Results after Winsorization

Variables	Degree of	Multidimensional	Multidimensional	Multidimensional
	Multidimensional	Poverty Status	Poverty Status	Poverty Status
	Poverty	($k \geq 0.4$)	($k \geq 0.3$)	($k \geq 0.5$)
	(1)	(2)	(3)	(4)
Digital Infrastructure	-0.0092*** (0.0005)	-0.0941*** (0.0086)	-0.0664*** (0.0076)	-0.0992*** (0.0110)
Observations	18,214	18,214	18,214	18,214
Control Variables	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.906			

4.3. Addressing Endogeneity

4.3.1. Instrumental Variable Approach

There may be endogeneity issues between digital infrastructure and multidimensional poverty, including the following three sources. First, omitted variables: factors such as regional historical and cultural endowments and geographical conditions may simultaneously influence both the distribution of digital infrastructure and the extent of multidimensional poverty. Second, reverse causality: regions with lower levels of multidimensional poverty may have greater capacity to construct and maintain digital infrastructure. Third, measurement error: the 4G base station data may not fully capture the true level of digital infrastructure. To address this endogeneity concern, this study constructs an instrumental variable (IV) to further examine the poverty-reduction effect of digital infrastructure.

Previous studies have used historical data on postal relay stations established during the Ming Dynasty as an instrumental variable for digital infrastructure. Li Lanbing et al. (2019), by compiling archival records from A Study of Ming Dynasty Postal Relay Stations, addressed endogeneity arising from historical differences in infrastructure conditions and development paths. Similarly, Bu Xiaoning et al. (2019) used the presence of Ming Dynasty relay stations in a region as an instrumental variable to mitigate the endogeneity problem associated with infrastructure development.

This instrumental variable is justified for two reasons. First, the location of infrastructure construction is influenced by various natural and geographical conditions. Due to technological limitations at the time, the

establishment of Ming Dynasty relay stations also tended to occur in locations with favorable geological conditions for construction. Modern digital infrastructure development in China is therefore more likely to build upon or upgrade infrastructure in areas with such preexisting favorable conditions, implying a strong correlation between the two. Second, Ming Dynasty relay stations were primarily established for military and administrative purposes, and thus are unlikely to have a direct impact on modern economic outcomes, satisfying the exclusion restriction.

TABLE 10.

Instrumental Variable Estimation Results for Multidimensional Poverty		
Variables	(1)	(2)
First-stage dependent variable	Digital Infrastructure	
Ming Dynasty Relay Stations	0.4634*** (0.0315)	0.7284*** (0.0309)
Second-stage dependent variable	Degree of Multidimensional Poverty	Multidimensional Poverty Status
Digital Infrastructure	−0.0358*** (0.0053)	−0.3828*** (0.0234)
Anderson canon. corr. LM statistic	214.713 [0.0000]	
Cragg-Donald Wald F statistic	216.988 {16.38}	
AR test		140.33 [0.0000]
Wald test		119.14 [0.0000]
Observations	18,214	18,214
Control Variables	Yes	Yes
Fixed Effects	Yes	Yes
Centered R^2	0.521	

Note: Values in () are robust standard errors, values in [] are p-values, and values in { } are the critical value for the Stock-Yogo weak identification test at the 10% significance level.

Accordingly, this study uses whether a region had Ming Dynasty relay stations as an instrumental variable and estimates the model using the two-stage least squares (2SLS) method (see Table 10).

The regression results reported in Table 10 show that the estimated coefficients of the instrumental variable are statistically significant. Regions that had relay stations during the Ming Dynasty tend to exhibit higher levels of digital infrastructure development, consistent with expectations. In the second-stage regression results using the “Ming Dynasty relay stations”

instrument, the estimated coefficients of digital infrastructure remain significantly negative. Moreover, the baseline linear model successfully passes both the underidentification and weak identification tests. Specifically, the Anderson canon. corr. LM statistic rejects the null of underidentification ($p = 0$), and the Cragg-Donald Wald F statistic exceeds the Stock-Yogo critical value at the 10% significance level, thus rejecting weak instruments. Furthermore, in the Probit model, both the AR test and the Wald test — which are robust to weak identification — yield statistically significant results. This indicates that the instrumental variable estimates are reliable across both model specifications. These findings indicate that digital infrastructure development significantly alleviates households' multidimensional poverty and further confirm the robustness of the empirical results.

4.3.2. Lagged Specification

Although the instrumental variable method mitigates endogeneity arising from omitted variables, reverse causality, and measurement error, it does not fully eliminate the concern of contemporaneous reverse causality — that is, the possibility that current multidimensional poverty may affect current digital infrastructure. To address this issue, we introduce a lagged specification of the digital infrastructure variable. This lag structure not only removes contemporaneous reverse causality by establishing a clear temporal ordering but also reflects the realistic time lag of digital infrastructure's impact on multidimensional poverty.

TABLE 11.

Regression Results with Lagged Variables				
Variables	Degree of	Multidimensional	Multidimensional	Multidimensional
	Multidimensional	Poverty Status	Poverty Status	Poverty Status
	Poverty	($k \geq 0.4$)	($k \geq 0.3$)	($k \geq 0.5$)
	(1)	(2)	(3)	(4)
L2. Digital	-0.0096***	-0.0684***	-0.0447***	-0.0907***
Infrastructure	(0.0006)	(0.0104)	(0.0091)	(0.0135)
Observations	15,127	15,127	15,127	15,127
Control Variables	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.905			

Given that the dataset used in this study consists of six waves of observations collected at two-year intervals, the analysis employs digital infrastructure lagged by two periods to verify that the observed effects are

not driven by contemporaneous feedback from multidimensional poverty to infrastructure development (see Table 11).

Column (1) of Table 11 shows that digital infrastructure lagged by two periods continues to exert a poverty-reducing effect on the degree of multidimensional poverty. Specifically, the estimated coefficient of digital infrastructure changes from -0.0109 in the baseline specification to -0.0096 in the lagged specification, indicating that the poverty-reducing effect of digital infrastructure remains present but operates at a slightly attenuated pace when considering the lagged impact. Column (2) further indicates that digital infrastructure lagged by two periods also has a mitigating effect on multidimensional poverty status. Overall, the regression results reported in Table 11 provide additional evidence supporting the robustness and reliability of the empirical findings in this study.

4.4. Mechanism Analysis

The preceding analysis demonstrates that digital infrastructure development exerts a significant multidimensional poverty-reducing effect at the household level. However, the strength of this effect may be influenced by regional innovation and entrepreneurship activity as well as the efficiency of public service provision. To examine how these two mechanism variables shape the poverty-reduction effect of digital infrastructure, this study follows the mediation analysis framework proposed by Baron and Kenny (1986) and applied in recent studies such as Wang Feng and Ge Xing (2022) and Tian Ge and Zhang Xun (2022). The following mediation models are constructed:

$$\text{Med}_{ijt} = \lambda_0 + \lambda_1 \text{DI}_{ijt} + \gamma_2 \text{Control}_{ijt} + \varphi_i + \delta_t + \varepsilon_{ijt} \quad (7)$$

$$\text{Poverty}_{ijt} = \omega_0 + \omega_1 \text{DI}_{ijt} + \omega_2 \text{Med}_{ijt} + \omega_3 \text{Control}_{ijt} + \varphi_i + \delta_t + \varepsilon_{ijt} \quad (8)$$

In these models, Med_{ijt} denotes the mediating variables, which include the innovation and entrepreneurship index, household entrepreneurship, and public service provision efficiency.

4.4.1. Innovation and Entrepreneurship Effect

The poverty-reducing effect of innovation and entrepreneurship primarily operates through enhancing regional economic vitality and expanding employment opportunities. Improvements in digital infrastructure can significantly stimulate urban entrepreneurial activity by reducing startup costs, expanding market access, and alleviating financing constraints (Wang Ke and Chao Xiaojing, 2023). During the process of innovation and entrepreneurship, a large number of employment opportunities are generated,

thereby promoting local economic development. Large-scale employment creation also produces multiplier and accelerator effects for the broader economy (Sato et al., 2012).

With the rapid development of the digital economy and the implementation of policies promoting e-commerce penetration in rural areas, numerous “Taobao villages” have emerged. These villages utilize digital platforms to engage in online commerce, forming integrated production chains that encompass production, management, wholesale, and retail activities. The resulting industrial agglomeration effect enhances regional economic vitality by improving competitiveness in the marketplace. Moreover, the vibrant e-commerce activity and widespread adoption of information technologies attract additional e-commerce firms and entrepreneurs, thereby providing new momentum for rural innovation and entrepreneurship.

TABLE 12.

Regression Results of the Mechanism Tests

Variables	Innovation & Entrepreneurship Effect			household Entrepreneurship			Public Service Provision Efficiency Effect		
	Innovation & Entrepreneurship Index	Degree of Multidimensional Poverty	Multidimensional Poverty Status ($k \geq 0.4$)	household Entrepreneurship Index	Degree of Multidimensional Poverty	Multidimensional Poverty Status ($k \geq 0.4$)	Public Service Provision Efficiency	Degree of Multidimensional Poverty	Multidimensional Poverty Status ($k \geq 0.4$)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Digital Infrastructure Innovation & Entrepreneurship Index	28.9450*** (0.4910)	-0.0088*** (0.0006)	-0.0872*** (0.0088)	0.0220* (0.0131)	-0.0090*** (0.0007)	-0.0914*** (0.0085)	0.0025*** (0.0005)	-0.0109*** (0.0005)	-0.0916*** (0.0089)
Household Entrepreneurship					-0.0180*** (0.0033)	-0.1489*** (0.0511)			
Public Service Provision Efficiency								-0.0016* (0.0008)	-0.0067*** (0.0011)
Observations	18,214	18,214	18,214	18,214	16,552	18,214	18,214	18,214	18,214
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.681	0.903			0.907		0.987	0.903	

Based on the above analysis, this study employs the Peking University Regional Innovation and Entrepreneurship Index to measure the level of innovation and entrepreneurship across regions. In addition, a household entrepreneurship variable is constructed as a mediating factor to fur-

ther examine the micro-level incentive effect of digital infrastructure on entrepreneurial behavior. This approach allows a more comprehensive exploration of the underlying mechanism through which digital infrastructure alleviates multidimensional poverty. The empirical results are reported in Table 12.

Column (1) reports the impact of digital infrastructure development on regional innovation and entrepreneurship. The results show that the estimated coefficient of digital infrastructure is 28.9450, which is statistically significant at the 1% level, indicating that digital infrastructure development significantly promotes regional entrepreneurial dynamism.

Next, the impact of regional innovation and entrepreneurship on multidimensional poverty is evaluated. Column (2) shows that the estimated coefficient of the innovation and entrepreneurship variable is -0.0001 , which is significant at the 1% level. Meanwhile, the coefficient of digital infrastructure decreases from -0.0109 in the baseline regression to -0.0088 , suggesting the presence of a partial mediation effect. The regression results for multidimensional poverty status in column (3) follow a similar pattern. These findings indicate that digital infrastructure alleviates multidimensional poverty partly by enhancing regional innovation and entrepreneurial activity.

Column (4) of Table 12 examines the effect of digital infrastructure development on household entrepreneurship. The results show an estimated coefficient of 0.0220, which passes the statistical significance test, indicating that digital infrastructure significantly promotes entrepreneurial activity at the household level. Continuing to evaluate the effect of household entrepreneurship on the degree of multidimensional poverty, column (5) shows that the estimated coefficient of the entrepreneurship variable is -0.0180 , which is significant at the 1% level. This result indicates that digital infrastructure can substantially reduce multidimensional poverty through the channel of household entrepreneurship. The mechanism test for multidimensional poverty status in column (6) yields consistent results.

Overall, these findings suggest that digital infrastructure development not only enhances regional economic vitality through innovation and entrepreneurship, but also encourages local residents to engage in entrepreneurial activities and increase income, thereby significantly reducing the likelihood that households fall into multidimensional poverty. Accordingly, Hypothesis H2 is supported.

4.4.2. *Public Service Provision Efficiency Effect*

Digital infrastructure development constitutes an important force through which governments can enhance the efficiency of public service provision. With the advancement of the digital economy, the application of digital platforms enables government agencies to access and process information more efficiently, thereby improving the precision and effectiveness of public service delivery and reducing the likelihood that households fall into multidimensional poverty.

In practice, the “One-stop Online Government Services” (Yi Wang Tong Ban) initiative promoted by the Chinese government leverages data integration and digital platforms to significantly reduce the time and financial costs faced by residents and enterprises when accessing public services. Through the integration, sharing, and effective utilization of information resources, government departments have substantially improved their social governance capacity and public service performance. Furthermore, by developing and implementing smart city systems and digital community platforms, governments are able to accelerate improvements in fundamental public services, including basic education, healthcare, elderly care, and environmental protection. These initiatives help address inequalities in the supply of public services, improve the efficiency of urban and rural community governance, and ultimately facilitate the implementation of government poverty-reduction policies.

Based on the above analysis, this study constructs a mechanism variable measuring public service provision efficiency using the Malmquist index method, in order to examine the role of this channel in the relationship between digital infrastructure development and multidimensional poverty. The empirical results are reported in columns (6)-(9) of Table 12.

Column (6) reports the effect of digital infrastructure development on public service provision efficiency. The estimated coefficient is 0.0025, which is statistically significant at the 1% level, indicating that digital infrastructure development significantly improves the efficiency of public service provision. Column (7) shows that the estimated coefficient of public service provision efficiency on the degree of multidimensional poverty is -0.0016 , which is statistically significant. This result suggests that improvements in regional public service provision efficiency can significantly reduce the degree of multidimensional poverty. At the same time, the estimated coefficient of digital infrastructure remains significantly negative, indicating that digital infrastructure alleviates multidimensional poverty partly by enhancing the efficiency of public service provision. The mecha-

nism test for multidimensional poverty status reported in column (9) yields similar results.

Overall, these findings indicate that the public service provision efficiency channel represents an important pathway through which multidimensional poverty can be reduced, thereby supporting Hypothesis H3.

As shown in columns (3), (6), and (9) of Table 12, after incorporating the mediating variables into the baseline model, the coefficient of digital infrastructure development changes to some extent, indicating the presence of partial mediation effects. This implies that mediating mechanisms play an important role in the process through which digital infrastructure contributes to multidimensional poverty reduction and inclusive economic growth. By leveraging internet access, households and households can participate more actively in the development of the regional digital economy, access digital employment opportunities, and benefit from improved public services such as high-quality basic education, healthcare services, and health insurance, thereby strengthening their ability to resist multidimensional poverty.

4.5. Heterogeneity Analysis

The impact of digital infrastructure development on households' multidimensional poverty may vary across different samples. To clarify the heterogeneous effects of digital infrastructure on poverty reduction, this study conducts heterogeneity analyses from four perspectives: different dimensions of poverty, city hierarchy, transportation infrastructure conditions, and group characteristics.

4.5.1. *Heterogeneity across different dimensions of poverty*

To further examine the effects of digital infrastructure development on various dimensions of poverty, multidimensional poverty status is decomposed into five sub-dimensions: household income, financial assets, quality of life, basic education, and healthcare. The corresponding results are presented in Appendix Tables A and B.

The estimation results in columns (1)-(5) of Tables A and B show that digital infrastructure development significantly improves poverty conditions in household income, financial assets, quality of life, basic education, and healthcare. Among these, the strongest poverty-alleviation effect is observed in the quality-of-life dimension, while the effect on health-related poverty is comparatively weak or even statistically insignificant.

One possible explanation is that the healthcare sector cannot rapidly overcome structural constraints such as the scarcity of physical medical re-

sources and the technical barriers associated with population ageing. Consequently, the alleviating effect on the healthcare dimension appears relatively weak in statistical terms. These findings suggest that digital infrastructure exerts heterogeneous effects across different dimensions of poverty. Only through coordinated institutional efforts across multiple sectors can digital technologies truly bridge the “last mile” in addressing multidimensional poverty.

4.5.2. Heterogeneity across prefecture-level city hierarchies

Based on criteria such as political and social activity levels, city size, population, economic development, and total GDP, the sample is divided into two subsamples: high-tier prefecture-level cities and low-tier prefecture-level cities. Separate regression analyses are then conducted.

Columns (1) and (2) of Appendix Tables C and D report the effects of digital infrastructure on household multidimensional poverty across cities of different tiers. The results indicate that digital infrastructure development significantly alleviates multidimensional poverty in both high-tier and low-tier cities, with significance at the 1% statistical level.

Further comparison shows that the reduction in the degree of multidimensional poverty is stronger in lower-tier cities, while the reduction in the status of multidimensional poverty is more pronounced in higher-tier cities. This suggests that the influence of digital infrastructure on poverty varies across city hierarchies. A possible explanation is that cities at different levels possess varying economic environments and fiscal capacities, leading digital infrastructure to play distinct “roles” in different regions.

4.5.3. Heterogeneity across transportation infrastructure conditions

Transportation infrastructure has a clear influence on economic development, which in turn affects the multidimensional poverty reduction effects of digital infrastructure. In this study, households located in cities where high-speed rail (HSR) services were operating in the given year are defined as the HSR-open sample, while households in cities without HSR are defined as the non-HSR sample. Subsample regression analyses are then conducted.

Columns (3) and (4) of Appendix Tables C and D present the effects of digital infrastructure development on household multidimensional poverty under the conditions of HSR availability and non-availability. The results indicate that, regardless of whether a prefecture-level city has opened HSR

services, digital infrastructure significantly alleviates both the degree and status of households' multidimensional poverty.

Moreover, the poverty-reduction effect of digital infrastructure is more pronounced in regions with HSR access. The estimated coefficient for the degree of multidimensional poverty is -0.0106 , while the coefficient for the multidimensional poverty status is -0.1051 ; both pass the 1% significance test. This suggests that HSR availability influences the poverty-reduction effect of digital infrastructure. One possible explanation is that cities without HSR tend to have relatively weaker economic strength and fewer resource advantages, limiting their ability to fully leverage the benefits of digital platforms and thus reducing their poverty-alleviation impact.

4.5.4. *Heterogeneity across different group characteristics*

To examine heterogeneity across different population groups within the same region, the sample is divided according to group characteristics: higher education level, lower education level, age ≤ 45 years, age > 45 years, female, male, married, and unmarried groups. Regression analyses are conducted for each subsample.

Appendix Tables E and F report the effects of digital infrastructure on multidimensional poverty across these groups. First, households are divided based on the household head's years of education: those with nine or more years form the high-education subsample, and those with less than nine years form the low-education subsample. Columns (1) and (2) of Tables E and F show that the estimated coefficients of digital infrastructure are significantly negative in both subsamples. This indicates that digital infrastructure reduces both the degree and status of multidimensional poverty regardless of the head's educational attainment. As an inclusive public service, digital infrastructure enables households with both high- and low-education heads to access digital platforms effectively, thereby alleviating multidimensional poverty.

Second, the study examines the poverty-reduction effects of digital infrastructure across household head age groups. Columns (3) and (4) of Tables E and F show that digital infrastructure has a stronger poverty-alleviation effect for household heads aged 45 or younger, significant at the 1% level. This indicates that younger household heads benefit more from digital infrastructure. A possible explanation is that younger household heads are more receptive to new technologies, more capable of expanding social networks online, and better positioned to seize employment and entrepreneurial opportunities enabled by digital platforms. Moreover, dig-

ital technologies broaden their horizons and provide access to abundant learning resources, facilitating poverty reduction.

Third, the study examines gender differences in the multidimensional poverty reduction effects of digital infrastructure. Columns (5) and (6) of Appendix Tables E and F show that digital infrastructure has a stronger poverty-reduction effect for women, with coefficients significant at the 1% level. This outcome may reflect differences in social roles and daily activities between men and women. Women may be more inclined to use online platforms for interpersonal interaction and social consumption, enabling them to obtain information, follow current events, and engage with social topics more actively. As a result, digital infrastructure affects multidimensional poverty differently across genders.

Finally, the study examines the effect of digital infrastructure development across marital status. Columns (7) and (8) of Appendix Tables E and F show that digital infrastructure reduces multidimensional poverty for both married and unmarried groups, with coefficients passing the significance tests. However, the poverty-alleviation effect is stronger for the married group. One possible explanation is that cooperative dynamics within households allow married families to share resources such as smartphones, computers, and internet expenses, thereby lowering per capita costs. This cost-sharing mechanism reduces the likelihood of households falling into survival crises and enables married households to more confidently utilize digital tools to escape multidimensional poverty.

4.6. Extended Analysis

The preceding analysis demonstrates that digital infrastructure development can significantly alleviate households' multidimensional poverty by enhancing regional innovation and entrepreneurship, stimulating household entrepreneurial activities, and improving the efficiency of public service provision. However, these positive effects may conceal disparities in the distribution of benefits across income groups. If the gains from digitalization are captured predominantly by high-income or highly skilled groups, the diffusion of digital technologies may not narrow social inequalities but instead reinforce them through a "Matthew effect," whereby advantages accumulate among those already privileged.

Against this backdrop, this study further investigates the heterogeneous impacts of digital infrastructure on households with different levels of wealth, with the aim of uncovering its potential "differentiation effect."

Specifically, using the mean value of household net assets as the threshold, the sample is divided into wealthy households (above the mean) and

less wealthy households (below the mean). Subsample mediation effect tests are then conducted, with the results reported in Appendix Tables G and H. In these tables, columns (1)-(3) present the mediation test results for wealthy households, while columns (4)-(6) report the corresponding results for less wealthy households.

The results indicate that, within the less wealthy household sample, the estimated coefficients of the three mediating variables — the innovation and entrepreneurship index, household entrepreneurship, and public service provision efficiency — are all significantly negative. This suggests that digital infrastructure alleviates multidimensional poverty among lower-income groups by activating innovation and entrepreneurship and by optimizing the delivery of public services.

In contrast, within the wealthy household sample, the regression coefficients of these mediating variables are generally close to zero or fail to reach statistical significance. This finding indicates that the poverty-reduction mechanism of digital infrastructure exhibits a clear “gap-bridging” characteristic rather than a “gap-widening” one.

A possible explanation is that wealthy households already possess relatively high levels of entrepreneurial activity and easier access to public services. Consequently, marginal improvements brought about by digital infrastructure exert only limited additional effects on their multidimensional poverty conditions. By contrast, for less wealthy households, digital infrastructure development lowers barriers to entrepreneurship, compensates for market deficiencies, and bridges the “last mile” of public service delivery, thereby providing critical initial momentum for alleviating multidimensional poverty.

These findings imply that, within the current process of digital transformation, resource allocation has not exhibited a pronounced tendency to exacerbate inequality. Instead, digital infrastructure appears to play a constructive role in narrowing social disparities to a certain extent.

5. MAIN CONCLUSIONS AND POLICY RECOMMENDATIONS

Drawing on panel data from the China Family Panel Studies (CFPS) for the period 2010-2020, this study constructs a multidimensional poverty index system covering five dimensions — household income, financial assets, quality of life, basic education, and healthcare — by applying the Alkire-Foster (A-F) method. The level of digital infrastructure development is measured by the number of 4G base stations in prefecture-level cities. On

this basis, the study systematically examines the impact of digital infrastructure on both the degree and status of households' multidimensional poverty, as well as the underlying mechanisms. The main findings are as follows.

(1) Digital infrastructure development significantly reduces both the degree and the status of households' multidimensional poverty.

Baseline regression results show that the estimated coefficient of digital infrastructure is significantly negative at the 1% statistical level. This conclusion remains robust after a series of robustness checks, including quantile regression, replacement of explanatory and dependent variables, and winsorization. To further address potential endogeneity issues, the study employs a combination of instrumental variable (IV) estimation and lagged variable treatment, all of which consistently confirm the robust multidimensional poverty-reduction effect of digital infrastructure.

(2) Mechanism analysis indicates that digital infrastructure alleviates multidimensional poverty through two main pathways.

First, digital infrastructure development significantly enhances regional innovation and entrepreneurial activity and stimulates household entrepreneurial behavior, thereby creating employment opportunities and income-generating channels for groups experiencing multidimensional poverty.

Second, by empowering government governance, digital infrastructure improves the efficiency of public service provision and reduces the barriers residents face in accessing basic public services. Both mechanisms exhibit statistically significant multidimensional poverty-reduction effects.

(3) Heterogeneity analysis reveals substantial variation in the poverty-reduction effects of digital infrastructure.

From the perspective of poverty dimensions, digital infrastructure exerts the strongest improvement in the quality-of-life dimension, while its effect on the health dimension is relatively weaker, reflecting the strong dependence of health improvement on physical medical resources and human capital.

From the perspective of city hierarchy, lower-tier cities benefit more in terms of reductions in the degree of poverty, whereas higher-tier cities show more pronounced improvements in poverty status.

From the perspective of transportation conditions, cities with high-speed rail access display stronger poverty-reduction effects, likely due to their greater capacity for resource agglomeration. From the perspective of group characteristics, the poverty-reduction effects of digital infrastructure differ across groups defined by educational attainment, age, gender, and marital

status, reflecting the differentiated impacts of digital technologies across population groups.

(4) Extended analysis shows that the poverty-reduction mechanism of digital infrastructure displays a clear “pro-poor” characteristic and does not exacerbate social inequality.

After dividing the sample into wealthy and less wealthy households and conducting subsample mediation tests, the results show that the mediating variables — innovation and entrepreneurship index, household entrepreneurship, and public service provision efficiency — play significant poverty-reduction roles primarily among less wealthy households, while their regression coefficients for wealthy households are largely insignificant or close to zero. This indicates that the benefits of digital infrastructure development tend to accrue more strongly to low-income groups that initially lack resources, thereby helping to narrow social disparities to some extent.

Based on the above findings, the following policy recommendations are proposed:

1. Accelerate the development of digital infrastructure. Enhance participation in and access to digital production and daily life, enabling internet platforms to better exert their multidimensional poverty-reduction effects and promote inclusive growth in the digital economy.

2. Improve the use of the internet by individuals and households. Promote digital transformation in both daily life and economic production, while simultaneously improving the efficiency and security of digital development to ensure that digitalization continues to support and enhance economic and social activities.

3. Innovate regional economic practice platforms and promote coordinated regional development. Strengthen training and education for older adults and low-education groups, deepen the inclusiveness of digital infrastructure, enable broader sharing of the benefits brought by digital transformation, and facilitate the advancement of inclusive growth.

APPENDIX

Table A. Heterogeneity Regression Results for the Degree of Multidimensional Poverty across Different Dimensions

Variable	Degree of Multidimensional Poverty				
	Household Income	Financial Assets	Quality of Life	Education	Health
	(1)	(2)	(3)	(4)	(5)
Digital Infrastructure	−0.0009*** (0.0003)	−0.0038*** (0.0002)	−0.0040*** (0.0003)	−0.0018*** (0.0002)	−0.0004*** (0.0001)
Number of Observations	18,214	18,214	18,214	18,214	18,214
Control Variables	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.216	0.957	0.475	0.797	0.304

Table B. Heterogeneity Regression Results for Poverty Status across Different Dimensions

Variable	Multidimensional Poverty Status ($k \geq 0.4$)				
	Household Income	Financial Assets	Quality of Life	Education	Health
	(1)	(2)	(3)	(4)	(5)
Digital Infrastructure	−0.1045*** (0.0122)	−0.1039*** (0.0192)	−0.0731*** (0.0080)	−0.0857*** (0.0142)	−0.0092 (0.0073)
Number of Observations	18,214	12,053	18,214	18,214	18,214
Control Variables	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table C. Heterogeneity Regression Results of City Hierarchy and High-Speed Rail Availability on the Degree of Multidimensional Poverty

Variable	Degree of Multidimensional Poverty			
	High-Tier Cities	Low-Tier Cities	High-Speed Rail Available	No High-Speed Rail
	(1)	(2)	(3)	(4)
Digital Infrastructure	−0.0091*** (0.0009)	−0.0106*** (0.0009)	−0.0106*** (0.0006)	−0.0061*** (0.0014)
Number of Observations	9,342	8,872	11,950	6,264
Control Variables	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.893	0.913	0.898	0.913

Table D. Heterogeneity Regression Results of City Hierarchy and High-Speed Rail Availability on Multidimensional Poverty Status

Variable	Multidimensional Poverty Status ($k \geq 0.4$)			
	High-Tier Cities	Low-Tier Cities	High-Speed Rail Available	No High-Speed Rail
	(1)	(2)	(3)	(4)
Digital Infrastructure	-0.0909*** (0.0141)	-0.0890*** (0.0132)	-0.1051*** (0.0117)	-0.0448** (0.0175)
Number of Observations	9,342	8,872	11,950	6,264
Control Variables	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes

Table E. Heterogeneity Regression Results of Multidimensional Poverty Degree across Different Population Groups

across Different Population Groups								
Variable	Degree of Multidimensional Poverty							
	High Education	Low Education	Age ≤ 45	Age > 45	Female	Male	Unmarried	Married
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Digital Infrastructure	-0.0094** (0.0008)	-0.0088*** (0.0007)	-0.0122*** (0.0009)	-0.0103*** (0.0007)	-0.0114*** (0.0008)	-0.0102*** (0.0007)	-0.0105** (0.0016)	-0.0109*** (0.0006)
Number of Observations	5,559	12,655	6,320	11,894	7,858	10,356	1,885	16,327
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.849	0.927	0.895	0.908	0.904	0.902	0.898	0.903

Table F. Heterogeneity Regression Results of Multidimensional Poverty Status across Different Population Groups

[illegible]

Table G. Extended Analysis Results for the Degree of Multidimensional Poverty

Variable	Degree of Multidimensional Poverty					
	Wealthy			Less Wealthy		
	(1)	(2)	(3)	(4)	(5)	(6)
Digital Infrastructure	−0.0075*** (0.0011)	−0.0091*** (0.0009)	−0.0091*** (0.0009)	−0.0077*** (0.0007)	−0.0091*** (0.0006)	−0.0091*** (0.0007)
Innovation and Entrepreneurship Index	−0.0000*** (0.0000)			−0.0001*** (0.0000)		
Household Entrepreneurship		0.0017 (0.0048)			−0.0148*** (0.0042)	
Public Service Provision Efficiency			0.0060 (0.0152)			−0.0015*** (0.0001)
Number of Observations	4,582	4,582	4,582	13,632	13,632	13,632
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.857	0.857	0.857	0.914	0.914	0.913

Table H. Extended Analysis Results for Multidimensional Poverty Status

Variable	Multidimensional Poverty Status ($k \geq 0.4$)					
	Wealthy			Less Wealthy		
	(1)	(2)	(3)	(4)	(5)	(6)
Digital Infrastructure	−0.0777*** (0.0221)	−0.0812*** (0.0194)	−0.0814*** (0.0194)	−0.0784*** (0.0100)	−0.0838*** (0.0098)	−0.0840*** (0.0098)
Innovation and Entrepreneurship Index	−0.0001 (0.0003)			−0.0008** (0.0003)		
Household Entrepreneurship		0.0005 (0.1009)			−0.1921*** (0.0600)	
Public Service Provision Efficiency			0.0118 (0.0309)			−0.0029*** (0.0011)
Number of Observations	4,582	4,582	4,582	13,632	13,632	13,632
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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