

Article

Towards Sustainable Income Growth: Exploring the Impact of Digital Financial Inclusion on Household Income Based on Chinese Micro-Survey Data

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Abstract

Digital financial inclusion (DFI) can broaden financial access for households historically underserved by traditional finance, yet the magnitude of its effect on household income and the channels through which it operates remain underexplored. This study examines the causal effect of DFI on household income and its mechanisms. We match the Peking University Digital Financial Inclusion Index (2011–2023) with household microdata from the China Family Panel Studies (2012–2022) at the prefecture-year level, yielding an unbalanced panel of 32,789 household-year observations across 105 prefecture-level cities. Using two-way fixed-effects models with instrumental-variable estimation to address endogeneity, we find that DFI significantly raises household income, a result robust to alternative measures, sample restrictions, and a difference-in-differences design. The effect operates through two channels, improved credit accessibility and greater participation in risky assets, and these gains are not accompanied by higher household leverage or financial fragility. The effects are stronger where local financial and market institutions are more developed, indicating a capability-dependent form of inclusion. By clarifying the causal effect and mechanisms linking DFI to household income, the study offers practical guidance for policies promoting sustainable, broadly shared income growth through digital finance.

Keywords: digital financial inclusion; household income; credit accessibility; risky asset allocation; financial fragility

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1. Introduction

Raising household income in a sustained and broadly shared manner is a central objective of development policy, particularly in emerging economies where large segments of the population remain financially underserved. Over the past decade, income growth has been markedly uneven across the global economy: per capita income has expanded far more rapidly in developing countries than in developed ones, with China growing at the frontier of this group (Figure 1). Indeed, China recorded the highest average annual growth among major economies over 2010–2024, at 8.42%. Access to finance has long been regarded as a lever for such growth: by lowering transaction costs, smoothing consumption, and easing the credit and liquidity constraints that bind low-income households and small entrepreneurs, it can support higher and more resilient incomes [1]. Yet these ben-

efits have been distributed unevenly: conventional banking systems, reliant on physical branches and collateral-based lending, tend to serve a relatively affluent minority while leaving low-income and rural households at the margins of the formal system. China offers an especially instructive setting in which to examine these issues. Its national per capita disposable income rose markedly over 2010–2024, more than tripling over the period (Figure 2). As broadening financial access has become an explicit national policy priority [2], these features make China a valuable setting for studying the income effects of digital financial inclusion (DFI).

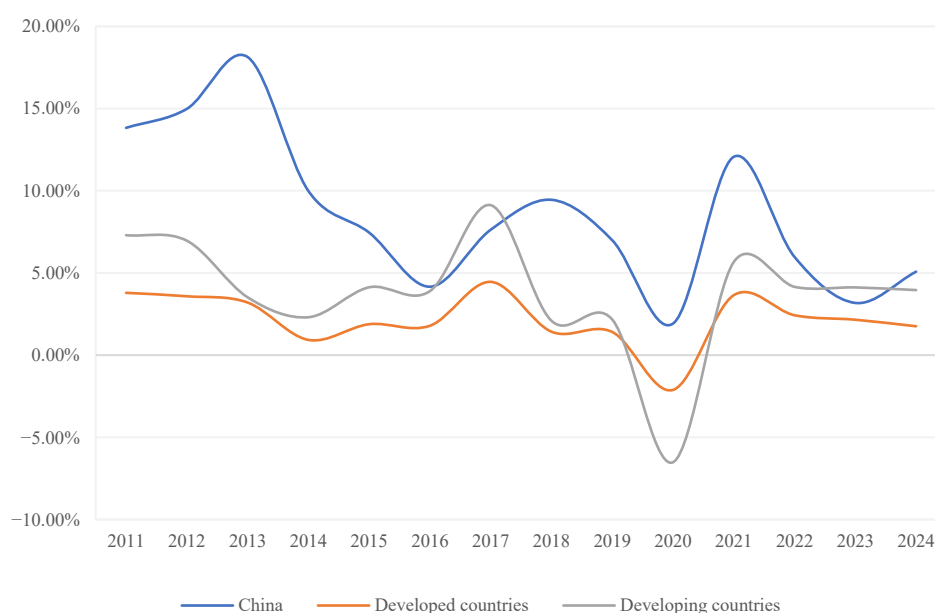


Figure 1. Per capita GNI growth in China, developed countries, and developing countries. Source: World Development Indicators. Notes: The vertical axis reports the annual growth rate of per capita gross national income (GNI). “Developed countries” denotes the simple average of the United States, Germany, Japan, and South Korea; “developing countries” denotes the simple average of Russia, Brazil, India, and Indonesia; China is shown separately.

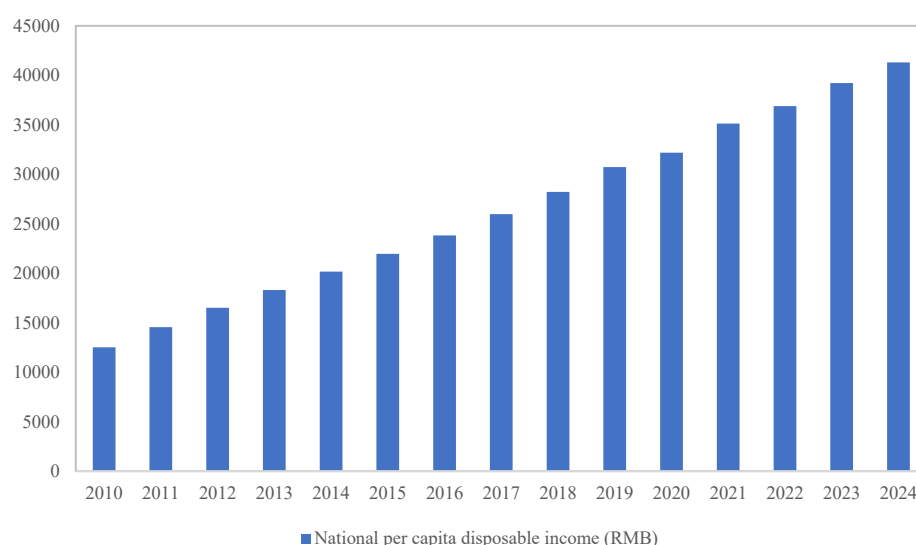


Figure 2. National per capita disposable income in China. Source: National Bureau of Statistics of China. Notes: Values are annual national per capita disposable income, measured in current RMB.

The expansion of DFI has been especially rapid in China, where it has reshaped how households access financial services. Built on mobile internet and fintech innovation, DFI lowers transaction costs, overcomes geographic barriers, and extends credit, payment, and investment services to households and small businesses that the traditional banking system struggled to reach; China's mobile payment and digital lending markets are among the world's largest. A defining feature is that it substitutes data for collateral: using transactional records and digital footprints, fintech lenders can reach borrowers who lack verifiable credit histories or pledgeable assets and would otherwise be rationed out of the conventional system [3,4]. These tools have real effects: in China, the access to fintech credit raises the sales and transaction growth of small vendors, with the largest gains accruing to those with greater information asymmetry and less collateral, precisely the borrowers that traditional finance underserves [5]. This broadening of access is unlikely to stop at how households manage their money: by easing liquidity and credit constraints and widening their investment opportunities, DFI may also shape the incomes they can generate. Even so, while a growing literature documents the consequences of DFI for consumption and financial-market participation, its effect on household income, and especially the channels involved, has received comparatively less attention. Establishing whether, and through which channels, DFI translates into higher household income is therefore of considerable academic and policy relevance, and it is the question this study sets out to answer.

DFI can plausibly raise household income through two main channels, while a third, exclusionary test, speaks to whether any such gains are sustainable. The first channel operates through access to credit. In imperfect credit markets, information asymmetries and collateral requirements lead lenders to ration credit away from households that lack documented credit histories or pledgeable assets, constraining their ability to invest in education, health, and productive or entrepreneurial activities [6,7]. By easing these constraints, DFI can extend credit to such households and unlock these investments, thereby raising their income [8]. The second channel operates through participation in risky financial markets. A large body of household-finance research shows that many households, especially less wealthy ones, hold few or no risky financial assets and therefore forgo the higher expected returns these assets offer [9,10]. By lowering entry thresholds, transaction costs, and information barriers, DFI broadens participation and helps households improve the risk-return profile of their portfolios [11,12]. Because both channels work through borrowing and risk-taking, a natural concern is that income gains might come at the cost of higher leverage and greater exposure to shocks [13,14]. For these income gains to be sustainable, it is not enough that income rises: the increase must be durable and broadly shared, and must be achieved without a build-up of household debt or financial fragility, so that households' financial resilience is strengthened rather than eroded [15,16]. We accordingly complement these income-generating channels with an examination of household leverage and financial fragility, asking whether DFI-driven gains are accompanied by rising indebtedness or instead coincide with improved liquidity and risk-sharing that leave households no more fragile [17,18]. Distinguishing these channels matters because they carry distinct welfare implications and speak directly to whether the income gains from DFI are sustainable rather than debt-driven.

This study examines the causal effect of DFI on household income in China and the channels through which it operates. We match prefecture-level measures of DFI with household microdata, estimate the relationship within a two-way fixed-effects framework, address endogeneity with an instrumental-variable strategy, and confirm the results through a battery of additional robustness checks. The study makes three contributions. First, it provides causal evidence that DFI raises household income and shows that the effect extends to its main components: estimated separately, DFI significantly increases

wage income, property income, and business income. Second, the mechanism analysis shows that DFI raises income by broadening households' access to credit and increasing the amount they borrow, and by providing them with a channel to participate in risky financial markets; crucially, it does so without raising household leverage or financial fragility, so the income gains reflect a sustainable expansion of financial access rather than a build-up of debt. Third, it shows that the income effect is uneven, being stronger for households and regions with greater capital endowments and with higher levels of regional development, marketization, and digital infrastructure, a pattern best described as capability-dependent inclusion.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 sets out the theoretical analysis and develops the research hypotheses. Section 4 describes the research design, including the data, variables, and empirical strategy. Section 5 presents the empirical results, baseline estimates, treatment of endogeneity, robustness checks, mechanism analysis, and heterogeneity in how contextual conditions shape the income effect of DFI, and concludes with a further analysis of its distributional effects. Section 6 offers concluding remarks and discusses the policy implications.

2. Literature Review

2.1. *The Concept and Determinants of Household Income*

Household income is conventionally defined as the total resources a household receives over a given period, and it is typically broken down into several components: wage income, property income from financial and physical assets, business income from household enterprises, and transfer income from public and private sources. Because these components respond to different forces, the level and composition of household income reflect a layered set of determinants operating at the individual, household, and contextual levels. At the individual level, human capital theory treats education and health as primary determinants of earnings, since they raise labor productivity and broaden access to higher-paying employment [19], while age and the dependency structure trace out the familiar life-cycle profile of income. At the household level, asset holdings, financial-market participation, physical capital, and entrepreneurial activity jointly shape the capacity to generate labor, property, and business income; the rapidly expanding household-finance literature shows that how households save, borrow, and allocate their portfolios translates into sizable and persistent differences in income and wealth [20]. At the contextual level, regional development, the quality of markets and institutions, and infrastructure condition the returns households earn on their endowments, producing persistent gaps across regions and between urban and rural areas.

Among these determinants, access to finance occupies a central place. Well-functioning financial systems can raise household income by mobilizing savings, channeling capital to its most productive uses, and relaxing the constraints households face in financing investment, education, and health. Where access is unequal, however, the gains accrue disproportionately to wealthier households, and credit-market imperfections can entrench initial disparities; even so, the balance of evidence suggests that broadening financial access tends to expand economic opportunity and, on net, to narrow inequality [21]. Recent micro-level evidence reinforces this view: improved financial access raises consumption and resilience in developing settings [1], and, in China, rising DFI is associated with higher household income [2]. This literature motivates a focus on the financial channel as a lever for household income, while leaving open how newer, digital forms of access reshape the relationship.

2.2. *The Economic and Social Effects of DFI*

A growing literature documents the wide-ranging effects of DFI on households. By lowering transaction costs and overcoming geographic barriers, digital finance stimulates household consumption and helps smooth it against shocks: in China, fintech adoption has been shown to raise household consumption [22,23], while cross-country evidence from developing countries finds that mobile money reduces consumption volatility [24]. Digital finance also supports entrepreneurship and small-business activity and strengthens household resilience by improving risk-sharing and access to liquidity [25], with longer-run benefits that include lifting households out of poverty.

Evidence on distributional effects, by contrast, is more mixed. Some studies find that DFI disproportionately benefits previously excluded, lower-income, and rural households, and can enhance upward income mobility, thereby narrowing disparities [18]. Others caution that unequal digital access, infrastructure, and financial literacy may allow better-endowed households to capture a larger share of the gains: in China, for instance, lower-income households benefit mainly through labor income while wealthier ones gain more from property income, pointing to a possible new form of inequality in the digital era [2]. Taken together, this evidence suggests that the effects of DFI are unlikely to be uniform and may depend on the surrounding economic and institutional environment [26], a contingency that prior work has not fully resolved, and one that this study addresses directly.

2.3. *Credit Access, Financial-Market Participation, and Household Income*

A further strand of research examines the specific channels through which financial access shapes household income. The first is credit access. Under imperfect information, credit is rationed away from borrowers who lack collateral or credit histories [6]; relaxing these constraints allows households to invest in human capital, entrepreneurship, and productive assets, raising subsequent income, an effect documented causally for expansions of formal financial access [27]. Digital lending sharpens this channel: by screening borrowers with alternative data rather than collateral, fintech platforms reach households and small firms that traditional lenders bypass [4]. The second channel is participation in financial markets. The household-finance literature shows that risky asset participation is an important source of returns, yet many households, especially less wealthy ones, underparticipate because of high entry thresholds, information costs, and limited financial literacy [9,20]. By lowering these barriers, DFI may broaden participation and improve portfolio efficiency, as recent evidence from China suggests [11].

A third dimension concerns household financial fragility, on which the literature is divided. One view stresses the risks of credit expansion: easier borrowing can raise household leverage and amplify vulnerability to income and asset-price shocks, and elevated household debt has been shown to predict weaker subsequent growth and deeper downturns [13]. A competing view emphasizes the resilience-enhancing role of digital finance, which lowers the cost of payments, saving, and remittances and improves access to emergency liquidity and informal risk-sharing [24]; consistent with this, recent evidence from China finds that DFI reduces household financial vulnerability [18]. Because these forces pull in opposite directions, whether DFI ultimately raises or lowers household leverage and fragility, and hence whether the income gains it generates are sustainable, remains an open empirical question.

2.4. *Summary and Research Gaps*

Taken together, the literature establishes that financial access matters for household income and points to credit access, risky asset participation, and financial fragility as the relevant channels. Three questions nonetheless remain less fully resolved. First, a considerable part of the evidence linking DFI to household income is associational in nature:

because DFI adoption tends to move together with local economic conditions, isolating its causal effect can be challenging, and comparatively few studies address this identification problem directly. Second, the transmission mechanisms are more often posited than subjected to direct empirical testing; in particular, whether DFI-driven income gains are accompanied by higher household leverage and financial fragility, and are therefore sustainable rather than debt-driven, has received comparatively little attention. Third, the conditions under which DFI actually delivers income gains, and especially the possibility that its returns depend on local financial, market, and institutional development, have so far received comparatively less systematic attention.

3. Theoretical Analysis

3.1. Theoretical Foundations

The analysis rests on four theoretical pillars. First, financial development theory holds that financial systems raise income by mitigating information asymmetries and transaction costs and by improving the efficiency of resource allocation [28,29]. DFI extends this logic to the household: by sharply reducing the fixed costs and geographic frictions that have historically limited the reach of formal finance, it brings previously excluded households within the ambit of the financial system. Second, credit-constraint theory posits that, under imperfect capital markets, collateral requirements and information asymmetries ration credit away from households that lack established credit records, constraining their investment in human capital and productive activities and, in turn, their income [30]. By relaxing these constraints, DFI expands the set of income-generating activities available to constrained households. Third, portfolio and household-finance theory implies that access to a broader and lower-cost menu of financial instruments allows households to improve the risk-return profile of their savings, making investment income a meaningful component of total income [9]. DFI lowers the entry thresholds and information costs that keep many households out of these markets, enabling wider participation. Fourth, theories of household financial resilience and over-indebtedness consider how borrowing alters a household's exposure to shocks: leverage can amplify vulnerability when income or asset prices fall [31], yet better access to liquidity, risk-sharing, and more stable income can strengthen a household's capacity to absorb shocks and reduce the likelihood of financial distress [17]. Together, these pillars imply that DFI may raise household income through the credit and participation channels, while its net effect on financial fragility remains theoretically ambiguous, an ambiguity this study resolves empirically.

3.2. Mechanism Analysis and Hypotheses

Building on these foundations, we develop the channels through which DFI affects household income and financial resilience. The effect follows from financial development theory, which holds that financial systems raise income by mitigating information asymmetries and transaction costs and improving the efficiency of resource allocation. By using digital technologies to lower entry barriers and usage costs, DFI enables broader household participation in the formal financial system, allowing previously underserved households to access credit, payment, and investment services. As financial frictions fall and access deepens, these improvements are expected to translate into higher household income. This leads to our first hypothesis:

Hypothesis 1 (H1). *The development of DFI increases total household income.*

The first channel through which this effect operates is credit access, and it follows from credit-constraint theory. Because digital lending platforms draw on alternative data,

such as e-commerce and mobile-payment records, and rely on automated screening, they can extend credit to households that lack conventional collateral or formal credit histories [3]. The resulting access to startup capital and liquidity helps households overcome financing constraints in entrepreneurship, agricultural production, and human capital investment, thereby raising their earning capacity; consistent with this logic, fintech credit has been shown to boost the growth of small businesses in China [5]. Accordingly:

Hypothesis 2 (H2). *DFI raises household income by improving household credit accessibility.*

The second channel operates through participation in risky financial markets, and it follows from portfolio and household-finance theory. Traditional finance imposes high minimum thresholds, information costs, and financial literacy requirements, leading low-income and rural households to hold portfolios concentrated in low-yield savings and cash. By offering low-threshold products and digital advisory services, DFI lowers these barriers and enables households to reallocate toward higher-return assets and earn additional investment income [32]. This yields:

Hypothesis 3 (H3). *DFI raises household income by facilitating household participation in risky asset markets.*

Beyond the level of income, DFI may also shape the sustainability of household finances by affecting leverage and financial fragility, and the direction of this effect is theoretically ambiguous. As noted above, the direction of this effect is theoretically ambiguous: easing credit constraints lets households borrow more and could raise leverage, whereas cheaper payments, better access to emergency liquidity, improved risk-sharing, and higher, more stable income can lower the debt-service burden relative to income and the likelihood of financial distress even as nominal borrowing rises. We expect the resilience-enhancing forces to dominate, consistent with recent evidence that DFI reduces household financial fragility in China [18]. If so, the income gains from DFI will be accompanied by lower, rather than higher, leverage and fragility, indicating that the gains are sustainable. We therefore hypothesize:

Hypothesis 4 (H4). *DFI reduces household leverage and financial fragility.*

4. Research Design

4.1. Data Source and Sample Construction

Our analysis draws on three authoritative data sources. Regional digital finance is measured by the Peking University Digital Financial Inclusion Index (PKU-DFIIC), jointly compiled by Peking University and Ant Group from large-scale anonymized transaction records; it provides annual prefecture-level measures along coverage breadth, usage depth, and digitalization degree, and is the most widely used measure of DFI development in China [33,34]. Household microdata come from the China Family Panel Studies (CFPS), a nationally representative biennial survey conducted by the Institute of Social Science Survey at Peking University [35,36]; we use the six waves from 2012 to 2022. Prefecture-level macroeconomic indicators are obtained from the Chinese Research Data Services (CNRDS) database.

We match the CFPS data with the PKU-DFIIC by prefecture and year and merge in the CNRDS macroeconomic variables. After dropping observations with missing values or unmatched prefecture codes, the final sample is an unbalanced panel of 32,789 household-year observations across 105 prefecture-level cities.

4.2. Variable Definitions

The dependent variable is the natural logarithm of total annual household income (lnHHInc), defined as the sum of wage, business, property, and transfer income. The key independent variable is regional DFI, measured by the PKU-DFIIC and scaled by 100 in the regressions [33,34]. Following the literature [36,37], we include controls at three levels: household-head characteristics comprise gender, age and its square, marital status, educational attainment, and health status. Household characteristics comprise household size, the child and elderly dependency ratios, net assets, and hukou (household-registration) status. Prefecture-level conditions comprise GDP per capita, internet penetration, and the level of financial development. Detailed variable definitions and data sources are reported in Table 1.

Table 1. Variable definitions.

Variables	Definition	Source
HHInc	Annual total household income.	CFPS
DFI	City-level digital financial inclusion index compiled by Peking University's Institute of Digital Finance.	DFIIC
Male	Dummy variable: equals 1 if the household head is male.	CFPS
Age	Age of the household head.	CFPS
Age2	Square of the household head's age.	CFPS
Edu	Years of education of the household head (0 = illiterate/semi-literate; 6 = primary school; 9 = junior high school; 12 = senior high school/vocational school; 15 = associate degree; 16 = bachelor's degree; 19 = master's degree; 22 = doctoral degree).	CFPS
Health	Self-reported health status of the household head, measured on a five-point scale ranging from 1 to 5, with higher values indicating better health.	CFPS
Married	Dummy variable: equals 1 if the household head is married.	CFPS
HHSIZE	Number of permanent residents in the household.	CFPS
Child	Ratio of children (aged ≤ 15) to working-age adults in the household	CFPS
Old	Ratio of elderly members (aged ≥ 65) to working-age adults in the household.	CFPS
HHAsset	Total household assets minus total liabilities, including financial assets, real estate, and land valuations.	CFPS
Urban	Dummy variable: equals 1 if the household head holds urban hukou.	CFPS
GDP	Year-on-year GDP growth rate at the prefecture level.	CNRDS
Internet	Share of regular internet users at the provincial level, measured as the number of internet broadband access ports per capita.	CNRDS
FinDev	Ratio of outstanding loans from financial institutions to GDP at the prefecture level.	CNRDS

4.3. Model Specification

To examine the effect of DFI on household income, we estimate the following two-way fixed-effects model:

$$\ln HHInc_level_{i,c,t} = \alpha_0 + \beta_1 DFI_{c,t-1} + \gamma X_{i,c,t} + \theta_i + \delta_t + \varepsilon_{i,c,t} \quad (1)$$

$$HHInc_struct_{ij,c,t} = \alpha_1 + \beta_2 DFI_{c,t-1} + \gamma X_{i,c,t} + \theta_i + \delta_t + \varepsilon_{ij,c,t} \quad (2)$$

where $\ln HHInc_level_{i,c,t}$ is the logarithm of household income and $HHInc_struct_{ij,c,t}$ is the level of income component j (wage, property, or business incomes) for household for i in prefecture c in year. α_0 represents the constant term. The independent variable, $DFI_{c,t-1}$, is the one-period lagged level of DFI in prefecture c , lagged to mitigate reverse-causality concerns [19]. $X_{i,c,t}$ is a vector of household-head, household, and regional controls; θ_i and δ_t denote household and year fixed effects; and $\varepsilon_{i,c,t}$ is the idiosyncratic error. Standard errors are clustered at the prefecture level. The coefficient β_1 identifies

the overall effect of DFI on household income, and β_2 its differential effect across income components.

Table 2 reports descriptive statistics for the main variables. Mean annual household income is approximately RMB 59,600. The rescaled DFI index averages 1.71 and ranges from 0.32 to 3.33, indicating substantial variation both across prefectures and over time, which we exploit to identify the effect of DFI on household income. The remaining household and regional characteristics fall within plausible ranges and are broadly consistent with China's socioeconomic conditions during the study period.

Table 2. Descriptive statistics.

Variables	Mean	SD	Min	Max	N
HHInc	5.96	6.01	0.03	39.60	32,789
DFI	1.71	0.77	0.32	3.33	32,789
Male	0.78	0.49	0.00	1.00	32,789
Age	48.64	12.14	16.00	92.00	32,789
Age2	25.14	11.88	2.56	84.64	32,789
Edu	7.85	4.50	0.00	22.00	32,789
Health	2.89	1.20	1.00	5.00	32,789
Married	0.84	0.32	0.00	1.00	32,789
HHSIZE	2.95	1.34	1.00	11.00	32,789
Child	0.31	0.44	0.00	5.00	32,789
Old	0.18	0.40	0.00	3.00	32,789
HHAsset	45.81	94.28	0.00	5008.88	32,789
Urban	0.45	0.50	0.00	1.00	32,789
GDP	6.77	4.03	−20.63	15.90	32,789
Internet	0.51	0.20	0.18	0.98	32,789
FinDev	0.03	0.07	0.00	0.67	32,789

5. Empirical Results

5.1. Baseline Regression Analysis Results

The baseline regression results are reported in Table 3. Column (1) includes only household and year fixed effects: the DFI coefficient is 1.171 and significant at the 1% level, indicating a positive association between DFI and household income. Column (2) adds household-head controls; the coefficient falls to 0.935 but remains significant at the 1% level. The controls carry plausible signs; education, health, and being married are each positively associated with income. Column (3) adds household-level controls, and the DFI coefficient declines to 0.754, still significant at the 1% level. Column (4) further adds prefecture-level controls, yielding a coefficient of 0.656, again significant at the 1% level. Across all four specifications, the DFI coefficient stays positive and highly significant, providing robust evidence consistent with H1.

The estimate is also economically meaningful. Based on Column (4), a one-unit increase in the rescaled DFI index, equivalent to a 100-point increase in the original index, is associated with an increase in household income of roughly 66%. Because a 100-point change is large (about the gap between the 25th and 75th percentiles of the sample), we also consider a more modest 0.1-unit increase in the rescaled index (a 10-point increase in the original index, roughly one-eighth of a standard deviation), which corresponds to about a 6.6% increase in household income. For comparison, an additional year of education is associated with about a 4.4% increase in income, and a one-standard-deviation increase in household net assets with about a 19.4% increase. The effect of DFI is therefore not only statistically robust but also economically substantial, reinforcing the practical case for advancing DFI as a lever for household income growth.

Table 3. Baseline regression results.

	(1)	(2)	(3)	(4)
DFI	1.171 *** (0.040)	0.935 *** (0.038)	0.754 *** (0.036)	0.656 *** (0.042)
Male		−0.066 *** (0.016)	−0.078 *** (0.015)	−0.065 *** (0.015)
Age		0.001 (0.004)	−0.016 *** (0.004)	−0.016 *** (0.004)
Age2		−0.002 (0.004)	0.017 *** (0.004)	0.016 *** (0.004)
Edu		0.059 *** (0.002)	0.048 *** (0.002)	0.044 *** (0.002)
Health		0.036 *** (0.006)	0.018 *** (0.006)	0.018 *** (0.006)
Married		0.377 *** (0.029)	0.096 *** (0.026)	0.104 *** (0.025)
HHSIZE			0.196 *** (0.005)	0.200 *** (0.005)
Child			−0.009 (0.017)	−0.006 (0.017)
Old			−0.184 *** (0.019)	−0.186 *** (0.019)
HHAsset			0.214 *** (0.007)	0.206 *** (0.007)
Urban				0.135 *** (0.016)
GDP				0.244 *** (0.095)
Internet				0.161 * (0.082)
FinDev				0.047 (0.098)
Constant	8.446 *** (0.069)	7.963 *** (0.117)	5.896 *** (0.124)	6.020 *** (0.129)
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Observations	32,789	32,789	32,789	32,789
Adjusted R ²	0.145	0.199	0.296	0.298

Notes: Table 3 reports baseline regression results. The dependent variable is the logarithm of household annual income. Column (1) includes only DFI without control variables. Column (2) adds household head characteristics (age, education, gender, health status). Column (3) further adds family characteristics (household size, marital status, dependency ratio, urban status). Column (4) adds city-level controls (GDP per capita, internet penetration rate, and financial development index). Standard errors are clustered at the city level and are reported in parentheses. ***, and * denote significance at the 1%, and 10% levels, respectively.

Table 4 reports the effects of DFI on different sources of household income, using wage, property, and business income as the dependent variables in Columns (1)–(3). DFI raises all three components significantly, with coefficients of 3.664 (wage income), 0.179 (property income), and 0.659 (business income), each significant at the 1% level. The effect is thus broad-based across income sources rather than confined to a single category. This

indicates that DFI not only raises total household income but also reshapes its composition.

Table 4. The effects of DFI on different sources of household income.

	(1)	(2)	(3)
	Wage Income	Property Income	Business Income
DFI	3.664 *** (0.221)	0.179 *** (0.063)	0.659 *** (0.151)
Constant	−12.515 *** (0.738)	−1.897 *** (0.231)	−6.503 *** (0.551)
Year FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Observations	32,789	32,789	32,789
Adjusted R ²	0.102	0.029	0.058

Notes: Table 4 reports the effects of DFI on household income composition. The dependent variables are wage income, property income, and business income in Columns (1)–(3), respectively. Standard errors are clustered at the city level and are reported in parentheses. *** denotes significance at the 1% levels.

5.2. Endogenous Treatment

Although our specifications include household and year fixed effects and a rich set of controls, DFI may still be correlated with unobserved local shocks that also affect household income, so that the fixed-effects estimates may remain biased by endogeneity. To address this concern, we adopt an instrumental-variable (IV) strategy that uses three instruments drawn from two distinct domains: historical communication infrastructure and economic geography. Each instrument takes a shift-share (Bartik) form, interacting a pre-determined cross-sectional measure with a time-varying national shifter. Following the literature [38], we treat the identifying assumption as resting on the exogeneity of the pre-determined cross-sectional component, which is plausibly unrelated to contemporaneous shocks to household income.

5.2.1. Historical Communication Infrastructure Instruments

We construct two instruments from China's historical communication infrastructure. The first interacts with the number of post and telecommunications offices in each city in 1984, with the lagged national number of Internet users. Cities with denser early postal-telecommunications networks built out digital infrastructure, and subsequently digital finance, earlier and more intensively, because the postal system historically carried the rollout of fixed-telephone lines, and early Internet access ran over the telephone network; this satisfies the relevance condition. The second instrument interacts the length of long-distance optical-fiber cable lines in 2002 with the lagged national number of broadband access ports, since optical-fiber forms the physical backbone for broadband connectivity and thus for the diffusion of digital finance. For both instruments, the cross-sectional component is fixed well before the large-scale expansion of digital finance and was shaped largely by national network planning and geography rather than by contemporaneous household income; its direct economic relevance has faded over time, leaving the diffusion of digital finance as the plausible remaining channel through which it affects household income.

Table 5 reports the IV estimates. In the first stage (Column 1), the historical-telecom instrument is strong and highly significant, with a Kleibergen–Paap rk Wald F statistic of 3255.9, far above conventional weak-instrument thresholds, and the Kleibergen–Paap rk LM statistic rejects underidentification. In the second stage (Column 2), the coefficient on

DFI is positive, highly significant, and equal to 0.849, somewhat larger than the baseline fixed-effects estimate, while the weak-instrument-robust Anderson–Rubin test rejects the null of no effect. Adding the optical-fiber instrument (Columns 3–4) leaves this conclusion intact: both instruments are individually significant in the first stage (1.169 and 0.377), the first-stage F remains very large (1693.0), and the second-stage coefficient on DFI is essentially unchanged at 0.836. Crucially, the Hansen J statistic ($p = 0.114$) does not reject the joint validity of the two instruments. Overall, the positive effect of DFI on household income is robust to address endogeneity.

Table 5. Instrumental variables estimation: historical infrastructure instruments.

	(1) First Stage	(2) Second Stage	(3) First Stage	(4) Second Stage
	DFI	lnHHInc	DFI	lnHHInc
Post1984 × Internet	1.164 *** (0.020)		1.169 *** (0.020)	
Fiber2002 × Ports			0.377 *** (0.064)	
DFI		0.849 *** (0.086)		0.836 *** (0.086)
Constant	0.128 *** (0.018)	6.388 *** (0.118)	0.120 *** (0.018)	6.389 *** (0.118)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Adjusted R ²	0.967	0.297	0.967	0.298
Kleibergen–Paap rk Wald F	3255.887		1693.006	
Kleibergen–Paap rk LM (<i>p</i> -value)	1459.610 (0.000)		1687.100 (0.000)	
Anderson–Rubin test (<i>p</i> -value)		95.550 (0.000)		47.850 (0.000)
Hansen J statistic (<i>p</i> -value)				2.498 (0.114)
Observations	32,789	32,789	32,789	32,789

Notes: Table 5 reports two-stage least squares (2SLS) estimates of the effect of DFI on log household income. Columns (1)–(2) use a single instrument, Post1984 × Internet, defined as the interaction of the number of posts in each city in 1984 and the lagged national number of Internet users. Columns (3)–(4) add a second instrument, Fiber2002 × Ports, the interaction of the length of long-distance optical-fiber cable lines in 2002 and the lagged national number of broadband access ports. Columns (1) and (3) report the first stage; columns (2) and (4) report the second stage. Standard errors clustered at the prefecture level in parentheses. *** denotes significance at the 1% levels.

5.2.2. A Geographic-Distance Instrument: Distance to Hangzhou

The third instrument interacts each city’s great-circle distance to Hangzhou with the leave-one-out national mean of the digital finance index. Hangzhou is the operational hub from which China’s digital finance diffused outward, so proximity to it predicts the speed and depth of local adoption; at the same time, distance is fixed by physical geography and is plausibly orthogonal to time-varying, city-specific determinants of household income once observable regional characteristics and fixed effects are controlled for [39]. Excluding a city’s own index from the national mean (the leave-one-out construction) ensures that the shifter is not mechanically driven by the city’s own level of digital finance.

Table 6 reports the estimates based on the distance instrument. In the first stage (Column 1), the instrument enters negatively and significantly: cities farther from Hangzhou exhibit lower levels of digital-finance development, consistent with the relevance condition. The Kleibergen–Paap rk Wald F statistic of 4306.6 far exceeds conventional weak-instrument thresholds, and the Kleibergen–Paap rk LM statistic rejects underidentification. In the second stage (Column 2), the coefficient on DFI is positive and highly significant at 0.750, and the weak-instrument-robust Anderson–Rubin test again rejects the null of no effect. This estimate is of similar magnitude to those obtained with the historical-infrastructure instruments in Table 5 (0.849 and 0.836). That instruments drawn from very different sources—economic geography and historical communication infrastructure—yield consistent conclusions substantially strengthens the case for a causal interpretation.

Table 6. Instrumental variables estimation: geographic distance instrument.

	(1) First Stage	(2) Second Stage
	DFI	lnHHInc
Distance × National DFI	−1.170 *** (0.018)	
DFI		0.750 *** (0.080)
Constant	0.354 *** (0.018)	6.394 *** (0.118)
Controls	Yes	Yes
Year FE	Yes	Yes
Household FE	Yes	Yes
Adjusted R ²	0.968	0.298
Kleibergen–Paap rk Wald F	4306.575	
Kleibergen–Paap rk LM (p-value)	1967.08 (0.000)	
Anderson–Rubin test (p-value)		86.680 (0.000)
Observations	32,789	32,789

Notes: Table 6 reports 2SLS estimates of the effect of DFI on log household income, using a single instrument, Distance × National DFI, defined as the interaction of the great-circle distance from each city to Hangzhou and the contemporaneous national mean of the digital finance index (excluding the city's own index). Column (1) reports the first stage and column (2) the second stage. Standard errors clustered at the prefecture level in parentheses. *** denotes significance at the 1% levels.

5.3. Robustness Checks

5.3.1. Alternative Measures of Household Income

To assess sensitivity to how household income is measured, we re-estimate the baseline model using two alternative dependent variables: household per capita income and household income over the past 12 months. As reported in Columns (1) and (2) of Table 7, the coefficient on DFI remains positive and significant at the 1% level under both measures. The estimated income effect is therefore not an artifact of the particular income definition used in the baseline.

Table 7. Robustness: estimates using alternative income measures.

	(1)	(2)
	Per Capita Income	Past 12 Months Income
DFI	1.238 *** (0.113)	4.652 *** (0.276)

Constant	−3.167 *** (0.309)	−20.387 *** (0.947)
Controls	Yes	Yes
Year FE	Yes	Yes
Household FE	Yes	Yes
Observations	32,789	32,789
Adjusted R ²	0.172	0.272

Notes: Table 7 examines robustness to alternative income measures. Column (1) uses household per capita income (total income divided by household size). Column (2) uses household income over the past 12 months (as opposed to annual income in the baseline). Standard errors are clustered at the city level and are reported in parentheses. *** denotes significance at the 1% levels.

5.3.2. Alternative Measures of DFI

To check whether the baseline results depend on how the DFI index is constructed, we replace the composite index with two of its core sub-dimensions, coverage breadth and usage depth, and estimate the model separately for each. As reported in Columns (1) and (2) of Table 8, both coefficients are positive and significant at the 1% level, indicating that broader coverage of digital financial services and deeper usage each raise household income. The baseline conclusion is therefore not driven by the particular way the composite index is constructed.

Table 8. Alternative measures of DFI.

	(1)	(2)
	Breadth	Depth
Breadth of Coverage	0.465 *** (0.034)	
Depth of Usage		0.486 *** (0.031)
Constant	6.342 *** (0.124)	6.304 *** (0.124)
Controls	Yes	Yes
Year FE	Yes	Yes
Household FE	Yes	Yes
Observations	32,789	32,789
Adjusted R ²	0.297	0.298

Notes: Table 8 examines robustness to alternative measures of DFI. Column (1) uses the breadth of coverage sub-index, which captures geographic penetration and account coverage. Column (2) uses the depth of usage sub-index, which measures the intensity and diversity of digital financial service usage. Standard errors are clustered at the city level and are reported in parentheses. *** denotes significance at the 1% levels.

5.3.3. Restricting the Sample to Working-Age Households

Because the income sources and labor-supply behavior of older households may differ systematically from those of working-age households, retirees could distort the estimates. We therefore restrict the sample to households whose head is aged 60 or below. As Column (1) of Table 9 shows, the DFI coefficient remains 0.655 and significant at the 1% level, indicating that the income-enhancing effect holds among working-age households.

Table 9. Robustness: sample restrictions and DiD.

	(1)	(2)	(3)	(4)
	Age ≤ 60	Non-Entre	Non-Tier 1	DiD
DFI	0.655 *** (0.043)	0.585 *** (0.041)	0.661 *** (0.044)	
Treat × Post				0.142 *** (0.016)
Constant	5.899 *** (0.155)	5.962 *** (0.128)	5.967 *** (0.133)	6.715 *** (0.122)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Observations	30,104	29,497	32,095	32,789
Adjusted R ²	0.298	0.326	0.295	0.293

Notes: Table 9 reports the results of sample restrictions and alternative specifications. Column (1): household heads aged ≤ 60 years old. Column (2): non-entrepreneurs only. Column (3): excluding tier-1 cities. Column (4): DiD specification with Post × Treated interaction. Standard errors are clustered at the city level and are reported in parentheses. *** denotes significance at the 1% levels.

5.3.4. Excluding Entrepreneurial Households

Entrepreneurial households may shape the results through their distinctive financing needs and intensive use of digital financial tools. To rule out this possibility, we exclude them and re-estimate the model. In Column (2) of Table 9, the DFI coefficient is 0.585 and remains significant at the 1% level, indicating that the income effect is not driven by entrepreneurship.

5.3.5. Excluding First-Tier City Households

DFI is far more developed in first-tier cities than elsewhere, so pooling them with other regions could make the estimates disproportionately reflect conditions in the most advanced areas. We therefore exclude households in the four first-tier cities, Beijing, Shanghai, Guangzhou, and Shenzhen. Column (3) of Table 9 shows that the DFI coefficient remains 0.661 and significant at the 1% level, indicating that DFI also raises income in non-first-tier cities, where traditional financial services are thinner and resource endowments weaker; evidence consistent with an inclusive income effect.

5.3.6. Difference-in-Differences (DiD)

As a complementary check, we exploit the staggered rollout of the “Broadband China” policy as a quasi-natural experiment. Beginning in 2013, the State Council designated “Broadband China” demonstration cities in three batches (2014–2016), prioritizing them for digital-infrastructure upgrades that plausibly raised local digital-finance penetration for reasons unrelated to household income [40,41]. We classify households in demonstration cities as treated and those elsewhere as controls, set Post to one in the years after a city’s designation, and estimate a multi-period difference-in-differences model with household and year fixed effects. As Column (4) of Table 9 shows, the Treat × Post coefficient is 0.142 and significant at the 1% level, indicating that households in demonstration cities experienced larger income gains after the policy-reduced-form, policy-based evidence that is consistent with our baseline and IV results.

5.3.7. Controlling for the Provincial Institutional Environment

Provinces differ markedly in institutional quality, regulatory stringency, and the capacity of local governments to implement policy, and these differences could simultaneously shape the diffusion of digital finance and the determination of household income. To address this concern, we augment the baseline specification with three province-level, time-varying controls. Institutional quality is proxied by the development of market intermediaries and the legal environment; the regulatory environment is captured by the intensity of local financial regulation (financial-regulation expenditure relative to financial value added); and the capacity to implement policy is proxied by fiscal self-sufficiency (local general budgetary revenue relative to expenditure). As reported in Column (1) of Table 10, the DFI coefficient remains positive and significant at the 1% level and close to the baseline estimate. The income effect of DFI is therefore robust to controlling for provincial institutional, regulatory, and governance differences, and is not an artifact of cross-provincial variation in the institutional environment.

Table 10. Robustness: controlling for the provincial institutional environment.

	(1)	(2)
	lnHHInc	lnHHInc
DFI	0.595 *** (0.048)	0.611 *** (0.038)
Constant	6.018 *** (0.133)	6.355 *** (0.117)
Controls	Yes	Yes
Year FE	Yes	Yes
Household FE	Yes	Yes
Observations	32,789	32,136
Adjusted R ²	0.299	0.316

Notes: Table 10 augments the baseline specification with three province-level, time-varying controls for the institutional environment: institutional quality (the development of market intermediaries and the legal environment), the intensity of local financial regulation (financial-regulation expenditure relative to financial value added), and fiscal self-sufficiency (local general budgetary revenue relative to expenditure). Standard errors clustered at the prefecture level are reported in parentheses. *** denotes significance at the 1% levels.

5.3.8. Truncating Extreme Values

To verify that the baseline estimate is not driven by outliers, we re-estimate the model on a truncated sample that excludes observations in the top and bottom 1% of household income and the main continuous variables. This leaves 32,136 household-year observations. As reported in Column (2) of Table 10, the coefficient on DFI remains positive and significant at the 1% level, close to the baseline estimate of 0.656. The positive effect of DFI on household income is therefore robust to the treatment of extreme values.

5.4. Mechanism Analysis

5.4.1. The Credit-Access Channel

Credit-constraint theory holds that, in traditional credit markets, information asymmetries, collateral requirements, and high transaction costs lead lenders to ration credit, disproportionately excluding middle- and low-income households, rural residents, and small businesses and thereby constraining their income growth [6]. DFI eases these frictions: by drawing on big-data analytics, algorithmic credit scoring, and automated approval, digital platforms lower screening costs, sharpen default-risk assessment, and

weaken the reliance on collateral [4], while mobile-based delivery overcomes the geographic barriers that leave remote populations underserved [1]. DFI should therefore broaden households' access to credit.

To test this channel, we construct two proxies from the CFPS. Credit denial is a binary indicator equal to one if the household was refused credit when seeking a large loan, and zero otherwise; outstanding loans is the total amount the household currently owes. The two capture the extensive and intensive margins of credit access, respectively. If DFI relaxes credit constraints, it should lower the probability of credit denial and raise household borrowing.

Table 11 reports the results. In Column (1), with credit denial as the dependent variable, the DFI coefficient is -0.090 and significant at the 1% level, indicating that DFI reduces the probability of being denied credit. In Column (2), with outstanding loans as the dependent variable, the coefficient is 0.983 and significant at the 10% level, suggesting that DFI also enables households to borrow more. DFI thus improves credit access along both the extensive margin (fewer denials) and the intensive margin (larger borrowing), supporting H2.

Table 11. Mechanism test: credit access.

	(1)	(2)
	Credit Denial	Outstanding Loans
DFI	-0.090^{***} (0.021)	0.983^* (0.544)
Constant	0.645^{***} (0.056)	-12.589^{***} (2.451)
Controls	Yes	Yes
Year FE	Yes	Yes
Household FE	Yes	Yes
Observations	24,992	24,992
Adjusted R ²	0.279	0.017

Notes: Table 11 reports the credit-access mechanism. The dependent variable is credit denial in Column (1), a binary indicator equal to one if the household was denied credit when seeking a large loan, and zero otherwise, and outstanding loans in Column (2), the total amount currently owed by the household. Standard errors clustered at the prefecture level are reported in parentheses. ***, and * denote significance at the 1%, and 10% levels, respectively.

5.4.2. The Risky Asset Participation Channel

Portfolio theory and the household-finance literature hold that risky assets carry higher expected returns and are an important source of wealth accumulation and property income [9]. Yet information and transaction costs and limited financial literacy keep many low-income, low-wealth households out of equity and mutual-fund markets [20]. DFI lowers these barriers: online trading platforms and robo-advisory services cut participation costs and improve access to information, while fractional and low-threshold products bring risky asset markets within reach of less wealthy households and help them diversify [42]. By facilitating risky asset participation, DFI should help households optimize their asset allocation and broaden their income sources.

To test this channel, we construct two proxies from the CFPS. Risky asset ownership is a binary indicator equal to one if the household holds any risky financial assets, and zero otherwise. Risky asset holdings are the total market value of the household's risky asset portfolio. The two capture the extensive and intensive margins of participation, respectively. If DFI promotes participation, it should raise both the likelihood of holding risky assets and the amount invested.

Table 12 reports the results. In Column (1), the DFI coefficient on risky asset ownership is 0.080 and significant at the 1% level, indicating that DFI raises the likelihood of holding risky assets. In Column (2), the coefficient on risky asset holdings is 1.658 and is also significant at the 1% level, indicating that DFI increases the amount invested. DFI therefore promotes risky asset participation along both the extensive margin (higher ownership) and the intensive margin (larger holdings); by widening access to higher-return assets and supporting portfolio diversification, it raises household income, supporting H3.

Table 12. Mechanism test: risky asset participation.

	(1)	(2)
	Risky Asset Ownership	Risky Asset Holdings
DFI	0.080 *** (0.012)	1.658 *** (0.626)
Constant	−0.448 *** (0.035)	−14.683 *** (3.392)
Controls	Yes	Yes
Year FE	Yes	Yes
Household FE	Yes	Yes
Observations	26,545	26,545
Adjusted R ²	0.227	0.039

Notes: Table 12 reports the risky asset participation mechanism. The dependent variable is risky asset ownership in Column (1), a binary indicator equal to one if the household holds any risky financial assets (stocks, mutual funds, bonds, trust products, foreign-exchange products, or online wealth-management products), and zero otherwise, and risky asset holdings in Column (2), the total market value of the household's risky financial assets. Standard errors are clustered at the prefecture level and reported in parentheses. *** denotes significance at 1%

5.4.3. Downside Risks: Household Leverage and Financial Fragility

The income gains documented above operate partly through expanded credit access and greater participation in financial markets. This raises a natural concern, one central to the literature on the consequences of credit expansion, that easier borrowing could also increase household indebtedness and exposure to financial distress. We therefore examine whether DFI affects two outcomes that bear directly on household financial well-being: the debt-to-income ratio and a composite index of financial fragility, asking whether the income benefits of digital finance come at the cost of greater vulnerability.

As discussed in Section 3, the net effect is theoretically ambiguous: by easing credit constraints, DFI may raise leverage and hence fragility, yet by raising and stabilizing income and facilitating risk-sharing, it may instead strengthen household resilience [1]. Which force dominates is therefore an empirical question, and one that is essential for interpreting our main results.

As reported in Table 13, DFI lowers both the debt-to-income ratio (Column 1) and the financial-fragility index (Column 2), with both coefficients negative and significant at the 1% level. The income gains from DFI therefore do not come at the cost of an unsustainable build-up of household debt or greater financial vulnerability, supporting a welfare-improving and sustainable interpretation of our main findings, consistent with H4.

Table 13. The effect of DFI on household leverage and financial fragility.

	(1)	(2)
	Household Leverage	Financial Fragility
DFI	−0.054 *** (0.018)	−0.208 *** (0.032)
Constant	0.266 *** (0.057)	2.960 *** (0.090)
Controls	Yes	Yes
Year FE	Yes	Yes
Household FE	Yes	Yes
Observations	32,789	32,789
Adjusted R ²	0.008	0.105

Notes: Table 13 reports the estimated effect of DFI on two measures of household financial risk. The dependent variable is the household debt-to-income ratio in Column (1), total outstanding loans divided by total household net income, and a composite financial-fragility index in Column (2), which ranges from 0 to 3 and is constructed from indicators of the income–expenditure balance, the emergency-liquidity buffer, and the debt burden, with higher values denoting greater fragility. Standard errors clustered at the prefecture level are reported in parentheses. *** denotes significance at the 1% levels.

5.5. Heterogeneity Analysis

5.5.1. Heterogeneity by Spatial Geography

China’s regions differ markedly in economic development, digital infrastructure, and financial literacy, disparities rooted in long-standing patterns of agglomeration and uneven development. These differences may make the income effect of DFI vary across space, and the direction is ambiguous a priori. On one hand, areas with more advanced digital infrastructure and deeper financial markets may enable faster adoption and more effective use of digital financial services, so that the returns to digital finance are larger where the surrounding environment is more developed [43]. On the other hand, less developed areas, where financial exclusion is more severe and traditional banking is thinner, may reap particularly large marginal benefits as digital finance fills the gap [18]. We examine this spatial heterogeneity along two dimensions: the east–west divide captured by the Hu Line, and the distinction between urban and rural households.

The Hu Line is a well-established demarcation in Chinese economic geography that captures a long-standing east–west divide in population density and economic development. It reflects a stable spatial pattern of economic activity and factor allocation shaped by geography and history. Because the income effects of DFI depend on the economic opportunities and market depth available locally, they may differ sharply across this divide: areas east of the Hu Line, with denser labor markets and more developed industrial structures, may convert expanded financial access into productive investment and income more effectively than the sparsely populated, less developed west.

We construct a Hu Line dummy equal to one if the household’s prefecture lies east of the line and zero otherwise, and interact it with DFI. As Column (1) of Table 14 shows, the DFI × Hu Line interaction is 0.059 and significant at the 1% level, indicating a stronger income effect east of the line. The split-sample estimates corroborate this: DFI is 0.700 in the east, and 0.630 in the west (Columns 2 and 3), both significant at the 1% level, and a test of the equality of the DFI slope across the two regions is rejected at the 1% level ($p = 0.002$). The eastern estimate is also the more precisely identified, as the western subsample is small (6147 observations). Overall, the income effect of DFI is conditioned by regional

economic structure and market depth, being most pronounced where local economic opportunities are richer.

Table 14. Spatial heterogeneity: east versus west of the Hu Line.

	(1)	(2)	(3)
	Full Sample	East of Hu Line	West of Hu Line
DFI × Hu Line	0.059 *** (0.021)		
Hu Line	−0.149 *** (0.042)		
DFI	0.637 *** (0.055)	0.700 *** (0.050)	0.630 *** (0.209)
Constant	6.039 *** (0.134)	5.927 *** (0.145)	7.007 *** (0.617)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Observations	32,789	26,642	6147
Adjusted R ²	0.299	0.300	0.283
Difference test		0.002	

Notes: Table 14 examines spatial heterogeneity in the income effect of DFI across the Hu Line. Column (1) adds the interaction between DFI and Hu Line, a dummy equal to one if the household's prefecture is located east of the line and zero otherwise; Columns (2) and (3) report split-sample estimates for households east and west of the line, respectively. Standard errors are clustered at the city level and are reported in parentheses. *** denotes significance at the 1% levels.

We next ask whether the income effect of DFI differs between urban and rural households. The direction is not obvious a priori: rural households face greater financial exclusion and might gain more as digital finance fills the gap, whereas urban households may be better able to convert financial access into income [43]. We define Urban as an indicator equal to one for urban households and interact it with DFI, and we also estimate the model separately for the two groups.

Column (1) of Table 15 reports the full-sample specification with the DFI × Urban interaction. The interaction is positive (0.048) and significant at the 1% level, indicating that the income effect of DFI is stronger for urban than for rural households. Columns (2) and (3) confirm this in the split samples: the DFI coefficient is 0.890 for urban households and 0.479 for rural households, both significant at the 1% level, and the difference between them is statistically significant. The income effect of DFI is therefore considerably stronger in urban areas, a capability-dependent pattern rather than one in which the most excluded gain the most.

Table 15. Spatial heterogeneity: urban versus rural.

	(1)	(2)	(3)
	Full Sample	Urban	Rural
DFI × Urban	0.048 *** (0.015)		
Urban	0.051 (0.034)		
DFI	0.631 *** (0.042)	0.890 *** (0.058)	0.479 *** (0.059)
Constant	6.051 ***	5.884 ***	6.125 ***

	(0.131)	(0.187)	(0.186)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Observations	32,789	14,649	18,140
Adjusted R ²	0.298	0.297	0.270
Difference test			0.002

Notes: Table 15 examines heterogeneity in the income effect of DFI between urban and rural households. Column (1) adds the interaction DFI $\times$ Urban; Columns (2) and (3) report split-sample estimates for urban and rural households, respectively. Standard errors clustered at the household level are in parentheses. Standard errors are clustered at the city level and are reported in parentheses. *** denotes significance at the 1% levels.

5.5.2. Heterogeneity by Household Capital Endowments

A household's wealth reflects its material capacity to act on financial opportunities and may shape how much it gains from digital finance [20]. We measure wealth by household net worth, the sum of physical capital (housing, durables, and productive assets) and financial capital (deposits, savings, and securities), net of liabilities, and split households at the median into high- and low-wealth groups.

Column (1) of Table 16 reports the full-sample specification with the DFI $\times$ Wealth interaction. The interaction is positive (0.045) and significant at the 1% level, indicating that the income effect of DFI rises with household wealth. Columns (2) and (3) confirm this: the DFI coefficient is 0.722 for high-wealth households and 0.583 for low-wealth households, both significant at the 1% level, and the difference between them is statistically significant. The income effect of DFI is thus larger for wealthier households, consistent with a capability-dependent pattern in which households with greater collateral, investable funds, and risk-bearing capacity are better able to convert expanded financial access into income [4].

Table 16. Heterogeneity by household wealth.

	(1)	(2)	(3)
	Full Sample	High Wealth	Low Wealth
DFI $\times$ Wealth	0.045 *** (0.015)		
Wealth	−0.143 *** (0.031)		
DFI	0.634 *** (0.042)	0.722 *** (0.055)	0.583 *** (0.054)
Constant	6.074 *** (0.131)	6.116 *** (0.173)	5.838 *** (0.175)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Observations	32,789	18,101	14,688
Adjusted R ²	0.299	0.285	0.323
Difference test			0.002

Notes: Table 16 reports the heterogeneity of the income effect of DFI by household wealth. Column (1) adds the interaction DFI $\times$ Wealth; Columns (2) and (3) report split-sample estimates for households with above- and below-median wealth, respectively. Standard errors are clustered at the city level and are reported in parentheses. *** denotes significance at the 1% levels.

Human capital, the learning capacity, information-processing ability, and financial literacy that come with education, may shape how much households gain from DFI. Because digital financial services are information-intensive and require a degree of technological and financial proficiency, realizing their benefits depends not only on access but on the capacity to understand and act on financial information [44]. Households with more human capital are better able to evaluate digital financial products, weigh risk against return, and channel access into employment, business expansion, or higher investment returns [10,45], and may therefore see larger income gains.

We measure human capital by the educational attainment of the household head and interact it with DFI. As Column (1) of Table 17 shows, the DFI $\times$ Human capital interaction is 0.056 and significant at the 1% level, indicating a stronger income effect for households with higher human capital. The split-sample estimates confirm this: DFI is 0.677 for high human capital households and 0.595 for low human capital households (Columns 2 and 3), both significant at the 1% level, and the difference in the DFI slope across the two groups is significant ($p = 0.009$). Households with greater human capital are thus better positioned to translate access to digital finance into income.

Table 17. Heterogeneity by human capital.

	(1)	(2)	(3)
	Full Sample	High Human Capital	Low Human Capital
DFI $\times$ Human capital	0.056 *** (0.021)		
Human capital	−0.112 *** (0.040)		
DFI	0.613 *** (0.046)	0.677 *** (0.046)	0.595 *** (0.069)
Constant	6.042 *** (0.131)	6.209 *** (0.153)	5.657 *** (0.198)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Observations	32,789	16,395	16,394
Adjusted R ²	0.298	0.346	0.230
Difference test		0.009	

Notes: Table 17 reports the heterogeneity of the income effect of DFI by human capital. Column (1) adds the interaction between DFI and human capital; Columns (2) and (3) report split-sample estimates for households with above- and below-median human capital, respectively. Standard errors are clustered at the city level and are reported in parentheses. *** denotes significance at the 1% levels.

5.5.3. Heterogeneity by the Institutional Environment

Government-business relations (GBR) capture the quality and transparency of local governance and are a central dimension of the institutional environment. Institutional economics holds that effective governance raises economic efficiency by lowering transaction costs and policy uncertainty and strengthening contract enforcement [46], and that the character of these relations determines whether the state acts as a “helping hand” or a “grabbing hand” in resource allocation [47]. Where the relations are supportive and transparent, financial development is more likely to translate into productive activity; where they are strained or opaque, rent-seeking can distort allocation and erode the inclusive benefits of financial expansion [48]. DFI may therefore yield larger income gains where GBR is healthier.

We proxy local institutional quality with a regional GBR index and interact it with DFI. As Column (1) of Table 18 shows, the $DFI \times GBR$ interaction is 0.075 and significant at the 1% level, indicating that a healthier GBR amplifies the income effect of DFI. The split-sample estimates confirm this: DFI is 0.735 in high-GBR regions and 0.490 in low-GBR regions (Columns 2 and 3), both significant at the 1% level, and the difference in the DFI slope across the two groups is significant ($p = 0.005$). The income effect of DFI is thus markedly stronger where local governance is of higher quality and more transparent.

Table 18. Heterogeneity by government-business relations.

	(1)	(2)	(3)
	Full Sample	High GBR	Low GBR
DFI $\times$ GBR	0.075 *** (0.016)		
GBR	−0.114 *** (0.034)		
DFI	0.582 *** (0.046)	0.735 *** (0.057)	0.490 *** (0.068)
Constant	6.110 *** (0.131)	5.825 *** (0.181)	6.510 *** (0.196)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Observations	32,789	16,355	16,434
Adjusted R ²	0.299	0.289	0.298
Difference test		0.005	

Notes: Table 18 reports the heterogeneity of the income effect of DFI by GBR. Column (1) adds the interaction between DFI and GBR; Columns (2) and (3) report split-sample estimates for regions with above- and below-median GBR, respectively. Standard errors are clustered at the city level and are reported in parentheses. *** denotes significance at the 1% levels.

Marketization captures the extent to which market mechanisms, rather than administrative intervention, govern resource allocation and is a key indicator of institutional maturity. Well-functioning market institutions improve allocative efficiency by lowering transaction costs, increasing information transparency, and strengthening property-rights protection. In more marketized environments, financial resources are channeled through competition toward their most productive uses rather than dissipated by institutional frictions, so financial development translates into income more effectively [49,50]. DFI should therefore generate larger income gains where marketization is more advanced.

We proxy marketization with a regional marketization index and interact it with DFI. As Column (1) of Table 19 shows, the $DFI \times$ Marketization interaction is 0.090 and significant at the 1% level, indicating that higher marketization amplifies the income effect of DFI. The split-sample estimates are consistent: DFI is 0.571 in high-marketization regions and 0.521 in low-marketization regions (Columns 2 and 3), both significant at the 1% level, and the difference in the DFI slope across the two groups is significant ($p = 0.004$). The income effect of DFI is thus stronger where market development and institutional efficiency are higher.

Table 19. Heterogeneity by marketization.

	(1)	(2)	(3)
	Full Sample	High Marketization	Low Marketization
DFI × Marketization	0.090 *** (0.020)		
Marketization	−0.089 ** (0.039)		
DFI	0.498 *** (0.051)	0.571 *** (0.054)	0.521 *** (0.085)
Constant	6.133 *** (0.151)	6.232 *** (0.183)	6.299 *** (0.242)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Observations	32,789	16,508	16,281
Adjusted R ²	0.299	0.311	0.234
Difference test			0.004

Notes: Table 19 reports the heterogeneity of the income effect of DFI by marketization. Column (1) adds the interaction between DFI and marketization; Columns (2) and (3) report split-sample estimates for regions with above- and below-median marketization, respectively. Standard errors are clustered at the city level and are reported in parentheses. ***, ** denote significance at the 1%, 5% levels, respectively.

5.5.4. Heterogeneity by Local Financial and Market Environment

Beyond the spatial dimension, we ask whether the income effect of DFI depends on the development of local financial and market institutions, along two dimensions: banking-sector development, proxied by bank-branch density, and product-market development. This is motivated by a long tradition in the finance-and-growth literature showing that the benefits of financial deepening depend on the surrounding institutional environment [51], and by the concern that regional differences in financial and market development may themselves shape the returns to digital finance, partly accounting for the spatial heterogeneity documented above. Digital finance does not operate in isolation: its capacity to expand credit, mobilize savings, and channel funds to productive uses is shaped by the complementary markets and financial infrastructure on which it builds. The direction of this moderating role is ambiguous a priori. Under a substitution view, digital finance matters most where traditional financial and market institutions are underdeveloped, filling the gaps left by the formal system. Under a complementarity view, it instead amplifies the returns to existing infrastructure, so its effect should be stronger where the banking sector and product markets are more developed [49].

We first examine whether the income effect of DFI varies with local banking development, measured by bank-branch density. As Column (1) of Table 20 shows, the DFI × BankDensity interaction is 0.113 and significant at the 1% level, indicating that the income return to DFI rises with the level of local banking development. The split-sample estimates corroborate this: DFI is larger in high-density regions (0.663) than in low-density regions (0.586), both significant at the 1% level, and the between-group difference is significant ($p < 0.001$). This pattern is consistent with a complementarity view, in which digital finance amplifies, rather than substitutes for, the returns to a well-developed banking sector.

Table 20. Heterogeneity by banking-sector development.

	(1)	(2)	(3)
	Full Sample	High Bank Density	Low Bank Density
DFI × BankDensity	0.113 *** (0.018)		
BankDensity	−0.155 *** (0.038)		
DFI	0.588 *** (0.043)	0.663 *** (0.049)	0.586 *** (0.075)
Constant	6.113 *** (0.131)	5.832 *** (0.178)	6.373 *** (0.188)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Observations	32,789	16,013	16,776
Adjusted R ²	0.299	0.318	0.254
Difference test		<0.001	

Notes: Table 20 reports the heterogeneity of the income effect of DFI by banking-sector development, proxied by bank-branch density. Column (1) reports the full sample with the interaction DFI × BankDensity; Columns (2) and (3) report split-sample estimates for regions with above- and below-median bank-branch density, respectively. Standard errors clustered at the prefecture level are reported in parentheses. *** denotes significance at the 1% levels.

We next ask whether the income effect of DFI depends on the development of local product markets (PMD), proxied by the product-market index. As Column (1) of Table 21 shows, the DFI × PMD interaction is 0.055 and significant at the 1% level, and the split-sample estimates point the same way: DFI is larger in regions with more developed product markets (0.640) than in those with less developed markets (0.417), both significant at the 1% level, with the between-group difference significant ($p < 0.001$). Well-functioning product markets thus appear to strengthen households' capacity to translate expanded digital financial access into realized income.

Taken together, these results indicate that the income-enhancing effect of DFI is amplified, rather than offset, by the development of local financial and product markets. This is consistent with a complementarity view of digital finance and reinforces our broader characterization of DFI as a form of capability-dependent inclusion: the returns to digital financial access are conditioned by the surrounding financial and market infrastructure. The findings also speak to the concern that the regional heterogeneity documented earlier might simply reflect underlying differences in financial and market development. Such differences do not confound the effect of DFI; rather, they shape the magnitude of its returns.

Table 21. Heterogeneity by product-market development.

	(1)	(2)	(3)
	Full Sample	High PMD	Low PMD
DFI × PMD	0.055 *** (0.018)		
PMD	−0.053 (0.036)		
DFI	0.589 *** (0.045)	0.640 *** (0.090)	0.417 *** (0.050)
Constant	6.134 ***	6.079 ***	6.676 ***

	(0.132)	(0.194)	(0.186)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Observations	32,789	16,464	16,325
Adjusted R ²	0.298	0.241	0.362
Difference test	<0.001		

Notes: Table 21 reports the heterogeneity of the income effect of DFI by PMD, measured by the product-market index. Column (1) reports the full sample with the interaction DFI $\times$ PMD; Columns (2) and (3) report split-sample estimates for regions with above- and below-median product-market development, respectively. Standard errors clustered at the prefecture level are reported in parentheses. *** denotes significance at the 1% levels.

5.6. Further Analysis: Distributional Implications of DFI

The preceding analysis shows that DFI raises household income; how those gains are distributed is less clear. By extending credit and basic services to previously excluded households, digital finance may disproportionately benefit the poor and narrow inequality; yet if wealthier, more digitally literate households capture more of the gains, it may widen disparities [2]. Which force dominates is an empirical question. We approach it from two angles. First, quantile regressions trace how the income effect of DFI varies across the conditional income distribution, indicating whether lower-income households gain relatively more. Second, we relate DFI to two inequality measures defined at different levels: a household-level relative deprivation index [52], which captures each household's income shortfall relative to the richer households in its reference group, and a regional Atkinson index evaluated at several inequality-aversion parameters ϵ , which weights the lower tail more heavily as ϵ rises. Together, these let us ask not only whether inequality falls but where in the distribution any compression occurs [53]. We treat these results as descriptive rather than as a fully identified causal effect of DFI on inequality and base our conclusions on formal tests rather than on raw coefficient magnitudes.

5.6.1. The Income Effect of DFI Across Income Quantiles

To examine whether the impact of DFI varies across the income distribution, we further estimate quantile regressions at the 10th, 30th, 50th, 70th, and 90th percentiles. Whereas OLS recovers the conditional mean effect, quantile regression traces how DFI affects different points of the conditional income distribution [22]. As reported in Table 22 and Figure 3, the DFI coefficient is positive and significant at the 1% level at every quantile but declines monotonically: 0.790 at the 10th percentile, 0.619 at the 30th, 0.568 at the 50th, 0.559 at the 70th, and 0.508 at the 90th. The marginal effect of DFI is therefore largest at the lower quantiles and smallest at the upper quantiles. This gradient is consistent with the inclusive character of digital finance: households lower in the distribution, who tend to face greater financial exclusion, gain more as DFI lowers entry barriers and eases credit constraints, whereas better-served higher-income households see smaller incremental gains. Because these are conditional quantile effects, they describe heterogeneity among otherwise-similar households.

Table 22. Quantile regression: DFI and household income across the distribution.

	(1)	(2)	(3)	(4)	(5)
	Q10	Q30	Q50	Q70	Q90
DFI	0.790 *** (0.151)	0.619 *** (0.101)	0.568 *** (0.090)	0.559 *** (0.091)	0.508 *** (0.092)
Constant	3.513 ***	5.386 ***	6.704 ***	7.664 ***	8.473 ***

	(0.426)	(0.246)	(0.186)	(0.157)	(0.137)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Observations	32,789	32,789	32,789	32,789	32,789
Pseudo R ²	0.292	0.293	0.293	0.294	0.291

Notes: Table 22 reports quantile regression results. Columns (1)–(5) report estimates at the 10th, 30th, 50th, 70th, and 90th percentiles of the conditional income distribution, respectively. Standard errors are clustered at the city level and are reported in parentheses. *** denotes significance at the 1% levels.

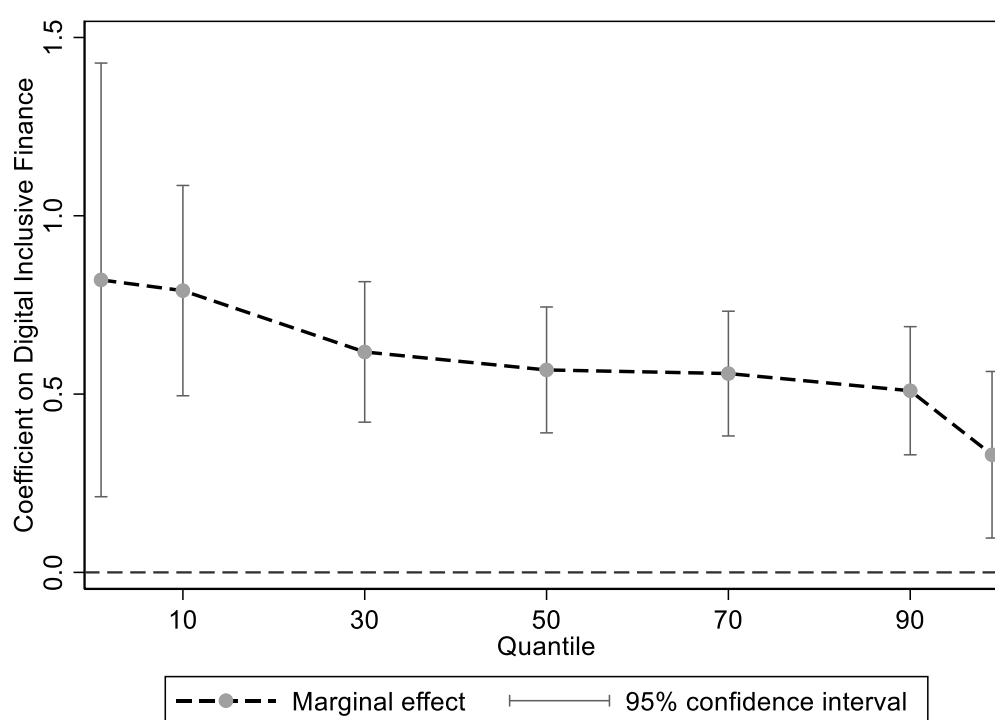


Figure 3. The DFI coefficient across income quantiles. Notes: Figure 3 plots the estimated DFI coefficient at each income quantile, with 95% confidence intervals shown as vertical bars; the dashed line connects the point estimates. The estimates correspond to the quantile regressions reported in Table 21. The coefficient declines monotonically across quantiles, indicating that the marginal income effect of DFI is larger for lower-income households.

5.6.2. Household-Level Relative Deprivation

We measure inequality with a Gini-based index of relative deprivation at the household level, following the standard construction in which each household's deprivation is its income shortfall relative to the richer households in its reference group, and whose mean across households equals mean income times the Gini coefficient. Column (1) of Table 21 shows that DFI enters with a coefficient of -0.813 , significant at the 1% level, where digital finance is more developed, households face lower relative deprivation. The estimate echoes recent evidence that digital finance reaches previously excluded households and benefits poorer ones disproportionately [2], and suggests that DFI improves not only the level of household income but also the relative position of those toward the bottom

5.6.3. Regional Inequality with Varying Aversion Parameters

We next turn to inequality at the regional level, using prefecture-level Atkinson indices computed at three inequality-aversion parameters ($\epsilon = 0.5, 1.0, 2.0$); a higher ϵ places greater weight on the lower tail of the income distribution. As Columns (2)–(4) of Table 23 show, the coefficient on DFI is negative and significant at the 1% level at every ϵ , so DFI is associated with lower regional inequality regardless of how heavily the lower tail is weighted, an association that does not depend on a particular degree of inequality aversion.

Because the Atkinson index is scaled differently at each ϵ , the raw coefficients are not directly comparable across columns. We therefore standardize the indices and compare the standardized DFI coefficients, testing their equality across ϵ using seemingly unrelated estimation. The standardized coefficients are $-0.88, -1.03$, and -1.35 for $\epsilon = 0.5, 1.0$, and 2.0 , increasing in magnitude as ϵ rises, and the differences across ϵ are statistically significant. Because a higher ϵ places greater weight on the lower tail, the inequality-reducing association is strongest precisely where the poorest households count most. We read this as a progressive, lower-tail compression of regional inequality: DFI is associated with larger proportional reductions in inequality at the bottom of the distribution, consistent with the household-level evidence that DFI lowers relative deprivation.

Table 23. DFI and income inequality.

	(1)	(2)	(3)	(4)
	Relative Deprivation Index	Atkinson Index		
		$\epsilon = 0.5$	$\epsilon = 1.0$	$\epsilon = 2.0$
DFI	−0.813 *** (0.009)	−0.049 *** (0.004)	−0.112 *** (0.007)	−0.230 *** (0.016)
Constant	5.642 *** (0.014)	0.294 *** (0.008)	0.636 *** (0.014)	1.191 *** (0.028)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Observations	32,789	32,789	32,789	32,789
Adjusted R ²	0.334	0.691	0.721	0.618

Notes: Table 23 reports the results of DFI and household income inequality. Column (1) uses a household-level relative-deprivation index as the dependent variable. Columns (2)–(4) use the city-level Atkinson indices with inequality-aversion parameters $\epsilon = 0.5, 1.0$, and 2.0 , respectively. Higher values of ϵ assign greater weight to income changes among lower-income groups. Standard errors are clustered at the city level and are reported in parentheses. *** denotes significance at the 1% levels.

6. Conclusions, Discussion, and Policy Recommendations

This study examines the causal effect of DFI on household income in China. Matching prefecture-level data from the PKU-DFIIC with household microdata from the CFPS, we assemble an unbalanced panel of 32,789 household-year observations across 105 prefecture-level cities and estimate two-way fixed-effects models. To address endogeneity, we instrument DFI using predetermined historical communication infrastructure—1984 postal-and-telecommunications density and 2002 optical-fiber cable length—and, as a robustness check, geographic distance to Hangzhou; the instrumental-variable estimates pass over-identification and weak-instrument-robust tests and confirm the baseline result, which is further corroborated by a difference-in-differences design, alternative income and DFI measures, and sample restrictions. We find that DFI significantly and robustly

raises household income. The mechanism analysis shows that these gains operate through two channels—broader credit access and greater participation in risky financial markets—and, importantly, that they are accompanied by lower, not higher, household leverage and financial fragility, indicating that the gains are sustainable rather than debt-driven. The effects are not uniform: in absolute terms, they are larger where digital, financial, and market infrastructure and household capabilities are more developed—in urban areas, east of the Hu Line, in more marketized regions with healthier government-business relations and deeper banking and product markets, and among households with greater human capital and wealth, a pattern we term capability-dependent inclusion. A descriptive distributional analysis offers a complementary picture: the proportional gains are larger at lower income quantiles, and DFI is associated with lower household relative deprivation and lower regional inequality, so that the gains are progressive in relative terms even as better-endowed households gain more in absolute terms.

These findings carry several specific and actionable policy implications.

First, since absolute gains concentrate in better-endowed areas, in lagging regions (west of the Hu Line, central-western and rural counties), broadband and 5G build-out should be paired with on-the-ground usability-agent-banking outlets and rural service stations and interoperable payment systems, and with human capital and local-market investment. Tying fiscal transfers and local-official evaluations to audited benchmarks for infrastructure coverage and active usage would help DFI narrow, rather than widen, absolute regional gaps.

Second, because the income channels require a basic level of financial capability, financial-literacy, and digital-skills programs should target the households least able to use DFI—those with low education, in rural areas, and headed by older adults—delivered through rural cooperatives, village committees, and schools under explicit coverage targets, and embedded in products via simplified interfaces, plain-language disclosure, and advisory features for first-time users. Building this capability is a precondition for converting access into realized income.

Third, since returns are larger where market institutions are stronger, institutional reform complements digital expansion: greater regulatory transparency, faster contract and credit-dispute enforcement, extension of credit-reference coverage to thin-file borrowers, and less discretionary intervention all lower the transaction costs that stand between financial access and productive use. In less-marketized regions, such reform may yield as large a return on DFI as additional infrastructure.

Fourth, although DFI lowers household leverage and fragility on average, expanding digital lending can still harm inexperienced or over-optimistic borrowers. Safeguards should include affordability and suitability checks, standardized disclosure of the total borrowing cost, debt-service-to-income ceilings, stronger financial-consumer protection, and supervisory monitoring of indebtedness with early-warning threshold-preserving income gains without rising fragility.

Fifth, because the relative gains, though progressive, still favor better-endowed households in absolute terms, a standing framework should track take-up, returns, and indebtedness by income group, region, and household type, letting policymakers detect exclusionary effects early and redirect capability-building and infrastructure toward groups for whom access has not yet translated into income.

Several limitations should be acknowledged. First, although our identification strategy combines an instrumental-variable approach and passes standard diagnostic tests, the exclusion restrictions underlying the instruments cannot be tested directly, and some residual endogeneity may remain. Second, household income in the CFPS is self-reported and subject to measurement error; while error in the dependent variable does not bias our estimates, systematic under-reporting correlated with DFI cannot be entirely ruled out.

Third, the distributional analysis is descriptive rather than causally identified and should be read as suggestive; isolating the causal effect of DFI on inequality remains an open task. Fourth, the structural changes in China's digital-finance environment since 2023 limit the extrapolation of our estimates to the current period. Future research could exploit more granular or transaction-level data to trace the mechanisms more precisely, examine additional channels such as job-matching and human capital investment, and assess how the income and distributional effects of DFI evolve under a maturing regulatory regime.

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