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Digital financial inclusion and rural labor allocation: The roles of credit and land markets[☆]

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ABSTRACT

Digital financial inclusion is transforming rural economies, yet how it reshapes intensive-margin labor allocation through credit and land markets remains insufficiently understood. Using micro-level household data from the China Family Panel Studies (2014–2020) and a geography-based instrumental variable strategy, we identify the causal effects of DFI on labor reallocation across sectors. Specifically, greater DFI reduces agricultural labor hours while increasing off-farm employment, revealing an intensive-margin adjustment rather than simple participation shifts. This reallocation occurs because DFI relaxes credit constraints, thereby lowering financial and risk-related entry barriers to non-agricultural activities through entrepreneurship and migration, while being accompanied by increased land leasing that facilitates a smoother exit from agricultural production among smallholders during the transition to off-farm work. The effects are strongest among younger, less-educated farmers in economically developed eastern regions. These results explain why digital finance accelerates structural transformation and underscores its role as financial infrastructure for inclusive rural development.

1. Introduction

The rapid growth of the digital economy is profoundly reshaping the modes of production and lifestyles in rural societies. In China, in particular, the widespread penetration of internet and communication technologies has infused new momentum into rural development. For instance, by 2022, China's digital economy reached approximately 50.2 trillion yuan, accounting for roughly 41.5 % of its GDP (Qiao et al., 2025). Amid this wave of digitalization, digital financial inclusion (DFI), as an integral component of the digital economy, has emerged as a new engine driving rural revitalization. DFI refers to the application of internet technologies—such as mobile payments and online credit platforms—to provide accessible, convenient, and low-cost financial services to populations traditionally underserved by the formal financial system, particularly benefiting low-income groups in rural and remote areas (Berger

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and Udell, 2006; Lee et al., 2023; Niu et al., 2022; Wang et al., 2022). As digital technologies increasingly penetrate rural communities, this expansion of financial digitalization offers unprecedented opportunities to rural residents.

Urban–rural income disparities have served as a structural driver of rural-to-urban labor migration, with younger rural workers increasingly relying on non-agricultural employment in urban areas as their primary strategy for income improvement. However, rural households face considerable obstacles in transitioning from agricultural to non-agricultural sectors, among which financial constraints represent a major impediment (Fu and Huang, 2018; Karaivanov, 2012). Traditional financial institutions generally exhibit limited presence in rural areas due to sparse physical branches, higher operational risks, and elevated service costs, resulting in inadequate coverage for agricultural and rural households. Consequently, rural households often struggle to obtain the necessary financial resources for initiating entrepreneurial ventures or migrating for non-agricultural employment. This financial exclusion compels many potential non-agricultural workers to remain in agriculture, thereby impeding the efficient allocation of rural labor resources.

The rise of DFI provides a promising solution to this predicament. By leveraging digital technologies, DFI significantly lowers barriers to financial services, enhancing rural households' access to credit and digital payments, thus alleviating financial constraints (Berger and Udell, 2006; Lee et al., 2023; Niu et al., 2022; Wang et al., 2022).[1] Understanding how DFI affects rural labor allocation also speaks to a broader question in development economics: what determines the efficiency and direction of labor reallocation? A growing body of literature highlights that the welfare and productivity gains from labor reallocation critically depend on the mechanisms driving factor mobility (Garcia-Louzao and Tarasonis, 2023; Li, 2024). These studies emphasize that the significance of reallocation lies not merely in the movement of labor itself, but in the institutional and market forces that enable, constrain, and channel such movement. Building on this insight, the present study identifies DFI as a novel institutional driver of rural labor reallocation, extending the literature on the determinants of labor reallocation from predominantly macro-structural and cyclical perspectives to a micro-institutional and financial dimension. Within this framework, a central question arises: how and to what extent digital financial inclusion promotes the reallocation of labor from agriculture to more remunerative non-agricultural employment. Understanding how DFI shapes rural households' labor supply decisions is therefore essential for explaining the broader mechanisms of structural transformation in developing economies.

To address the above research question, we employ micro-level household data from the China Family Panel Studies (CFPS) combined with the digital inclusive finance index developed by Peking University to investigate the impact of DFI on rural households' labor supply decisions. Our empirical findings reveal that a one-unit increase in the DFI index reduces the agricultural labor hours of rural households by approximately 3.66 %, while increasing their non-agricultural labor hours by around 3.23 %. These results remain robust across a variety of sensitivity tests. Mechanism analyses further suggest that DFI facilitates rural labor reallocation through two distinct margins. First, the non-farm entry margin (credit-constraint alleviation): by lowering the financial and risk-related entry barriers to non-agricultural activities (e.g., start-up capital needs for self-employment and migration costs), DFI strengthens rural households' capacity for self-employment and expands their geographic scope of job opportunities. Second, the agricultural exit margin (land adjustment): DFI is associated with more active land leasing and land-use adjustment, which can facilitate smallholders' smoother exit from, or downscaling of, agricultural production as they reallocate labor to off-farm work. Consequently, this process releases surplus agricultural labor from smallholder households, enabling their reallocation to non-agricultural employment more effectively. Our heterogeneity analyses suggest that these effects are particularly pronounced among younger, less-educated farmers residing in China's eastern regions.

This paper contributes to the literature on digital financial inclusion and rural labor reallocation by addressing several important gaps in existing research. First, prior studies largely rely on binary indicators such as off-farm employment or entrepreneurship to measure rural labor supply (Ren et al., 2023; Yan Wang et al., 2024; Zhan et al., 2025). Such measures capture participation decisions but fail to reflect the intensity and marginal adjustments of labor allocation between agricultural and non-agricultural sectors. To fill this gap, we construct a continuous measure of labor hours, allowing for a more nuanced understanding of how DFI affects both the extent and direction of rural labor shifts. Second, much of the existing evidence suffers from limited causal identification, as DFI is often endogenous to local economic development. We address this challenge by employing a time-varying instrumental variable based on the geographic distance to Ant Financial's headquarters (Han et al., 2023; Yang and Zhang, 2022) interacted with year fixed effects within a panel 2SLS framework. This design leverages the spatial diffusion of digital finance to capture exogenous variation in DFI intensity. Third, prior studies mainly focus on credit constraint alleviation as the only mechanism(Peng and Mao, 2023), without systematically explaining how DFI affects relative returns and entry costs across sectors. We extend this research by identifying and testing two specific channels—the non-farm entry margin (credit constraint alleviation) and the agricultural exit margin (land adjustment)—through which DFI promotes rural labor reallocation.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 presents a simplified theoretical framework, proposes the core hypotheses, and outlines the empirical strategy. Section 4 describes the data sources, key variables, and summary statistics. Section 5 discusses the main empirical findings in detail. Finally, Section 6 concludes with a summary of the results and offers corresponding policy implications.

[1] While global research on DFI has predominantly focused on developing countries such as Kenya and India, where digital finance is limited to basic mobile payments and informal credit (Bharadwaj and Suri, 2020; Ghosh and Hom Chaudhury, 2022), China presents a distinct context characterized by large-scale private digital platforms, extensive mobile internet penetration, and an integrated financial ecosystem. These features make China an ideal setting to explore how DFI may drive structural transformation in rural labor markets, providing valuable insights for inclusive digital development globally.

2. Literature review

2.1. Socioeconomic effects of digital financial inclusion

A growing body of research has examined the macro-level socioeconomic impacts of DFI. Overall, existing studies suggest that the development of DFI contributes positively to economic growth and inclusive development (Becha et al., 2025; Lee et al., 2023; Zhang et al., 2023). On one hand, DFI facilitates growth directly by enhancing the accessibility and efficiency of financial services traditionally underserved by formal institutions. On the other hand, it indirectly stimulates aggregate demand by expanding household consumption in rural areas (Li and Feng, 2020; Yi and Zhou, 2018), thereby further driving economic expansion.

Moreover, DFI has been shown to play a constructive role in poverty reduction and narrowing income inequality (Kling et al., 2022; Song, 2017; Yu et al., 2022). Empirical evidence based on provincial panel data in China demonstrates that greater diffusion of DFI significantly reduces rural poverty rates, promotes structural upgrading of rural industries, and raises rural income levels, thereby contributing to a reduction in the urban-rural income gap (Luo et al., 2023). These findings suggest that, at the macro level, DFI expands the reach of financial services, fosters more inclusive economic growth, and is associated with higher GDP growth, lower poverty incidence, and a more equitable distribution of income.

However, these macro-level studies primarily focus on aggregated economic outcomes and offer limited insights into the underlying mechanisms through which DFI affects the behavior of microeconomic agents. For example, the influence of DFI on household labor supply decisions—particularly among rural farmers—remains insufficiently explored. This gap underscores the need for more granular, micro-level evidence to better understand how DFI shapes rural economic activity and household behavior. In this regard, a microeconomic perspective is essential to complement the macro-level findings and to uncover the channels through which DFI operates in rural contexts.

2.2. Digital financial inclusion and the rural economy

At the micro level, a growing body of literature has examined the effects of DFI on rural household production and behavioral decision-making. Overall, DFI helps ease credit constraints and mitigate financial risks by providing more accessible services such as digital lending and mobile payments (Fu and Huang, 2018), thereby improving rural households' production capacity and consumption outcomes (Yang et al., 2022; Yin et al., 2025).

On the production side, DFI has been shown to influence farmers' decision-making. Some studies find that the development of DFI reduces households' incentives to remain in agriculture, leading to decreased agricultural input and output (Liu et al., 2021). This shift is largely attributable to the expanded income-generating opportunities in non-agricultural sectors made possible by digital finance; as the relative returns to non-agricultural employment rise, farmers become less motivated to continue agricultural production (Liu et al., 2021).

On the employment side, DFI creates favorable conditions for rural entrepreneurship and off-farm employment (Wang, 2022; Yu et al., 2024; Zhang et al., 2023). For example, studies focusing on returning migrant workers show that the expansion of DFI significantly improves wage performance among returning rural laborers (Gaspar et al., 2024; Wehrheim et al., 2020). The diffusion of digital technologies and financial services has also enhanced farmers' digital engagement and financial service utilization, both of which are crucial pathways to entrepreneurial success (Chen et al., 2024; Xie et al., 2018; Xun et al., 2020).

In addition, DFI plays an increasingly important role in factor market development, particularly by facilitating more efficient resource allocation in rural areas. Empirical studies show that improved financial access enables some farmers to lease out contracted land in exchange for rental income, while those with greater production capacity can more easily obtain financing to lease in land and expand operations (Yuyu Wang et al., 2024). In this process, DFI mitigates financial constraints and facilitates the reallocation of key production factors such as land, thereby promoting more efficient land use and enhancing household income levels (Fu and Huang, 2018; Yuyu Wang et al., 2024).

Despite these advances, several areas remain underexplored. One particularly critical yet insufficiently addressed issue concerns the impact of DFI on rural households' labor supply decisions. In response, an increasing number of studies are beginning to shift their focus toward the relationship between DFI and rural labor reallocation.

2.3. Digital financial inclusion and rural labor supply

In recent years, growing attention has been paid to how DFI affects rural households' labor supply decisions. A consistent finding across the literature is that the expansion of DFI plays a significant role in promoting the reallocation of rural labor from agriculture to non-agricultural sectors. Empirical analyses based on nationally representative microdata confirm that higher levels of DFI are associated with a greater likelihood of rural households engaging in non-agricultural employment (Ren et al., 2023; Yan Wang et al., 2024; Zhan et al., 2025). Compared with traditional financial services, digital finance has greater inclusivity and reach, enabling it to serve underdeveloped regions and financially constrained populations more effectively. As a result, DFI facilitates the transition of rural labor from low-productivity agricultural sectors to higher-return non-agricultural activities, accelerating rural labor reallocation.

Several studies have also begun to explore the mechanisms through which DFI promotes non-agricultural employment among rural households. One prominent mechanism is the alleviation of credit constraints: DFI lowers the entry barriers for off-farm work by improving access to small loans, digital payment systems, and insurance products, thus enhancing households' ability to finance entrepreneurship or absorb income fluctuations during employment transitions (Yan Wang et al., 2024). This, in turn, increases both the willingness and ability of rural workers to engage in non-agricultural employment. Another mechanism emphasizes entrepreneurship as a pathway: DFI is found to stimulate innovation and business creation in rural areas, which generates employment opportunities and facilitates labor shifts out of agriculture (Ren et al., 2023; Zhan et al., 2025). In addition, as noted earlier, DFI promotes factor market development—particularly land transfers—which creates conditions for smallholders to exit agriculture and reallocate labor to more productive sectors (Yuyu Wang et al., 2024).

The literature has also recognized heterogeneity in DFI's labor supply effects. Some studies find that DFI is more effective in promoting wage employment than self-employment (Yan Wang et al., 2024). Moreover, the magnitude of DFI's impact varies across population groups. For instance, stronger effects have been observed among unmarried individuals, male laborers, and residents of eastern China (Ren et al., 2023). These findings highlight that DFI's influence on labor supply is not uniform and is moderated by demographic characteristics and regional development levels.

2.4. Limitations of existing studies

Despite these advances, several limitations remain in the current literature. First, the intensity of labor supply is insufficiently measured. Most existing studies focus on binary employment outcomes—whether a household engages in non-agricultural work—while overlooking intensive margin indicators such as hours worked (Ren et al., 2023; Yan Wang et al., 2024; Zhan et al., 2025). Without quantifying changes in labor input—such as the extent to which agricultural hours decline or non-agricultural hours rise—it is difficult to assess the full impact of DFI on labor supply behavior.

Second, many studies suffer from a lack of causal identification. Much of the empirical work relies on cross-sectional or simple panel regressions, yielding correlational rather than causal inferences. Few studies incorporate rigorous identification strategies such as instrumental variables or quasi-experimental designs. Since DFI development may be jointly determined with local economic conditions, failure to address endogeneity may lead to biased estimates (Angrist et al., 1996; Conley et al., 2012). As such, concerns about reverse causality and omitted variable bias remain insufficiently addressed.

Third, the existing literature offers limited analysis of the underlying mechanisms and income effects. Mechanism analyses often focus on isolated pathways—such as credit constraint alleviation (Yan Wang et al., 2024) or entrepreneurship promotion (Ren et al., 2023; Zhan et al., 2025)—without providing a comprehensive view of the multiple channels through which DFI may influence labor supply.

These gaps underscore the need for further research. Future work should more precisely measure labor supply intensity, adopt stronger identification strategies for causal inference, and systematically examine the multifaceted mechanisms—particularly income effects—through which DFI shapes labor supply decisions. These shortcomings form the basis and motivation for the present study. In the next section, we develop a theoretical model to more systematically illustrate how DFI affects rural households' labor allocation behavior.

3. Theoretical hypotheses and empirical strategy

3.1. Theoretical hypotheses

In this section, we construct a simple theoretical model to obtain the key hypotheses of this study.

3.1.1. Digital financial inclusion and rural households' labor supply

Rural households' labor supply decisions can be conceptualized as an optimization problem involving the allocation of labor time between agricultural and non-agricultural activities. According to standard labor economics theory, households choose their optimal labor allocation by weighing the marginal returns from agricultural and non-agricultural work against the disutility of labor (or foregone leisure). Traditionally, agricultural work tends to generate lower and more volatile returns, while non-agricultural employment—including wage labor or self-employment—typically offers higher and more stable income prospects. However, households' actual decisions are often constrained by various factors such as access to credit and availability of employment opportunities. The development of DFI has the potential to relax some of these constraints, thereby systematically influencing labor reallocation from agricultural to non-agricultural sectors.

To formalize this intuition, we construct a simple utility-maximization model to illustrate how DFI affects rural households' labor supply decisions. We assume that the household allocates its total available labor time H between two types of activities: agricultural production and non-agricultural work (including wage employment or entrepreneurial activities). Let H_A denote the time allocated to agricultural labor, and H_N denote time allocated to non-agricultural labor. For simplicity, we assume $H = H_A + H_N$, and we abstract from leisure to focus on the income-maximization behavior of the household.

Under this framework, households choose H_A and H_N to maximize income, which is a function of the returns to each activity. The central question is how DFI, by easing financial constraints and expanding access to off-farm income-generating opportunities, shifts this allocation in favor of non-agricultural labor. The following sections derive and analyze this relationship more formally.

A rural household's agricultural output is determined by the amount of labor allocated to agricultural production,[2] denoted as $Y_A =$

[2] To simplify the analysis, all agricultural inputs other than labor are treated as exogenously given and are thus omitted from the formal derivation.

$f(H_A)$, where the production function $f(\cdot)$ is strictly concave, satisfying $f'(H_A) > 0$ and $f''(H_A) < 0$, indicating diminishing marginal returns to agricultural labor.

Non-agricultural income is defined as:

$$Y_N = (\omega + \delta(D, S))H_N - F \tag{1}$$

where ω represents the baseline return or wage rate from non-agricultural activities, and $\delta(D, S)$ captures the marginal enhancement in non-agricultural returns attributable to DFI. This enhancement effect is a function of both the level of DFI (D) and household-specific characteristics such as operational scale (S). We assume that $\frac{\alpha\delta}{\alpha D} > 0$ i.e., higher levels of DFI increase the marginal returns to non-agricultural labor.

The term F denotes a fixed cost associated with engaging in non-agricultural employment—such as startup capital for self-employment or the costs of labor migration. Importantly, we assume that rural households are credit constrained under traditional financial systems and cannot cover F without external financial support. Consequently, in the absence of access to DFI or similar financial mechanisms, households may be unable to participate in non-agricultural work, i.e., $H_N = 0$. Only when DFI alleviates financial constraints—by enabling households to overcome the fixed entry costs—can they allocate positive labor hours to non-agricultural activities.[3]

The household's consumption is composed of both agricultural and non-agricultural income, such that $Y = Y_A + Y_N$. Assuming all income is used for current consumption, with no savings or borrowing, the household's objective is to maximize total income (or utility, which is simplified here as income maximization)[4]:

$$\begin{aligned} \max_{H_N,\ H_N} Y &= f(H_A) + (\omega + \delta(D, S))H_N - F \\ s.t.\ H &= H_A + H_N \end{aligned} \tag{2}$$

Taking the first-order condition with respect to H_N, the necessary optimality condition is:

$$f'(H_A) = \omega + \delta(D, S) \tag{3}$$

This implies that, at the optimum, the marginal product of agricultural labor equals the effective marginal return to non-agricultural labor.

Economically, DFI improves households' access to external finance and lowers entry barriers such as start-up costs or migration expenses (F), effectively reducing the fixed cost of engaging in non-agricultural work and enhancing its expected marginal return (δ(D, S)). Consequently, an increase in DFI raises the right-hand side of the equilibrium condition, leading households to reduce agricultural labor H_A and allocate more time to non-agricultural activities H_N.

Consequently, non-agricultural labor $H_N = H - H_A$ increases. This establishes that DFI facilitates the reallocation of labor from agriculture to non-agriculture.

Differentiating the optimality condition totally with respect to D yields:

$$f''(H_A)\frac{\alpha H_A}{\alpha D} = \frac{\alpha\delta}{\alpha D} \tag{4}$$

Given that $f''(H_A) < 0$ and $\frac{\alpha\delta}{\alpha D} > 0$, it follows that $\frac{\alpha H_A}{\alpha D} < 0$. In other words, as DFI increases, agricultural labor input declines. Since total labor is fixed, this implies that $\frac{\alpha H_N}{\alpha D} > 0$, i.e., non-agricultural labor increases.

This theoretical result leads to our **first testable hypothesis:**

Hypothesis 1. **(Overall Effect):** An increase in DFI significantly reduces agricultural labor supply and increases non-agricultural labor supply among rural households, thereby promoting the reallocation of labor from agricultural to non-agricultural sectors.

3.1.2. *Risk-adjusted extension*

To address income uncertainty and risk management, we augment the baseline setup with a mean–variance preference under risk aversion.

Let household income be $Y = f(H_A) + (\omega + \delta(D, S))H_N - F + \varepsilon_A + \varepsilon_N$, where $\varepsilon_A$and ε_N represent random shocks to agricultural and non-agricultural income, respectively, both with zero mean $\mathbb{E}[\varepsilon_A] = \mathbb{E}[\varepsilon_N] = 0$. The household is assumed to be risk-averse with coefficient $\rho > 0$and maximizes the mean–variance utility: $\max_{H_A, H_N} \mathbb{E}[Y] - \frac{\rho}{2}\mathrm{Var}(Y)$, s.t. $H = H_A + H_N$. The total income variance is given by $\mathrm{Var}(Y) = \sigma_A^2(H_A) + \sigma_N^2(H_N; D) + 2\,\mathrm{Cov}(H_A, H_N; D)$,where $\sigma_A^2(H_A)$ is the variance of agricultural income, $\sigma_N^2(H_N; D)$ is the variance of non-agricultural income (which declines as DFI improves, i.e., $\partial\sigma_N^2/\partial D < 0$), and $\mathrm{Cov}(H_A, H_N; D)$ denotes the covariance between agri-

[3] In practice, entering non-agricultural sectors often requires rural households to pay a fixed cost F, or overcome financing constraints. Let I denote disposable funds (savings and available credit), with the entry condition $I \geq F$. Under traditional financial systems, many households cannot meet this threshold due to credit barriers, resulting in $H_N = 0$. DFI relaxes this constraint by improving access to microcredit, digital payments, and credit scoring. As DFI increases, effective funds $I(D)$ rise, or equivalently, the burden of F declines. Consequently, more households can enter non-agricultural work, allowing for $H_N > 0$ in the optimal allocation.

[4] The household derives utility from consumption, with the utility function, $u'(C) > 0$ and $u''(C) < 0$.Assuming that all income is fully allocated to current consumption, the utility maximization problem can be equivalently expressed as an income maximization problem in this setting.

cultural and non-agricultural income, which may also fall with DFI due to diversification ($\partial \mathrm{Cov}/\partial D \le 0$).

The first-order condition equates risk-adjusted marginal returns between agricultural and non-agricultural labor:

$$f'(H_A) - \frac{\rho}{2}\left(\frac{\partial \sigma_A^2}{\partial H_A} + 2\frac{\partial \mathrm{Cov}}{\partial H_A}\right) = (\omega + \delta(D,S)) - \frac{\rho}{2}\frac{\partial \sigma_N^2}{\partial H_N} \tag{5}$$

In this condition, the left-hand side represents the risk-adjusted marginal product of agricultural labor, while the right-hand side represents the risk-adjusted marginal return to non-agricultural labor. DFI affects this equality through two main channels: (i) by increasing expected non-agricultural returns ($\partial\delta/\partial D > 0$); and (ii) by reducing the income risk associated with non-agricultural activities ($\partial\sigma_N^2/\partial D < 0$).

Totally differentiating Eq. (5) with respect to D and using $f''(H_A) < 0$ yields $\frac{\partial H_A}{\partial D}\left\langle 0, \frac{\partial H_N}{\partial D}\right\rangle 0$. Thus, incorporating income uncertainty strengthens the baseline prediction: DFI simultaneously raises expected non-agricultural returns and reduces income volatility, thereby increasing the risk-adjusted marginal return to non-agricultural work and accelerating rural labor reallocation.

3.1.3. Potential mechanisms

Building on existing research, we highlight two complementary margins through which DFI may relate to farmers' labor allocation: (i) easing financial constraints that lowers barriers to non-farm entry; and (ii) improving land-market conditions (e.g., lower transaction/enforcement frictions) that facilitate agricultural exit/scale adjustment, which may co-move with non-farm transitions.

$$\delta(D,S) = \varnothing(\delta_1(D), \delta_2(D,S), \varepsilon) \tag{6}$$

Let $\delta_1(D)$ capture the financial constraint alleviation effect, which reflects improvements such as increased entrepreneurial opportunities, expanded geographic scope of employment, and other favorable changes. Let $\delta_2(D,S)$ denote the labor release effect through enhanced land transfer, which depends on both the level of digital financial inclusion D and the household's operational scale S. The term ε represents other potential channels, which are omitted from the formal derivation for simplicity.

We assume $\frac{\alpha\delta_1}{\alpha D} > 0$ and $\frac{\alpha\delta_2}{\alpha D} > 0$, indicating that both effects strengthen with greater DFI. Additionally, we posit that the marginal impact of DFI on land transfer decreases with operational scale,[5] i.e., $\frac{\alpha^2\delta_2}{\alpha D \alpha S} < 0$.

Taking these mechanisms into account, the household's income maximization problem can be extended as follows:

$$\max_{H_N,\ H_N} Y = f(H_A) + (\omega + \varnothing(\delta_1(D), \delta_2(D,S), \varepsilon))H_N - F \qquad s.t.\ H = H_A + H_N \tag{7}$$

Considering the financial constraint alleviation effect, we model this channel as a function $\varphi(\xi_1, \xi_2, \eta)$, where ξ_1 represents the likelihood of non-agricultural entrepreneurship, ξ_2 captures the geographic expansion of employment opportunities, and η denotes other factors conducive to easing credit constraints. Taking the partial derivative of agricultural labor H_A with respect to ξ_1, we obtain:

$$\frac{\alpha H_A}{\alpha \xi_1} = \frac{1}{f''(H_A)}\frac{\alpha\varnothing}{\alpha\delta_1}\frac{\alpha\delta_1}{\alpha\xi_1} \tag{8}$$

Given that $f''(H_A) < 0$ and both $\frac{\alpha\varnothing}{\alpha\delta_1}$ and $\frac{\alpha\delta_1}{\alpha\xi_1}$ are positive, it follows that $\frac{\alpha H_A}{\alpha\xi_1} < 0$. Similarly, we derive $\frac{\alpha H_A}{\alpha\xi_2} < 0$.

These results indicate that both an increase in the probability of non-agricultural entrepreneurship and an expansion in the spatial scope of employment reduce agricultural labor input H_A, thereby increasing non-agricultural labor supply H_N.

This leads to Hypothesis 2.1:

Hypothesis 2.1. (Non-farm entry margin: credit-constraint alleviation): DFI facilitates rural households' entry into non-agricultural sectors by easing financing constraints, which in turn promotes self-employment and expands the geographic scope of employment opportunities.

Considering the labor release effect, we differentiate the optimality condition with respect to the land transfer mechanism $\delta_2(D,S)\delta_2(D,S)$. Using the fact that $\frac{\alpha H_A}{\alpha\delta_2}$ and assuming $\frac{\alpha^2\delta_2}{\alpha D\alpha S} < 0$, we obtain:

$$\frac{\alpha^2 H_A}{\alpha D \alpha S}\Big|_{\delta_2} = \frac{\alpha H_A}{\alpha\delta_2}\frac{\alpha^2\delta_2}{\alpha D\alpha S} > 0 \tag{9}$$

This implies that as operational scale S increases, the marginal land-adjustment effect associated with DFI becomes weaker. In our empirical setting where the sample is dominated by smallholders, this channel is therefore interpreted as an exit/scale-adjustment margin that can accompany labor reallocation, rather than a stand-alone causal pathway.

[5] This reflects the fact that large-scale farmers are typically specialized agricultural producers who tend to expand their farm operations. As a result, the effect of digital financial inclusion on promoting land transfer is relatively limited for this group. In contrast, small-scale farmers are more likely to release surplus labor through land rental, making land transfers a more effective channel for increasing non-agricultural labor supply.

This leads to Hypothesis 2.2:

Hypothesis 2.2. (Agricultural exit margin: land adjustment)[6]: DFI promotes the development of land transfer markets, facilitating the reallocation of land from smallholders to larger-scale farmers. This process releases agricultural labor from small-scale households and enables their transition to non-agricultural employment.

Taken together, the total effect of DFI (D) on agricultural labor input (H_A) can be expressed as:

$$\frac{\alpha H_A}{\alpha D} = \frac{\alpha H_A}{\alpha \delta_1}\frac{\alpha \delta_1}{D} + \frac{\alpha H_A}{\alpha \delta_2}\frac{\alpha \delta_2}{D}(S) \tag{10}$$

The first term captures the financial constraint alleviation effect, which operates through increased likelihood of non-agricultural entrepreneurship, broader employment geography, and other supportive factors—all of which reduce agricultural labor H_A and increase non-agricultural labor H_N. The second term reflects the labor release effect through land transfer, which also promotes non-agricultural labor, but whose marginal impact weakens as operational scale SSS increases.

Accordingly, we refine **Hypothesis 1 (Overall Effect)** as follows:

Hypothesis 1. (Revised Overall Effect): Higher levels of DFI significantly reduce agricultural labor supply and increase non-agricultural labor supply, facilitating the reallocation of rural labor from agriculture to non-agricultural sectors. This positive effect is more pronounced among small-scale farming households.

3.2. Statistical challenges and identification strategy

3.2.1. Statistical challenge

To empirically test these two theoretical hypotheses, establishing a causal relationship between DFI and rural labor supply is a crucial step. However, several empirical challenges must be addressed to ensure consistent and reliable results.

First, there is the potential for omitted variable bias. DFI is inherently a composite index, comprising three dimensions—breadth of financial coverage, depth of financial use, and degree of financial digitalization—along with 33 specific indicators. Any of these indicators may be correlated with socioeconomic factors that simultaneously affect rural labor supply. This multidimensional nature makes the issue of endogeneity particularly pronounced. For example, consider the proportion of payments made using credit products, such as China's "Huabei" (a digital credit platform), as part of the financial inclusion framework. Individual risk preferences, if unaccounted for, may lead to two effects: on one hand, higher risk tolerance could significantly increase the usage of digital credit; on the other hand, individuals with higher risk preferences are more likely to pursue higher-income opportunities, such as off-farm employment, by altering their existing work patterns. Ignoring risk preferences could introduce downward bias when estimating agricultural employment and upward bias when estimating off-farm employment. If baseline results suggest that DFI reduces agricultural labor supply while increasing off-farm labor supply, such biases might lead to an overestimation or underestimation of these effects. Ultimately, whether ordinary least squares (OLS) overestimate or underestimate the impact must be empirically verified.

Second, issues related to self-selection and reverse causality among rural households may also distort OLS estimates. Regarding self-selection, regions with higher levels of DFI are often more economically developed (Cernisevs et al., 2022; Ding and Kang, 2024). In such areas, rural households are more likely to engage in off-farm employment, but this trend could primarily result from higher off-farm wages rather than the direct impact of DFI. As for reverse causality, the adoption of digital financial services may encourage farmers to shift toward off-farm employment, such as entrepreneurship or industries with higher returns compared to agriculture. This transition could, in turn, drive further economic development and enhance the activity level of DFI in those regions. Both factors could introduce significant bias into OLS estimates.

Therefore, when examining the causal relationship between DFI and rural labor supply, it is imperative to account for these challenges to ensure robust and credible findings.

3.2.2. Identification strategy

To address potential endogeneity in the estimation of DFI's effects, we employ a geography-based instrumental variable—the interaction between "distance to Hangzhou" and year fixed effects—following Angrist and Krueger (1994) and Bai and Jia (2016). This design transforms the otherwise time-invariant distance variable into a time-varying instrument that captures the temporal evolution of digital finance diffusion while maintaining exogeneity.

The rationale for this instrument is twofold. First, regarding relevance, proximity to Hangzhou—the headquarters of Ant Financial, the parent company of Alipay—strongly affects the regional penetration of digital financial services (Han et al., 2023; Yang and Zhang, 2022). During the rapid expansion of digital finance in China, regions closer to Hangzhou experienced earlier adoption due to network externalities, marketing spillovers, and better access to digital infrastructure, resulting in higher DFI indices. Second, regarding exogeneity, geographical distance and topographic features are independent of local labor market conditions and remain stable over

[6] We note that land transfer decisions may be jointly determined with non-farm choices for smallholders; accordingly, in the empirical section we treat land-transfer outcomes as evidence consistent with a smoother exit margin, rather than as an independent causal mediator.

time; thus, the interaction term affects rural labor allocation only through its impact on the diffusion intensity of DFI.[7]

Economically, this diffusion-based instrumental variable reflects the spatial propagation of digital finance from its origin city, Hangzhou, to surrounding areas. By combining distance with time variation, the instrument captures cross-regional heterogeneity in DFI exposure across different diffusion stages (Angrist and Krueger, 1994; Bai and Jia, 2016). This design not only leverages the exclusion restriction of geographic distance but also improves causal identification by aligning with the temporal dynamics of digital finance development.

It is worth noting that, although geography-based distance instruments have been widely used in the DFI literature, geographic proximity may still be correlated with broader regional development gradients. To further address this concern, we provide supplementary 2SLS estimates using non-distance shift–share (Bartik) instruments in the robustness section. Specifically, following Manacorda and Tesei (2020) and related studies, we construct a time-varying instrument of the form:

$$z_{ct} = Lightning_c \times g_t \tag{11}$$

Here, Lightning_c denotes the county's long-run average lightning-strike density (annual strikes per km^2). Given that our CFPS sample starts in 2014, we define Lightning_c as the pre-sample average over 1995–2014, aggregated from NASA/GHRC LIS/OTD HRFC gridded data. This exposure measure is therefore predetermined with respect to the study period and strengthens the plausibility of the exclusion restriction. The term g_t captures a common national shock to digital expansion, which we proxy using two complementary measures: (i) the national DFI growth rate, which is conceptually closest to our core DFI variable and directly reflects year-to-year variation in nationwide DFI diffusion; and (ii) the growth rate of national long-distance fiber backbone lines, which reflects supply-side expansion of communication infrastructure and provides an additional robustness check against potential endogeneity concerns.

We motivate the validity of this instrument along two dimensions. First, relevance: lightning activity and related electromagnetic interference increase the risk of communication equipment failures and raise expenditures on lightning protection, redundancy, and disaster recovery, thereby increasing the cost of building and maintaining digital infrastructure and slowing digital diffusion. Consistent with this logic, Tian et al. (2025) propose and validate "lightning frequency × national fiber-backbone growth" as an instrument for digital adoption, and Manacorda and Tesei (2020) document that areas with more intense lightning activity experience slower expansion of mobile coverage. Second, exogeneity: lightning exposure is a natural, long-run geographic characteristic that is plausibly orthogonal to short-run economic fluctuations; by using a pre-period long-run average, we further reduce the risk that the exposure co-moves with contemporaneous shocks. In line with Manacorda and Tesei (2020), we additionally include weather controls and maintain the same fixed effects and control-variable structure as in the baseline specification, thereby minimizing the scope for lightning exposure to affect labor allocation through channels other than digital finance.

3.3. Empirical model

We employ the standard two-stage least squares (2SLS) approach for instrumental variable (IV) estimation. The specific model framework is outlined as follows:

$$working\ time_{ijt} = \alpha + \beta_1 \widehat{DFI}_{jt} + X_{ijt} + \gamma_i + Year_t + \mu_{ijt} \tag{12}$$

$$DFI_{jt} = \alpha + \sum_{t \neq 2016}^{t=year} \gamma_t Distance_j \times D_t + X_{ijt} + \gamma_i + Year_t + \varepsilon_{ijt} \tag{13}$$

Here, $working\ time_{ijt}$ represents the agricultural labor hours and off-farm working hours of farmer i in county j at year t. DFI_{jt} is the core explanatory variable of interest in this study, capturing the DFI index of region j at year t.

X_{ijt} represents time-varying socioeconomic variables, primarily encompassing two categories: (1) individual characteristics of farmers, such as age, marital status, and educational attainment; and (2) county-level socioeconomic variables, including government general budget expenditures and the gross output value of industrial enterprises above a designated scale. While the instrumental variable used in this study incorporates relatively exogenous geographic characteristics, farmers' decisions to pursue off-farm employment may be influenced by the industrial spillover effects from urban areas, which are likely to intensify as the distance to Hangzhou decreases. Therefore, it is essential to comprehensively control for regional socioeconomic variables in the analysis.

This study employs the geographic distance from each region to Hangzhou ($Distance_j$) as the instrumental variable for constructing the baseline model. To introduce temporal variation to "distance to Hangzhou", we interact it with year-specific fixed effects, allowing for over-identification of the instrumental variable ($Distance_j \times D_t$) as suggested by Angrist and Krueger (1994) and Bai and Jia (2016).

Here, $Distance_j$ denotes the distance of region j from Hangzhou. The term $\sum_{t \neq 2016}^{t=year} \gamma_t Distance_j \times D_t$ represents a series of estimated coefficients (γ_t) for the years 2014 to 2020, with 2016 set as the reference group. Under this framework, γ_t reveals the relative annual change in DFI for every unit increase in distance from Hangzhou, compared to the baseline year of 2016.

The parameter of primary interest in this study is β_1, which captures the core relationship under investigation. However, any unobserved factors simultaneously influencing DFI and agricultural working hours could result in estimation bias. To address this

[7] Following the approach of Yang and Zhang (2022) and using Google Maps as a reference, we calculate the spherical distance of each city from Hangzhou based on their geographical coordinates.

concern, the study leverages the advantages of panel data by incorporating comprehensive fixed effects and key control variables to mitigate the influence of confounding factors.

Specifically, γ_i represents individual fixed effects, accounting for all time-invariant individual characteristics, such as inherent differences across regions and stable individual traits like ability or preferences. $Year_t$ denotes time fixed effects, which capture nationwide time-varying factors, such as policy changes implemented at the national level or macroeconomic shocks affecting the entire country. Lastly, ε_{ijt} is the error term, and clustering at the county level is employed to address potential spatial correlation across different counties.

4. Data

4.1. Data sources and variable construction

4.1.1. CFPS data, sample selection

This study utilizes individual- and household-level data from the China Family Panel Studies (CFPS), initiated by the Institute of Social Science Survey at Peking University in 2010. The dataset encompasses information from 25 provinces and 162 counties across China, providing detailed statistics on individuals' demographic characteristics, employment status, job types, income, and family relationships. To align with the research objectives, the analysis focuses exclusively on working-age individuals (16–60 years). Given that the DFI index is available at the county level from 2014 to 2020, the study incorporates four waves of CFPS data: 2014, 2016, 2018, and 2020. This selection ensures consistency between the temporal coverage of the financial inclusion index and the household survey data.

To differentiate agricultural and off-farm laborers among rural households, we first classified all residents based on household registration type (hukou) into agricultural and off-farm hukou categories, retaining only the agricultural hukou sample for analysis. Subsequently, individuals were categorized as "employed" or "unemployed" based on their employment status. "Employed" individuals are defined as those engaged in income-generating activities, including agricultural work, part-time jobs, or assisting with family businesses, excluding volunteer work, student employment, and household chores. Finally, using the CFPS question on agricultural labor participation—"In the past 12 months, have you engaged in activities related to farming, forestry, animal husbandry, sideline production, or fishing (e.g., cultivating land, managing orchards, collecting agricultural or forestry products, fish farming, fishing, or raising livestock)?"—we further subdivided the employed agricultural hukou sample into agricultural and off-farm laborers. Based on this classification, the final dataset comprises 18,797 valid observations, with the sample distribution illustrated in Fig. 1.

4.1.2. Labor and other key channel variable construction

To better capture the labor allocation decisions of rural households, we employ a continuous measure of working hours rather than

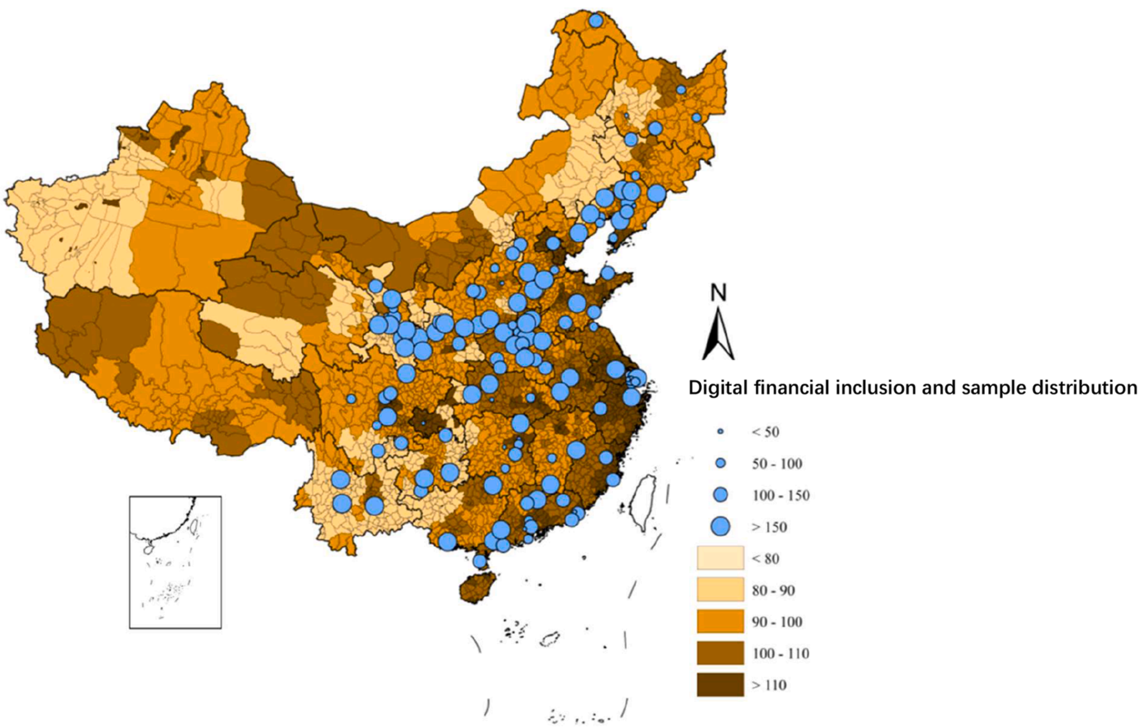


Fig. 1. Digital financial inclusion and sample distribution.

a binary indicator of employment participation. This design offers two advantages: it captures both the extensive margin (whether individuals engage in agricultural or off-farm work) and the intensive margin (the amount of time devoted to each activity), and it allows for more precise identification of marginal adjustments in labor supply induced by digital financial inclusion. By reflecting the continuous nature of rural labor allocation, this specification enhances the sensitivity and interpretability of our empirical estimates.

To define agricultural and off-farm working hours, we utilized specific questions from the CFPS dataset, calculated as follows:

- *"How many hours do you typically work per week at this job?"*

To align with the annual time frame of the core explanatory variable, we converted weekly working hours into total annual working hours by multiplying the weekly figure by the number of workweeks in a year.

To identify whether a household participates in off-farm self-employment or off-farm wage employment, we relied on two key CFPS questions:

- "*Is this job for yourself/your family, or are you employed by someone else/another household/organization/company?*"
- "*Is this job agricultural or non-agricultural?*"

Respondents who answered "for yourself/your family" to the first question and "non-agricultural" to the second were classified as engaging in off-farm self-employment, including entrepreneurs, freelancers, and sole proprietors.

Conversely, Respondents who answered "employed by someone else/another household/organization/company" to the first question and "non-agricultural" to the second were classified as engaging in off-farm employment.

To assess whether a household participated in land transfer activities, we referred to two CFPS questions:

- "*Has your household rented out collectively allocated land to others?*"
- "*Has your household rented land from others or from the collective?*"

Table 1
Index structure and specification of digital financial inclusion.

Primary Dimension	Secondary Dimension		Specific Indicators
Breadth of coverage	Account coverage rate		Number of Alipay accounts per 10,000 people
			Proportion of Alipay users with linked bank cards
			Average number of bank cards linked per Alipay account
Depth of use	Payment services		Average number of payments per user
			Average payment amount per user
			Proportion of high-frequency active users among users active at least once annually
	Monetary fund services		Average number of purchases per user in Yu'E Bao
			Average purchase amount in Yu'E Bao per user
			Number of Yu'E Bao purchasers per 10,000 Alipay users
	Credit business	Personal consumer loans	Number of users with internet consumer loans per 10,000 adult Alipay users
			Average number of loans per user
			Average loan amount per user
		Small business loans	Number of small business loan users per 10,000 adult Alipay users
			Average number of loans per small business user
			Average loan amount for small businesses
Degree of digitalization	Insurance services		Number of insured users per 10,000 Alipay users
			Average number of insurance policies per user
			Average insurance premium per user
	Investment services		Number of users with internet consumer loans per 10,000 adult Alipay users
			Average number of loans per user
			Average loan amount per user
	Credit operations		Average number of credit calls per user
			Number of users accessing credit-based services per 10,000 Alipay users
	Mobility		Proportion of transactions made via mobile payments
			Proportion of payment amounts made via mobile payments
	Affordability		Average loan interest rate for small businesses
			Average personal loan interest rate
	Credit integration		Proportion of payments made via Huabe
			Proportion of payment amounts made via Huabei
			Proportion of deposit-free transactions enabled by Sesame Credit
			Proportion of deposit-free transaction amounts enabled by Sesame Credit
	Convenience		Proportion of QR code payment transactions
			Proportion of payment amounts made via QR codes

Note: The digital financial inclusion index, developed by the Peking University Institute of Digital Finance and Ant Group Research Institute, consists of three primary dimensions and 33 indicators. Using the Analytic Hierarchy Process (AHP), the index was compiled for 31 provinces, 337 prefecture-level cities, and approximately 2800 counties in mainland China. It covers provincial and city-level data from 2011 to 2020 and county-level data from 2014 to 2020.

Households responding “yes” to renting out land were classified as land-outflow households, while those responding “yes” to renting land from others or the collective were classified as land-inflow households.

4.1.3. Digital financial inclusion index

The Digital Financial Inclusion (DFI) Index, jointly developed by the Peking University Institute of Digital Finance and Ant Financial Group, is based on user data from Ant Financial. It illustrates the development and evolution of digital finance in China from 2011 to 2020, with county-level data available for the period 2014–2020 (Fu and Yi, 2023; Guo et al., 2019). The index construction follows three main steps.

First, the indicator system is built across three dimensions: breadth of *coverage, depth of use*, and *degree of digitalization*. Table 1 outlines the comprehensive structure of the index, as proposed by Guo et al. (2019).

- *Coverage breadth* measures the accessibility of digital financial accounts, mainly based on the number of Alipay accounts and the ratio of active accounts to the local population.
- *Usage depth* captures the intensity and diversity of digital financial services, combining the usage frequency of digital payment, credit, wealth management, and insurance services.
- *Digitalization level* reflects the technological and online features of financial activities, such as mobile payment penetration and online consumption frequency.

Second, each raw indicator x_{ij} is normalized using min-max scaling:

$$z_{ij} = \frac{x_{ij} - \min\left(x_j\right)}{\max\left(x_j\right) - \min\left(x_j\right)} \tag{14}$$

This process converts all indicators to a 0–1 range, eliminating unit differences and ensuring cross-regional comparability.

Third, standardized indicators within each dimension are aggregated using the geometric mean to obtain sub-indices:

$$S_{id} = \left(\prod_{j=1}^{n_d} z_{ij}\right)^{1/n_d} \tag{15}$$

The overall DFI index is then calculated as the geometric mean of the three sub-indexes:

$$DFI_i = (S_{i1} \times S_{i2} \times S_{i3})^{1/3} \times 100 \tag{16}$$

The index ranges from 0 to 100, with higher values indicating broader coverage, deeper use, and higher levels of digitalization in financial services. In subsequent robustness checks, we further reconstruct the DFI index using a PCA-based approach and separately examine the effects of the three sub-indices to assess the sensitivity of our results to alternative weighting schemes and to clarify the roles of each component.

Since its release, this index has been widely employed to study the effects of digital finance on household income, consumption, and employment (Fu and Yi, 2023; Yuyu Wang et al., 2024; Xie et al., 2018; Yu et al., 2024). The index is available at the provincial, municipal, and county levels.

The period from 2014 to 2020 coincides with a critical stage in the development of DFI in China. As shown in Fig. 2, the provincial DFI index shifted from a rapid expansion phase (2011–2014) to a more stable, regulated period (2014–2020). This transition reflects the government’s increasing efforts to institutionalize digital finance through inclusive finance strategies, rural internet infrastructure investment, and targeted support for rural areas. These measures have had lasting effects on rural economies and household behavior.

In this study, the county-level DFI index is integrated with individual and household data from the CFPS to construct a county-level DFI-CFPS database. The baseline model employs the DFI index as the main explanatory variable to examine its effects on rural labor allocation. For robustness, we also analyze the separate impacts of the three dimensions—breadth of coverage, depth of use, and degree of digitalization—on farmers’ employment decisions.

4.1.4. Individual and social control variables

The individual-level control variables used in this study are sourced from the CFPS and include years of education, age, health status, household per capita income, and household size. Social control variables are at the county level, drawn from the China County Statistical Yearbook. By integrating yearbook data with relevant county-level economic indicators, we constructed a comprehensive and robust set of control variables. Key variables include public budget revenue and industrial output value, which help account for regional economic and fiscal conditions that may influence labor allocation decisions.

4.2. Descriptive statistics

Table 2 presents the descriptive statistics for the key variables used in this study. For dependent variables, the number of hours in agricultural work during the year for workers is 810.76 h, approximately 3 h per day based on an assumption of 250 working days per year. This aligns with the seasonal nature of agricultural production and the presence of downtime during the off-season. For off-farm labor, the number of days in off-farm work during the year is 1575.29 h, or roughly 6 h per day under the same assumption.

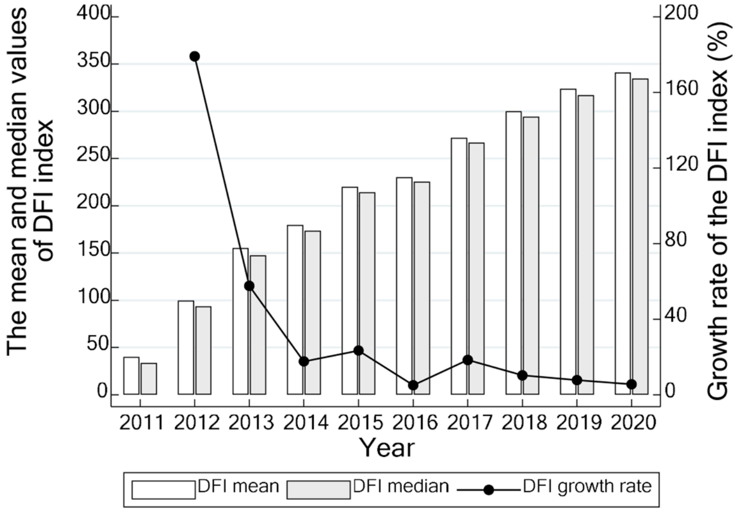


Fig. 2. The mean, median and growth rate (%) of DFI index.

Table 2
Summary statistics.

Variable	Definition (Unit)	Mean	SD	Min	Max
Individual employment					
Agricultural working hours	The number of hours in agricultural work during the year (hours/year)	810.8	1228	0	3664
Off-farm working hours	The number of days in off-farm work during the year (hours/year)	1575	1570	0	4452
Geographical location					
Distance to Hangzhou	The geographic distance between each county and Hangzhou (km)	1063.9	468.7	86.62	2516.6
Distance to provincial capital	The geographic distance between each county and its provincial capital city (km)	183.8	122.3	2.63	828.0
Digital financial inclusion					
Digital financial inclusion index	Measured by breadth of coverage, depth of use, and degree of digitalization	88.58	29.79	13.21	143.8
Breadth of coverage index	Measured by the account penetration rate of Alipay accounts	80.86	25.63	5.42	116.6
Depth of use index	Measured by the actual utilization of internet financial services	103.9	41.12	0	214.7
Degree of digitalization index	Measured by mobility, affordability, credit-based accessibility, and convenience	86.28	34.37	10.17	134.8
Individual & Social variables					
Years of education	Years of educational attainment (years)	7.26	5.13	0	22
Age	Age of labor force participants	45.03	14.36	16	60
Health status	Self-rated health in the past month, 1–5; 1: very good - 5: very bad	2.95	1.22	1	5
Household income	Logarithm of per capita household income	9.28	1.83	0	14.51
Family size	Number of household members	3.87	1.91	0	21
Local public budget revenue	Local public budget revenue (in billion yuan)	12.76	0.7	11.08	14.99
Industrial output value	Industrial output value of enterprises above designated size (in billion yuan)	154.3	238.2	1	2047

Note: The sample size consists of 18,797 observations. Data on DFI is sourced from the Ant Financial Digital Financial Inclusion Index (for detailed definitions and index components, see Table 1). Labor data is derived from the China Family Panel Studies (CFPS), while socioeconomic data is obtained from the China Statistical Yearbook.

Regarding the composition of non-agricultural employment, CFPS data show that rural workers are primarily engaged in labor-intensive and low-entry-barrier sectors (Fig. A3). Manufacturing (27.8 %), wholesale and retail trade (16.3 %), construction (13.0 %), accommodation and catering (7.3 %), transport, storage and postal services (5.0 %), and resident and other services (5.0 %) together account for nearly 75 % of total off-farm employment. These sectors require limited formal education and capital input, indicating that most rural households are realistically capable of participating in them once financing constraints are relaxed.

For independent variables, this study evaluates DFI at the county level across four dimensions. First, the overall DFI index, which integrates breadth of coverage, depth of use, and degree of digitalization, has an average value of 88.58. Second, examining the three subdimensions individually, the breadth of coverage has an average index value of 80.86, depth of use averages 103.87, and degree of digitalization 86.28.

Fig. A1 further illustrates the distribution of key variables across the sample. There is a clear spatial disparity in annual agricultural labor supply: farmers in central and western regions exhibit higher agricultural labor hours, while those in eastern coastal areas—such as Zhejiang and Shanghai—tend to supply significantly less agricultural labor. In contrast, the distribution of the DFI index shows the opposite pattern, with higher values concentrated in economically advanced coastal provinces and lower values in inland regions. The accompanying histograms provide additional insight into the distributional characteristics of these variables. Agricultural labor hours exhibit a right-skewed distribution, while the DFI index follows a more symmetric, approximately normal distribution.

The control variables provide additional insights into individual, household, and county-level characteristics. On average, workers in the sample have 7.26 years of education, reflecting a generally low level of formal education but one that covers basic education requirements. The average age of workers is 45.03 years, indicating a predominance of middle-aged individuals, consistent with the demographic distribution of rural labor. Health status, measured on a 1-to-5 scale, averages 2.95, suggesting a moderate level of health among the sampled individuals. At the household level, the average logged per capita household income is 9.28, reflecting relatively balanced economic conditions across the sample. The average household size is 3.87, consistent with typical rural family structures. At the county level, the average public budget revenue is 12.76, indicating relatively small fiscal disparities across counties in the sample. Meanwhile, the average gross industrial output above the designated scale is 154.26 million yuan, suggesting a generally low level of industrialization but with notable regional variation.

5. Results

5.1. Baseline results

To test Hypothesis 1—that an increase in DFI reduces agricultural labor supply while increasing non-agricultural labor supply—we begin with a baseline fixed effects regression. Specifically, we estimate a model that includes county and year fixed effects, along with a set of individual- and household-level controls, to mitigate potential bias from omitted variables.

Table 3 reports the main results. Columns (2) and (4) present the coefficient estimates from the fixed effects model with full controls. The results indicate that the DFI index is significantly negatively associated with agricultural labor hours and positively associated with non-agricultural labor hours. In terms of magnitude, a one-unit increase in the DFI index is associated with a 1.61 % decrease in agricultural labor supply and a 1.98 % increase in non-agricultural labor supply, both statistically significant at the 1 % level. These findings support Hypothesis 1 and are consistent with the theoretical framework, suggesting that DFI serves as a structural instrument that facilitates the reallocation of rural labor toward higher-productivity non-agricultural sectors.

It is important to note, however, that while the fixed effects model helps control for time-invariant unobserved heterogeneity, it does not fully address potential endogeneity concerns, such as reverse causality or measurement error in key variables. As such, we proceed with an instrumental variable approach to strengthen the causal interpretation of our findings.

5.2. Two-Stage regression results

To more rigorously identify the causal impact of DFI on rural labor allocation, we employ a two-stage least squares (2SLS) instrumental variable (IV) approach. Given the potential simultaneity between DFI and labor supply—both potentially shaped by unobserved factors—we follow Czernich et al. (2011) and employ an interaction between geographic distance to Hangzhou and year fixed effects as the instrument. This variable captures exogenous variation in DFI driven by spatial diffusion dynamics.

The instrument is grounded in strong theoretical justification. Hangzhou is the headquarters of Ant Financial, the operator of Alipay, a leading digital finance platform in China. In the early stages of DFI expansion, the diffusion of services exhibited significant spatial and temporal dependence, with regions closer to Hangzhou receiving earlier and more intensive access to digital financial services. The interaction of geographic distance with year dummies thus captures exogenous variation in DFI rollout while plausibly remaining uncorrelated with the error term in the labor supply equation.

In the first-stage regression, the instrument demonstrates strong predictive power for the DFI index. As reported in Table 4, Panel A, coefficients on the instrument are significantly negative, indicating that DFI levels decrease with distance from Hangzhou—consistent with a "core–periphery" diffusion pattern. This pattern reflects platform-driven expansion strategies that prioritize infrastructure development, user acquisition, and service piloting in spatially proximate areas. The Kleibergen-Paap F-statistic is 22.868, well above the conventional threshold of 16 proposed by Stock et al. (2002), ruling out concerns about weak instruments. The Hansen over-identification test yields p-values of 0.18 (agricultural labor) and 0.15 (non-agricultural labor), so we fail to reject the null that the instruments are jointly valid (i.e., satisfy the orthogonality conditions). Accordingly, the overidentifying restrictions are not rejected in either specification.

The second-stage results, presented in Table 4, Panel B, show that a one-unit increase in the DFI index leads to a statistically significant 3.66 % decrease in agricultural labor time and a 3.23 % increase in non-agricultural labor time, both significant at the 1 % level. These findings provide strong empirical support for Hypothesis 1 and the predictions of our theoretical framework. Notably, the magnitude of the IV estimates exceeds that of the baseline fixed effects estimates, suggesting that the latter may underestimate the true effect due to measurement error or omitted variable bias.

These results align with prior empirical evidence. Yang and Geng (2022) emphasize the role of DFI in driving rural structural transformation in developing economies. Ren et al. (2023) and Han et al. (2025) find that DFI promotes non-farm employment among rural laborers, while Peng and Mao (2023) show that DFI alleviates relative poverty by improving credit accessibility and mitigating financial risks. Building on these insights, this paper extends the analysis to the rural context, emphasizing that similar mechanisms operate through changes in relative returns between agricultural and non-agricultural sectors, thereby facilitating cross-sector labor mobility. Unlike prior studies that rely on binary employment indicators (e.g., whether individuals engage in off-farm work), we employ a continuous measure—working hours—to capture the intensity of labor input (intensive margin) between agricultural and off-farm activities. This approach provides a more nuanced assessment of how DFI influences labor reallocation across sectors and explains why our estimated coefficients may differ from those using binary measures.

These results are not only statistically robust but also highly relevant for policy. First, they highlight DFI as an institutional financial

Table 3
Baseline result (OLS).

Dependent variable:	Log (Agricultural working hours)		Log (Off-farm working hours)	
	(1)	(2)	(3)	(4)
DFI index	−0.0141**	−0.0161***	0.0175***	0.0198***
	(0.0055)	(0.0048)	(0.0058)	(0.0064)
Mean [SD] of D.V.	3.02 [3.63]		4.53 [3.86]	
Individual & Social controls	No	Yes	No	Yes
Year *FE*	Yes	Yes	Yes	Yes
Individual *FE*	Yes	Yes	Yes	Yes

Note: $N = 18{,}797$. Individual and social controls include years of education, age, health status, log of household per capita income, household size, local public budget revenue, and gross industrial output above the designated size. Standard errors are clustered at the county level and reported in parentheses. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4
Baseline result (2SLS).

Panel A: *1st-stage estimation*	*Dependent variable*: DFI index
	(1)
Distance to Hangzhou × Dummy (Year = 2014)	−10.511***
	(1.684)
Distance to Hangzhou × Dummy (Year = 2018)	−3.431***
	(0.497)
Distance to Hangzhou × Dummy (Year = 2020)	−3.247***
	(0.623)

Panel B: *2nd-stage estimation*	*Dependent variable*:	
	Log (Agricultural working hours) (1)	Log (Off-farm working hours) (2)
DFI index	−0.0366***	0.0323***
	(0.0116)	(0.0122)
Mean [SD] of D.V.	3.02 [3.63]	4.53 [3.86]
KP F-statistics	22.868	22.868
Individual & Social controls	Yes	Yes
Individual *FE*	Yes	Yes
Year *FE*	Yes	Yes

Note: $N = 18{,}797$. Individual and social controls include years of education, age, health status, log of household per capita income, household size, local public budget revenue, and gross industrial output above the designated size. Standard errors are clustered at the county level and reported in parentheses. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

innovation that not only expands access to financial services in rural areas but also reshapes the structural incentives for labor mobility. Second, in the context of China's "Rural Revitalization" strategy, the labor reallocation induced by DFI provides a feasible pathway for promoting non-agricultural employment and addressing structural challenges such as underemployment and rural hollowing. Finally, from the perspective of development economics, our findings contribute to the empirical literature linking financial development to structural transformation, reinforcing the proposition that improved access to financial services plays a critical role in optimizing labor allocation in developing economies (Beck et al., 2007; Czernich et al., 2011).

5.3. Robustness check

To ensure the robustness of our baseline results, we conduct a series of supplementary tests across multiple dimensions.:

First, to address measurement sensitivity of the composite DFI index, we implement two alternative measurement checks. We reconstruct a PCA-based DFI index using the three publicly available sub-indices and re-estimate the baseline 2SLS model (Table A1, Column 1).[8] We then separately replace the composite DFI with each sub-index—coverage breadth, usage depth, and digitalization level—to verify that the results are not driven by any single dimension (Table A1, Columns 2–4). Across these specifications, the estimated effects remain highly consistent: higher DFI is associated with significantly lower agricultural working hours and

[8] Because the PKU-DFI does not release more disaggregated third-level raw indicators, PCA is implemented using the three publicly available second-level sub-indices (coverage breadth, usage depth, and digitalization level). We extract principal components from these three sub-indices, standardize component scores to z-scores, and construct the PCA-DFI as a variance-share weighted sum. In our sample, the explained variance shares of the first three components are 0.8727, 0.0840, and 0.0433, respectively.

significantly higher off-farm working hours.

Second, to mitigate potential bias stemming from regional heterogeneity, we exclude China's four centrally-administered municipalities, given their unique advantages in economic development and digital infrastructure. The re-estimated results confirm robustness, alleviating concerns related to sample selection (Table A1, Column 5).

Third, to account for potential serial correlation and heteroskedasticity, we re-cluster standard errors at the higher prefecture level instead of the county level. The results maintain statistical significance under this more conservative inference approach (Table A1, Column 6).

Fourth, to control for region-specific temporal trends that might confound identification, we incorporate province (municipality) × year fixed effects. This strengthens our identification strategy by further capturing potential omitted trends (Table A2).

Fifth, to address the possible endogeneity associated with Alibaba's choice of Hangzhou as its headquarters, we introduce a more plausibly exogenous instrumental variable—distance to the provincial capital—in place of the original instrument. Results from this additional two-stage regression verify the robustness of our main findings and support the validity of the causal inference (Table A3).

Finally, to further address the concern that distance-based instruments may proxy for broader regional development gradients, we supplement our analysis with non-distance shift–share (Bartik) instruments in a 2SLS framework. Specifically, we use the county-level long-run average lightning-strike density (mean over 1995–2014) as a predetermined exposure and interact it with two alternative national shifters: the national DFI growth rate and the growth rate of the national long-distance fiber-backbone network. The first-stage results indicate strong instrument relevance (*KP F*-statistics of 41.397 and 138.180), and the second-stage estimates are highly consistent across the two instruments: higher DFI significantly reallocates labor away from agriculture and toward non-farm employment (Table A6).

Moreover, to further assess the validity and exogeneity of our instrumental variable—*distance to Hangzhou*—we conduct a series of complementary robustness tests.

First, we examine its time-varying relationship with labor allocation. The Digital Financial Inclusion Index expanded rapidly between 2011 and 2020, coinciding with the nationwide adoption of Alipay and WeChat Pay and key policy initiatives promoting digital finance. If distance to Hangzhou affects labor allocation only through digital finance, its effect should be weak in the early years (2012–2014) and become stronger after 2016 as digital finance diffused nationwide. Consistent with this logic, we find that DFI has no significant impact on agricultural or off-farm working hours in 2012–2014, but from 2016 onward, it significantly reduces agricultural labor and increases off-farm labor. The reduced-form results using distance directly show the same temporal pattern, reinforcing the instrument's validity (Fig. A2).

Second, we perform a spatial placebo test by replacing the instrument with distances to three comparable cities—Wenzhou, Changsha, and Nanjing—that share similar economic and transportation characteristics but are not origins of digital finance diffusion. As shown in Table A4, when using distance to Hangzhou, DFI significantly decreases agricultural working hours and increases off-farm working hours (both at the 1 % level). However, when distance to the other cities is used, the results become insignificant. This confirms that only distance to Hangzhou captures the true diffusion of digital finance rather than general regional factors.

Third, we test for potential local market or transport effects by sequentially excluding counties within 100 km, 300 km, and 900 km of Hangzhou. As shown in Table A5, the results remain stable and significant across all exclusion radii, and the first-stage *KP F*-statistics remain above 10, indicating strong instrument relevance. These findings suggest that the results are not driven by local proximity effects but operate through the diffusion of digital finance itself.

5.4. Mechanism analysis

Thus far, we have demonstrated that DFI significantly promotes the reallocation of rural labor from agriculture to non-agriculture. In this section, we further examine two distinct margins highlighted in Section 3 through which this reallocation may occur: (i) the non-farm entry margin, whereby DFI alleviates households' financial constraints and lowers barriers to non-agricultural participation;

Table 5
Mechanism analysis: Non-farm entry margin (credit-constraint alleviation).

Dependent variable:	Log (Total expenditure) (1)	Prob. (Off-farm self-employment) (0: No; 1: Yes) (2)	Working place (1–5, near to far) (3)	Log (Off-farm working hours) (4)
DFI index	0.0123*** (0.0030)	0.0345** (0.0171)	0.0171*** (0.0025)	0.0252** (0.0120)
DFI index × Expenditure group (1: High, 0: Low)				0.0069*** (0.0010)
KP F-statistics	22.868	22.868	22.868	19.958
Mean [SD] of D.V.	14.22 [1.55]	0.10 [0.31]	1.08 [1.50]	4.53 [3.86]
Individual & Social controls	Yes	Yes	Yes	Yes
Individual *FE*	Yes	Yes	Yes	Yes
Year *FE*	Yes	Yes	Yes	Yes

Note: $N = 18{,}797$. Individual and social controls include years of education, age, health status, log of household per capita income, household size, local public budget revenue, and gross industrial output above the designated size. Standard errors are clustered at the county level and reported in parentheses. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and (ii) the agricultural exit margin, whereby DFI is associated with land-adjustment patterns that accompany a smoother reduction of agricultural labor input.

To empirically assess these margins, we adopt two complementary approaches. First, guided by the theoretical framework, we examine the relationship between DFI and key margin-related outcomes (e.g., consumption-based proxies for financial flexibility, and land transfer behaviors as land adjustment patterns). Second, we introduce interaction terms to estimate moderation models, providing indirect evidence on whether these margins shape the strength of the DFI–labor allocation relationship. This approach helps clarify how DFI relates to farmers' non-agricultural labor supply decisions while maintaining a cautious interpretation of land-transfer evidence.

5.4.1. Non-farm entry margin (credit-constraint alleviation)

To examine whether DFI promotes the reallocation of rural labor through the easing of financial constraints, we test Hypothesis 2.1: that DFI reduces the entry barriers to non-agricultural sectors by alleviating credit constraints, thereby increasing farmers' likelihood of engaging in self-employment and expanding their access to geographically distant non-agricultural employment opportunities.

We begin by testing whether DFI effectively relaxes household-level financial constraints, using annual household consumption expenditure as a proxy. While direct measurement of credit constraints is challenging, prior research (Peng and Mao, 2023; Yang and Zhang, 2022) suggests that rising consumption levels can indirectly signal improved financial access. Column (1) of Table 5 shows that a one-unit increase in the DFI index leads to a 1.23 % increase in total household consumption—comparable in magnitude to previous findings (e.g., Yang et al., 2022: 1.5 %; Yang and Zhang, 2022: 0.8 %). This suggests that DFI improves financial accessibility for rural households and provides foundational resources for engaging in entrepreneurial and employment activities beyond the agricultural sector.

Next, we directly assess how alleviated credit constraints translate into non-agricultural labor responses at the individual level. Specifically, we focus on two key dimensions: (1) whether improved access to finance increases farmers' likelihood and intensity of self-employment, and (2) whether it enables greater geographic mobility by reducing the financial and risk-related costs of migration. Both mechanisms are expected to encourage labor reallocation from agriculture to non-agriculture and increase the time spent in non-agricultural work.

Empirical tests reported in Columns (2) and (3) of Table 5 use non-agricultural self-employment hours as a proxy for entrepreneurial activity, and the geographic distance between a household's residence and work location as a proxy for employment scope. The results show that higher DFI significantly increases both self-employment hours and employment distance, supporting the view that DFI facilitates entrepreneurship and enables rural workers to access broader labor markets by easing financial constraints. These findings are consistent with the view that DFI relaxes non-farm entry barriers by easing financial constraints. They are also similar to the findings of existing studies (Ma et al., 2025; Ren et al., 2023; Yin et al., 2025; Zhan et al., 2025).

Finally, we explore heterogeneous effects by constructing a moderation model. We divide households into high- and low-consumption groups based on the median of total annual household expenditure, using consumption as a proxy for the degree of credit constraint relief. We then interact the DFI index with group dummies to test whether the effect of DFI on labor allocation is stronger among households with fewer financial constraints.

Columns (4) of Table 5 show that the interaction term between DFI and the high-consumption group is significantly positive in the non-agricultural labor model. This indicates that, relative to low-consumption households, high-consumption households supply significantly more hours to non-agricultural employment as DFI increases. Overall, the result suggests that the labor reallocation effect of DFI is stronger among households with greater financial flexibility.

Together, these results reinforce Hypothesis 2.1: DFI facilitates the transition of labor from agriculture to non-agriculture by easing credit constraints, enabling entrepreneurial activity and employment beyond local markets. The effect is particularly pronounced among households with relatively relaxed financial constraints, highlighting the importance of credit access in unlocking structural labor mobility.

5.4.2. Agricultural exit margin (land adjustment)

The development of DFI has the potential to facilitate the reallocation of rural labor by promoting more efficient land transfer markets. In this section, we focus on the second mechanism proposed in this paper—namely, that DFI improves the financial environment and reduces transaction costs in land markets, thereby promoting the transfer of land use rights from small-scale to large-scale farmers and releasing surplus labor from agriculture (Hypothesis 2.2).[9]

Rather than treating land transactions as an independent causal channel, we examine whether DFI is associated with land adjustment behaviors that are **consistent** with a smoother agricultural exit (or scale-adjustment) margin. This distinction is important because, for smallholders, non-farm employment and land transfer decisions may be jointly determined and mutually reinforcing. Accordingly, we present the land-transfer evidence as complementary patterns aligned with the reallocation process, rather than as a stand-alone causal mechanism.

China's agricultural sector is characterized by a dual structure: on the one hand, traditional smallholder households account for

[9] The underlying logic is that as DFI alleviates credit constraints, larger or more commercialized farms obtain financing and expand land demand, thereby creating opportunities for smallholders to transfer out their land and release labor from agriculture. Because the CFPS sample mainly covers smallholder households rather than large-scale farms, this mechanism is referred to as labor release rather than credit constraint to ensure conceptual precision.

more than 98 % of all farm operators and cultivate approximately 70 % of total arable land; on the other hand, new forms of large-scale, specialized agricultural operations (e.g., large farms, family farms) account for less than 2 % of all farm units.[10] Since the CFPS dataset primarily targets traditional rural households, our sample largely consists of smallholders.[11] Accordingly, the observed land transfer effects of DFI are interpreted primarily from the perspective of small-scale farmers.

We first test whether DFI is associated with land transfer behavior. We construct two binary indicators for whether a household transfers land out or transfers land in during the survey period. As shown in Columns (1) and (3) of Table 6, higher DFI is significantly associated with a higher likelihood of land transfer-out and a lower likelihood of land transfer-in, which is consistent with smallholders being more able to complete land adjustment when reallocating labor away from agriculture.

Next, to explore heterogeneity in this adjustment margin, we proxy local land endowment using county-level rural per capita cultivated land (constructed by matching satellite-based cultivated land area with county rural population)[12] and split counties into land-abundant versus land-scarce groups. Columns (2) and (4) show that the interaction between DFI and the land-abundant group is significantly negative in the land-out model and significantly positive in the land-in model, suggesting that the land adjustment patterns associated with DFI vary systematically with local land endowment.

Finally, we link this adjustment margin to labor allocation by examining whether the DFI–labor reallocation association differs across land-endowment groups. Column (5) shows that, in land-abundant counties, the reduction in agricultural labor hours associated with DFI is weaker. Overall, these results are consistent with the interpretation that, alongside easing non-farm entry constraints, DFI is accompanied by land adjustment patterns aligned with a smoother agricultural exit/scale-adjustment process. We emphasize that we do not use land transfer as a mediator for causal decomposition; instead, we present it as supportive evidence on whether the exit/adjustment margin is easier to achieve in the reallocation process (Table 6).

These findings are consistent with Hypothesis 2.2: by improving the financial environment and reducing transaction costs in land markets, DFI is associated with a reallocation of land use rights from small to larger-scale operators, thereby releasing agricultural labor among smallholders and enabling their shift toward non-agricultural employment; in contrast, larger-scale farmers are more likely to expand agricultural operations and retain or even increase labor input in agriculture. This heterogeneity underscores the important role of the land transfer–adjustment margin in shaping the labor reallocation effects of DFI in rural China. Consistent with Shen et al. (2023), who find that digital finance significantly promotes land transfer and enhances agricultural green total factor productivity, our results provide complementary micro-level evidence from a labor allocation perspective, suggesting that DFI not only supports land optimization but also contributes to more efficient factor reallocation and rural structural transformation.

5.5. Heterogeneous analysis

Since we have established that DFI promotes the reallocation of rural labor from agriculture to non-agriculture. Heterogeneous effects are expected because the net impact of DFI reflects two opposing forces: on the one hand, the marginal gains from relaxing constraints (e.g., liquidity, risk-bearing capacity, and transaction frictions) can be larger for more constrained groups; on the other hand, adoption/adjustment costs and limited local opportunity sets may dampen behavioral responses. Hence, the effect of DFI does not necessarily increase monotonically with “advantage”. Below, we interpret heterogeneity through a unified lens: adjustment space (education), adjustment costs (age), and opportunity sets/supporting conditions (region).

5.5.1. Heterogeneous analysis: Education

As shown in Table 7, the left column reports the regression results for individuals with below junior high school education, while the right column focuses on those with junior high school education or above. This classification aligns with the educational structure of China’s rural labor force: 6.4 % of agricultural operators have no schooling, 37.0 % completed primary school, 48.4 % completed junior high school, 7.1 % finished high school or vocational school, and only 1.2 % attained college education or above.[13] Thus, dividing education into primary or below and junior high or above not only reflects the real distribution of educational attainment in rural areas but also covers over 90 % of the population, ensuring strong representativeness and interpretability.

The results indicate that DFI has a statistically significant association with labor reallocation primarily among the lower-education group: agricultural working hours decline significantly while off-farm working hours increase significantly. For individuals with junior high school education or above, the estimated effects are smaller and not statistically significant. Importantly, this pattern does not imply that less-educated farmers are “better” at using digital finance. Instead, it is more consistent with differences in baseline constraints and adjustment space. In the pre-period (2014), individuals with junior high school education or above are already predominantly engaged in nonfarm work (about 65 % nonfarm), whereas those with primary education or below remain mostly in agriculture (about 71 % agricultural). This stark baseline gap implies that the low-education group faces tighter nonfarm-entry constraints but also has greater scope for reallocation, so DFI-induced improvements translate into larger marginal shifts. By contrast, the higher-education group starts from a much higher nonfarm participation rate and therefore has less room for further adjustment, leading to weaker estimated effects.

[10] Please refer to China’s Ministry of Agriculture and Rural Affairs https://www.gov.cn/xinwen/2019-03/01/content_5369755.htm in Chinese
[11] Please refer to the CFPS technical manual https://www.isss.pku.edu.cn/cfps/docs/20210511113545661703.pdf in Chinese
[12] See Tu et al. (2024) reproduction from satellite data: A 30 m annual cropland dataset of China from 1986 to 2021.
[13] Source: https://www.stats.gov.cn/sj/pcsj/nypc/202302/U020230223531273769774.pdf, in Chinese.

Table 6
Mechanism analysis: The agricultural exit margin (land adjustment).

Dependent variable:	Prob. (Land outflow) (0: No; 1: Yes)		Prob. (Land inflow) (0: No; 1: Yes)		Log (Agricultural working hours)
	(1)	(2)	(3)	(4)	(5)
DFI index	0.0424***	0.0524***	−0.0163***	−0.0210***	−0.0644***
	(0.0061)	(0.0099)	(0.0035)	(0.0057)	(0.0166)
DFI index × Land scale		−0.0128***		0.0051**	0.0221***
(1: Large, 0: Small)		(0.0043)		(0.0025)	(0.0072)
KP F-statistics	22.868	18.723	22.868	18.723	18.723
Mean [SD] of D.V.	0.19 [0.39]		0.10 [0.31]		3.02 [3.63]
Individual & Social controls	Yes	Yes	Yes	Yes	Yes
Individual *FE*	Yes	Yes	Yes	Yes	Yes
Year *FE*	Yes	Yes	Yes	Yes	Yes

Note: $N = 18{,}797$. Individual and social controls include years of education, age, health status, log of household per capita income, household size, local public budget revenue, and gross industrial output above the designated size. Standard errors are clustered at the county level and reported in parentheses. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7
Heterogeneous analysis: Education.

Dependent variable:	Log (Agricultural working hours)	Log (Off-farm working hours)	Log (Agricultural working hours)	Log (Off-farm working hours)
	Primary and below		Junior and above	
	(1)	(2)	(3)	(4)
DFI index	−0.0592***	0.0538**	−0.0240	0.0206
	(0.0226)	(0.0216)	(0.0147)	(0.0159)
KP F-statistics	19.514	19.514	21.798	21.798
Individual & Social controls	Yes	Yes	Yes	Yes
Individual *FE*	Yes	Yes	Yes	Yes
Year *FE*	Yes	Yes	Yes	Yes
Observation	8659	8659	10,117	10,117

Note: Individual and social controls include years of education, age, health status, log of household per capita income, household size, local public budget revenue, and gross industrial output above the designated size. Standard errors are clustered at the county level and reported in parentheses. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.5.2. Heterogeneous analysis: Age

Given potential heterogeneity across age groups, we categorize the sample into two groups: a youth group (16–50 years old) and a middle-aged and older group (above 50 years old). This division corresponds to 9217 and 9580 observations, respectively, indicating adequate and balanced subsample sizes. Moreover, the cutoff at age 50 aligns with the demographic pattern of China's rural labor force reported in the Third National Agricultural Census, where most agricultural operators are between 35 and 54 years old, making 50 a reasonable threshold to distinguish younger and older cohorts in the rural labor market.

As shown in Table 8, DFI is associated with a significant reduction in agricultural labor input and a significant increase in off-farm labor input for the youth group, whereas the response of off-farm labor input is not statistically significant among those aged 50 and above. We interpret this pattern primarily through **adjustment costs**. Older rural workers tend to face higher costs of occupational switching and migration-related adjustments (e.g., retraining and information frictions, mobility constraints, and family responsibilities), which can limit their ability to translate improved financial access into increased off-farm labor supply. In contrast, younger individuals typically bear lower switching and mobility costs, so improvements in liquidity and risk-bearing capacity associated with DFI are more likely to materialize as observable shifts toward off-farm work.

5.5.3. Heterogeneous analysis: Region

Given significant disparities in economic development and infrastructure across regions in China, we categorize the sample into three major geographic regions—eastern, central, and western—to examine regional variations in the impact of DFI on labor allocation. As shown in Table 9, DFI has a statistically significant effect on the shift of labor from agricultural to non-agricultural sectors in the eastern region, whereas this effect is not statistically significant in the central and western regions.

We interpret this heterogeneity through differences in opportunity sets and supporting conditions. In the east, denser labor markets, stronger market linkages, and more abundant nonfarm opportunities allow reductions in constraints associated with DFI to translate more effectively into actual labor reallocation. In the central and western regions, limited nonfarm opportunities and weaker market connectivity may prevent improved financial access from generating sizeable shifts in labor allocation, resulting in weaker and statistically insignificant estimates.

Table 8
Heterogeneous analysis: Age.

Dependent variable:	Log (Agricultural working hours) Young Labor Force (< 50 years old)	Log (Off-farm working hours)	Log (Agricultural working hours) Middle-aged and older Labor Force (≥ 50 years old)	Log (Off-farm working hours)
	(1)	(2)	(3)	(4)
DFI index	−0.0335***	0.0306**	−0.0351*	0.0281
	(0.0119)	(0.0128)	(0.0190)	(0.0198)
KP F-statistics	23.278	23.278	22.029	22.029
Individual & Social controls	Yes	Yes	Yes	Yes
Individual *FE*	Yes	Yes	Yes	Yes
Year *FE*	Yes	Yes	Yes	Yes
Observation	9217	9217	9580	9580

Note: Individual and social controls include years of education, age, health status, log of household per capita income, household size, local public budget revenue, and gross industrial output above the designated size. Standard errors are clustered at the county level and reported in parentheses. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9
Heterogeneous analysis: Region.

Dependent variable:	Log (Agricultural working hours) Eastern Region	Log (Off-farm working hours)	Log (Agricultural working hours) Central Region	Log (Off-farm working hours)	Log (Agricultural working hours) Western Region	Log (Off-farm working hours)
	(1)	(2)	(3)	(4)	(5)	(6)
DFI index	−0.0365***	0.0442***	0.0081	−0.0198	−0.0125	0.0397
	(0.0093)	(0.0099)	(0.0376)	(0.0335)	(0.0653)	(0.0815)
KP F-statistics	16.058	16.058	12.529	12.529	15.146	15.146
Individual & Social controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual *FE*	Yes	Yes	Yes	Yes	Yes	Yes
Year *FE*	Yes	Yes	Yes	Yes	Yes	Yes
Observation	7505	7505	5621	5621	5651	5651

Note: Individual and social controls include years of education, age, health status, log of household per capita income, household size, local public budget revenue, and gross industrial output above the designated size. Standard errors are clustered at the county level and reported in parentheses. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6. Conclusions and policy implications

6.1. *Conclusions*

Extensive research has documented the positive socio-economic effects of DFI, including its role in fostering innovation and entrepreneurship (Xie et al., 2018; Xun et al., 2020), promoting household consumption (Li and Feng, 2020; Yi and Zhou, 2018), and enhancing firm performance (Gaspar et al., 2024; Wehrheim et al., 2020). Building on this literature, this study uses four waves of individual-level panel data from China to provide new evidence that DFI significantly affects rural labor allocation by facilitating the transition of labor from agriculture to off-farm sectors.

First, we find that a one-unit increase in the DFI index leads to a 3.66 % reduction in agricultural labor time and a 3.23 % increase in off-farm labor time, with results robust across multiple specifications.

Second, mechanism analysis suggests that DFI promotes labor reallocation primarily through two margins: (i) the non-farm entry margin (credit-constraint alleviation), whereby DFI relaxes financial constraints and lowers the financial and risk-related barriers to entering off-farm activities through entrepreneurship and spatial mobility; and (ii) the agricultural exit margin (land adjustment), whereby DFI is associated with more active land leasing and land-use adjustment that facilitate smallholders' exit from, or downscaling of, agricultural production as they shift labor to off-farm work.

Third, heterogeneity analysis shows that the effects of DFI are more pronounced among farmers with lower education levels, younger age groups, and those living in eastern regions. This underscores the inclusive nature of DFI in enabling economically disadvantaged rural populations to access off-farm employment opportunities, while also highlighting the uneven impact of digital finance across regions with varying levels of development and infrastructure.

This paper makes three key contributions. First, it departs from the binary employment framework commonly used in prior studies and instead examines labor supply intensity using continuous measures of agricultural and off-farm labor time, thus providing a more nuanced understanding of labor reallocation. Second, by exploiting geographic variation in proximity to Hangzhou—the headquarters of a major digital finance platform—as an instrumental variable, we address endogeneity concerns and offer more credible causal estimates. Third, we identify and empirically test two distinct mechanisms—non-farm entry margin (credit-constraint alleviation) and agricultural exit margin (land adjustment)—thereby advancing the theoretical understanding of how DFI reshapes rural labor dynamics.

In light of these contributions, it is important to situate our findings within the broader international discourse on digital financial inclusion. Our results resonate with global evidence on the role of DFI in fostering economic participation and structural transformation. For example, studies from India (Ghosh and Hom Chaudhury, 2022) and Kenya (Bharadwaj and Suri, 2020) show that digital finance can help households manage risk and diversify income sources. However, the Chinese context presents notable differences, including the dominant role of large private digital platforms (e.g., Ant Financial), widespread mobile internet access, and relatively advanced digital infrastructure even in rural areas. These institutional and technological features may amplify the effects of DFI on rural labor mobility, particularly by facilitating land transfers and access to credit. As such, our findings contribute to a broader understanding of how digital finance interacts with rural labor markets under diverse development models.

6.2. Policy implications

This study examines how DFI affects rural labor allocation, particularly by facilitating the transition from agricultural to off-farm employment. Empirical results confirm two central mechanisms through which DFI operates: alleviating financial constraints and enabling land transfer. Based on these findings, we offer four policy recommendations to enhance the developmental impact of DFI, with attention to regional disparities and group-specific barriers.

First, embed DFI more explicitly within the rural revitalization strategy (A national strategy aimed at promoting the development of rural areas in China) to expand both the breadth and depth of financial access in underserved areas. Our results suggest that higher levels of DFI significantly reduce agricultural labor input and increase off-farm labor participation, thereby accelerating structural transformation. Policymakers should actively promote the integration of digital financial services—such as mobile credit, payments, and insurance—into remote rural regions. Strengthening digital infrastructure and incentivizing cooperation between formal financial institutions and platform-based providers can improve financial reach, especially in central and western China.

Second, lower financial entry barriers to off-farm employment by promoting inclusive and targeted financial products. Given that younger, less-educated farmers are particularly responsive to DFI, tailored microcredit and guarantee schemes could support their entrepreneurial and migration decisions. At the same time, embedding digital literacy and financial skills training into rural labor and entrepreneurship programs can reduce usage frictions and expand effective demand for DFI services.

Third, promote the formalization and digitization of rural land transfer markets. Our findings show that DFI facilitates land transfer by improving liquidity and supporting exit decisions among smallholders. Yet current rural land markets remain hampered by high transaction costs and institutional frictions. Developing transparent and secure digital land transaction platforms, supported by appropriate regulatory frameworks, can reduce search and enforcement costs and unlock greater labor mobility.

Fourth, adopt regionally differentiated policy strategies to ensure inclusive access to DFI. Since DFI effects are stronger in more developed eastern regions, targeted public investment in digital infrastructure should prioritize lagging areas, especially those with poor mobile connectivity and low financial penetration. Simultaneously, supporting marginalized groups—such as older farmers, women, and migrant households—through adaptive outreach, bundled services, and community-based digital support systems will further enhance the inclusive potential of DFI.

6.3. Limitations and future research

Several limitations remain that warrant further investigation.

First, this study is based on panel data from 2014 to 2020, a period that primarily captures the short-term effects of digital financial inclusion during its expansion and institutionalization in rural China. Future research could extend the sample to include more recent data to explore the long-term impacts of DFI in its mature phase.

Second, while we use a geography-based instrumental variable to address endogeneity concerns, the location choices of digital finance institutions may still involve potential selection bias. Future studies could employ policy experiments or natural experiments to further validate causal relationships.

Third, due to data limitations, this paper adopts a static analytical framework that focuses on short- to medium-term labor reallocation between agricultural and non-agricultural sectors. As a result, it does not capture the dynamic effects of DFI on human capital accumulation or long-term employment trajectories. In addition, because the CFPS sample mainly covers smallholder farmers, the mechanism analysis reflects behavioral responses primarily within this group. Future research could build on this foundation by combining dynamic models with multi-source data to examine the long-term effects and heterogeneity of DFI's impact.

CRediT authorship contribution statement

Haijian Ye: Writing – original draft, Conceptualization. **Ze Chen:** Methodology. **Chen Xu:** Formal analysis, Data curation.

Appendix

Table A1
Robustness check.

	Alternative index				Removed municipalities	Alternative Cluster (City)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *Dependent variable*: Log (Agricultural working hours)						
DFI-PCA	−0.0511***				−0.0144***	−0.0366***
	(0.0131)				(0.0050)	(0.0129)
Breadth of coverage index		−0.0323***				
		(0.0062)				
Depth of use index			−0.0643***			
			(0.0142)			
Degree of digitalization index				−0.0547***		
				(0.0189)		
KP F-statistics	22.642	22.726	29.211	19.122	18.650	19.650
Panel B: *Dependent variable*: Log (Off-farm working hours)						
DFI-PCA	0.0482***				0.0182***	0.0323**
	(0.0136)				(0.0066)	(0.0136)
Breadth of coverage index		0.0306***				
		(0.0053)				
Depth of use index			0.0625***			
			(0.0149)			
Degree of digitalization index				0.0565***		
				(0.0194)		
KP F-statistics	22.642	22.726	29.211	19.122	18.650	19.650
Observation	18,797	18,797	18,797	18,797	17,765	18,797

Note: The specification is consistent with the baseline model, including time fixed effects, individual fixed effects, and control variables. Individual & social controls include years of education, age, health status, log of household per capita income, household size, local public budget revenue, and gross industrial output above the designated size. Standard errors are reported in parentheses. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2
Baseline regression (2SLS) using different fixed effects.

Dependent variable:	Log (Agricultural working hours)		Log (Off-farm working hours)	
	(1)	(2)	(3)	(4)
DFI index	−0.0530***	−0.0443***	0.0533***	0.0413***
	(0.0030)	(0.0065)	(0.0031)	(0.0068)
KP F-statistics	23.561	20.671	23.561	20.671
Individual & Social controls	Yes	Yes	Yes	Yes
Province-by-year *FE*	Yes	No	Yes	No
City-by-year *FE*	No	Yes	No	Yes
Individual *FE*	Yes	Yes	Yes	Yes

Note: $N = 18{,}797$. Individual and social controls include years of education, age, health status, log of household per capita income, household size, local public budget revenue, and gross industrial output above the designated size. Standard errors are clustered at the county level and reported in parentheses. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3
Alternative IV: Distance to provincial capital.

Panel A: *1st-stage estimation*	*Dependent variable*: DFI index
	(1)
Distance to Pro. capital × Dummy (Year = 2014)	−6.0980***
	(1.4831)
Distance to Pro. capital × Dummy (Year = 2018)	−2.3154***
	(0.3408)
Distance to Pro. capital × Dummy (Year = 2020)	−1.9205***
	(0.3941)

Panel B: *2nd-stage estimation*	*Dependent variable*:	
	Log (Agricultural working hours)	Log (Off-farm working hours)
	(1)	(2)
DFI index	−0.0269**	0.0283**

(*continued on next page*)

Table A3 (*continued*)

	(0.0119)	(0.0126)
KP F-statistics	21.978	21.978
Individual & Social controls	Yes	Yes
Individual *FE*	Yes	Yes
Year *FE*	Yes	Yes

Note: $N = 18{,}797$. We use the *distance to the provincial capital* as an instrumental variable for robustness checks. Individual and social controls include years of education, age, health status, log of household per capita income, household size, local public budget revenue, and gross industrial output above the designated size. Standard errors are clustered at the county level and reported in parentheses. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4
Placebo test using distance to different cities as instruments.

Panel A:	*Dependent variable*:			
	Log (Agricultural working hours)			
	(1)	(2)	(3)	(4)
DFI index	−0.0366***	−0.0300	−0.0595	−0.0222
	(0.0116)	(0.0262)	(0.0543)	(0.0337)
Panel B:	*Dependent variable*:			
	Log (Off-farm working hours)			
	(1)	(2)	(3)	(4)
DFI index	0.0323***	0.0256	0.0387	0.0128
	(0.0122)	(0.0273)	(0.0541)	(0.0348)
Distance to different city	Hangzhou	Wenzhou	Changsha	Nanjing
KP F-statistics	21.978	22.707	19.853	21.395
Individual & Social controls	Yes	Yes	Yes	Yes
Individual *FE*	Yes	Yes	Yes	Yes
Year *FE*	Yes	Yes	Yes	Yes

Note: $N = 18{,}797$. Individual and social controls include years of education, age, health status, log of household per capita income, household size, local public budget revenue, and gross industrial output above the designated size. Standard errors are clustered at the county level and reported in parentheses. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5
Excluding counties within different radii from Hangzhou.

Panel A:	*Dependent variable*:			
	Log (Agricultural working hours)			
	(1)	(2)	(3)	(4)
DFI index	−0.0366***	−0.0344***	−0.0284***	−0.0367***
	(0.0116)	(0.0046)	(0.0098)	(0.0111)
Panel B:	*Dependent variable*:			
	Log (Off-farm working hours)			
	(1)	(2)	(3)	(4)
DFI index	0.0323***	0.0370***	0.0316***	0.0342***
	(0.0122)	(0.0067)	(0.0121)	(0.0105)
Exclusion radius	0 km	100 km	300 km	900 km
KP F-statistics	21.978	20.385	18.670	18.189
Individual & Social controls	Yes	Yes	Yes	Yes
Individual *FE*	Yes	Yes	Yes	Yes
Year *FE*	Yes	Yes	Yes	Yes
Observation	18,797	18,683	17,356	11,656

Note: Individual and social controls include years of education, age, health status, log of household per capita income, household size, local public budget revenue, and gross industrial output above the designated size. Standard errors are clustered at the county level and reported in parentheses. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6
Alternative IV: Non-distance instruments.

Panel A: *1st-stage estimation*	*Dependent variable*: DFI index	
	(1)	(2)
Lightning × DFI Grow	−0.0242***	
	(0.0038)	

(*continued on next page*)

Table A6 (*continued*)

Lightning × Fiber Grow			−0.7115***	
			(0.0642)	
Panel B: *2nd-stage estimation*	*Dependent variable*:			
	Log (Agricultural working hours) (1)	Log (Off-farm working hours) (2)	Log (Agricultural working hours) (3)	Log (Off-farm working hours) (4)
DFI index	−0.0813***	0.0922***	−0.0919***	0.1032***
	(0.0237)	(0.0246)	(0.0268)	(0.0280)
KP F-statistics	41.397	41.397	138.180	138.180
Individual & Social controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Individual *FE*	Yes	Yes	Yes	Yes
Year *FE*	Yes	Yes	Yes	Yes

Note: $N = 16{,}204$. Panel A and Panel B reports first and second-stage regressions, respective. The instrument is constructed as the interaction between a predetermined county exposure and a national shifter: **Lightning** × g_t. *Lightning* is the county's long-run average lightning density (annual lightning strikes per km^2) computed over 1995–2014. g_t is measured alternatively by the national DFI growth rate (col. 1) or the national long-distance fiber backbone growth rate (col. 2). Individual and social controls include years of education, age, health status, log of household per capita income, household size, local public budget revenue, and gross industrial output above the designated size. Standard errors are clustered at the county level and reported in parentheses. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

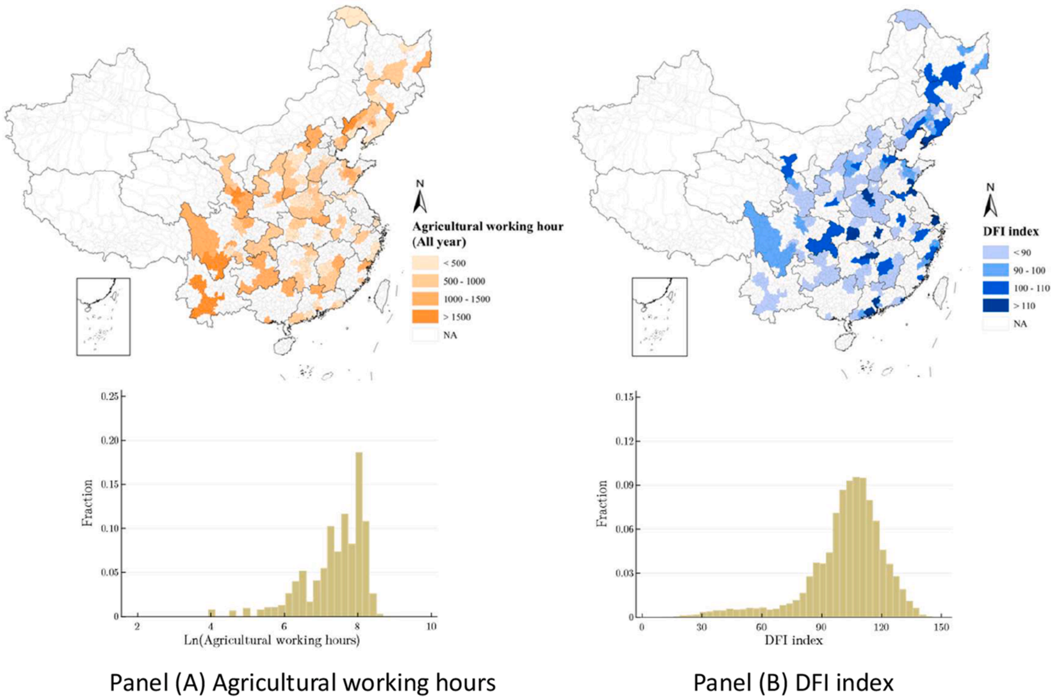
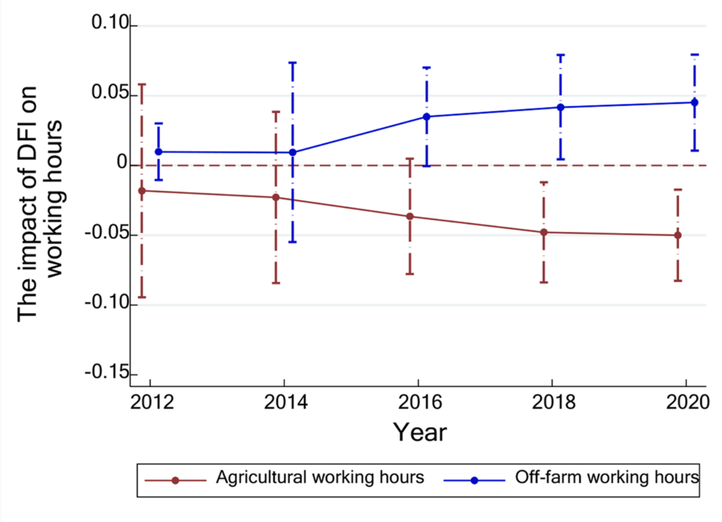
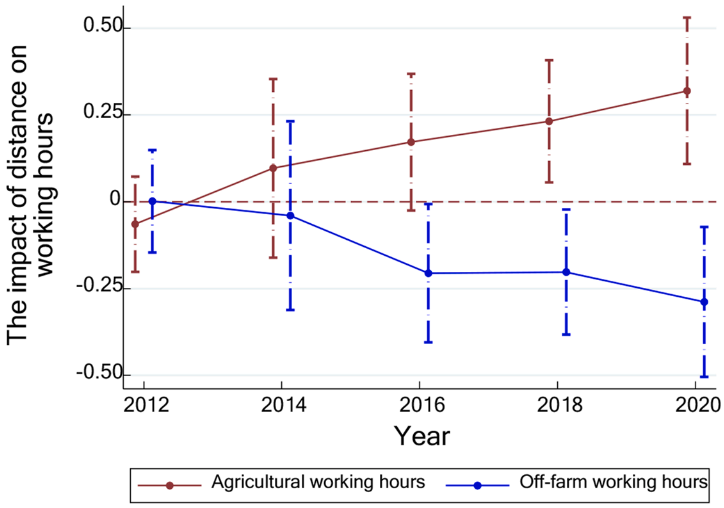


Fig. A1. Agricultural working hours and DFI index over 2014–2020.
Note: This figure illustrates the spatial distribution of agricultural working hours (Panel A) and the DFI index (Panel B) across regions in the study sample during the period 2014–2020. The color intensity on the maps indicates the magnitude of each variable, and the accompanying histograms below provide a visual representation of their distributional characteristics. Extreme values have been appropriately adjusted to more accurately reflect the structural features of the variables within the main sample. This highlights the regional disparities in DFI development. All maps are based on the GS(2019)1822 authorization and adopt the "Beijing 1954 GK_18N" projected coordinate system. The complete nine-dash line is displayed in the inset box on the left.



Panel A The impact of DFI on agricultural and off-farm working hours



Panel B The impact of distance to Hangzhou on agricultural and off-farm working hours

Fig. A2. The impact of DFI and distance to Hangzhou on labor allocation.

Note: This figure presents the estimated effects of digital financial inclusion (DFI) and the instrumental variable (distance to Hangzhou) on rural labor allocation across survey years. Panel A reports the two-stage results using distance to Hangzhou as the instrument for DFI. Panel B shows the reduced-form estimates. Blue lines represent off-farm working hours, and brown lines represent agricultural working hours. The effects are insignificant in 2012–2014 but become significant after 2016, consistent with the rapid diffusion of digital finance. Vertical bars denote 95 % confidence intervals.

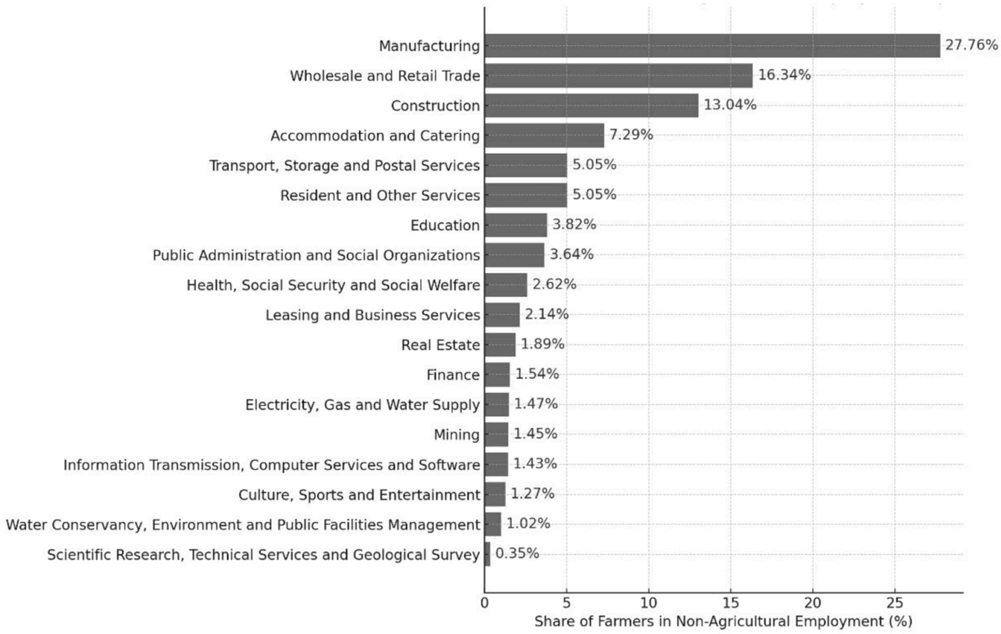


Fig. A3. Distribution of farmers' non-agricultural employment by industry.
Note: This figure shows the distribution of rural households' non-agricultural employment across different industries based on the CFPS sample. Farmers' off-farm employment is highly concentrated in labor-intensive and low-entry-barrier sectors. Manufacturing (27.8 %), wholesale and retail trade (16.3 %), construction (13.0 %), accommodation and catering (7.3 %), transport, storage and postal services (5.0 %), and resident and other services (5.0 %) together account for nearly 75 % of total non-agricultural employment.

References

Angrist, J., Krueger, A.B., 1994. Why do World War II veterans earn more than nonveterans? J. Labor. Econ. 12 (1), 74–97.

Angrist, J.D., Imbens, G.W., Rubin, D.B., 1996. Identification of causal effects using instrumental variables. J. Am. Stat. Assoc. 91 (434), 444–455.

Bai, Y., Jia, R., 2016. Elite Recruitment and Political Stability: the Impact of the Abolition of China's Civil Service Exam. Econometrica 84 (2), 677–733. https://doi.org/10.3982/ecta13448.

Becha, H., Kalai, M., Houidi, S., Helali, K., 2025. Digital financial inclusion, environmental sustainability and regional economic growth in China: insights from a panel threshold model. J. Econ. Struct. 14 (1), 4.

Beck, T., Demirgüç-Kunt, A., Levine, R., 2007. Finance, inequality and the poor. J. Econ. Growth 12, 27–49.

Berger, A.N., Udell, G.F., 2006. A more complete conceptual framework for SME finance. J. Bank. Financ. 30 (11), 2945–2966.

Bharadwaj, P., Suri, T., 2020. Improving financial inclusion through digital savings and credit. In: Paper presented at the AEA Papers and Proceedings.

Cernisevs, O., Surmach, A., Buka, S., 2022. Analysis of aspects of the regional economy in the digital economy, us-ing the example of financial services. Rev. Econ. Finance 20, 203–207.

Chen, Y., Huang, R., Zeng, Y., Huang, Q., 2024. Research on the impact of digital inclusive finance on the performance of rural returnee entrepreneurs in China. Sci. Rep. 14 (1), 22077.

Conley, T.G., Hansen, C.B., Rossi, P.E., 2012. Plausibly exogenous. Rev. Econ. Stat. 94 (1), 260–272.

Czernich, N., Falck, O., Kretschmer, T., Woessmann, L., 2011. Broadband infrastructure and economic growth. Econ. J. 121 (552), 505–532.

Ding, G., Kang, N., 2024. The impact of digital financial inclusion on China's regional disparities in the quality of economic development: based on the relational data paradigm. Econ. Anal. Policy. 81, 629–651.

Fu, Q., Huang, Y., 2018. Digital finance's heterogeneous effects on rural financial demand: evidence from China household finance survey and inclusive digital finance index. J. Financ. Res. 11, 68–84.

Fu, Y., Yi, Z., 2023. Multi-province comparisons of digital financial inclusion performance in China: a group ranking method with preference analysis. China Econ. Rev. 80, 102014.

Garcia-Louzao, J., Tarasonis, L., 2023. Productivity-enhancing reallocation during the Great Recession: evidence from Lithuania. Oxf. Econ. Pap. 75 (3), 729–749.

Gaspar, J.-M., Wang, S., Xu, L., 2024. Digitalization and the performance of non-technological firms: evidence from the COVID-19 and natural disaster shocks. J. Corpor. Finance 89, 102670.

Ghosh, C., Hom Chaudhury, R., 2022. Determinants of digital finance in India. Innov. Dev. 12 (3), 343–362.

Guo, F., Kong, T., Wang, J., Zhang, X., Cheng, Z., Ruan, F., . . . Wang, F. (2019). The Peking University Digital Financial Inclusion Index of China.

Han, L., Lv, Q., Zhang, Q., 2025. Digital financial inclusion, credit access and non-farm employment. Fina. Rese. Lett. 72, 106510.

Han, X., Zhang, H., Zhu, W., 2023. The impact of digital finance on women's bargaining power: evidence from China. China Econ. Rev. 80. https://doi.org/10.1016/j.chieco.2023.102007.

Karaivanov, A., 2012. Financial constraints and occupational choice in Thai villages. J. Dev. Econ. 97 (2), 201–220.

Kling, G., Pesqué-Cela, V., Tian, L., Luo, D., 2022. A theory of financial inclusion and income inequality. Eur. J. Finance 28 (1), 137–157.

Lee, C.-C., Lou, R., Wang, F., 2023. Digital financial inclusion and poverty alleviation: evidence from the sustainable development of China. Econ. Anal. Policy. 77, 418–434.

Li, M., Feng, S., 2020. Digital financial inclusion and urban-rural income gap: a literature based analysis. Contemp. Econ. Manage. 42, 93–102.

Li, W., 2024. Structural change, labour reallocation, and productivity growth in post-reform China. Oxf. Econ. Pap. 76 (4), 1147–1167.

Liu, Y., Liu, C., Zhou, M., 2021. Does digital inclusive finance promote agricultural production for rural households in China? Research based on the Chinese family database (CFD). China Agric. Econ. Rev. 13 (2), 475–494.

Luo, G., Yang, Y., Wang, L., 2023. Driving rural industry revitalization in the digital economy era: exploring strategies and pathways in China. PLoS. One 18 (9), e0292241.

Ma, J., Wang, A., Luo, S., Weng, Z., He, K., 2025. Where to Go: how Does Digital Finance Influence Labor Mobility Preferences?—A Dual Perspective on Regional and Industry Mobility. Popul. Space Place 31 (3), e70025.

Manacorda, M., Tesei, A., 2020. Liberation technology: mobile phones and political mobilization in Africa. Econometrica 88 (2), 533–567.

Niu, G., Jin, X., Wang, Q., Zhou, Y., 2022. Broadband infrastructure and digital financial inclusion in rural China. China Econ. Rev. 76, 101853.

Peng, P., Mao, H., 2023. The effect of digital financial inclusion on relative poverty among urban households: a case study on China. Soc. Indic. Res. 165 (2), 377–407.

Qiao, X., He, Y., Du, Q., 2025. How does the urban digital economy drive labor allocation in China?—A perspective of factor mobility between digital and non-digital enterprises. Econ. Anal. Policy. 85, 1159–1175.

Ren, J., Gao, T., Shi, X., Chen, X., Mu, K., 2023. The impact and heterogeneity analysis of digital financial inclusion on non-farm employment of rural labor. Chin. J. Popul., Resour. Environ. 21 (2), 103–110.

Shen, Y., Guo, X., Zhang, X., 2023. Digital financial inclusion, land transfer, and agricultural green total factor productivity. Sustainability. 15 (8), 6436.

Song, X., 2017. Empirical analysis of digital inclusive finance bridging the urban-rural residents' income gap. Finance Econ. 6, 14–25.

Stock, J.H., Wright, J.H., Yogo, M., 2002. A survey of weak instruments and weak identification in generalized method of moments. J. Bus. Econ. Stat. 20 (4), 518–529.

Tian, L., Li, Z., Shi, B., 2025. Cloud Adoption and Corporate Innovation: insights from Data as a Factor of Production. J. *World Econ.* 48, 178–210.

Tu, Y., Wu, S., Chen, B., Weng, Q., Bai, Y., Yang, J., Xu, B., 2024. A 30 m annual cropland dataset of China from 1986 to 2021. Earth. Syst. Sci. Data 16 (5), 2297–2316.

Wang, X., Wang, X., Ren, X., Wen, F., 2022. Can digital financial inclusion affect CO2 emissions of China at the prefecture level? Evidence from a spatial econometric approach. Energy Econ. 109, 105966.

Wang, Y., Qi, Y., Li, Y., 2024a. How does digital inclusive finance influence non-agricultural employment among the rural labor force?——Evidence from micro-data in China. Heliyon. 10 (13).

Wang, Y., Zhao, Z., Lu, C., 2024b. Does digital inclusive finance increase land rent? Evidence from rural China. Econ. Anal. Policy. 82, 1025–1043.

Wang, Z., 2022. Digital finance, financing constraint and enterprise financial risk. J. Math. 2022 (1), 2882113.

Wehrheim, D., Dalay, H.D., Fosfuri, A., Helmers, C., 2020. How mixed ownership affects decision making in turbulent times: evidence from the digital revolution in telecommunications. J. Corp. Finance 64, 101626.

Xie, X., Shen, Y., Zhang, H., Guo, F., 2018. Can digital finance promote entrepreneurship? Evidence from China. China Econ. Quart. 17 (4), 1557–1580.

Xun, Z., Guanghua, W., Jiajia, Z., Zongyue, H., 2020. Digital economy, financial inclusion and inclusive growth. China Econ. 15 (3), 92–105.

Yang, B., Ma, F., Deng, W., Pi, Y., 2022. Digital inclusive finance and rural household subsistence consumption in China. Econ. Anal. Policy. 76, 627–642.

Yang, L., Geng, Z., 2022. Impact of digital financial inclusion on optimization of employment structure: evidence from China. Appl. Econ. 54 (57), 6625–6638.

Yang, T., Zhang, X., 2022. FinTech adoption and financial inclusion: evidence from household consumption in China. J. Bank. Financ. 145, 106668.

Yi, X., Zhou, L., 2018. Does digital financial inclusion significantly influence household consumption? Evidence from household survey data in China. J. Financ. Res. 11 (461), 47–67.

Yin, X., Chen, Y.-E., Chang, C.-P., 2025. The effectiveness of China's fiscal subsidy policies in supporting the development of rural inclusive finance. Econ. Anal. Policy. 85, 392–406.

Yu, C., Hui, E.C.-m., Dong, Z., 2024. Digital inclusive finance and entrepreneurship in rural areas: evidence from China. China Agric. Econ. Rev.

Yu, C., Jia, N., Li, W., Wu, R., 2022. Digital inclusive finance and rural consumption structure–evidence from Peking University digital inclusive financial index and China household finance survey. China Agric. Econ. Rev. 14 (1), 165–183.

Zhan, Y., Gao, D., Feng, M., Yan, S., 2025. Digital finance, non-agricultural employment, and the income-increasing effect on rural households. Int. Rev. Financ. Anal. 98, 103897.

Zhang, X., Li, J., Xiang, D., Worthington, A.C., 2023. Digitalization, financial inclusion, and small and medium-sized enterprise financing: evidence from China. Econ. Model. 126, 106410.