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How can digital financial inclusion crack the urban–rural income gap? New insights from China

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Introduction: The urban–rural income gap is a significant challenge faced by countries worldwide. In recent years, inclusive finance, emerging alongside the development of the digital economy, has provided a new pathway to mitigate this gap due to its inclusive and accessible nature.

Methods: Based on panel data from 1,081 county-level regions in China spanning 2014–2022, this study employs a double machine learning model to empirically examine the impact of digital inclusive finance (DIF) on the urban–rural income gap and its underlying mechanism.

Results: The results indicate that DIF significantly narrows the urban–rural income gap, and this conclusion remains valid after a series of robustness tests. Further mechanism analysis reveals that DIF alleviates the urban–rural income gap primarily by enhancing county-level entrepreneurial activity and technological innovation levels, with government fixed-asset investment playing a significant positive moderating role in this process. Heterogeneity analysis shows that the gap-narrowing effect of digital inclusive finance varies significantly across counties with different resource endowments, geographical locations, and economic agglomeration degrees.

Discussion: This study provides theoretical and empirical references for promoting urban–rural integrated development and achieving sustainable development goals (SDGs).

KEYWORDS

digital inclusive finance, double machine learning, mechanism analysis, sustainable development, urban–rural income gap

1 Introduction

Reducing urban–rural income inequality constitutes a pivotal component of achieving the United Nations Sustainable Development Goals (SDGs), and has garnered widespread attention from the international community within the macro framework of global sustainable development (Mensah, 2019). The urban–rural income gap is directly linked to the maintenance of social stability and the enhancement of public well-being (De Magalhães and Santaaulàlia-Llopis, 2018; Kanbur et al., 2021). Therefore, curbing the escalating trend of income inequality and reducing the number of people living in extreme poverty represent key priorities for advancing sustainable development, which also aligns with the shared objectives of governments around the world (Wan and Knight, 2023).

Against the backdrop of the digital economy profoundly reshaping industrial structures and the macroeconomic landscape, DFI serves as a transformative approach (Agbenyo et al., 2025), offering a potential pathway to address the predicament of the urban–rural income gap. Existing literature defines DFI as the digital access of traditionally excluded vulnerable groups to formal financial services (Bourreau, 2015). Its core value lies in leveraging digital tools to

provide accessible financial services for vulnerable groups, thereby activating the development potential of economically underdeveloped regions (Kumar and Jie, 2023). Relying on mobile terminals and internet platforms, DFI effectively mitigates the high costs and accessibility constraints inherent in traditional financial services, enabling marginalized groups—including vulnerable populations and small enterprises—to access financial services and enjoy the benefits of fairness and convenience. In turn, this injects impetus into narrowing the urban–rural income gap (Luo and Zeng, 2020; Parlasca et al., 2022). From the perspective of international practical experience, countries such as India and Kenya have significantly improved financial accessibility for vulnerable groups through the extensive implementation of digital financial services, thus fostering improvements in economic conditions (Gautam et al., 2022) and further narrowing income disparities. Among BRICS countries, nearly 1.3 billion people live below the poverty line. By enhancing women's economic empowerment and promoting social equity and inclusive growth, digital inclusive finance has emerged as a pivotal force for bridging economic gaps (Adera and Abdisa, 2023; Suhrah et al., 2024).

As the world's largest developing country, China has witnessed robust growth in the digital economy and achieved remarkable accomplishments in the field of DFI. However, the issue of unbalanced urban–rural development remains prominent (Wang et al., 2025). In 2024, the ratio of per capita disposable income between urban and rural residents stood at 2.2 (rural residents: RMB 22,519; urban residents: RMB 49,608). Although the urban–rural gap has narrowed compared with previous years, the absolute gap remains significant, hindering the realization of China's goal of common prosperity. Notably, as a link connecting central cities and serving rural areas, county-level regions assume unique geographical and social functions and occupy a strategic role as a bridge between urban and rural areas (Fang et al., 2025). As a natural carrier for the integration of urban–rural factors and the coordinated development of industries, counties not only serve as a bridge for urban economic spillover to rural areas but also act as crucial nodes for narrowing the urban–rural income gap. Based on this, this study takes China as a case study to explore the impact of DFI on the urban–rural income gap at the county level, which holds important theoretical value and practical significance for deepening financial reform and achieving sustainable development goals.

Existing studies have shown that DFI plays a crucial role in promoting inclusive economic growth (Corrado and Corrado, 2017; Luo and Zeng, 2020), reducing poverty vulnerability (Liu et al., 2024), driving farmers' entrepreneurship and employment (Li et al., 2023; Agbenyo et al., 2025), increasing grain yields (Li M. et al., 2025), enhancing agricultural economic resilience (Wan et al., 2025), improving farmers' well-being (Li F. et al., 2025), and advancing green development (Luo and Zeng, 2020; Guo et al., 2023). Regarding the exploration of the relationship between DFI and the urban–rural income gap, scholars have drawn different conclusions. First, some argue that DFI can narrow the urban–rural income gap. The inclusive growth effect of DFI can not only promote economic growth but also mitigate the digital divide, accelerate the accessibility of financial services, and provide increasingly extensive opportunities for society, thereby helping to improve the living standards and welfare of low-income groups and narrowing the income gap (Ahmad et al., 2021; Marcelin et al., 2022; Zhang et al., 2024; Zou et al., 2024a; Sahay et al., 2021). Meanwhile, DFI has the dual functions of data analysis and fund aggregation, which can effectively alleviate information

asymmetry (Geng and He, 2021), increase the capital concentration of technological innovation projects, optimize resource allocation efficiency, and improve the financing efficiency of technological innovation projects. Second, others contend that the digital divide between urban and rural areas has long existed, and remote areas may see this gap widen with the deepening of the digital economy, exacerbating the urban–rural income gap through the “Matthew Effect” (Menza et al., 2024; Zhang et al., 2025). Third, some scholars believe that DFI has both “digital dividend” and “digital divide” effects, and the final impact on the urban–rural income gap depends on the intensity of these two effects (Zhao and Wang, 2023). Therefore, attention should be paid to the coverage and usage intensity of DFI (Siddiki and Bala-Keffi, 2024; Zou et al., 2024b). In summary, there is no consensus on whether DFI can help narrow the urban–rural income distribution, and more empirical data are needed to verify relevant conclusions.

The controversies over relevant empirical results stem from multiple aspects. First, in terms of research methods, most studies mainly adopt traditional econometric causal inference and spatial econometric analysis. However, as composite indicators, the urban–rural income gap and DFI are affected by various economic and social factors. Traditional econometrics cannot solve the problems of “dimension explosion” of control variables, non-linear economic relationships, and model specification bias, leading to inconsistent research results. Second, in the discussion of mechanisms, existing studies on the impact of DFI on the urban–rural income gap have rarely explored the mediating roles of county-level entrepreneurial vitality and technological advancement, which are most critical for promoting urban–rural income equality. Meanwhile, as an important promoter of narrowing the urban–rural income gap, the existing literature lacks quantitative analysis of government functions and fails to construct a systematic analytical framework involving the government, entrepreneurial entities, technological innovation, and urban–rural residents, resulting in significant differences in mechanisms from different perspectives. Third, in terms of analytical dimensions, most existing studies focus on the provincial level, while the core issue of the urban–rural income gap lies more in the income distribution at the county level. The mismatch between the research level and the core of the problem leads to large discrepancies in empirical results.

In view of this, based on panel data from 1,081 counties in China spanning 2014–2022, this study constructs a systematic analytical framework centered on DFI, entrepreneurial vitality, technological innovation level, government fixed-asset investment, and the urban–rural income gap. It employs a double machine learning model to examine the impact of DFI on narrowing the urban–rural income gap and the relevant transmission mechanisms, and explores the heterogeneous performance of DFI under different conditions of resource endowments, geographical locations, and economic concentration degrees. Compared with existing literature, the potential contributions of this study are as follows: (1) Utilizing the advantages of double machine learning algorithms in controlling “high-dimensional variables” and non-linear relationships to analyze and accurately quantify the impact of DFI on narrowing the urban–rural income gap. (2) Taking county-level technological innovation, entrepreneurial vitality, and government fixed-asset investment scale—factors that directly affect the income of urban and rural residents—as the analytical entry points, to explore the mediating and

moderating mechanisms of the long-tail effect of DFI on narrowing the urban–rural income gap, thereby providing a useful supplement to relevant research. (3) Focusing on counties where the problem of urban–rural income distribution is most prominent, systematically analyzing the county-level heterogeneous characteristics of DFI under different resource and economic backgrounds, laying a foundation for China and other developing countries to formulate targeted development policies at the same level of grassroots administrative units to reduce the urban–rural income gap.

The subsequent arrangement of this paper is as follows: the second part focuses on explaining the corresponding theoretical analysis and research hypotheses; the third part introduces variable definitions and the specification of the double machine learning model; the fourth part conducts specific analysis and discussion on the empirical results; the sixth part presents the research conclusions and suggestions of this paper.

2 Theoretical model analysis and research hypotheses

this paper defines it as follows. This section constructs a four-sector theoretical model involving internet financial institutions, traditional financial institutions, micro and small business operators, and large enterprises, focusing on distinguishing the credit conditions and income gaps of micro and small business operators under the following three scenarios:

- (1) The scenario where only traditional financial institutions exist in the credit market with incomplete information, from which the actual credit level accessible to micro and small business operators is derived.
- (2) The digital credit level available to micro and small business operators after the introduction of internet financial institutions.
- (3) Through comparative static analysis, it is illustrated that digital credit can not only directly narrow the urban–rural income gap by improving loan accessibility and convenience as well as reducing financing costs, but also further alleviate urban–rural income imbalance through indirect channels such as empowering technological innovation and activating entrepreneurial dynamism.

Note: Detailed analysis of the theoretical model for Sections (1) and (2) is provided in the [Appendix](#).

2.1 Income gap definition and comparative static analysis

2.1.1 Income gap definition

It is assumed that high-income households own large enterprises. Let ε denote the proportion of micro and small operators among low-income households—these operators earn both profit income and wage income, consistent with high-income households—while the remaining $1 - \varepsilon$ proportion of low-income households only earn wage income. Enterprise profit is defined as $\pi_i = f(k_i, n_i) - (1 + r_i)q_i - w_i n_i$.

In the literature, the income gap is usually defined as the ratio of the average income of high-income groups to that of low-income

groups (Piketty et al., 2018; Farber et al., 2021). Following the approach of relevant studies (Gu et al., 2019), this paper defines it as follows:

$$\text{gap} = \frac{w_b n_b + \pi_b}{\varepsilon(w_m n_m + \pi_m) + (1 - \varepsilon)w_m n_m} \tag{1}$$

In Equation 1, the numerator represents the operating and wage income of high-income households, while the denominator represents those of low-income households. This equation indicates that the profit growth of micro and small operators (π_m) will increase the demand for labor (n_m), thereby boosting the income of low-income households and narrowing the income gap.

2.1.2 Comparative static analysis

Proposition 1: Internet financial institutions improve the availability and convenience of credit for micro-entrepreneurs, alleviate their liquidity constraints, and thereby increase their income levels. Given that micro-entrepreneurs account for a higher proportion and gain greater benefits in rural areas, this helps narrow the urban–rural income gap.

Proof:

- (1) *Internet financial institutions can enhance credit availability for micro-entrepreneurs.*

To prove that internet financial institutions can provide higher credit availability for micro-entrepreneurs, it is necessary to verify that $q_{md} > q_m$. In the credit market, the sufficient condition for the coexistence of two lending technologies (digital credit and traditional credit) is given by: $\omega(s)(1 + r_{md}) - 1 \geq \theta_{md}(1 + r_{md}) + (1 - \theta_{md})\gamma_{md} - 1$. This condition implies that the efficiency of the digital credit technology adopted by internet financial institutions is at least not inferior to that of traditional credit technology; otherwise, the digital credit technology is not feasible for market adoption. When the above constraint is binding (i.e., holds with equality), substituting it into Equation 1 and simplifying yields: $q_{md} = \left[\frac{\theta_{md}(1 + r_{md}) + (1 - \theta_{md})\gamma_{md} - 1}{\lambda} \right]^{\eta(s)}$. Further derivation results in $q_{md} = q_m^{\eta(s)}$. Given that $\eta(s) > 1$, it follows that $q_{md} > q_m$, which confirms that internet financial institutions offer higher credit availability.

- (2) *Internet financial institutions can improve credit convenience and reduce financing costs for micro-entrepreneurs.*

Consider the optimal capital input decision of micro-entrepreneurs:

$$k_{md} = \left[\frac{(1 - v_m)}{(1 + r_{md})\alpha_m z_m} \right]^{1 - \alpha_m} n_m \tag{2}$$

In Equation 2, taking the partial derivative with respect to v_m , we obtain $\partial k_{md} / \partial v_m < 0$. In addition, since $\partial v_m(s) / \partial s < 0$, digital technologies can improve credit convenience. Further, taking the derivative with respect to r_{md} yields $\partial k_{md} / \partial r_{md} < 0$. Therefore,

internet financial institutions can reduce the financing costs of micro-entrepreneurs by lowering loan interest rates.

- (3) *Internet financial institutions improve the income level of micro-entrepreneurs by enhancing credit availability and convenience, and reducing financing costs, thereby narrowing the urban-rural income gap.*

Given the profit of micro-entrepreneurs as $\pi_m(k_m) = f(k_m, n_m) - \frac{(1+r_m)}{(1-v_m)}$, where k_m is an increasing function of itself and a decreasing function of r_m . Since $q_{md} > q_m$, it follows that $k_{md} > k_m$. Thus, $\pi_m(k_{md}) > \pi_m(k_m)$, indicating that the profit of micro-entrepreneurs rises with the expansion of loan scale.

In addition, the labor income of micro-entrepreneurs is expressed as $w_m n_m = (1-\alpha_m)f(k_m, n_m) = f(k_m, n_m) - (1+r_m)k_m$. Accordingly, $income_l(k_{md}) > income_l(k_m)$ and $gap(k_{md}) < gap(k_m)$. This shows that after the introduction of digital credit services provided by internet financial institutions, the income level of micro-entrepreneurs increases, and the income gap relative to other groups narrows. In other words, digital inclusive finance can reduce individual-level income inequality. By aggregating individual income to the regional level, we obtain the income of high-income households ($Income_h$) and low-income households ($Income_l$) in the region. Let λ_h and λ_l denote the proportions of urban high-income and low-income households, respectively. Then the proportions of rural high-income and low-income households are $1-\lambda_h$ and $1-\lambda_l > 0.5$, respectively. The urban-rural income gap within a region can be expressed as Equation 3:

$$gap_{uc} = \frac{\lambda_h Income_h + \lambda_l Income_l}{(1-\lambda_h) Income_h + (1-\lambda_l) Income_l} \tag{3}$$

Considering that internet financial institutions are unable to cover all micro-entrepreneurs in a region, we assume that they can provide loans to a certain proportion (κ) of micro-entrepreneurs, among which rural households account for $1-\phi(1-\phi > 0.5)$. Therefore, internet financial institutions can benefit $\phi\kappa\lambda_l$ of urban micro-entrepreneurs and $(1-\phi)\kappa(1-\lambda_l)$ of rural micro-entrepreneurs. After the introduction of internet financial institutions, the urban-rural income gap can be rewritten as Equation 4:

$$gap_{uc}^* = \frac{\lambda_h Income_h + (1-\phi\kappa)\lambda_l Income_l + \phi\kappa\lambda_l Income_l^*}{(1-\lambda_h) Income_h + (1-(1-\phi)\kappa)(1-\lambda_l) Income_l + (1-\phi)\kappa(1-\lambda_l) Income_l^*} \tag{4}$$

where $Income_l^* = income_l(k_{md})$ represents the income of micro-entrepreneurs who obtain loans from internet financial institutions. Given that the numerator of Equation 3 is greater than the denominator, it is easy to conclude that $gap_{uc}^* < gap_{uc}$ when both λ_l and ϕ are less than 0.5.

This result demonstrates that with the introduction of digital credit services from internet financial institutions, rural micro-entrepreneurs, who account for a larger proportion and gain more benefits, drive up the overall rural income level (reflected by the increase in the denominator). Consequently, the growth rate of rural

income exceeds that of urban income, which means that DIF is capable of narrowing the urban-rural income gap.

Proposition 2: Internet financial institutions can narrow the urban-rural gap through technological innovation.

We assume endogenous technology, where the technological level follows the relationship: $z_m = z_0 R_m^\varphi$. Here, R_m denotes R&D investment, $\varphi \in (0,1)$ represents the R&D output elasticity, and z_0 is the initial technology constant. We adopt a dual credit allocation mechanism, which satisfies the constraint: $(1-v_m(s))q_{md} = k_m + R_m$. In other words, digital credit provides financial support for both production capital and R&D investment simultaneously. We further incorporate the latecomer advantage hypothesis: the initial R&D investment of micro and small operators is lower than that of large enterprises ($R_m < R_b$), while their marginal R&D output is higher, such that $\partial z_m / \partial R_m > \partial z_b / \partial R_b$. For large enterprises, their technological level z_b is an exogenous variable. It is funded by the traditional financial system and is not directly affected by digital technologies, i.e., $(\partial z_b / \partial s = 0)$.

Objective function setting as shown in Equation 5

$$\max_{k_m, R_m, n_m} \pi_m = z_0 R_m^\varphi k_m^{\alpha_m} n_m^{1-\alpha_m} - \frac{(1+r_{md})(k_m + R_m)}{1-v_m(s)} - w_m n_m \tag{5}$$

By computing the first-order partial derivatives respectively, we derive the following optimality conditions. Optimal labor condition: $w_m = (1-\alpha_m)z_0 R_m^\varphi k_m^{\alpha_m} n_m^{-\alpha_m}$. Optimal production capital condition:

$$\frac{1+r_{md}}{1-v_m(s)} = \alpha_m z_0 R_m^\varphi k_m^{\alpha_m-1} n_m^{1-\alpha_m} \text{ (marginal output equals marginal}$$

financing cost). Optimal R&D investment condition:

$$\frac{1+r_{md}}{1-v_m(s)} = \varphi z_0 R_m^{\varphi-1} k_m^{\alpha_m} n_m^{1-\alpha_m} \text{ (marginal R\&D output equals marginal}$$

financing cost).

To solve for the optimal R&D investment R_m^* , we combine the first-order conditions for production capital and R&D investment, yielding $k_m = \frac{\alpha_m}{\varphi} R_m$. Substituting this result into the credit constraint, we obtain Equation 6:

$$R_m^* = \frac{\phi(1-v_m(s))q_{md}}{\alpha_m + \phi} \tag{6}$$

we know that $q_{md} / \partial s > 0$ and $\partial v_m / \partial s < 0$, we can thus derive the response of R&D investment to digital technology as shown in Equation 7, which indicates that the urban-rural technology gap exhibits a convergence trend

$$\frac{\partial R_m^*}{\partial s} = \frac{\phi}{\alpha_m + \phi} \left[(1-v_m(s)) \frac{\partial q_{md}}{\partial s} + q_{md} \frac{\partial(-v_m(s))}{\partial s} \right] > 0 \tag{7}$$

The rate of technological progress is given by $\frac{dz_m}{ds} = \varphi z_0 R_m^{\varphi-1} \frac{\partial R_m}{\partial s} >$, whereas the rate of technological progress for large enterprises satisfies $\frac{dz_b}{ds} = 0$. It follows that $\frac{dz_m}{ds} > \frac{dz_b}{ds}$, which indicates that the urban-rural technology gap exhibits a convergence trend. The contribution of

technological progress to the profits of micro and small operators is $\partial \pi_m / \partial z_m = k_m^{\alpha_m} n_m^{1-\alpha_m} > 0$. Hence, we obtain Equation 8:

$$\frac{d(\text{gap})}{ds} = \frac{-\text{Income}_b \cdot (\partial \pi_m / \partial z_m \cdot dz_m / ds)}{\text{Income}_m^2} < 0 \tag{8}$$

This indicates that technological progress can significantly boost the profits of micro and small operators, and this mechanism ultimately drives the convergence of the urban–rural income gap.

In summary, internet finance raises the R&D investment level of micro and small operators, accelerates their technological innovation and progress by virtue of the latecomer advantage, narrows the urban–rural technology gap, and ultimately drives the convergence of the urban–rural income gap.

Proposition 3: Internet financial institutions narrow the urban–rural gap by enhancing “entrepreneurial vitality.”

We assume that individuals are heterogeneous, with their entrepreneurial ability θ following a continuous distribution $F(\theta)$. Specifically, higher entrepreneurial ability corresponds to higher entrepreneurial profits. There exists a fixed cost C for entrepreneurial activities (e.g., expenditures on equipment procurement, qualification certification, etc.). The labor market is in equilibrium, with the total labor supply L fixed. Entrepreneurship requires labor recruitment, and the scale of wage labor supply adjusts dynamically with the proportion of entrepreneurial entities.

The entrepreneurial decision function is determined by profit levels (including fixed costs):

$$\pi_m(\theta^*, q_{md}, s) = \theta z_m k_m^{\alpha_m} n_m^{1-\alpha_m} - \frac{(1+r_{md})q_{md}}{1-v_m(s)} - C. \tag{9}$$

The wage w_m is an endogenous variable, determined by the labor market equilibrium condition. The critical entrepreneurial ability θ^* which satisfies $\pi_m(\theta^*, q_{md}, s) = w_m$, is given by:

$$\pi_m(\theta^*, q_{md}, s) = \theta z_m k_m^{\alpha_m} n_m^{1-\alpha_m} - \frac{(1+r_{md})q_{md}}{1-v_m(s)} - C. \tag{10}$$

Entrepreneurial vitality μ is defined as the proportion of individuals whose entrepreneurial ability exceeds the critical value θ^* , i.e., $\mu = 1 - F(\theta^*)$. The development of digital technology increases q_{md} and reduces $v_m(s)$, which in turn drives down the critical entrepreneurial ability θ^* . Accordingly, we obtain Equation 9:

$$\frac{\partial \theta^*}{\partial s} = \frac{1}{z_m k_m^{\alpha_m} n_m^{1-\alpha_m}} \left(\frac{(1+r_{md}) \frac{\partial q_{md}}{\partial s}}{1-v_m(s)} + \frac{(1+r_{md})q_{md} \cdot \partial v_m / \partial s}{(1-v_m(s))^2} \right) < 0 \tag{9}$$

Since the distribution function $F(\theta)$ is increasing, a decrease in θ^* leads to a reduction in $F(\theta^*)$. Thus, we obtain Equation 10:

$$\frac{\partial \epsilon}{\partial s} = -f(\theta^*) \cdot \frac{\partial \theta^*}{\partial s} > 0 \tag{10}$$

where f denotes the probability density function of F .

The labor market equilibrium condition satisfies $\mu n m = L - c$ (entrepreneurial labor demand = wage labor supply). Solving this yields

$n_m = \frac{L - \mu}{\mu}$. Substituting this into the wage determination formula $w_m = (1 - \alpha_m) z_m k_m^{\alpha_m} n_m^{1-\alpha_m}$ and differentiating with respect to μ , we have Equation 11:

$$\frac{\partial w_m}{\partial \epsilon} = (1 - \alpha_m) z_m k_m^{\alpha_m} \cdot \alpha_m \left(\frac{L - \mu}{\mu} \right)^{-\alpha_m - 1} \cdot \frac{L}{\mu^2} > 0 \tag{11}$$

The income of low-income households consists of wage income and entrepreneurial profits, i.e., $\text{Income}_l = w_m \cdot (L - \mu) + \mu \cdot \pi_m$. In contrast, the income of high-income households derives from large enterprises, i.e., $\text{Income}_b = w_b n_b + \pi_b$, which is less affected by digital technology. Differentiating the income gap with respect to the digital technology variables, we get Equation 12:

$$\frac{d(\text{Income}_b / \text{Income}_l)}{ds} = \frac{-\text{Income}_b \cdot \left(\frac{\partial w_m}{\partial \mu} \cdot (L - \mu) - w_m \cdot \frac{\partial \mu}{\partial s} + \pi_m \cdot \frac{\partial \mu}{\partial s} + \mu \cdot \frac{\partial \pi_m}{\partial s} \right)}{\text{Income}_l^2} < 0 \tag{12}$$

In summary, internet financial institutions enhance the entrepreneurial vitality of rural micro and small operators, drive an increase in wage income, and thereby narrow the urban–rural income gap.

Based on the above theoretical analysis, this paper proposes the following research hypotheses:

- H1: DFI contributes to narrowing the urban-rural income gap.
- H2: DFI narrows the urban-rural income gap by promoting the level of technological innovation.
- H3: DFI narrows the urban-rural income gap by enhancing county-level entrepreneurial vitality.

2.2 The moderating effect of government fixed-asset investment on the impact of DIF on the urban–rural income gap

DFI accurately matches the supply and demand in the financial market, and plays a significant role in promoting the goals of increasing income and reducing poverty. However, the full exertion of its effectiveness is constrained by the actual conditions of regional infrastructure. In regions with superior location conditions, improved infrastructure, and sound financial markets, DFI, relying on its characteristics of wide coverage, in-depth application, and high digitization, can effectively promote the construction of digital villages. On the contrary, in regions with weak infrastructure and underdeveloped financial markets, its boosting effect is correspondingly weakened (Altunbaş and Thornton, 2020; Ndlovu and Toerien, 2020). As a key driving force, the government can effectively improve development bottlenecks such as logistics and transportation,

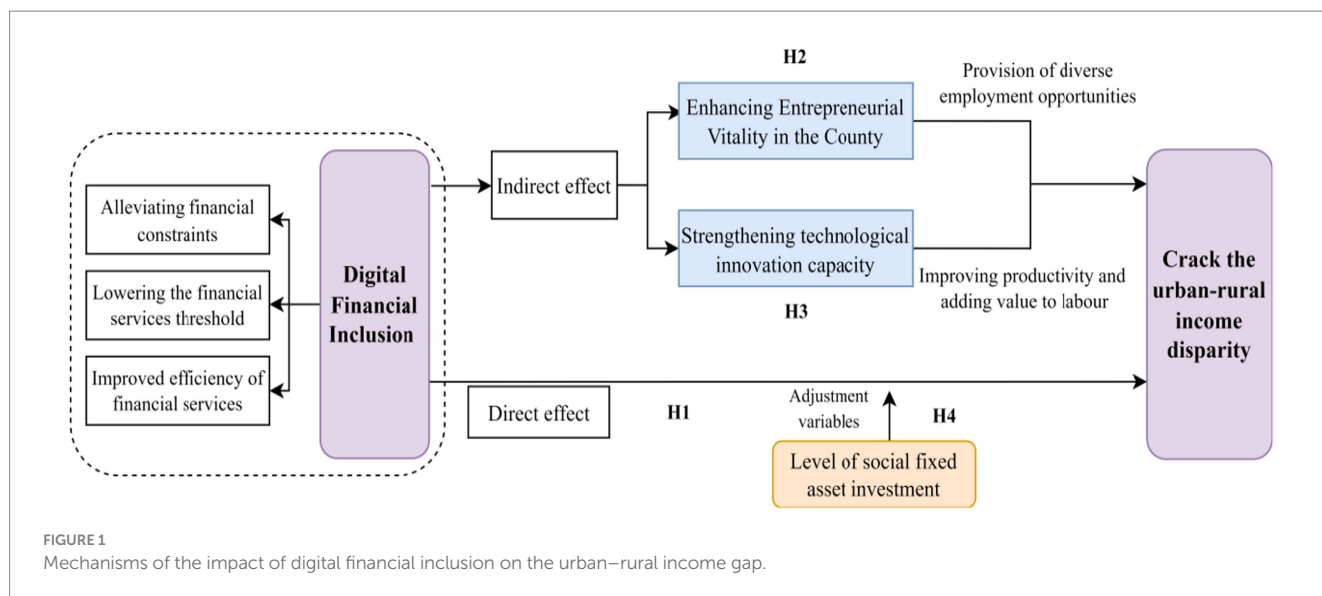


FIGURE 1 Mechanisms of the impact of digital financial inclusion on the urban-rural income gap.

personnel flow, and real-time communication by increasing fixed-asset investment in areas such as infrastructure, providing strong support for DFI to expand its service boundaries (Cao et al., 2024). This not only helps alleviate the spatial dilemma of insufficient coverage of financial services in rural and remote areas, enabling vulnerable groups such as farmers to access financial resources more conveniently (Wang and Liu, 2024), but also significantly reduces information acquisition costs, mitigates information asymmetry, provides them with new ways of thinking, and thereby enhances residents' digital literacy (Neves et al., 2023). On this basis, the regional resource advantages guided by the government are activated, the channels for farmers to increase their income are further broadened, and the expanding trend of the urban-rural income gap can be effectively curbed. Based on this, Hypothesis 4 is proposed:

H4: Government fixed-asset investment plays a positive moderating role in the impact of DFI on narrowing the urban-rural income gap.

The relevant impact mechanism and its path are illustrated in Figure 1.

3 Research design and data description

3.1 Variable selection

Dependent variable. The urban-rural income gap (URG) is measured by the *Thiel* index, which accounts for both the absolute income gap and the overall shape of the income distribution, providing a more comprehensive measure of income inequality. It allows comparisons between different points in time or regions, offering more insightful information for policymakers. The calculation process is shown in Equation 13.

$$Theil = \sum \left(\frac{I_i}{I} \times \log \left(\frac{I_i/I}{P_i/P} \right) \right) \tag{13}$$

In Equation 13, where *Thiel* is the urban-rural income gap, P_i is the population of area i , P is the total population, I_i is the income of region i , and I is the total income.

The core explanatory variable. Digital financial inclusion (DFI) is derived from the county-level digital financial inclusion index report published by Peking University and Alipay Group.

The mediating variables. County-level science and technology innovation (*innovate*) and entrepreneurial vigor (*entre*) are represented by the logarithm of the number of invention patents and newly registered enterprises in the county during the year, respectively.

The moderating variable. Government fixed-asset investment (*invest*) is measured by the fixed-asset investment volume at the county level.

Other Control Variables. Drawing on the research of relevant scholars, this study selects the following control variables: regional consumption levels (*consume*), size of non-farm employment (*employ*), development of the secondary sector (*sec*), development of the tertiary industry (*ter*), level of traditional financial development (*tf*), level of agricultural mechanization (*agri-mech*), level of information development (*info*), social welfare level (*welfare*), medical level (*hos*), and education level (*edu*). The descriptive statistics for all variables are shown in Table 1.

3.2 Data sources and descriptive statistics

The data used to calculate the urban-rural income gap are sourced from the *China County Statistical Yearbook* (2015–2023). Data on the DFI are derived from the *County-Level DFI Index* (2015–2023) report published by the Digital Finance Research Center of Peking University. The number of newly registered enterprises, used as an indicator of

TABLE 1 Descriptive statistics.

Variable type	Code	Definition	Mean	SD	N
Dependent variable	<i>URG</i>	Urban–rural income gap	−4.248	1.760	9,733
Core explanatory variable	<i>DIF</i>	Digital financial inclusion index	4.515	0.331	9,733
Mediating variables	<i>innovate</i>	Technological innovation	4.774	1.700	9,733
	<i>entre</i>	Entrepreneurial vitality	8.288	0.842	9,733
Moderation variables	<i>invest</i>	Investment in fixed assets	14.245	0.876	9,733
Control variables	<i>consume</i>	Regional consumption levels	0.365	0.150	9,733
	<i>employ</i>	Size of non-farm employment	11.620	0.989	9,733
	<i>sec</i>	Development of the secondary sector	0.396	0.142	9,733
	<i>ter</i>	Development of the tertiary industry	0.422	0.104	9,733
	<i>tf</i>	Level of traditional financial development	1.548	0.861	9,733
	<i>agri-mech</i>	Level of agricultural mechanization	3.582	0.901	9,733
	<i>info</i>	Level of information development	6.959	1.452	9,733
	<i>press</i>	County-level fiscal pressure	0.307	0.219	9,733
	<i>welfare</i>	Social welfare level (bed/ 10 ⁴ people)	33	27.340	9,733
	<i>hos</i>	Medical level (beds/ 10 ⁴ people)	43.740	17.03	9,733
	<i>edu</i>	Education level (people/ 10 ⁴ people)	458	139.500	9,733

entrepreneurial activity in counties, is obtained from *Tianyancha Data*. Data on road area and road length are sourced from the *China County Construction Statistical Yearbook* (2015–2023), while county invention patent statistics are compiled from the *Annual Report of the State Intellectual Property Office*. The raw data for other control variables in this paper are derived from *the China County Statistical Yearbook* and *the China Demographic Statistical Yearbook*. During the analysis, the counties with too many missing variables were excluded, and linear interpolation was applied to address other missing values, resulting in a panel dataset of 1,081 counties covering the years 2014–2022.

3.3 Double machine learning model

This study examines the DIF on the urban–rural income gap by constructing a double machine learning (DML) model. Existing studies have shown that the effect of digital development presents a U-shaped relationship (Gong et al., 2025; Yang et al., 2025), indicating a nonlinear characteristic. Thus, when using traditional linear models for empirical estimation, multicollinearity is likely to occur, which undermines the accuracy of estimation results. To ensure the reliability

of estimation results, this study incorporates as many control variables as possible. However, high-dimensional sets of control variables lead to the “curse of dimensionality” for traditional linear models. By introducing regularization methods and machine learning algorithms, the DML model can automatically identify and select effective control variable sets. This not only addresses the nonlinearity and “curse of dimensionality” issues but also achieves robust and unbiased inference on the net effect between DIF and the urban–rural income gap through K-fold cross-fitting. In light of relevant scholarly studies (Chernozhukov et al., 2017; Athey et al., 2019; Knittel and Stolper, 2021), this study constructs a partially linear double machine learning model as follow:

$$Y_{it+1} = \theta_0 D_{it} + h(X_{it}) + U_{it}, \quad E(U_{it} | D_{it}, X_{it}) = 0 \quad (14)$$

$$D_{it} = m(X_{it}) + V_{it}, \quad E[V_{it} | X_{it}] = 0 \quad (15)$$

In Equations 14, 15, where *i* represents the county; *t* represents the year; *Y_{it+1}* denotes the Dependent variable, which is the urban–rural income gap; and *D_{it}* refers to the treatment variable, the DIF index.

The model analysis focuses on the treatment effect coefficient θ_0 . U_{it} and V_{it} represent the main and auxiliary equation error terms, respectively, with a conditional mean of 0. X_{it} represents the set of influencing factors across dimensions, while $\hat{h}(X_{it})$ and $\hat{m}(X_{it})$ are estimated through machine learning algorithms to mitigate model misspecification due to nonlinear relationships. This process obtains the auxiliary equation residuals $\hat{V}_{it} = D_{it} - \hat{m}(X_{it})$ and adjusts the main regression form to. By estimating Equations 14, 15 as a system of simultaneous equations, unbiased treatment effect estimates can be obtained, as shown in Equation 16. n is the number of sample observations, and the detailed proof of unbiasedness is provided in the Appendix.

$$\hat{\theta}_0 = \left(\frac{1}{n} \sum_{i \in I, t \in T} \hat{V}_{it} D_{it} \right)^{-1} \frac{1}{n} \sum_{i \in I, t \in T} \hat{V}_{it} (Y_{it+1} - \hat{h}(X_{it})) \quad (16)$$

4 Empirical results and analysis

4.1 Baseline analysis

The baseline analysis employs a double machine learning model, with the sample partitioned at a ratio of 1:4 ($K = 5$). This ratio can effectively balance bias control and computational efficiency (Chernozhukov et al., 2018). It not only ensures that the training set has sufficient sample size to train relatively complex models, but also guarantees the validity of the debiasing process through multiple cross-validation rounds, thereby enhancing the reliability of estimation results. This approach has been widely verified in empirical studies. For both primary and auxiliary regression predictions, this study adopts the Support Vector Machine (SVM) algorithm. The core advantage of this algorithm lies in its ability to map the original feature space to a higher-dimensional space via kernel tricks, thus implicitly capturing complex interaction effects and nonlinear relationships between variables. This feature is highly compatible with the high-dimensional and mixed-type characteristics of the control variable set in this study. In addition, the SVM algorithm optimizes the objective of minimizing structural risk, which endows it with strong generalization ability. It can effectively avoid overfitting, making it well-suited for the research context where the sample size of county-level panel data is not excessively large. To ensure the robustness of the research findings, this study further supplements robustness tests based on other algorithms (Table 2).

The model is analyzed using the full sample, and (1)–(3) incorporate control variables, regional fixed effects, time fixed effects, and squared terms of the control variables. The results show that the regression coefficients for the DIF on the urban–rural income gap are negative and statistically significant at the 1% level, indicating that DIF can effectively reduce the urban–rural income gap, thereby confirming the hypothesis H1. Further, to clarify the internal composition of the narrowing income gap, this paper remeasures the urban–rural income gap using the ratio of per capita disposable income of urban residents to that of rural residents (denoted as URG1), and further examines the relationship between DIF and the per capita disposable income of rural residents (RRI). The regression results in Columns (4) and (5) show that the coefficient of DIF's impact on URG1 is significantly

negative at the 1% statistical level, while its coefficient of impact on RRI is significantly positive at the 1% statistical level. This finding indicates that the narrowing of the urban–rural income gap is mainly driven by the increase in rural residents' income level, which provides more direct empirical evidence for the core research hypothesis of this paper.

Based on model (1), the explanatory variables are replaced with county entrepreneurial vitality (*entre*) and the county's level of scientific and technological innovation (*innovate*). The regression results in (4)–(5) show that all regression coefficients are significantly positive at the 1% level, indicating that DIF promotes entrepreneurial vitality and technological innovation in counties.

4.2 Robustness analysis

4.2.1 Controlling for the interaction effects of region and time

To further control for the time-varying characteristics of each administrative area, this study incorporates province-time and city-time interaction fixed effects into the baseline regression. The specific regression results are shown in Table 3 (1), where findings indicate a significantly negative relationship at the 1% level and closely align with those of the baseline regression. This consistency reinforces the robustness of our baseline results.

4.2.2 Adjustment of sample size and shrinkage treatment

To ensure that our findings remain robust across different temporal contexts, we analyze two distinct periods: 2014–2017 and 2018–2022, as detailed in Table 3 (2). To mitigate the influence of outliers on our conclusions, the variables are winsorized at the 1st, 99th, 5th, and 95th percentiles, as shown in Table 3 (3). The impact of DIF index on the rural–urban income gap within these subsamples continues to exhibit a significantly negative correlation at the 1% level and remains consistent with benchmark regression outcomes, thereby affirming the robustness of our findings.

4.2.3 Adjustment of machine learning sample segmentation ratios

To avoid the dependence of research results on the sample split ratio, cross-fitting verification with different folds is conducted. The original sample split ratio of 1:4 is adjusted to 1:3 and 1:5, resulting in fold numbers of $K_{folds} = 4$ and $K_{folds} = 6$. The results, presented in column (1) of Table 4, show that the coefficient of DIF remains significantly negative at the 1% level, confirming the robustness of the regression results.

4.2.4 Replacing machine learning algorithms

To avoid the calculation bias of regression results caused by a single machine learning algorithm, the previously used support vector machine (SVM) algorithm for prediction is replaced with three other algorithms—gradient boosting (*Gradboost*), random forest (*Rf*), and neural network (*Nnet*)—for verification. The number of folds is set to $K_{folds} = 5$, consistent with the baseline regression. As shown in column (2) of Table 4, the analysis results of all three machine learning algorithms are significantly negative at the 1% significance level, verifying that the regression results remain robust.

TABLE 2 Benchmark regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	<i>URG</i>	<i>URG</i>	<i>URG</i>	<i>URG1</i>	<i>RRI</i>	<i>entre</i>	<i>innovate</i>
DIF	-0.829*** (0.053)	-0.836*** (0.053)	-0.812*** (0.051)	-0.477*** (0.021)	0.685*** (0.011)	0.809*** (0.023)	1.848*** (0.044)
cons	-0.523*** (0.018)	-0.527*** (0.018)	-0.577*** (0.018)	0.051*** (0.006)	0.042*** (0.003)	0.104*** (0.008)	0.085*** (0.017)
Control I	YES	YES	YES	YES	YES	YES	YES
Control II	NO	NO	YES	YES	YES	YES	YES
Provincial FE	NO	YES	YES	YES	YES	YES	YES
Time FE	NO	YES	YES	YES	YES	YES	YES
N	9,733	9,733	9,733	9,733	9,733	9,733	9,733

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 3 Robustness results 1.

Variables	(1)		(2)		(3)	
	Introduction of region-time fixed effects		Adjusting sample		Shrinkage Treatment	
	Province-Time	City-Time	2014–2017	2018–2022	(1.99%)	(5.95%)
DIF	-0.810*** (0.049)	-0.812*** (0.051)	-0.682*** (0.060)	-1.503*** (0.093)	-0.823*** (0.052)	-0.857*** (0.059)
cons	-0.578*** (0.016)	-0.578*** (0.018)	-0.671*** (0.025)	-0.586*** (0.020)	-0.570*** (0.018)	-0.558*** (0.017)
Control I	YES	YES	YES	YES	YES	YES
Control II	YES	YES	YES	YES	YES	YES
Provincial FE	YES	YES	YES	YES	YES	YES
Province-Time	YES	NO	NO	NO	NO	NO
City-Time	NO	YES	NO	NO	NO	NO
Time FE	YES	YES	YES	YES	YES	YES
N	9,733	9,733	5,453	7,585	9,733	9,733

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 4 Robustness results 2.

Variables	(1)		(2)			(3)
	Adjust the sample splitting ratio		Replacing the machine learning model			Instrumental variable
	<i>Kfolds</i> = 4	<i>Kfolds</i> = 6	<i>Rf</i>	<i>Gradboost</i>	<i>Nnet</i>	
DIF	-0.807*** (0.051)	-0.809*** (0.051)	-0.871*** (0.090)	-1.013*** (0.074)	-0.345*** (0.005)	-0.312*** (0.003)
cons	-0.580*** (0.018)	-0.576*** (0.018)	-0.023*** (0.008)	-0.000 (0.014)	-268.709*** (5.874)	-0.217*** (0.004)
Control II	YES	YES	YES	YES	YES	YES
Control II	YES	YES	YES	YES	YES	YES
Provincial FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
N	9,733	9,733	9,733	9,733	9,733	9,733

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2.5 Instrumental variable

To mitigate the endogeneity issue caused by omitted variables, this paper employs the instrumental variable (IV) approach to re-test the baseline empirical results. Drawing on the research design of (Guo and Ma, 2023), we construct an instrumental variable, which is defined as the sum of the lagged one-period regional digital inclusive finance level and the first-order difference of the national digital inclusive finance level, i.e., $(DIF_{n,t-1} + DIF_{t-1})$. This instrumental variable captures the expected level of DIF in each region under the same development trend. The rationality of constructing this instrumental variable is based on two considerations. First, the national-level DIF development level is the average of regional development levels, and changes in the DIF level of a single county cannot exert a significant impact on it. Thus, this indicator is relatively exogenous at the county level. Second, urban–rural residents' income and income gap may be affected by other unobservable shocks. However, as long as such shocks do not substantially affect the national DIF development level, the instrumental variable constructed in this paper satisfies the validity requirement. To examine the impact of DIF on the urban–rural income gap within the instrumental variable framework, this paper extends the baseline double machine learning model to a Flexible Partially Linear IV Model. The regression results, reported in Column (3) of Table 4, show that the coefficient of DIF on the urban–rural income gap remains significantly negative at the 1% statistical level, indicating that the baseline regression results are robust.

5 Mechanism analysis

5.1 Mediation effect

After analyzing the relevant literature, it is found that the situation of technological innovation in counties and entrepreneurial vitality in counties are the possible paths for financial inclusion to reduce the urban–rural income gap. In this section, the Bootstrap-sgmediation method (Preacher and Hayes, 2008) is adopted, and the number of resampling iterations (reps) is set to 500 and 1,000 respectively, the test results are presented in Table 5. The analysis reveals that the total effects across various mediation path tests, all significantly negative at the 1% level, do not alter the conclusion that financial inclusion reduces the urban–rural income gap.

5.1.1 Technological innovation

To examine the transmission mechanism through which DIF reduces the urban–rural income gap by increasing the level of scientific and technological innovation in counties, we use the number of innovative inventions in each county to measure the degree of science and technology innovation in each region. Both the direct and indirect effects are negative and significant at the 1% level, confirming that DIF reduces the urban–rural income gap through regional technological innovation, thus confirming H2.

5.1.2 Entrepreneurial vitality

This paper investigates how DIF impacts the urban–rural income gap by enhancing county entrepreneurial vitality. County entrepreneurial vitality is measured by the number of business

registrations in each county for the current year, sourced from the Eye of Heaven. Both the indirect and direct effects in the transmission mechanism, where the DIF influences the urban–rural income gap through county entrepreneurial vitality, are significantly negative at the 1% level. This verifies the transmission pathway of county entrepreneurial vitality and confirms H3.

5.2 Moderating effect

The moderating effect of government fixed asset investment is further analyzed, with the interaction term between the two incorporated into a double machine learning model for analysis. This is validated using three machine learning algorithms: *Gradboost*, *Rf*, and *Nnet*, as shown in Table 6. The moderating effects are significantly negative at the 1% level of significance, indicating that fixed asset investment promotes DIF to reduce the urban–rural income gap, thus verifying H4.

6 Heterogeneity analysis

6.1 Heterogeneity between east and west of the Hu Huanyong line

As a highly iconic dividing line in China's regional development pattern, the "Hu Huanyong Line" not only clearly outlines the significant east–west gap in China's population distribution,¹ but also profoundly reflects the notable differences in physical geographical conditions, economic development levels, and resource endowments between the two sides. Such inherent regional development differences may lead to heterogeneous characteristics in the effect of DIF on narrowing the urban–rural income gap. To accurately explore this heterogeneity, this study divides China's county-level regions into two sample groups (east and west) based on the Hu Huanyong Line and conducts empirical analysis using the grouped regression method. According to the heterogeneity regression results in Column (1) of Table 7, the estimated coefficients of DIF are significantly negative at the 1% statistical level in both the eastern and western regions of the Hu Huanyong Line, but the absolute value of the regression coefficient in the eastern region is larger. This indicates that the role of DIF in narrowing the urban–rural income gap is more significant in the eastern region of the Hu Huanyong Line.

This gap may stem from the differentiated transmission efficiency of two mechanisms—technological innovation and entrepreneurship—on the income gap-narrowing effect of DIF. Specifically, relying on endowment advantages such as dense population, developed economy, and improved digital infrastructure, the eastern region leverages its high human capital stock and mature innovation ecosystem to enable DIF to

¹ According to data from the 2020 Seventh National Census, the eastern region, covering 43.18% of the national territory, contains 93.68% of the population, while the western region, covering 56.82% of the national territory, accounts for only 6.32% of the population.

TABLE 5 Mediation effect analysis.

Variables	Sgmediation			Bootstrap-sgmediatio(reps:500)			Bootstrap-sgmediation(reps:1000)		
	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect
innovate	-0.614***	-0.366***	-0.248***	-0.614***	-0.366***	-0.248***	-0.614***	-0.366***	-0.248***
	(0.058)	(0.059)	(0.018)	(0.053)	(0.055)	(0.019)	(0.054)	(0.054)	(0.019)
entre	-0.614***	-0.484***	0.130***	-0.614***	-0.484***	0.130***	-0.614***	-0.484***	0.130***
	(0.058)	(0.058)	(0.013)	(0.056)	(0.058)	(0.012)	(0.058)	(0.058)	(0.013)
Control I	YES	YES	YES	YES	YES	YES	YES	YES	YES
Control II	YES	YES	YES	YES	YES	YES	YES	YES	YES
Provincial FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	9,733	9,733	9,733	9,733	9,733	9,733	9,733	9,733	9,733

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 6 Analysis of moderating effects.

Variables	(1)		(2)	(3)	(4)	
	Svm			Rf	Gradboost	Nnet
	Kfolds = 4	Kfolds = 5	Kfolds = 6	Kfolds = 5	Kfolds = 5	Kfolds = 5
invest	-0.080***	-0.079***	-0.079***	-0.022***	-0.045***	-0.059***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.021)
_cons	-0.597***	0.600***	-0.596***	-0.023***	-0.000	4.14***
	(0.017)	(0.017)	(0.017)	(0.008)	(0.014)	(0.394)
Control I	YES	YES	YES	YES	YES	YES
Control II	YES	YES	YES	YES	YES	YES
Provincial FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
N	9,733	9,733	9,733	9,733	9,733	9,733

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 7 Analysis of the heterogeneity of coastal areas.

	(1)		(2)		(3)	
	Hu Huanyong Line		Economic circle		Coastal regions	
	East of the line	West of the line	Within the circle	Outside the circle	Coastal regions	Inland regions
DIF	-0.731***	-0.447***	-1.895***	-0.443***	-0.825***	-0.506***
	(0.058)	(0.086)	(0.114)	(0.060)	(0.100)	(0.055)
cons	-0.476***	-0.306***	-0.141***	-0.364***	0.415***	-0.604***
	(0.021)	(0.031)	(0.030)	(0.021)	(0.029)	(0.021)
Control I	YES	YES	YES	YES	YES	YES
Control II	YES	YES	YES	YES	YES	YES
Provincial FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
N	8,214	1,519	3,395	6,338	3,666	6,067

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

accurately empower technological innovation activities and accelerate the dissemination of technological achievements to rural areas. Meanwhile, the developed market environment and sufficient entrepreneurial resources ensure the full implementation of DIF's support for micro and small enterprise entrepreneurship. By boosting employment through entrepreneurship, rural residents' incomes are increased, thereby strengthening the income gap-narrowing effect. In contrast, constrained by sparse population, weak digital infrastructure and other factors, the western region suffers from insufficient human capital reserves in technological innovation, as well as limited market space and resource support for entrepreneurial activities. Consequently, DIF's support can hardly be quickly converted into driving forces for income growth.

6.2 Heterogeneity between coastal and inland regions

The geographical division between coastal and inland areas reflects significant differences in the degree of opening-up, infrastructure improvement, and resource allocation efficiency between the two types of regions. Such inherent geographical differences and acquired economic development disparities may lead to variations in the effect of DIF on narrowing the urban-rural income gap. Based on this, this study divides China's county-level regions into two sample groups (coastal and inland) according to the criterion of whether they are coastal, and conducts empirical analysis using the grouped regression method. According to the regression results in Column (2) of Table 7, the estimated coefficients of DIF are significantly negative at the 1% statistical level in both coastal and inland regions, but the absolute value of the regression coefficient in coastal regions is larger. This indicates that the role of DIF in narrowing the urban-rural income gap is more significant in coastal regions. Urban-rural income gap is fully released, which is also consistent with the basic reality of the relatively high level of financial development in China's coastal regions.

This discrepancy stems from coastal areas' high opening-up level, solid economic foundation, and government fixed asset investment focused on digital infrastructure and innovation carriers, which enhance the transmission efficiency of technological innovation and entrepreneurship mechanisms to the gap-narrowing effect of DIF. Specifically, government fixed asset investment has improved digital financial infrastructure and innovation incubation platforms, enabling DIF to accurately meet sci-tech entities' financing needs, provide low-cost support for R&D and rural scenario application, and boost rural productivity and residents' income via technological empowerment. On the other hand, ample entrepreneurial resources from open markets, combined with government-invested entrepreneurial environment optimization, maximize DIF's support for micro and small enterprises' entrepreneurship, strengthening the gap-narrowing effect by driving employment and expanding income channels. In contrast, inland areas suffer from low opening-up, weak economic foundations, and insufficient government fixed asset investment in innovation and digital fields, hindering the transmission of technological innovation and entrepreneurship, weakening

government regulatory effects, and further restricting DIF's service penetration and efficiency release.

6.3 Heterogeneity between within and outside economic zones

Regional economic zones have become key growth poles of China's economic development. Core zones such as the Yangtze River Delta Economic Circle, Guangdong-Hong Kong-Macao Greater Bay Area, Beijing-Tianjin-Hebei, Middle Yangtze River, and Chengdu-Chongqing Twin-City Economic Circles (dubbed the "Five Golden Flowers") feature sound division of labor, cooperation, and radiating effects, enabling large-scale optimized resource allocation and economic agglomeration—factors that may affect DIF's role in narrowing the urban-rural income gap. Accordingly, this study classifies samples into "within economic zones" and "outside economic zones" based on State Council planning outlines for heterogeneity testing. As shown in Column (3) of Table 7, DIF's estimated coefficients are significantly negative at the statistical level in both groups, but the absolute value is notably larger within economic zones, indicating a more prominent gap-reducing effect there. This is attributed to high industrial agglomeration, smooth factor flow, advanced digital infrastructure, high residents' digital literacy, and superior market and institutional environments in these zones, which facilitate DIF's efficient reach to low-income groups. In contrast, multiple constraints limit DIF's effectiveness outside economic zones.

This may be attributed to the more prominent role of governments within economic circles in resource allocation, industrial guidance, and market regulation. By formulating scientific and rational policy plans, governments guide the concentration of resources in key areas and weak links. Meanwhile, they strengthen market regulation to standardize the order of the digital inclusive finance market, which helps optimize the development environment for DIF and further enhance its positive effect on narrowing the urban-rural income gap. In contrast, the role of governments in areas outside economic circles in these aspects is relatively limited, which to a certain extent weakens the effectiveness of DIF in reducing the urban-rural income gap.

7 Conclusion and implications

Based on panel data from 1,081 county-level administrative regions in China during 2014–2022, this study employs the double machine learning model to systematically examine the impact, transmission mechanisms, and heterogeneous characteristics of DIF on the urban-rural income gap. The main conclusions are drawn as follows:

First, DIF exerts a significant effect on narrowing the urban-rural income gap at the county level. This provides direct empirical support for the "digital dividend" school at the county level, confirming that in counties—the core area of urban-rural integration—the "long-tail effect" of DIF is significantly stronger than its "Matthew effect," highlighting its core value in reducing income disparities. It directly responds to the core requirements of SDG 1 and SDG 10, thereby offering Chinese experience for developing countries worldwide to achieve relevant sustainable development goals.

Second, DIF narrows the urban-rural income gap through two paths: enhancing entrepreneurial vitality and promoting technological innovation. Moreover, government fixed-asset investment plays a

significant positive moderating role in this effect, addressing the disparities in existing studies regarding insufficient discussion of core transmission mechanisms and the lack of quantification of government functions. It also enriches the mechanism analysis framework of the “digital dividend” school, and the identified mechanism is highly consistent with SDG 8 and SDG 9.

Third, the gap-narrowing effect of DIF shows significant regional heterogeneity, being more pronounced in regions east of the Hu Huanyong Line, coastal areas, and economic circles. Precise analysis at the county level can more clearly reveal the conditional heterogeneity of DIF in exerting its effects, and clarify the prerequisite for DIF to unlock the “digital dividend”—that is, it must be compatible with regional development models and policy environments. This finding confirms the core essence of SDG 10, which emphasizes “formulating targeted policies based on national conditions to reduce inequalities.” It also provides important insights for countries worldwide facing regional development imbalances to achieve this goal through targeted policy interventions.

To effectively leverage digital finance in narrowing the urban–rural income gap and advance relevant SDGs, this paper proposes the following policy recommendations:

First, empirical results confirm that DIF effectively narrows the urban–rural income gap. Thus, efforts should focus on consolidating DIF’s foundational support: accelerating data centers and big data infrastructure, expanding coverage of 5G and distributed computing, and strengthening digital infrastructure in remote areas for vulnerable groups to boost incomes of poor rural populations. This ensures financial inclusiveness to support SDG 1 and underpins digital finance development to underpin SDG 10.

Second, county-level entrepreneurial vitality and technological innovation are key channels for DIF’s effect, with government investment enhancing these intermediary paths. Accordingly, improve the DIF policy framework, optimize government fixed asset allocation, and provide institutional support for farmers’ non-agricultural employment and entrepreneurship. For example, offer targeted loan interest subsidies to agricultural tech R&D and rural e-commerce entities to cut financing costs. Invest in county-level tech innovation financial platforms and supporting transformation facilities in key parks, prioritizing agricultural tech commercialization and micro-enterprise innovation to amplify DIF’s transmission effect, in alignment with SDG 8 and SDG 9.

Third, adopt dynamic, differentiated strategies to advance coordinated regional DIF development. DIF’s income-gap-narrowing effect is more significant east of “Hu Huanyong Line,” in coastal areas and economic circles. For agriculture-dominated counties with weak endowments (west of the line, non-coastal, outside economic circles), focus on “basic financial coverage + agricultural empowerment.” Build traceability, supply chain finance platforms, township logistics centers and village tech stations, and guide order-based online financing to stabilize farmers’ operating income, thus advancing the implementation of SDG1. For economically stronger counties (east of the line, coastal, outside economic circles), emphasize “entrepreneurial ecosystem optimization + high-end financial services.” Construct cross-regional digital finance platforms and tech transformation centers, alongside IP pledge financing platforms and full-subsidy skill training for rural laborers to facilitate high-end industry transfer. Industrial upgrading drives balanced urban–rural incomes, further advancing SDG 8 and SDG 9.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

JL: Conceptualization, Data curation, Methodology, Writing – original draft. ZH: Conceptualization, Methodology, Software, Writing – original draft. HZ: Supervision, Project administration, Validation, Funding acquisition.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fsufs.2026.1745110/full#supplementary-material>

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