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EMPOWERING MIGRANT WORKER HOUSEHOLDS: DIGITAL FINANCE FOR INCLUSIVE GROWTH

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Abstract. This study establishes a Digital Buffer Enhancement framework based on the buffer-stock model to investigate how digital finance affects consumption levels of migrant worker households, with implications for inclusive growth and sustainable development. Utilizing microdata from the 2019 China Household Finance Survey (CHFS) and applying Endogenous Switching Regression (ESR), Instrumental Variable (IV) approach, and quantile regression analysis, the research reveals three key findings. First, digital finance adopters exhibit 13.74% higher consumption levels, while non-adopters could increase consumption by 5.62% via adoption. Intriguingly, the Digital Buffer Enhancement framework identifies three complementary mechanisms: transaction convenience leapfrogging, liquidity constraint mitigation, and income uncertainty reduction, which together reduce precautionary savings thresholds. Second, enhanced marginal effects emerge among elderly households, eastern regions, and low-consumption quantile groups. Third, analysis of consumption structure heterogeneity indicates that developmental consumption elasticity substantially exceeds hedonic and subsistence consumption, with credit functions demonstrating the strongest impact among digital finance types, followed by payment and wealth management services. These findings advance theoretical understanding of technology-driven consumption transformation and provide practical guidance for developing inclusive digital finance policies in emerging economies.

Keywords: digital finance, migrant worker household consumption, buffer-stock model, ESR model.

JEL Classification: D81, J61, O16, O33.

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1. Introduction

Consumption, a crucial driver of economic growth, not only directly promotes economic development but also facilitates resource allocation optimization, leading to economic structural upgrades and improvements in long-term development capacity (Li et al., 2022; Šlander Wostner et al., 2022). However, significant disparities in consumption levels persist globally, particularly in developing economies, hindering the full realization of consumption potential. For instance, in China, final consumption expenditures comprised only 53.4% of GDP in 2022, substantially lower than the global average of 80.4% (World Bank, n.d.). Therefore, effectively stimulating and unleashing resident consumption potential has become a critical challenge for developing economies such as China in achieving sustainable growth and promoting structural transformation.

As rural-to-urban migration intensifies in China, the migrant worker population continues to expand significantly. In 2023, the total number of migrant workers exceeded 298 million, constituting over one-third of the total employed population. Despite an increase in average monthly income from 2,609 yuan in 2013 to 4,780 yuan in 2023 (National Bureau of Statistics, 2014, 2024), the household consumption levels of migrant workers remain notably lower than those of urban residents, particularly regarding consumption structure and quality of life (Cao et al., 2017; Chen et al., 2015). This disparity results from factors such as income instability, inadequate social security, and the marginalized status of migrant workers in urban areas (Tang et al., 2020). Thus, enhancing the consumption levels of migrant workers and unlocking their consumption potential has become essential for promoting inclusive economic growth and sustainable development.

Financial exclusion further constrains the consumption capacity of migrant workers. Due to insufficient collateral and guarantees, migrant workers have historically encountered barriers in accessing formal financial services, while traditional social networks have failed to provide adequate informal financial support (Wang & Fu, 2021). However, the rapid advancement of digital finance may present a solution to this challenge. By providing accessible payment and credit services, digital finance reduces barriers to financial service access, enabling marginalized groups to more readily obtain financial resources and significantly enhance their consumption capacity. Research has demonstrated that digital financial inclusion initiatives in rural areas have improved consumption levels among low-income households and facilitated the optimization of consumption structures (He et al., 2022).

Furthermore, digital finance enhances household consumption capacity and optimizes consumption structures through the alleviation of liquidity constraints and reduction of income uncertainty (Yu et al., 2021). By leveraging internet technologies to lower financial service costs, it improves access to credit resources for low-income groups, thereby expanding their consumption potential (Li et al., 2019). However, limited evidence exists regarding the specific effects of digital finance on migrant worker households. Three critical questions remain unresolved: (1) Can digital finance serve as a key driver for migrant worker household consumption? (2) Through which mechanisms does it operate? (3) How do its effects vary across demographic subgroups? These knowledge gaps, therefore, necessitate rigorous empirical investigation.

To address these research questions, the Digital Buffer Reinforcement framework, a theoretical analytical framework integrating the buffer-stock model with digital finance mechanisms, was developed. Therefore, this framework rigorously examined the consumption behaviors of migrant worker households. Next, microdata from the 2019 China Household Finance Survey (CHFS) were analyzed, with self-selection bias in digital finance adoption addressed through Endogenous Switching Regression (ESR) modeling. Consumption distribution heterogeneity was examined using methodological triangulation, combining quantile regression techniques and Instrumental Variable (IV) identification strategies (see Figure 1). The academic contributions of this study are threefold: (1) the development of the Digital Buffer Reinforcement framework, which explains how digital technologies reconfigure precautionary savings behaviors through tripartite mechanisms; (2) the establishment of causal inference validity for digital finance consumption effects through counterfactual simulation techniques; and (3) the identification of heterogeneous distribution patterns in digital financial interventions, providing novel perspectives for optimizing inclusive policies.

This research is organized as follows. Section 2 presents a comprehensive review of the literature on digital finance and household consumption. Section 3 establishes the theoretical framework and formulates the hypotheses. Section 4 describes the data and methodology employed in the study. Section 5 presents the empirical findings, including baseline estimates, robustness checks, and heterogeneity analyses. Section 6 examines the theoretical and policy implications. Lastly, Section 7 provides the concluding remarks of the study.

Figure 1. Methodological framework

2. Literature review

Migrant workers, a significantly vulnerable group in China's urbanization process, have garnered increasing scholarly attention regarding their consumption behaviors. Research has identified three primary consumption constraints. Firstly, income instability from informal employment and cyclical migration leads to consumption volatility (Li & Luo, 2021; Wang et al., 2022a). Secondly, exclusion from urban-rural social security systems increases precautionary savings, as migrant workers face barriers in accessing healthcare and pension benefits (Cao et al., 2017; Chen et al., 2015). Thirdly, financial exclusion limits credit and insurance access, constraining households to low-consumption equilibria (Li et al., 2019; Wang et al., 2022a). However, these studies predominantly characterize migrant worker consumption as passive responses to structural constraints, overlooking their agency in utilizing financial innovations to optimize consumption-savings decisions.

Over the years, the inclusive potential of digital finance in rural areas and low-income populations has been extensively documented. Research identifies four primary mechanisms underlying digital financial inclusion: First, the liquidity constraint alleviation mechanism, where digital payment and lending services enhance rural household consumption by mitigating financing constraints (Hu et al., 2023) and optimizing financial asset allocation (Ma et al., 2024; Zhao et al., 2022). Second, the transaction cost reduction mechanism, through which mobile payment enhances consumption efficiency by reducing payment friction (Zhao et al., 2022) and expanding financial service coverage (Yu et al., 2021). Third, the income distribution adjustment mechanism, where digital finance decreases consumption inequality by reducing income disparities (Wang et al., 2022a) and increasing risk asset allocation ratios (Ma et al., 2024). Fourth, the consumption scenario expansion mechanism, where e-commerce and digital payment jointly drive consumption upgrading through channel diversification (Hu et al., 2023) and promotion of developmental consumption in rural households (Yu et al., 2021). However, existing research primarily emphasizes urban-rural comparisons, while the dual identity of migrant workers, marked by simultaneous integration into urban digital ecosystems and rural financial exclusion, remains inadequately theorized.

Taken together, the discourse on digital financial inclusion highlights unresolved contradictions. Proponents assert that digital tools reduce consumption disparities by empowering marginalized groups (Wang & Fu, 2021; Wang et al., 2022a; Zhao et al., 2022). Critics argue that these tools may increase consumption sensitivity to income fluctuations through induced short-term borrowing behaviors (Lai et al., 2020), with institutional barriers like hukou restrictions potentially undermining inclusive effects systematically (Chen et al., 2015). Besides, the binary opposition in current theoretical frameworks overlooks the institutional intersectionality characteristics of migrant workers, arising from their dual embeddedness in urban technological infrastructure and rural social networks, which creates differentiated technology adoption patterns. Nevertheless, existing literature either homogenizes migrant workers as rural samples or conflates their behaviors with urban residents, hindering the understanding of unique financial behavioral strategy formation mechanisms among migrant workers within the urban-rural dual institutional structure.

3. Theoretical framework and research hypotheses

Consumer behavior has remained a central focus of economic research for decades. Early theoretical frameworks, such as the absolute income hypothesis and the relative income hypothesis (Ackley, 1951; Barger, 1936), identified current income as the primary determinant of consumption patterns. Subsequent theoretical developments, particularly the lifecycle hypothesis (Modigliani, 2005) and permanent income hypothesis (Friedman, 1957), shifted analytical attention toward long-term income expectations. Recent studies have increasingly adopted the precautionary savings hypothesis, notably through the buffer-stock model (Carroll et al., 1992), to explain consumption patterns under income uncertainty. This framework proves particularly relevant for migrant workers due to their income volatility and employment mobility. The model effectively captures their behavioral characteristics: elevated savings rates and suppressed consumption emerge as rational responses to income unpredictability.

This study, therefore, extends the buffer-stock model, introducing the Digital Buffer Reinforcement framework to examine the impact of digital finance on migrant worker household consumption patterns. Within this theoretical construct, consumers facing future uncertainty establish target wealth-to-permanent-income ratios (Carroll et al., 1992). When actual wealth-income ratios exceed this threshold, consumption increases and savings decrease; conversely, ratios below the threshold prompt consumption reduction and savings accumulation.

Analogously, through three digitally driven mechanisms – transaction convenience leapfrogging, liquidity constraint substitution, and income stabilization – migrant workers modify their consumption and saving behaviors in response to changes in the time preference rate, consumption growth trajectory, and income variance. To formalize these effects, the Digital Buffer Enhancement framework can be represented using a log-linearized consumption Euler Equation:

$$E_t \Delta \ln C_{t+1} = \rho^{-1}(r - \delta) + (\rho/2) var_t(\Delta \ln C_{t+1}) + e_{t+1,}$$

where t denotes the decision period, C represents the consumption level, ρ signifies the coefficient of relative risk aversion (assuming that consumption utility follows the Constant Relative Risk Aversion (CRRA) utility function), $var_t\,(\Delta \ln C_{t+1})$ indicates the conditional variance of consumption growth, incorporating uncertainty factors, r denotes the market interest rate, δ represents the time preference rate, and e_{t+1} is an independently distributed error term. As shown in Figure 2a, the consumption growth rate $\Phi(\chi) = E_t \Delta \ln C_{t+1}$ displays strict concavity (at low wealth levels, consumers generally exhibit a high MPC); therefore, for low-income consumers, an income change produces a larger consumption change, while for higher-income consumers, the same income change results in a lower MPC). When Φ(χ) equals the permanent income growth rate, consumers reach the target wealth-to-income ratio.

First, digital finance adoption enhances transaction efficiency, which is the initial pillar of the digital buffer reinforcement framework. Hence, digital payments substantially reduce transaction time costs. According to McCallum and Goodfriend's (1986) purchasing-time model, when transaction time decreases, consumers obtain more leisure time. This increases their current utility and consequently raises their time preference rate δ. Additionally, digital finance has facilitated the expansion of e-commerce, enabling migrant workers in urban peripheries to access a wider range of goods, thereby fulfilling consumption demands previously limited by supply constraints. Likewise, e-commerce also broadens the supply range in the consumer market, allowing migrant workers to remotely purchase goods for their families in rural areas. Without digital financing, these consumption needs typically require migrant workers to return home, postponing their purchases. This reinforces their immediate consumption utility and further increases their time preference rate.

As shown in Figure 2b, the improved transaction convenience enabled by digital finance results in an increase in the time preference rate δ for migrant workers to δ′. Subsequently, the curve $\Phi(\chi)$ shifts to $\Phi'(\chi)$, and the consumption growth rate under income certainty conditions decreases from $\rho^{-1}(r - \delta)$ to $\rho^{-1}(r - \delta')$. This change leads to a lower target wealth-to-income ratio χ_1^* and a higher level of immediate consumption, assuming a constant permanent income growth rate.

Second, the reduction of liquidity constraints through digital credit accessibility emerges as the second theoretical pillar. As illustrated in Figure 2c, consider two categories of migrant

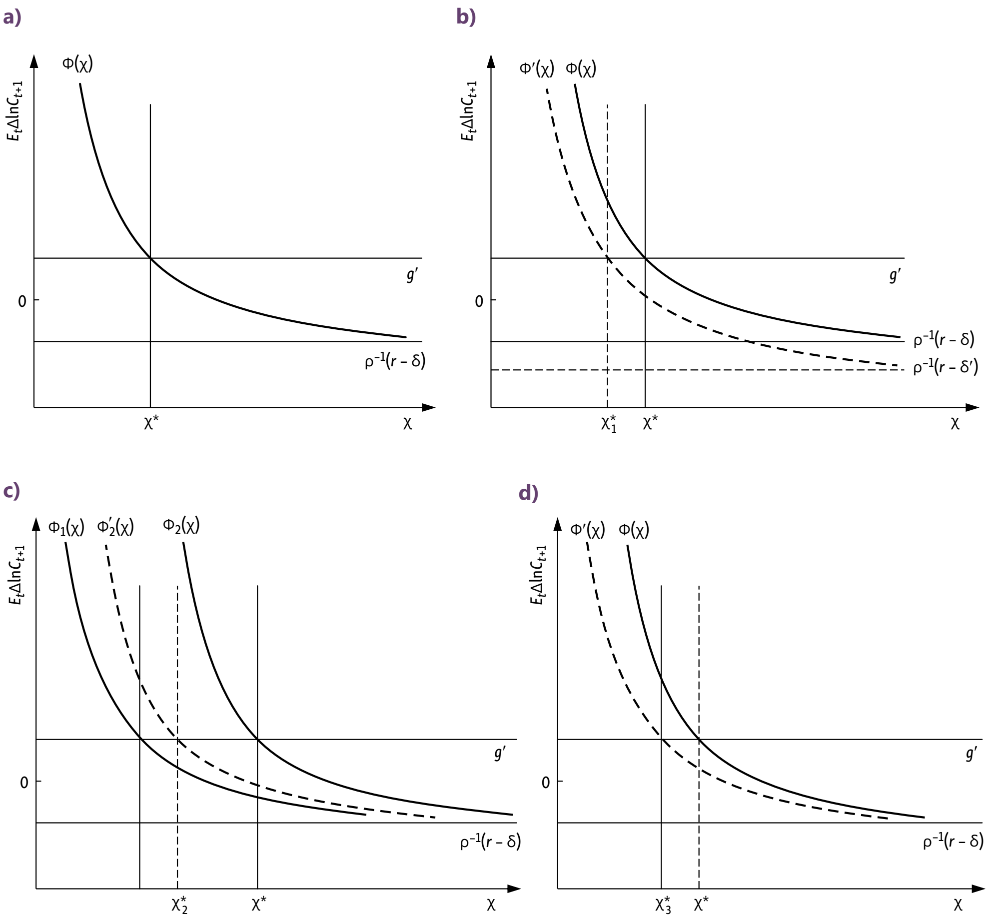

Figure 2. Effects of digital finance on migrant worker household consumption: a – Baseline model; b – Transaction convenience; c – Liquidity constraint mitigation; d – Income uncertainty reduction

workers in the economy: those unaffected by liquidity constraints, represented by a consumption growth rate curve labeled $\Phi_1(\chi)$, and those constrained by liquidity, represented by a consumption growth rate curve labeled $\Phi_2(\chi)$. Given that $\Phi_2(\chi)$ demonstrates a flatter slope compared to $\Phi_1(\chi)$, $\Phi_2(\chi)$ intersects the permanent income growth rate (g') at a higher wealth-to-income ratio. This finding indicates that migrant workers facing liquidity constraints tend to maintain higher savings levels.

Migrant workers experiencing liquidity constraints typically have restricted access to financial and social capital, as well as labor skills. This limitation impedes their competitiveness in the labor market and constrains their ability to obtain traditional financial resources. Digital finance, however, extends financial services to underserved populations through digital technology, providing migrant workers with improved access to credit and thus alleviating liquidity constraints. Consequently, with the adoption of digital finance, liquidity-constrained migrant workers can potentially shift their consumption growth rate curve closer to $\Phi_1(\chi)$, ultimately resulting in a reduction in the target wealth-to-income ratio and an increase in consumption levels.

Third, digital finance constitutes a fundamental theoretical pillar by reducing income uncertainty among migrant workers through diversified financial products and optimized asset allocation. This implies that digital platforms enable household participation in money and securities markets, thereby reducing income volatility and stabilizing cash flows. Also, financial instruments such as online credit and digital insurance help mitigate risks associated with income fluctuations, enhance economic security, and promote more stable consumption patterns (Lai et al., 2020; Zhao et al., 2022).

As illustrated in Figure 2d, a reduction in income uncertainty for migrant workers corresponds to a decrease in the conditional variance $var_t(\Delta \ln C_{t+1})$. This decrease results in a leftward shift of the consumption growth rate curve $\Phi(\chi)$ to $\Phi_2'(\chi)$. Consequently, the target wealth-to-income ratio declines from χ^* to $\chi_3{}^*$, prompting migrant workers to enhance their consumption and reduce their savings.

By extending the buffer-stock model, this study introduces the Digital Buffer Reinforcement framework, which incorporates digital finance mechanisms. Based on this framework, the following hypotheses are proposed in this study:

H1: *The utilization of digital finance significantly enhances the consumption levels of migrant worker households.*

H2: *Digital finance elevates the consumption levels of migrant worker households through three primary mechanisms: enhancing transaction convenience, mitigating liquidity constraints, and diminishing income uncertainty.*

4. Research design

4.1. Data sources

This study employs data from the 2019 CHFS, which encompasses 29 provinces (including autonomous regions and municipalities), 343 counties, and 1,360 village (or residential) committees, collecting information from 34,643 households. The CHFS data provide representative samples at both national and provincial levels within China. Additional provincial-level data are obtained from various provincial statistical yearbooks. In accordance with the *2022 Migrant Workers Dynamic Monitoring Data* published by the National Bureau of Statistics, migrant workers are defined as individuals with rural household registration (hukou) who engage in nonagricultural employment either locally or outside their hometowns for a minimum of six months within a year. Following these criteria, this study selects samples from the CHFS database comprising individuals with rural household registration employed in nonagricultural work. After excluding incomplete entries, the final analysis includes 5,712 valid samples.

4.2. Variable specification

4.2.1. Dependent variable

The consumption level of migrant worker households is represented by the total household consumption expenditure over the previous year. To normalize this variable, a logarithmic transformation is applied.

4.2.2. Independent variables

Digital finance usage. Following the methodologies of Wang et al. (2022b) and Zhao et al. (2022), digital finance usage is assessed across three dimensions: digital payments, digital lending, and digital wealth management. A household is classified as a user of digital payment services if the respondent has established a third-party payment account (such as Alipay, WeChat Pay, JD Wallet, or Baidu Wallet). Engagement in digital lending is determined by whether the respondent has borrowed or lent money through an online platform. Utilization of digital wealth management services is indicated by the respondent's purchase of financial products via an app, website, or third-party platform. A household is categorized as a digital finance user and assigned a value of 1 if it employs any of these three services; otherwise, it is assigned a value of 0.

4.2.3. Control variables

Following the methodological approach of Yi and Zhou (2018) and Hu et al. (2023), this study incorporates ten control variables encompassing three dimensions: the characteristics of the household head, household attributes, and regional factors.

Household head characteristics: The study includes five variables to account for individual differences: gender, age, marital status, education, and social security status.

Household characteristics: Three variables are employed to address family differences: total household income, home ownership status, and the proportion of non-labor force members within the household.

Regional characteristics: Two variables are incorporated to assess the influence of regional economic conditions and macroeconomic policies: regional economic development and traditional financial development.

Table 1 provides the names, definitions, assignments, and descriptive statistics for each of these variables.

Table 1. Variable definitions and descriptive statistics

Variable	Definition and assignment	Mean	Standard deviation	Skew	Kurt.
Household consumption	Log of total household consumption expenditure	10.971	0.800	0.306	5.169
Digital payment usage	Digital payment usage = 1, not used = 0	0.659	0.474	–0.672	1.452
Digital lending usage	Digital lending usage = 1, not used = 0	0.012	0.107	9.141	84.557
Digital wealth management usage	Digital wealth management usage = 1, not used = 0	0.092	0.290	2.814	8.92
Digital finance usage	Use any digital finance (payment, lending, wealth management) = 1, not used = 0	0.660	0.474	–0.673	1.453
Household head gender	Male = 1, Female = 0	0.895	0.307	–2.573	7.622
Household head age	Age (years)	48.821	10.623	–0.031	2.843
Marital status	Married = 1, Unmarried = 0	0.924	0.266	–3.191	11.184
Education	Illiterate/semi-illiterate = 0, Primary = 1, Junior High = 2, Senior High/ Vocational = 3, Associate Degree = 4, Bachelor and above = 5	2.009	0.940	0.527	3.925
Social security	Number of social insurance types (pension, health, commercial insurance, etc.)	1.798	0.627	–0.658	3.999
Total household income	Log of total household income	10.923	1.128	–2.064	16.561
Housing ownership	Number of houses owned by household	1.157	0.643	6.149	164.661
Non-labor force ratio	Ratio of population under 16 and over 60 in household	0.266	0.255	0.813	3.45
Economic development level	Per capita GDP (RMB) in each province	11.082	0.327	0.634	2.806
Traditional financial development level	Ratio of RMB loan balance to GDP in each province	1.483	0.333	0.99	3.759

Note: N = 5,712.

4.3. Analysis of sample differences

Table 2 presents the mean differences of various variables between digital finance users and non-users within migrant households. Column (2) shows the mean values for the digital finance user group, while Column (3) presents the corresponding values for the non-user group. Column (4) displays the mean differences. Our econometric analysis reveals that consumption levels of migrant households using digital finance are significantly higher than those not utilizing such services, providing preliminary evidence that digital finance adoption may enhance consumption levels in migrant households.

Table 2. Analysis of digital finance usage and consumption differences in migrant worker households

Variable	Digital finance users	Non-users	Mean difference
Household consumption	11.18 (0.01)	10.56 (0.02)	0.618***
Gender	0.89 (0.01)	0.91 (0.01)	–0.022***
Age	45.80 (0.16)	54.67 (0.22)	–8.870***
Marital status	0.93 (0.00)	0.91 (0.01)	0.015***
Education	2.17 (0.02)	1.69 (0.02)	0.484***
Social security	1.82 (0.01)	1.75 (0.01)	0.076***
Total household income	11.09 (0.02)	10.60 (0.02)	0.493**
Housing ownership	1.19 (0.01)	1.10 (0.01)	0.084***
Non-labor force ratio	0.25 (0.01)	0.29 (0.00)	–0.041***
Economic development level	11.08 (0.01)	11.08 (0.01)	0.001
Traditional financial development level	1.47 (0.01)	1.51 (0.01)	–0.038***
Observations	3766	1946	5712

Note: Robust standard errors are in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Hereinafter, the same applies.

Regarding household head characteristics, digital finance users demonstrate notably younger age profiles, higher educational attainment, and better social security coverage. In terms of household characteristics, families using digital finance show higher total income levels and increased homeownership rates, coupled with lower proportions of non-working-age population. Geographically, migrant workers using digital finance services are primarily situated in regions with less developed traditional financial sectors. These findings indicate substantial heterogeneity between the two sample groups across multiple dimensions. However, establishing causal relationships between digital finance usage and the observed differences requires rigorous empirical verification through appropriate econometric methods.

4.4. Model specification

4.4.1. Baseline regression model

To examine the impact of digital financial services on the consumption patterns of migrant worker households, this study adapts the methodological framework that was specified by Ma et al. (2024) to construct the following regression model:

$$Consu_i = \alpha_0 + \alpha_1 DigFin_i + \alpha_2 HouseHolder_i + \alpha_3 Family_i + \alpha_4 Area_i + \varepsilon_i, \quad (1)$$

where, $Consu_i$ represents the total consumption of household i; $DigFin_i$ denotes the primary independent variable, indicating digital finance utilization. If a household uses digital payments, lending, or wealth management, $DigFin_i$ = 1; otherwise, $DigFin_i$ = 0. $HouseHolder_i$, $Family_i$, and $Area_i$ represent vectors of control variables, encompassing household head characteristics, family structure, and regional factors, respectively. ε_i denotes the error term, assumed to be independent and identically distributed. The model addresses self-selection bias at the 1% and 99% confidence levels. Equally, we applied individual-level clustering to standard errors across all regression specifications.

4.4.2. ESR model

The decisions regarding digital finance usage among migrant worker households were influenced by various observable and unobservable factors, resulting in a random selection process. When these factors affect both the likelihood of digital finance adoption and household consumption levels, selection bias may arise. To address this selection bias associated with both observable and unobservable factors, this study employs the ESR model to evaluate the impact of digital finance usage on consumption levels of migrant worker households. The ESR model consists of two stages:

Selection equation: The initial stage employs a probit model to examine how household head characteristics, household attributes, and regional factors influence migrant worker households' adoption of digital finance.

Outcome equation: The second stage estimates the impact of digital finance usage on household consumption levels by constructing separate outcome equations for users and non-users of digital finance.

The selection and outcome equations are formulated as follows:

Selection equation:

$$Digfin_i^* = \alpha_i X_i + \gamma_i I_i + \mu_i, \ Digfin_i = \begin{cases} 1, Digfin_i^* > 0 \\ 0, Digfin_i^* < 0 \end{cases}. \tag{2}$$

Outcome equations:

$$Consu_{1i} = \beta_0 + \beta_{1j} X_{1i} + \sigma_{T1}\lambda_T + \varepsilon_{1i}, \ \text{if } Digfin_i = 1, \tag{3}$$

$$Consu_{0i} = \beta_0 + \beta_{0j} X_{0i} + \sigma_{T0}\lambda_U + \varepsilon_{0i}, \ \text{if } Digfin_i = 0. \tag{4}$$

In Eq. (2), i represents an individual migrant worker household; $Digfin_i$ is a binary variable indicating the household's digital finance usage decision, derived from the latent variable $Digfin_i^*$; X_i represents a vector of control variables affecting household consumption; μ_i denotes the error term; α_i and γ are parameters for estimation; and I_i functions as the IV.

In Outcome Eqs. (3)–(4), $Consu_{0i}$ represents the household's consumption level, β denotes the parameters for estimation, and ε_i represents the error term. λ_T and λ_U indicate the inverse Mills ratios, which address selection bias from unobservable factors; $\sigma_{T1} = \text{cov}\left(\varepsilon_1, \mu\right)$ and σ_{T0} represent the covariance between the selection and outcome equation error terms. Statistical significance of σ_{T1} and σ_{T0} indicates that the ESR model effectively addresses selection bias from unobserved factors.

5. Empirical results

5.1. Analysis of baseline regression results

Table 3 presents the baseline regression results. Our analysis employs a stepwise regression approach to examine incremental effects across control variable categories through sequential covariate inclusion. In Eq. (1), without control variables, digital finance usage shows a coefficient of 0.619 ($p < 0.01$), providing initial evidence of its positive impact on migrant worker household consumption.

Table 3. Baseline regression results

Variables	(1)	(2)	(3)	(4)
Digital financial usage	0.619*** (28.91)	0.446*** (19.07)	0.370*** (15.92)	0.367*** (15.87)
Gender	—	0.010 (0.33)	–0.006 (–0.19)	0.003 (0.09)
Age	—	–0.013*** (–12.10)	–0.014*** (–13.15)	–0.015*** (–13.91)
Education	—	0.090*** (8.33)	0.059*** (5.63)	0.054*** (5.14)
Marital status	—	0.363*** (9.10)	0.298*** (7.82)	0.297*** (7.80)
Social security	—	0.061*** (4.03)	0.034** (2.34)	0.041*** (2.83)
Total household income	—	—	0.166*** (12.51)	0.158*** (12.13)
Non-labor force ratio	—	—	0.107*** (2.80)	0.118*** (3.09)
Housing ownership	—	—	0.097*** (3.77)	0.097*** (3.85)
Economic development level	—	—	—	0.227*** (7.52)
Traditional financial development level	—	—	—	–0.004 (–0.14)
Constant	10.563*** (589.80)	10.699*** (131.73)	9.015*** (56.73)	6.646*** (19.91)
Observations	5,712	5,712	5,712	5,712
R^2	0.134	0.193	0.255	0.263

In Eq. (2), after controlling for household head characteristics, the digital finance usage coefficient decreases to 0.446 ($p < 0.01$), suggesting that omitting household head characteristics may overestimate digital finance's impact on household consumption. Additionally, the household head's age shows a negative effect on household consumption, while marital status, education level, and social security coverage demonstrate positive effects. Thus, the household head's gender shows no significant influence on household consumption.

Eq. (3) includes controls for both household head and family characteristics. The digital finance usage coefficient further decreases to 0.370 ($p < 0.01$). Interestingly, total household income, non-labor force ratio, and housing ownership significantly affect household consumption, indicating that family characteristics constitute important determinants of total household consumption.

In Eq. (4), when regional factors were set as control variables, the digital finance usage coefficient decreases to 0.367 ($p < 0.01$), confirming that household head and family characteristics have a stronger influence on household consumption than regional factors.

5.2. Endogenous problems

5.2.1. IV method

To address potential endogeneity issues from omitted variables and reverse causality, despite selecting control variables from multiple dimensions, the study employs various types of IVs for Two-Stage Least Squares (2SLS) estimation.

Following Ma et al. (2024), urban households were categorized into four groups based on income levels. The first IV utilized was the average digital finance usage of other households within the same region and income stratum during the current year. This approach is supported by the correlation between digital finance adoption and regional characteristics, as well as household wealth levels. Furthermore, wealth-homogeneous groups tend to display spatial clustering. A household's digital finance usage pattern may be shaped by peer effects within its geographical proximity. Notably, digital finance usage by other households sharing the same regional and income attributes is unlikely to directly influence the consumption behavior of the focal household, thus fulfilling the relevance and exogeneity conditions required for valid IVs.

In accordance with peer effect mechanisms in behavioral economics, the second IV was derived by calculating the proportion of digital finance users among households sharing similar regional and income stratum characteristics during the survey year, following the methodologies of Duflo and Saez (2003). Additionally, given the heterogeneity among communities within the same region, household connections within a community are typically stronger than those with the broader region. Households with similar wealth levels in the same community exhibit statistically significant behavioral convergence. The digital finance usage of neighboring households may affect individual choices through peer effects. Total income and assets function as indicators of household wealth levels. Following the methodology developed by Zhao et al. (2022), the third IV employs the average digital finance usage level of other households within the same community and asset quintile as the surveyed household in the same year.

On top of that, the study implemented the Lewbel (2012) method to generate IVs based on heteroskedasticity-robust standard errors. These IVs were specifically constructed as exogenous variables derived from demeaning residuals obtained by regressing endogenous variables on exogenous variables.

As shown in Table 4, all four IVs reject the under-identification null hypothesis at the 1% significance level (i.e., Kleibergen-Paap rk Wald F statistic exceeds the 10% critical value). This confirms strong instrument relevance and the absence of weak instrument problems.

Table 4. IV-2SLS estimation results

Variables	IV1	IV2	IV3	IV4
Digital finance usage	2.172*** (5.94)	0.459*** (16.20)	1.505*** (7.11)	0.217** (2.08)
Gender	0.053 (1.21)	0.005 (0.17)	0.056 (1.36)	–0.001 (–0.03)
Age	0.014** (2.29)	–0.014*** (–12.33)	0.004 (1.02)	–0.018*** (–8.91)
Education	–0.030 (–1.32)	0.050*** (4.73)	0.003 (0.16)	0.060*** (5.32)
Marital status	0.161*** (2.71)	0.290*** (7.64)	0.225*** (4.15)	0.308*** (7.89)
Social security	–0.017 (–0.68)	0.038*** (2.61)	–0.028 (–1.24)	0.047*** (3.11)
Household income	0.063*** (2.74)	0.153*** (11.86)	0.094*** (5.38)	0.166*** (11.46)
Non-labor ratio	0.240*** (3.91)	0.124*** (3.26)	0.217*** (3.96)	0.108*** (2.80)
Housing ownership	0.017 (0.68)	0.093*** (3.82)	0.074*** (2.80)	0.103*** (3.88)
Economic development level	0.181*** (3.97)	0.225*** (7.45)	0.207*** (4.91)	0.231*** (7.64)
Traditional financial development	0.101** (2.19)	0.001 (0.05)	0.064 (1.61)	–0.013 (–0.45)
Constant	5.810*** (11.04)	6.606*** (19.78)	6.004*** (12.76)	6.707*** (20.03)
Under identification test	40.352	2256.177	82.972	138.577
Weak identification test	41.492	8332.243	85.415	25.131
Hansen J test	—	—	—	0.928
Observations	5646	5712	4195	5712
R^2	–0.643	0.261	–0.114	0.257

Eqs. (1)–(3) represent precisely identified models where the number of instruments equals the number of endogenous variables. For Eq. (4), the Hansen J test produced a p-value of 0.928 (exceeding 0.1), confirming instrument exogeneity under overidentification conditions.

The aforementioned tests validate the appropriateness of the IVs selected for this study. Besides, the regression analyses produce consistently positive and statistically significant coefficients for digital finance usage across all four equations. This finding reinforces the primary conclusion, even when addressing potential endogeneity through the application of the IV method.

5.2.2. ESR model

Table 5 presents the results of the simultaneous estimation of digital finance usage on migrant worker household consumption levels. The Likelihood Ratio (LR) test for independence between the two-stage equations rejects the null hypothesis of mutual independence at the 1% significance level, confirming the necessity of joint estimation. This implies that the correlation coefficient ρ_0 is statistically significant at the 10% level, indicating the presence of unobserved variables that simultaneously affect digital financial adoption decisions and household consumption. Consequently, this finding supports the correction for selection bias using the ESR model.

To enable identification in the selection equation, the usage of digital finance by other households within the same region and income stratum was incorporated as an exogenous variable. Notably, the theoretical foundation for this variable has been established in the preceding IV methodology section and is not repeated here.

Column (1) of Table 5 presents regression results from the selection equation. Regarding household head characteristics, the coefficient for gender is negative at the 10% significance level, indicating that female-headed households demonstrate a stronger tendency toward digital finance adoption. Also, age coefficient shows a statistically significant negative impact

Table 5. ESR model estimation results

Variable	Selection equation	Outcome equation	
	Digital finance usages	Digital finance users	Nondigital finance users
	(1)	(2)	(3)
Gender	–0.118* (–1.78)	–0.001 (–0.04)	0.081 (1.23)
Age	–0.050*** (–24.25)	–0.009*** (–4.48)	0.005* (1.73)
Education level	0.147** (1.97)	0.063*** (4.73)	–0.066*** (–2.85)
Marial status	0.115*** (3.73)	0.204*** (4.55)	0.310*** (4.53)
Social security	0.130*** (7.18)	0.050*** (2.86)	–0.044 (–1.38)
Total household income	0.103*** (3.59)	0.133*** (12.09)	0.126*** (6.10)
Non-labor force ratio	0.079 (1.39)	0.256*** (4.84)	0.073 (1.18)
Housing ownership	0.199*** (8.75)	0.110*** (6.06)	–0.018 (–0.62)
Economic development level	–0.082 (–1.10)	0.226*** (6.46)	0.158*** (2.87)
Traditional Financial	–0.161*** (–2.92)	–0.003 (–0.09)	0.102* (1.92)
IV	0.516*** (7.52)		
Constant	–0.178 (–0.28)	7.045*** (17.73)	6.304*** (10.28)
ρ_0	–0.179* (–1.86)		
ρ_1	–0.762*** (21.77)		
LR test of indep	185.63***		

(–0.050, $p < 0.01$), suggesting that younger household heads are more likely to adopt digital finance. Conversely, educational attainment and marital status demonstrate significant positive effects, with coefficients of 0.147 ($p < 0.05$) and 0.115 ($p < 0.01$), respectively. Moreover, the significant positive coefficient for social security coverage (0.130, $p < 0.01$) suggests that migrant workers with more comprehensive social security protections exhibit a greater propensity to adopt innovative financial instruments.

Regarding family characteristics, total household income and housing ownership show significant positive effects on digital finance usage, with coefficients of 0.103 ($p < 0.01$) and 0.199 ($p < 0.01$), respectively. For regional characteristics, the level of traditional financial development exhibits a significant negative effect on digital finance usage (–0.161, $p < 0.01$). This indicates that migrant workers in areas with limited traditional financial services depend more heavily on digital finance to address their financial needs.

Columns (2)–(3) of Table 5 present the regression results for the outcome equation. The household head's age negatively and significantly affects the consumption of migrant worker households utilizing digital finance (–0.009, $p < 0.01$). Conversely, education level and social security benefits exclusively enhance the consumption level of households employing digital finance, with education level particularly hindering consumption improvement for households not using digital finance. Nevertheless, marital status demonstrates a significant positive effect on the consumption of both categories of migrant worker households.

Equally, total household income exhibits a significant positive correlation with consumption levels (0.133 and 0.126, both $p < 0.01$). The non-labor force ratio and housing ownership demonstrate significant positive associations with consumption among households using digital finance (0.256 and 0.110, both $p < 0.01$). Regarding regional characteristics, economic development levels positively influence the consumption of both household categories (0.226 and 0.158, both $p < 0.01$). Notably, traditional financial development shows a significant positive effect exclusively on consumption among households not utilizing digital finance, suggesting that traditional financial services remain influential in driving consumption levels for this group.

5.2.3. Analysis of the Average Treatment Effect (ATE) of digital finance usage on migrant worker household consumption

Table 6 presents the Average Treatment Effect (ATE) of digital finance usage on migrant worker household consumption patterns, highlighting its considerable impact on spending behaviors. Specifically, Columns (a)–(b) display the actual consumption values for households with and without digital finance usage, respectively. Likewise, Columns (c)–(d) present the counterfactual consumption levels under hypothetical scenarios.

The analysis reveals substantial effects of digital finance usage on household consumption among migrant workers. For current digital finance users, the results show that without such usage, their household consumption level would decrease from 11.179 to 9.644, representing a decline of 1.536 or 13.74% ($p < 0.01$). Conversely, for non-users of digital finance, the counterfactual analysis indicates that adoption would increase their household consumption level from 10.566 to 11.160, reflecting a rise of 0.594 or 5.62% ($p < 0.01$).

Table 6. Average treatment effect of digital finance usage on migrant worker household consumption

Variable	Digital finance users	Nondigital finance users
Digital finance users	(a) 11.179 (0.005)	(c) 11.160 (0.006)
Nondigital finance users	(d) 9.644 (0.004)	(b) 10.566 (0.007)
ATT	1.536*** (0.006)	—
ATU	—	0.594*** (0.009)

Note: ATT represents the expected household consumption level for migrant workers who currently use digital finance under the hypothetical scenario where they do not use it. ATU represents the expected household consumption level for migrant workers who do not currently use digital finance under the hypothetical scenario where they do use it. The same applies in subsequent tables.

Analogously, the evidence presented in Table 6 supports Hypothesis H1, confirming that digital finance usage significantly enhances consumption levels within migrant worker households. The analysis demonstrates a positive impact regardless of current digital finance usage status, underscoring its crucial role in promoting increased household consumption among this population.

To demonstrate the impact of digital finance usage on migrant worker household consumption, this study presents predicted fitted consumption values for households utilizing digital finance (y11) and their counterfactual consumption values (y21). It also shows fitted consumption values for households not using digital finance (y22) and their counterfactual consumption values (y12). Figure 3 illustrates these results through kernel density curves. The analysis indicates that the kernel density curve center for y11 lies to the right of the counterfactual consumption curve, suggesting a significant reduction in counterfactual consumption levels. On the contrary, the kernel density curve center for y22 appears to the left of the counterfactual consumption curve, indicating a substantial increase in counterfactual consumption levels.

5.3. Robustness test

5.3.1. Propensity Score Matching (PSM) regression

Given the non-random nature of digital finance adoption among migrant worker households, potentially influenced by household head characteristics, family demographics, regional economic development levels, and traditional financial development, this study employs PSM to address potential sample selection bias. The analysis incorporates covariates including the household head's gender, age, educational attainment, and marital status, along with family dependency ratio, traditional financial development level, and regional economic level.

The post-matching balance test reveals significant pre-matching differences between the treatment (digital finance users) and control groups (non-users) through t-tests. After PSM implementation, the percentage bias for all covariates reduced to below 10%, with t-statistics showing no significant inter-group differences. The common support range encompasses more than 95% of samples, indicating satisfactory matching quality.

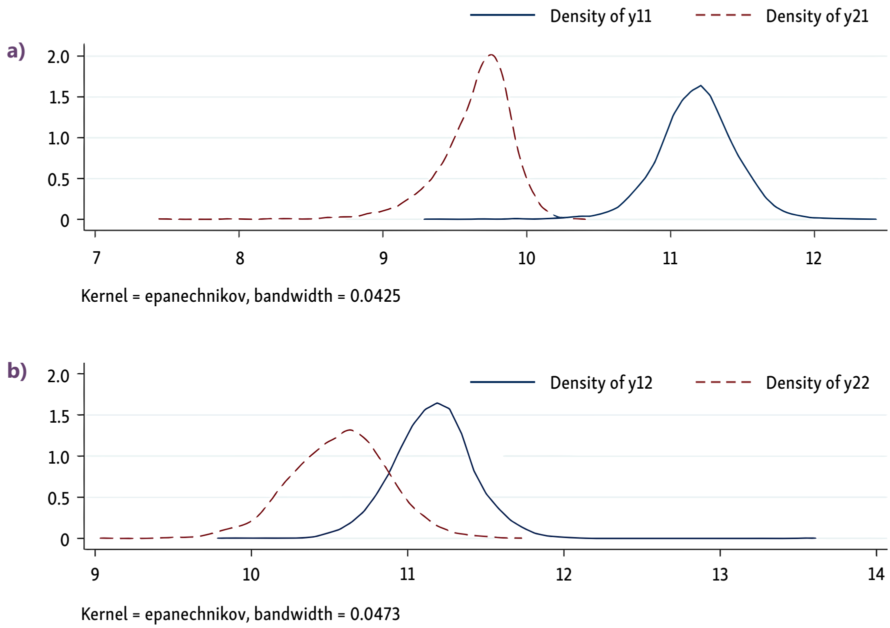

Figure 3. Kernel density curves of migrant worker household consumption

Table 7 presents the average treatment effects on the treated (ATT) using four matching methods to assess PSM robustness. All ATT estimates remain positive with substantial t-statistics ($p < 0.01$), consistently showing higher consumption levels in households adopting digital finance compared to non-adopting households.

Table 7. Average treatment effects on the treated (ATT)

Variable	Matching method	Treatment group	Control group	ATT	Std. dev.	T-value
Household consumption	Nearest neighbor 1:1 (with replacement)	11.082	10.716	0.366	0.05	7.37
	Nearest neighbor 1:1 (without replacement)	11.08	10.605	0.475	0.034	13.90
	Caliper matching	11.082	10.729	0.354	0.04	8.89
	Kernel matching	11.176	10.766	0.41	0.03	13.87

Next, Table 8 presents the baseline model regression results using post-PSM samples. The regression coefficients for digital finance adoption maintain positive values and statistical significance at the 1% level across all four matching methods. Combined with the ATT estimates in Table 7, these findings confirm that the primary conclusions persist after addressing sample selection bias, demonstrating robust model performance.

Table 8. PSM regression results

Variable	NN 1:1 (with replacement)	NN 1:1 (without replacement)	Caliper matching	Kernel matching
Digital finance usage	0.377*** (13.02)	0.359*** (14.52)	0.366*** (15.79)	0.366*** (15.79)
Control variables	Yes	Yes	Yes	Yes
Constant	7.043*** (13.71)	6.652*** (15.93)	6.677*** (19.81)	6.664*** (19.78)
Observations	2,533	3,646	5,653	5,655
R^2	0.193	0.226	0.257	0.259

5.3.2. Addressing selection bias

In addition to addressing the previously discussed self-selection bias, this study implements three robustness checks to mitigate potential selection bias. First, durable goods consumption was excluded from total household consumption due to its irregular expenditure pattern and infrequent purchase nature, which might distort the estimation of digital finance effects. As shown in Column (1) of Table 9, the coefficient for digital finance usage maintains its positive value and statistical significance at the 1% level after this adjustment.

Table 9. Regression results addressing selection bias

Variables	Durables excluded	Municipalities excluded	Alternative measure
Digital finance usage	0.383*** (16.07)	0.363*** (14.94)	—
Digital finance usage frequency	—	—	0.271*** (15.59)
Control variables	Yes	Yes	Yes
Constant	6.442*** (18.94)	6.314*** (15.81)	6.780*** (20.31)
Observations	5,712	5,311	5,712
R^2	0.253	0.259	0.261

Second, municipalities under direct central government administration (Beijing, Shanghai, Tianjin, Chongqing) were excluded to minimize regional heterogeneity, as their consumption patterns could disproportionately influence national estimates. Column (2) demonstrates that the primary findings remain robust after excluding these four municipalities.

Third, an alternative measure of digital finance adoption was constructed by combining usage frequencies of digital payments, internet wealth management, and online lending. Column (3) validates the robustness of the baseline results, with the coefficient for the composite index remaining significant at the 1% level.

5.3.3. Quantile regression

To strengthen model robustness, this study implements quantile regression to estimate coefficients at the 10th, 25th, 50th, 75th, and 90th quantiles. Table 10 demonstrates that digital finance usage coefficients maintain positive significance at the 1% level across all quantiles. The coefficient magnitude exhibits a monotonically decreasing pattern as quantile levels increase, suggesting stronger marginal effects of digital finance on consumption enhancement for households in lower consumption quantiles.

Table 10. Quantile regression results

Variables	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
Digital finance usage	0.435*** (11.22)	0.371*** (13.84)	0.326*** (12.35)	0.384*** (13.72)	0.356*** (8.27)
Control variables	Yes	Yes	Yes	Yes	Yes
Constant	6.067*** (10.97)	6.050*** (14.59)	6.482*** (17.02)	6.797*** (15.35)	7.509*** (12.56)
Observations	5,712	5,712	5,712	5,712	5,712

To further validate model robustness, this study employs quantile regression for estimation. Table 10 presents regression results at the 10%, 25%, 50%, 75%, and 90% quantiles. The regression coefficients of digital financial usage remain significantly positive across all five quantiles ($p < 0.01$), confirming model robustness. Regarding coefficient magnitude, the regression coefficients of digital financial usage show a downward trend with higher quantiles, indicating that digital financial usage demonstrates stronger consumption-enhancing effects for migrant worker households with lower consumption levels.

5.4. Mechanism tests under the digital buffer enhancement framework

The Digital Buffer Enhancement framework extends traditional buffer-stock models by proposing three channels through which digital finance enhances migrant worker household consumption: (1) improving transaction convenience, (2) mitigating liquidity constraints, and (3) decreasing income uncertainty. While initial analyses have demonstrated the consumption-promoting effects of digital finance, this study aims to empirically validate these mechanisms. To address potential endogeneity issues in explanatory variables, we employed the IV approach. The IV selection draws upon the peer effects theoretical framework from behavioral economics (Duflo & Saez, 2003), which has been thoroughly explained in the IV methodology section, hence was not repeated here. For mechanism validation, following the method proposed by Ma et al. (2024), the analysis first regresses digital finance usage on mediating variables, then examines these mediators' impact on the dependent variable to investigate transmission channels. All relevant results are presented in Table 11.

5.4.1. Enhancing transaction convenience

Following the initial pathway of this framework, transaction convenience was measured through online shopping frequency, utilizing the methodology employed by Zhang et al. (2020). Column (1) of Table 11 presents IV-2SLS results, indicating a statistically significant digital finance usage coefficient of 0.145 ($p < 0.01$), which confirms enhanced transaction

Table 11. Mediation effect analysis of digital finance on migrant household consumption

Variables	Transaction convenience	Household consumption	Liquidity constraint	Household consumption	Income uncertainty	Household consumption
Digital finance usage	0.145*** (11.53)	—	–0.432*** (–7.82)	—	–0.044*** (–5.76)	—
Transaction convenience	—	0.378*** (14.20)	—	—	—	—
Liquidity constraint	—	—	—	–0.130*** (–6.29)	—	—
Income uncertainty	—	—	—	—	—	–0.963*** (–17.90)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	–1.108*** (–6.92)	7.201*** (21.26)	2.932*** (4.69)	6.989*** (20.42)	–5.258*** (–61.32)	1.722*** (4.01)
Observations	5,712	5,712	5,712	5,712	5,712	5,712
R^2	0.118	0.25	—	0.231	0.97	0.277

convenience. Column (2) demonstrates the positive impact of transaction convenience on consumption (0.378, $p < 0.01$). Mechanism tests reveal that digital finance enhances time preference rates by improving transactional efficiency, consequently stimulating consumption growth.

5.4.2. Alleviating liquidity constraints

This study adopts the second pathway of the analytical framework and applies the methodology proposed by Yao and Zang (2021). It models households as receiving income at the end of each period and consuming it at a constant rate. Under this assumption, the average value of high-liquidity assets should equal half of the current income (y/2). Using this threshold, the study classifies migrant worker households as liquidity-constrained if their high-liquidity asset holdings (m) – which include cash, bank deposits, and liquid financial instruments such as stocks, following Zang and Zhang (2018) – fall below y/2 (coded as 1). Otherwise, the household is categorized as unconstrained (coded as 0).

The regression results in Column (3) of Table 11 provide evidence that digital financial service usage significantly reduces the likelihood of liquidity constraints. The IV-Probit model reports a negative and statistically significant coefficient of –0.432 ($p < 0.01$), indicating that digital finance mitigates liquidity constraints among migrant worker households. Column (4) further demonstrates a statistically significant and negative coefficient (–0.130, $p < 0.01$) for the liquidity constraint variable on household consumption levels, confirming the inhibitory effect of liquidity constraints on consumption. Taken together, these findings – as illustrated in Columns (3)–(4) – demonstrate that digital finance enhances migrant worker household consumption by alleviating liquidity constraints. This finding substantiates that liquidity-constrained migrant worker households accessing digital financial services experience reduced liquidity constraints, causing their target wealth-to-income ratios to converge with those of unconstrained households, ultimately resulting in higher current consumption levels.

5.4.3. Reducing income uncertainty

Following the third pathway of the framework, this study employs the methodology of Yi and Zhou (2018) to conduct OLS regression. The dependent variable is household income, while the independent variables include household head age, gender, educational attainment, marital status, household size, and regional economic development level. Regression residuals are utilized to measure income uncertainty faced by surveyed households. Column 5 of Table 11 presents IV estimation results, revealing a statistically significant negative coefficient for digital finance usage on migrant worker household income uncertainty (–0.044, $p < 0.01$), indicating that digital finance adoption effectively reduces income volatility. Column 6 further demonstrates a significant negative coefficient of income uncertainty on household consumption (–0.963, $p < 0.01$), confirming the suppressive effect of income fluctuations on consumption expenditure. The combined results from Columns 5–6 suggest that digital finance enhances migrant worker household consumption by mitigating income uncertainty. These findings substantiate that digital finance adoption reduces income uncertainty for migrant worker households. Under the Digital Buffer Enhancement framework, such households demonstrate decreased precautionary savings and increased current consumption.

The digital buffer enhancement framework receives substantial empirical support, with digital finance demonstrably promoting migrant worker household consumption through three distinct transmission pathways: enhancement of transaction convenience, alleviation of liquidity constraints, and reduction of income uncertainty. These findings comprehensively validate research Hypothesis H2, which was derived from the framework analysis.

5.5. Heterogeneity analysis

5.5.1. Age heterogeneity analysis

This study investigates age heterogeneity in life-cycle consumption demand through split-sample regression analysis. Following Zhao et al. (2022), households are categorized into two groups: the elderly group (household heads aged ≥ 60 years, N = 772) and the younger group (remaining households, N = 4,940). To ensure analytical rigor, an interaction effect regression was conducted between household head age and the digital finance usage dummy variable. The regression results in Column (1) of Table 12 reveal a positive coefficient for the interaction term ($p < 0.01$), indicating that household head age positively moderates the relationship between digital finance usage and household consumption. Columns (2)–(3) demonstrate significant consumption promotion effects in both the elderly group (0.529, $p < 0.01$) and the younger group (0.333, $p < 0.01$). To assess intergroup regression differences, the Bootstrap method with 300 replications was employed, yielding an empirical p-value of 0.000. More so, this result indicates statistically significant differences between the two regression models. Coefficient comparison reveals that digital finance usage exhibits a stronger promotional effect on consumption in migrant worker households with older household heads.

5.5.2. Wealth heterogeneity analysis

Household wealth forms the essential material foundation for consumption expenditure and significantly influences financial asset alocation strategies. This assertion is supported by the life-cycle hypothesis (Modigliani, 2005) and the Precautionary Saving Theory (Carroll et al., 1992).

Table 12. Heterogeneity analysis: age differences

Variables	Full sample	Elderly group	Young group
Digital finance usage	–0.052 (–0.40)	0.529*** (8.56)	0.333*** (13.45)
Age	–0.021*** (–10.08)	–0.003 (–0.38)	–0.013*** (–9.22)
Digital finance usage × Age	0.008*** (3.37)	—	—
Control variables	Yes	Yes	Yes
Constant	6.897*** (20.48)	6.061*** (6.66)	6.572*** (17.86)
Observations	5,712	772	4,940
R^2	0.265	0.314	0.214

To investigate the impact of household wealth, this study adopted the methodology of Ma et al. (2024), categorizing households into high-wealth (N = 3,101) and low-wealth (N = 2,611) groups based on the median net asset value. Subsample regressions were subsequently conducted, as presented in Table 13. To ensure the robustness of the findings, the study further estimated interaction effects between household wealth and a digital finance usage dummy variable.

Table 13. Heterogeneity tests: wealth disparities

Variables	Full sample	High-wealth group	Low-wealth group
Digital finance usage	1.09716	0.335*** (9.16)	0.278*** (9.77)
Wealth	0.110*** (9.29)	—	—
Digital × Wealth	0.059*** (4.04)	—	—
Control variables	Yes	Yes	Yes
Constant	7.021*** (20.54)	7.709*** (17.78)	8.028*** (14.92)
Observations	5,712	3,101	2,611
R^2	0.309	0.186	0.231

Column (1) of Table 13 reveals that the interaction term coefficient is 0.059 ($p < 0.01$), indicating that household wealth enhances the positive impact of digital finance usage on migrant worker household consumption. In Columns (2)–(3), the regression coefficients for digital finance usage are 0.335 ($p < 0.01$) and 0.278 ($p < 0.01$), respectively. A Bootstrap test yields a p-value of 0.09, suggesting statistically significant differences between the two groups at the 10% significance level. These findings demonstrate that digital finance usage has a more pronounced consumption-stimulating effect on high-wealth migrant worker households.

5.5.3. Regional heterogeneity analysis

Considering the regional disparities in China's development, the influence of digital finance usage on migrant worker household consumption may exhibit spatial heterogeneity. Following the regional classification framework of the National Bureau of Statistics, the sample is categorized into Eastern, Central, and Western regions based on household location. As illustrated in Table 14, digital finance usage demonstrates statistically significant positive coefficients across all three regions (Eastern: 0.377, $p < 0.01$; Central: 0.334, $p < 0.01$; Western: 0.358, $p < 0.01$). Notably, the effect magnitude in the Eastern region exceeds those in the Central and Western regions by 12.9% and 5.3%, respectively.

Table 14. Heterogeneity tests: regional disparities

Variables	Eastern region	Central region	Western region
Digital finance usage	0.377*** (9.51)	0.334*** (8.28)	0.358*** (9.67)
Control variables	Yes	Yes	Yes
Constant	5.603*** (11.93)	3.801** (2.46)	11.374*** (10.78)
Observations	2508	1547	1657
R^2	0.269	0.297	0.244

5.5.4. Heterogeneous effects across consumption categories and digital finance types

The benchmark analysis examines the comprehensive consumption effects of digital financial services usage. Following Hu et al. (2023), household total consumption is categorized into three groups: subsistence consumption (local transportation, clothing, daily necessities, food, and utilities), developmental consumption (cultural/recreational activities, healthcare, and education/training), and hedonic consumption (domestic services, durable goods, tourism, and luxury goods). Columns (1)–(3) of Table 15 demonstrate statistically significant and positive coefficients of digital financial services usage across all consumption categories (subsistence: 0.441, $p < 0.01$; developmental: 0.901, $p < 0.01$; hedonic: 0.771, $p < 0.01$). The effect magnitudes follow a sequential pattern: developmental consumption (104.3% higher than subsistence and 16.9% higher than hedonic) > hedonic > subsistence, indicating that digital finance primarily stimulates expenditures that enhance quality of life.

Table 15. Heterogeneity analysis: consumption categories and digital finance types

Variables	Subsistence	Developmental	Leisure-oriented	Digital payment	Digital lending	Digital wealth management
Digital finance usage	0.441*** (12.18)	0.901*** (14.77)	0.771*** (14.47)	0.367*** (15.84)	0.488*** (5.52)	0.153*** (4.89)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.881*** (5.93)	8.168*** (9.02)	–2.826*** (–3.63)	6.647*** (19.91)	6.784*** (19.93)	6.864*** (20.08)
Observations	5,712	5,712	5,712	5,712	5,712	5,712
R^2	0.154	0.185	0.178	0.263	0.23	0.228

Columns (4)–(6) further classify digital finance by functional types. The utilization of digital payments (0.367, $p < 0.01$), online borrowing (0.488, $p < 0.01$), and internet wealth management (0.153, $p < 0.01$) all exhibit significant consumption-stimulating effects. The hierarchy of effects (borrowing > payment > wealth management) suggests that transaction convenience and liquidity enhancement serve as the primary transmission channels.

6. Discussion and recommendations

This study systematically investigates the empowerment mechanism of digital finance on migrant worker household consumption patterns. Empirical findings reveal significant consumption enhancement effects, with counterfactual analysis showing a 13.74% consumption loss upon service discontinuation and 5.62% gains for new adopters. These effects are theoretically grounded in the Digital Buffer Enhancement framework, which reconciles the tension between time preference theory (McCallum & Goodfriend, 1986) and buffer-stock models (Carroll et al., 1992) through three mechanisms: transaction convenience (14.5% increase in online shopping), liquidity constraint alleviation (43.2% reduction among constrained households), and income uncertainty mitigation (4.4% decrease). Notably, the weaker uncertainty mitigation effects compared to urban residents (Lai et al., 2020; Zhao et al., 2022) underscore institutional barriers in digital wealth management applications for migrant workers.

Heterogeneity analysis identifies three reconstructed digital redistribution mechanisms: enhanced responsiveness among elderly households, the advantage paradox under institutional exclusion in eastern regions (Chen et al., 2015), and pronounced elasticity in developmental consumption. These findings challenge traditional digital divide assumptions (Wang et al., 2022a), aligning with life-cycle time preference dynamics (Hu et al., 2023). Regional disparities stem from the coevolution of institutional and digital exclusion, contrasting hukou-linked credit discrimination in developed areas (Chen et al., 2015; Tang et al., 2020) with digital infrastructure deficits in central-western regions (Song et al., 2020).

This study, therefore, presents a three-tier coordinated policy framework that establishes closed-loop institutional innovation, technological governance, and capacity-building mechanisms, providing developing countries with actionable pathways to construct inclusive digital financial systems. At the national level, governments should implement dynamic credit assessment systems that integrate digital transaction behaviors with public identity authentication infrastructure, replacing traditional asset verification with continuous behavioral analytics. Regional differentiation strategies require the deployment of financial service transparency commitment mechanisms in areas with significant institutional exclusion, while aligning digital service nodes with telecommunications network deployment in infrastructure-deficient regions.

We, therefore, recommend that industry regulators establish dual mechanisms to ensure both algorithm transparency and product innovation, requiring disclosure of key parameters influencing credit decisions. Also, financial instruments incorporating income volatility buffer features should be developed to address the characteristics of the non-formal economic sector. Additionally, the integration of service accessibility into corporate social responsibility evaluation frameworks remains essential.

At the community empowerment level, comprehensive digital literacy and financial capability programs should be implemented through community centers offering multilingual support services. Streamlined dispute resolution systems and electronic evidence preservation channels require institutionalization to establish mechanisms for converting digital behavior into social capital. This framework addresses traditional collateral dependency through interdepartmental data sharing for optimizing income stability assessments, balances innovation and protection through algorithmic regulation, and enhances technological accessibility via community networks. Its modular structure enables flexible adaptation to migrant populations at various stages of development, providing institutional adaptability and technological resilience for sustainable, inclusive growth.

7. Conclusions

This study extends the buffer-stock model to empirically examine the impact of digital finance on migrant worker household consumption, utilizing 2019 CHFS data with identification strategies including the ESR model, IV approach, and quantile regression. The findings remain robust across PSM, exclusion of durable goods consumption, and regional subsample analyses. Expectedly, the principal results indicate that: (1) Digital finance adoption significantly enhances migrant worker household consumption levels. Counterfactual analysis from the ESR model reveals that current users would experience a 13.74% decrease in household consumption without digital finance, while non-adopters could achieve a 5.62% increase through adoption. (2) Mechanism tests based on the Digital Buffer Reinforcement framework, grounded in the buffer-stock model, demonstrate that digital finance promotes consumption through three channels: enhancing transaction convenience (14.5% increase in online shopping frequency), reducing liquidity constraints (43.2% reduction in constrained households), and decreasing income uncertainty (4.4% reduction in uncertainty levels). (3) Heterogeneity analysis indicates stronger consumption-enhancing effects for elderly households, high-wealth households, and eastern-region households, with quantile regression demonstrating amplified impacts on lower consumption quantile groups. Interestingly, consumption category heterogeneity shows developmental consumption elasticity substantially exceeding hedonic and subsistence consumption, while functional heterogeneity among digital finance types confirms the dominant role of lending functions over payment and wealth management services.

This study, therefore, puts forward three primary contributions to the literature: (1) It introduces the Digital Buffer Enhancement framework by integrating time preference theory with buffer-stock models. This framework explicates how digital finance influences consumption-saving decisions through three channels: transaction convenience optimization, liquidity constraint mitigation, and income stabilization. These findings complement the traditional income-based explanatory paradigm of financial technology effects. (2) The research demonstrates systematic heterogeneity in the consumption-promoting effects of digital finance, showing that life cycle stages, regional institutional environments, and consumption category characteristics collectively determine the effectiveness distribution of inclusive finance. (3) The study establishes the superior performance of digital lending functions in facilitating consumption upgrading, with liquidity constraint alleviation and developmental expenditure promotion emerging as key mechanisms. These findings provide novel micro-level evidence supporting the transition of inclusive finance from technology penetration to functional adaptation, thereby advancing the understanding of technology-driven empowerment in the inclusive transition of developing economies.

Despite its contributions to this research area, this study has certain limitations. Firstly, while the cross-sectional design constrains the analysis of long-term dynamic effects, the concurrent application of ESR modeling and IV strategies has been essential in mitigating contemporaneous selection biases. Future research could incorporate longitudinal data to systematically examine temporal adaptation patterns in digital finance adoption. Secondly, although robust identification approaches – including over-identification tests and alternative IV specifications – address primary endogeneity concerns, residual unobserved confounders may be further explored through natural experiments leveraging exogenous policy shocks in digital infrastructure investment.

Disclosure statement

The authors report there is no competing interests to declare.

Data sharing agreement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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