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Abstract:

With the rapid advancement of digital finance in China, accessing wealth management services through digital platforms has become considerably convenient. However, the potential impact of digital platform investments on residents' consumption remains a relatively unexplored question. This study addresses this gap by leveraging a unique dataset obtained from one of China's largest fintech companies, encompassing individual-level data on consumption and investment. Our findings indicate that engaging in digital platform investments can indeed stimulate residents' consumption. Importantly, participation in digital platform investment has an inclusive effect, with a more pronounced marginal impact on consumption among low-income residents and individuals residing in finance-underdeveloped cities. Additionally, the positive influence of digital platform investment on consumption primarily stems from two channels, the wealth effect resulting from investment returns and from investment diversification in a diverse range of wealth management products. The wealth effect is more pronounced among low-risk investments when risk diversification is limited, while more pronounced among high-risk investments when the portfolio is diversified.

Keywords: Digital finance, Digital wealth management, Financial inclusiveness

1. Introduction

Finance plays an important role in the allocation of resources and is regarded as an important force in alleviating income inequality. International experience shows that residents can accumulate wealth through financial investment, cope with uncertain shocks, and ease credit constraints, thereby alleviating poverty and narrowing income gaps (Bruhn & Love, 2014; Burgess & Pande, 2005; Prina, 2015).

In China, there are insufficient investment channels for residents to manage their wealth. Even for the limited financial channels, participation rates are strikingly low; the stock market participation rate among urban households is 11.5% and only 0.6% among rural households (Xu, Lu, & He, 2019). A possible reason is that the high financial transaction costs have greatly reduced the accessibility of financial services (Guiso, Sapienza, & Zingales, 2008; Guo & Liang, 2014; Hong, Kubik, & Stein, 2004). This is especially true for low-income residents; the high threshold of purchase fees, minimum investment requirement, etc., excludes them from potential investment opportunities. In contrast, high-income residents have more channels, potentially with a high proportion of investment income. This financial exclusion may increase income gaps (Greenwood & Jovanovic, 1990; Claessens and Perotti, 2007; Ye, Chen, & Zhang, 2011).

The emergence of inclusive finance seems to be a solution to the challenge of financial inequality. Microfinance is one of the most popular programs aimed at helping low-income families start from scratch and escape poverty (Imai, Arun, & Annim, 2010; Imai & Azam, 2012; Imai, Gaiha, Thapa, & Annim, 2012; Khandker, 2005). However, it is difficult to replicate the Grameen Bank model in countries around the world at low cost and in batches (Huang & Qiu, 2021; Zhang & Yan, 2020). In addition, recent evidence shows that extending small loans to low-income households does not necessarily improve poverty (Banerjee, Duflo, Glennerster, & Kinnan, 2015).

In the current wave of digital finance development, the deep integration of technology and finance has brought new hope for breaking the barriers of financial exclusion. The development of digital finance has significantly increased the financial participation rate of low-income residents. Mobile payment has significantly increased the ownership of bank accounts in Kenya (Demombynes & Thegeya, 2012; Jack & Suri, 2011; Mbiti & Weil, 2016), increases consumption in Kenya (Jack & Suri, 2014; Suri, Jack, & Stoker, 2012; Suri, 2017), and India (Munyegera & Matsumoto, 2016; Agarwal, Ghosh, Li and Ruan, 2020) and improves the living standards of residents (Agarwal & Chua, 2020).

In China, digital finance has become a heated topic in the literature, partially due to Chinese residents having limited investment channels. It has been found to increase consumption (Yi & Zhou, 2018; Zhang, Yang, Wang, & Wan, 2020), promote entrepreneurship (He & Li, 2019; Yin, Gong, & Guo, 2019; Zhang, Wan, Zhang, & He, 2019), improve the ability to cope with risks (Zhang & Yin, 2018) and reduce the incidence of poverty (Yin and Zhang, 2020).

With the rise and development of digital finance, digital wealth management brought about by digital platforms has brought more possibilities for finance inclusiveness (Hong, Lu, & Pan, 2020). By providing great operational convenience and relaxing the requirements for initial investment, they may clear the way for financial investment among lower-income families. Undoubtedly, digital finance brings convenience for residents to manage their financial assets, but whether this convenience ultimately translates into financial inclusiveness remains controversial. Indeed, it is not uncommon for investors to lose due to information disadvantages, lack of knowledge, and experience in the capital market. In addition, residents have the opportunity to benefit from financial services brought by digital finance only if they have access to the internet and their own smartphones. The thresholds can still prevent residents from equally harnessing the benefits brought by digital finance (Qiu, Zhang, Liu, & Xu, 2016).

Therefore, the convenience of digital wealth management may be a double-edged sword, and it becomes an empirical question of whether participation in financial investment increases consumption. This paper intends to first identify whether residents' participation in digital wealth management helps promote the growth of their consumption. Specifically, it addresses the question of whether digital finance benefits the residents with lower endowments so as to achieve financial inclusiveness. Second, this paper explores potential mechanisms of how residents' digital wealth management affects their consumption patterns.

We utilize a unique dataset provided by Ant Group, a prominent fintech company in China, to examine the relationship between digital platform investments and residents' consumption. The dataset comprises consumption records of nearly 20,000 individuals using Alipay, as well as their fund investment transactions on Ant Fortune, spanning from August 2017 to July 2019. To the best of our knowledge, this dataset is the most comprehensive in terms of linking residents' consumption data with their digital platform investment activities. Our dataset offers several advantages over traditional survey data typically used in household finance research. First, it provides high-frequency records, enabling us to capture detailed consumption and investment patterns. Second, by utilizing transaction data, we mitigate potential statistical biases that can arise from self-reported consumption and investment information often encountered in household finance literature. Additionally, we augment our analysis by incorporating city-level macroeconomic data, such as the Digital Financial Inclusion Index, from the Digital Finance Research Center at Peking University and the Ant Group Research Institute in addition to GDP, loan balance, and other relevant factors. The richness and depth of our dataset, along with the inclusion of pertinent macroeconomic indicators, enhance the robustness and reliability of our study.

Our baseline results show that participating in digital finance has a positive impact on consumption. Notably, residents living in finance-underdeveloped cities experience a significantly greater increase in consumption compared to residents in finance-developed cities. At the individual level, the beneficial effect of digital platform investment on consumption is more pronounced among low-income residents than high-income residents. These results highlight the potential of digital platform investments to cater to traditionally underserved customers, thereby addressing issues of financial exclusion. When examining the consumption structure, we uncover that the average increase in non-subsistence consumption is higher for low-income residents and those residing in finance-underdeveloped cities, as compared to high-income residents and those in finance-developed cities, respectively. Moreover, low-income residents not only experience consumption increase through digital platform investment but also benefit from consumption upgrading. Their participation in investment exerts a larger promotional effect on non-subsistence consumption compared to subsistence consumption.

To address concerns regarding potential confounding factors that may simultaneously influence both digital platform investment and resident consumption (such as unanticipated changes in income), we employ an instrumental variable approach to tackle the endogeneity problem. Specifically, we utilize the average investment level of other residents in the same city as an instrumental variable, allowing us to identify the causal relationship between investment and consumption. Another potential concern is that residents might consume more via Alipay while maintaining unchanged total consumption when investing in Ant Fortune. This possibility arises because investors are encouraged to switch from other mobile payment platforms (e.g., WeChat Pay) to Alipay. To mitigate this concern, we control the number of payments made through Alipay. Our findings reveal that even after accounting for the payment-switching effect, the promotional effect of digital platform investment on consumption remains, albeit to a lesser extent.

We further investigate the underlying mechanism for the causal relationship between digital platform investment and consumption growth. Our analysis reveals two mechanisms at play, the wealth effect and risk diversification. To examine the wealth effect, we introduce investment returns into our regression model. Additionally, we construct the Herfindahl-Hirschman Index (HHI) as a proxy for measuring the degree of risk diversification reflected in investors' portfolios. Furthermore, we decompose investment returns based on fund risks to explore the interplay between investment returns and diversification.

Our findings demonstrate that the nature and magnitude of the wealth effect arising from investment returns depend on the extent of portfolio diversification. Digital platforms not only offer residents convenient access to investment returns but also provide a wide range of investment products that facilitate risk diversification. Both aspects contribute to the increase in residents' consumption. By elucidating these mechanisms, our study highlights the pivotal role played by digital platforms in enabling residents to access investment returns and diversify their portfolios. These factors, in turn, foster consumption and enhance financial well-being.

Our research significantly contributes to the literature by providing valuable insights into the inclusiveness of digital platform investment on consumption. While previous studies have demonstrated the inclusiveness of digital finance in terms of household income, family entrepreneurship, and household consumption (He & Li, 2019; Xie, Shen, Zhang, & Guo, 2018; Yi & Zhou, 2018; Zhang et al., 2019; Zhang et al., 2020), few have delved into the specific components of digital finance, likely due to data limitations. Our study stands out by utilizing a unique dataset that enables us to examine the inclusiveness of digital wealth management and expand the scope of digital finance into the realm of wealth management. By exploring the relationship between digital platform investment and consumption, we provide novel empirical evidence that sheds light on the dynamics between digital financial development and residents' consumption upgrading. This research not only enriches the existing literature but also contributes to a deeper understanding of the transformative effects of digital finance on individuals' financial well-being and consumption patterns.[1]

The rest of the paper is organized as follows. Section 2 describes data and model specifications. Section 3 reports the baseline results. Section 4 conducts robustness tests. Section 5 investigates mechanisms of consumption growth. Section 6 further discusses digital platform investment and consumption upgrading. Section 7 concludes the paper.

2. Data and model specification

2.1. Data

Residents' consumption and investment data comes from Ant Group. To protect the users' privacy, all data are anonymized in the Ant Open Research Laboratory. We obtained access to a laboratory sandbox environment, which enabled us to remotely log in and conduct empirical analysis. The dataset used in our study consists of records pertaining to individuals' monthly consumption amount and frequency, as facilitated by Alipay, one of China's most widely used mobile payment applications. Additionally, the dataset includes information on individuals' investment activities within Ant Fortune, a prominent online digital wealth management platform in China. Since Alipay and Ant Fortune are fintech products offered by Ant Group, and they share the same user account, our unique dataset provided us with an opportunity to investigate the relationship between digital platform investment and consumption.

Through random sampling of Alipay users, we initially obtained a sample comprising monthly consumption panel data for 200,000 residents over a period of 24 months, spanning from August 2017 to July 2019. Among this sample, over 150,000 residents had investment records for at least one month within the sample period, accounting for 75% of the initial sample.

Apart from the unique individual-level data, we also collect city-level data to control macroeconomic conditions. The first is the digital financial inclusion index, released by the Digital Finance Research Center at Peking University and the Ant Group Research Institute (Guo et al., 2020). It is one of the most representative data on digital finance development in China. The second is the number of financial institution branches[2] released by China Banking and Insurance Regulatory Commission. We also collect city-level GDP and year-end loan balance data from the *China City Statistical Yearbook* and the *Statistical Bulletin on National Economic and Social Development* for years 2017–2019.

2.2. Empirical specification

To investigate the effect of digital platform investments on residents' consumption, we first use the ordinary least squares (OLS) approach to estimate the following regression:

$$\begin{aligned} Ln\left(Consumption_{i,c,t}\right) &= \alpha + \beta DPI_{i,c,t} + \sum \gamma_i controls_i \\ &\quad + \sum \theta_i city_{c,t} + id_i + mon_t + \varepsilon_{i,c,t} \end{aligned} \tag{1}$$

[1] There has been extant literature on the relationship between digital finance and household consumption while the literature on the relationship between digital finance and household consumption structure is very limited. Wang and Zhao (2020) investigated the impact of digital financial development on different types of household consumption using Digital Financial Inclusion Index and China Labor Dynamics Survey (CLDS). They focus on the mechanism of the Matthew effect of digital finance and the relationship between digital finance and household income rather than household expenditure.

[2] It includes the five major state-owned banks, joint-stock banks, city commercial banks, rural commercial banks, foreign banks, and the Postal Bank.

The subscripts *i*, *c*, and *t* represent the individual, the city where the resident is located, and the report year-month. The dependent variable $Ln(Consumption_{i,c,t})$ refers to the logarithm of consumption of resident *i* in city *c* in month *t*. In the empirical estimation, we use three different dependent variables, i.e., total consumption, the e-commerce subsistence consumption, and the e-commerce non-subsistence consumption. Total consumption refers to the consumption of the user paid via Alipay in a given month. *E*-commerce subsistence consumption refers to the user's expenditure on Alibaba's e-commerce platform to purchase food, clothing, daily necessities, etc. E-commerce non-subsistence consumption includes consumption for enjoyment and development. It refers to the consumption of office supplies, educational services, and medical care services.

The key explanatory variable $DPI_{i,c,t}$ measures the investment participation of resident *i* in city *c* in month *t*. We use three indicators to depict resident's investment participation. The first is a dummy variable $I(DPI_{i,c,t} > 0)$ to indicate whether resident *i* has nonzero investment position on Ant Fortune in month *t*. The second is the logarithm of investment position on Ant Fortune, denoted as $Ln(DPI_{i,c,t})$. The third is *Relative* $DPI_{i,c,t}$. We construct this variable by dividing resident *i*'s investment position by the average investment position of all residents' investment position in his or her corresponding investable asset level in month *t*.

$controls_i$ denotes individual-level characteristics. Individual-level characteristics that change over time are $Ln\left(Consumption_{i,c,t-2}\right)$ and $Ln\left(CreditPay_{i,c,t-1}\right)$. $Ln\left(Consumption_{i,c,t-2}\right)$ is the logarithm of two-month-lagged total consumption. We add this variable to control the possible inertia effect of residents' consumption behavior. The two-month lagged dependent variable is used to avoid estimation bias caused by serial correlation (Baltagi, 2001). $Ln\left(CreditPay_{i,c,t-1}\right)$ indicates the logarithm of resident's credit payments amount in the previous month.

Individual characteristics that only change with the individual are demographics, i.e., gender, age, occupation, living in rural, and probability of property. In addition, there are two types of categorical variables related to investment, including risk attitude and investable assets, as well as two types of category variables related to payment, including frequency of use and the associated bank card level. The specific variable definitions are as follows:

A set of *risk attitude* variable indicates residents' risk attitudes and their preference for investment strategy. This is based on a questionnaire that individuals filled out before they purchased any funds on the Ant Fortune Platform. Individual investors self-assess their risk attitudes, ranging from extremely conservative, more conservative, conservative, balanced, radical, and extremely radical, totaling six categories. If their risk attitude falls into a category, the corresponding dummy variable takes a value of 1 and zero otherwise. We use the extremely conservative as the reference group.

A set of *investable asset* variables show individuals' available funds for investments. They are classified into seven categories (Grade 1–7): the higher the grade, the more the investable funds. If the share of residents' investable properties falls within a range, the corresponding dummy variable takes a value of 1; it takes a value of zero otherwise. We use Grade 1 as the reference group.

A set of *payment frequency of Alipay account* is included to show Alipay account activity. It is divided into three activity levels: high, medium, and low, based on residents' Alipay cash inflow. If the cash inflow of residents meets the corresponding level, the dummy variable takes a value of 1; otherwise, it is 0. We use medium frequency as the reference group.

Income is a proxy derived from the rank of bank card added on Alipay. We classify individuals into low-income and high-income groups.

$city_{c,t}$ indicates macroeconomic variables of the city where residents live, including the number of financial institution branches, the development of digital finance, GDP, and the year-end loan balance. All macroeconomic variables are annual frequency, except that the number of financial institution branches is the cross-sectional data in 2018.

id_i and mon_t represent individual fixed effects and year-month fixed effects, respectively, to capture characteristics that do not change over time. Unless otherwise stated, we cluster the standard errors at city-month level to account for autocorrelations among residents in the same city in each month. In the following context, we omit the subscript *i* and *c* of each variable for simplicity.

2.3. Descriptive statistics

We process the data screening and cleaning as follows. We first aggregate the fund transaction data monthly, given the holding and income of different types of funds. Second, we match the consumption data and wealth management data according to the user code and transaction month and then match it with the corresponding macroeconomic data according to where the residents are located. Then we remove observations with missing values in our key variables. To ensure data reliability, we exclude from our analysis those who do not have a financial risk assessment, or the assessments have expired. Finally, we winsorize our continuous variables at the top and bottom 1% to address extreme values in the continuous variables. This ensures that extreme values do not unduly influence our regression analyses. Following the data screening process, we retain a final sample comprising 184,762 residents.

Table 1 reports the descriptive statistics of variables included in the analysis. In our sample, residents are located in 2838 counties, 338 cities, and 31 provinces. Individuals' average monthly consumption[3] is 3745.12 *yuan*, of which 1543.02 *yuan* are paid via credit. The averages of monthly e-commerce subsistence consumption and non-subsistence consumption are 311.99 *yuan* and 306.32 *yuan,* respectively. Individuals' average consumption per payment is 121.78 *yuan.* The standard deviations of all consumption variables are

[3] In our sample, total consumption is usually higher than the sum of e-commerce subsistence consumption and non-subsistence consumption. This is because total consumption also includes other online and offline consumption via Alipay.

Table 1
Descriptive statistics.

Variables	N	Min	Max	Median	Mean	Std Dev
Consumption						
Total consumption (*yuan*)	4,064,764	0	42,407.35	1635.68	3745.12	6409.13
Credit payment consumption (*yuan*)	4,064,764	0	16,927.13	546.25	1543.02	2755.05
E-commerce subsistence consumption(*yuan*)	4,064,764	0	4277.30	68	311.99	656.15
E-commerce non-subsistence consumption (*yuan*)	4,064,764	0	5735.04	427	306.32	828.95
Average consumption per payment (*yuan*)	4,064,764	0	43,407.70	55.85	121.78	347.64
Total consumption growth rate	3,880,002	−10.68	10.68	0.01	0.04	1.51
Investment						
Digital platform investment dummy $I(DPI_t > 0)$	4,064,764	0	1	0	0.40	0.49
Digital platform investment position (full sample)	4,064,764	0	104,550.30	0	3695.09	14,885.17
Relative digital platform investment (full sample)	4,064,764	0	19.24	0	0.85	2.89
Investment return (full sample)	4,064,764	−586.51	815.14	0	11.17	128.38
Low-risk investment return (full sample)	4,064,764	−77.23	399.10	0	10.27	54.24
High-risk investment return (full sample)	4,064,764	−381.80	389.32	0	−0.03	64.66
Digital platform investment amount (investment sample)	1,641,846	0.01	104,550.30	112.68	9148.05	22,330.67
Relative digital platform investment (investment sample)	1,641,846	0	19.24	0.16	2.11	4.24
Investment return (investment sample)	1,641,846	−586.51	815.14	0	26.99	197.54
Low-risk investment return (investment sample)	1,641,846	−77.23	399.10	0	24.62	82.01
High-risk investment return (investment sample)	1,641,846	−381.80	389.32	0	0.08	99.86
HHI (investment sample)	1,641,846	0.38	1	1	0.88	0.20
Individual characteristics						
Female	184,762	0	1	0	0.393	0.488
Rural	184,762	0	1	0	0.263	0.440
Probability of owning property	184,762	0.078	1	0.531	0.554	0.224
Age						
Between 18 and 20 years	184,762	0	1	0	0.066	0.248
Between 20 and 25 years	184,762	0	1	0	0.266	0.442
Between 25 and 30 years	184,762	0	1	0	0.260	0.438
Between 30 and 35 years	184,762	0	1	0	0.168	0.374
Between 35 and 40 years	184,762	0	1	0	0.101	0.302
Between 40 and 45 years	184,762	0	1	0	0.059	0.256
Between 45 and 50 years	184,762	0	1	0	0.043	0.203
Between 50 and 55 years	184,762	0	1	0	0.021	0.143
Between 55 and 60 years	184,762	0	1	0	0.010	0.098
Over 60 years	184,762	0	1	0	0.006	0.077
Occupation						
Civil Servant	184,762	0	1	0	0.011	0.102
White-collar	184,762	0	1	1	0.518	0.500
Blue-collar	184,762	0	1	0	0.260	0.439
Student	184,762	0	1	0	0.079	0.269
Retiree	184,762	0	1	0	0.014	0.117
Other	184,762	0	1	0	0.119	0.323
Investable asset						
Grade 1	184,762	0	1	0	0.213	0.410
Grade 2	184,762	0	1	0	0.232	0.422
Grade 3	184,762	0	1	0	0.191	0.393
Grade 4	184,762	0	1	0	0.161	0.368
Grade 5	184,762	0	1	0	0.173	0.378
Grade 6	184,762	0	1	0	0.025	0.157
Grade 7	184,762	0	1	0	0.004	0.061
Risk attitude						
Extremely Conservative	184,762	0	1	0	0.063	0.242
Conservative	184,762	0	1	0	0.093	0.291
Moderate	184,762	0	1	0	0.466	0.499
Balanced	184,762	0	1	0	0.192	0.394
Positive	184,762	0	1	0	0.172	0.377
Aggressive	184,762	0	1	0	0.014	0.118
Payment frequency of Alipay account						
High frequency	184,762	0	1	1	0.821	0.383
Medium frequency	184,762	0	1	0	0.152	0.359
Low frequency	184,762	0	1	0	0.028	0.164
Income						
Low-income	184,762	0	1	1	0.771	0.420
High-income	184,762	0	1	0	0.229	0.420
Regional characteristics						
GDP (100 billion *yuan*)	1002	0.08	26.93	1.50	2.73	3.87
Loan balance (100 billion *yuan*)	1002	0.08	79.84	1.37	3.92	8.44
Digital inclusive finance index	1002	182.66	321.65	227.34	231.56	25.11
Number of financial institution branches	336	25	5537	443	582.54	607.88

very large, indicating a substantial variation in consumption among residents.

Regarding individual characteristics, 39.3% of residents are female, 73.7% live in cities, 76% are under the age of 35, 51.8% are white-collar workers, 62.2% are risk-neutral or risk-averse, 82.1% are high frequency users of Alipay account, 77.1% are low-income.[4]

As for participation in digital platform investment, 142,171 individuals, or 76.9% have invested through digital platforms at least in one month. To focus our analysis on the investment-related observations, we filter the full sample using the condition $I(DPI_{i,c,t} > 0) = 1$, resulting in an "investment sample". We provide details on the investment position and return for both the full sample and the investment sample, allowing for a comprehensive understanding of the investment landscape within our data.[5] In the full sample (investment sample), residents invest 3695.09 *yuan* (9148.05 *yuan*) and gain 11.17 *yuan* (26.99 *yuan*) as return per month on average.

We categorize the wealth management products into two groups based on their risk levels: lower-risk investments and higher-risk investments. The lower-risk group consists of currency, short-term bonds, pensions, bonds, and index funds. The higher-risk group includes blends, stocks, fund of funds (fof), and QDII.

In the full sample, individuals, on average, gain 10.27 *yuan* per month from lower-risk investments and experience a marginal loss of 0.03 *yuan* per month from higher-risk investments. In the investment sample, individuals, on average, gain 10.27 *yuan* per month from lower-risk investments and 0.08 *yuan* per month from higher-risk fund investments.

Furthermore, we calculate the average relative digital platform investment to assess the level of investment engagement. In the full sample, the average relative digital platform investment is 0.85, while in the investment sample, it is 2.11. These figures provide insights into the extent of individuals' participation in digital platform investment.

We preliminarily examine the univariate analysis before conducting formal regressions. Table 2 reports the comparison of the average consumption with and without digital platform investment. It shows that consumption among residents with digital platform investment is statistically higher than that of without digital platform investment. This suggests that residents' participation in digital platform investment may have nontrivial impact on consumption, and we will explore the causal relationship in the next section.

3. Empirical results

3.1. Baseline regression

Table 3 presents the estimation results of eq. (1), where the dependent variable is the logarithm of resident *i*'s total consumption in month *t*.

In Column (1), the variable of interest is whether resident *i* participates in Ant Fortune in month *t*. To account for various factors that may influence residents' consumption, we include city and year-month fixed effects. These fixed effects allow us to capture the relationship between digital wealth management and residents' consumption, as well as the impact of individual characteristics on consumption patterns. In Column (2), we further include individual fixed effects to mitigate the potential omitted variables. This addition helps address factors such as financial investments from other channels and individual consumption habits that may affect consumption but are unobserved.[6]

In Columns (3) and (4), we focus on the depth of residents' participation[7] in Ant Fortune incorporating individual and year-month fixed effects. Specifically, the variables of interest are the logarithm of resident i's investment during month *t* in column (3) and the relative investment position in column (4) scaled by the average monthly position of residents with the same level of investable assets. These variables provide insights into the extent and relative position of residents' engagement in Ant Fortune.

In all estimations, we consistently observe a significant positive effect of digital wealth management on total consumption, regardless of whether we use a binary variable, the investment position, or relative investment position as our measure. In Column (3), we find that a 1% increase in a resident's investment on Ant Fortune corresponds to a 0.0153% increase in their consumption. Moreover, Column (4) reveals that if a resident's investment position on Ant Fortune doubles the average position of residents with the same investable asset level, their consumption is estimated to increase by 1.84% (= 2 multiplied by 0.0092).

Table 3 also identifies several other factors that are associated with residents' consumption. Notably, credit payment exhibits a significantly positive coefficient, indicating that utilizing credit payment alleviates liquidity constraints and stimulates consumption. Furthermore, the positive coefficient of the two-month lagged consumption variable suggests the presence of time inertia in residents' consumption patterns, indicating that past consumption levels have an impact on current consumption behavior.[8] Meanwhile, within our sample of Alipay users, we find that certain characteristics are associated with higher levels of consumption. Specifically, younger and female users, individuals with larger investable assets, those exhibiting risk-seeking behavior, and those with active cash flow tend to have higher levels of consumption. On the other hand, we do not find significant impacts of annual macroeconomic characteristics on residents' consumption within the given sample range. This lack of significance can be attributed to the limited variation in macroeconomic factors over the observed time.

[4] Due to privacy protection, we do not have information on the cutoff of the two income groups.

[5] For those observations without digital platform investment participation in current month, we fill his or her investment position and return as zero in the full sample.

[6] The personal characteristics and city fixed effect are collinear with the individual fixed effects, as they only change with the individual and do not change over time in the sample.

[7] Thanks to the suggestion of an anonymous referee.

[8] According to Baltagi (2001), a two-month lagged consumption help avoid biases in the panel data estimation.

Table 2
Average monthly consumption with and without digital platform investment.

	$I(DPI_t > 0) = 1$ ($N = 1,641,846$)	$I(DPI_t > 0) = 0$ ($N = 2,422,918$)	*t*-test
Total consumption	4183.59	3448.00	111.87***
	(6721.60)	(6170.75)	
E-commerce subsistence consumption	330.92	299.16	47.42***
	(676.23)	(641.88)	
E-commerce non-subsistence consumption	332.32	288.70	51.36***
	(863.90)	(803.93)	

Note: *** represent the difference of means is significant at 1% significance level. The numbers in parentheses are standard deviations.

3.2. Inclusiveness of digital financial participation

Our baseline regression results reveal a positive relationship between residents' participation in digital platform investment and consumption. This finding aligns with the advantages offered by digital wealth management, i.e., lower barriers to entry and easier access to financial services. We hypothesize that digital wealth management plays a crucial role in stimulating consumption, particularly among low-income residents who may face financial exclusion in traditional financial markets, as well as residents residing in cities with underdeveloped traditional finance systems. To further explore the heterogeneous impact of digital wealth management on residents' consumption, Table 4 presents subsample regressions based on individual income and regional financial development. In Panel A, we examine the investment position (in logarithms) of resident i in month t and in Panel B, focus on the relative investment position scaled by the average monthly position of residents with the same level of investable assets.

To examine whether the effect of digital wealth management on consumption differs across different income groups, we divide Alipay users into lower-income and higher-income groups based on their type of bank cards (regular or gold/silver). This allows us to analyze the potential income group variations in the impact of digital wealth management on consumption. In Columns (1) and (2) of Panel A, we present the results. We find that a 1% increase in residents' investment positions on Ant Fortune leads to a consumption increase of 0.0164% for the lower-income group and 0.0121% for the higher-income group. Importantly, the effects on consumption for the low-income group is 0.0043% higher than that of the high-income group, and this difference is statistically significant at a 1% level of significance.

Furthermore, Columns (1) and (2) of Panel B indicate that the consumption of low-income groups exhibits higher sensitivity to digital wealth management compared to high-income groups.

These findings align with our conjecture. Unlike traditional financial institutions that often have stringent requirements for minimum investment amounts, digital wealth management platforms have relaxed these requirements, thus expanding investment opportunities for low-income residents. Consequently, the low-income group benefits more from the accessibility and inclusiveness of digital wealth management, leading to a relatively higher consumption compared to the high-income group.

Similarly, we partition the sample into two groups based on regional finance development, specifically the number of financial institution branches in each city. In Columns (3) and (4), we present the results. Cities with the number of financial institution branches exceeding the 75th percentile are classified as the developed group, while those below this threshold are considered underdeveloped. By categorizing the cities in this manner, we investigate whether the effect of digital wealth management on consumption varies between regions with differing levels of financial development.[9]

As shown in Columns (3) and (4) of Panel A, a 1% increase in digital platform investment on consumption in cities with underdeveloped finance is associated with a 0.0066% higher marginal effect than in cities with developed finance, in line with our conjecture. The number of financial institution branches in a city serves as an indicator of the accessibility of wealth management participation for residents on the supply side. In cities with a limited number of financial institution branches, residents often face higher transaction costs when seeking relevant financial services and searching for wealth management products. The emergence of digital wealth management platforms has addressed these challenges by facilitating the shift from offline to online wealth management services. This transition has made wealth management more convenient and cost-effective, which is particularly significant for residents living in cities with underdeveloped finance. Taken together, the results presented in Columns (1)–(4) confirm the inclusive nature of digital wealth management at both the individual and regional levels. Digital platforms have enabled broader access to wealth management services, benefiting individuals across various income groups and residents in regions with different levels of financial development.

Next, moving on to regional digital finance, we divide regions into underdeveloped and developed groups based on the aggregate digital financial inclusion index. Cities with an aggregate digital financial inclusion index surpassing the 75th percentile of the sample are classified as the developed group, while others are categorized as the underdeveloped group. By comparing the regression results for these two subsamples, we find that residents in cities with underdeveloped digital finance experience a relatively more substantial increase in consumption compared to residents in cities with developed digital finance. It suggests that as digital finance develops, the marginal effect of digital wealth management on consumption diminishes. However, in cities that are in the early stages of digital

[9] The reason for using 75th percentiles as classification criteria is that most of the users in the sample live in cities with developed traditional finance. If the median is used for grouping, the sample size among different groups would be highly uneven.

Table 3
Baseline results of digital wealth management and consumption.

Dependent variable	$Ln(Consumption_t)$			
	(1)	(2)	(3)	(4)
$I(DPI_t > 0)$	0.0638***	0.1535***		
	(0.0110)	(0.0140)		
$Ln(DPI_t)$			0.0153***	
			(0.0013)	
$Relative\ DPI_t$				0.0092***
				(0.0010)
$Ln(CreditPay_{t-1})$	0.1068***	0.0907***	0.0913***	0.0916***
	(0.0040)	(0.0057)	(0.0057)	(0.0058)
$Ln(Consumption_{t-2})$	0.4108***	0.1744***	0.1754***	0.1758***
	(0.0133)	(0.0289)	(0.0291)	(0.0291)
Female	0.0832***			
	(0.0140)			
Rural	−0.0664***			
	(0.0055)			
Age between 20 *and* 25 *years*	0.0401**			
	(0.0162)			
Age between 20 *and* 30 *years*	0.0147			
	(0.0237)			
Age between 30 *and* 35 *years*	−0.0076			
	(0.0286)			
Age between 35 *and* 40 *years*	−0.0373			
	(0.0343)			
Age between 40 *and* 45 *years*	−0.0932**			
	(0.0389)			
Age between 45 *and* 50 *years*	−0.1861***			
	(0.0408)			
Age between 50 *and* 55 *years*	−0.3072***			
	(0.0404)			
Age between 55 *and* 60 *years*	−0.2745***			
	(0.0449)			
Over 60 *years*	−0.2535***			
	(0.0508)			
Probability of owning property	0.2041***			
	(0.0164)			
$White-collar$	0.2080***			
	(0.0164)			
Civil Servant	0.2026***			
	(0.0229)			
Student	0.2546***			
	(0.0343)			
Retiree	0.0629**			
	(0.0271)			
Other	0.2535***			
	(0.0151)			
Asset grade 2	0.1396***			
	(0.0113)			
Asset grade 3	0.1542***			
	(0.0131)			
Asset grade 4	0.2087***			
	(0.0144)			
Asset grade 5	0.4032***			
	(0.0141)			
Asset grade 6	0.3812***			
	(0.0141)			
Asset grade 7	0.5202***			
	(0.0283)			
Risk attitude : *Conservative*	−0.0251***			
	(0.0089)			
Risk attitude : *Stable*	0.0150*			
	(0.0091)			
Risk attitude : *Balanced*	0.0546***			
	(0.0123)			
Risk attitude : *Positive*	0.0570***			
	(0.0131)			
Risk attitude : *Aggressive*	0.0753***			
	(0.0193)			
High frequency of Alipay wallet	0.2778***			

(*continued on next page*)

Table 3 (*continued*)

Dependent variable	$Ln(Consumption_t)$			
	(1)	(2)	(3)	(4)
	(0.0196)			
Low frequency of Alipay wallet	−0.2228***			
	(0.0344)			
High income	0.0757***			
	(0.0051)			
City digital finance	0.0003	−0.0004	−0.0006	−0.0006
	(0.0007)	(0.0010)	(0.0010)	(0.0010)
City GDP	−0.0040	−0.0154	−0.0162	−0.0157
	(0.0039)	(0.0058)	(0.0059)	(0.0058)
Loan balance	0.0000	−0.0016	−0.0017	−0.0017
	(0.0006)	(0.0013)	(0.0014)	(0.0014)
Individual FE	NO	YES	YES	YES
City FE	YES	NO	NO	NO
Year × month FE	YES	YES	YES	YES
R^2	0.3786	0.0861	0.0624	0.0620
N	4,064,764	4,064,764	4,064,764	4,064,764

***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Standard errors clustered at the City-Year×month level are shown in parentheses.

Table 4
The Inclusive effect of the digital wealth management.

Dependent variable: $Ln(Consumption_t)$	Individual Income		Regional traditional finance development		Regional digital finance development	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: $Ln(DPI_t)$						
$Ln(DPI_t)$	0.0164***	0.0121***	0.0202***	0.0136***	0.0223***	0.0127***
	(0.0015)	(0.0011)	(0.0018)	(0.0012)	(0.0021)	(0.0010)
$Ln(CreditPay_{t-1})$	0.0890***	0.0984***	0.1018***	0.867***	0.0977***	0.0828***
	(0.0056)	(0.0066)	(0.0067)	(0.0056)	(0.0065)	(0.0052)
$Ln(Consumption_{t-2})$	0.1785***	0.1600***	0.1734***	0.1759***	0.1509***	0.1577***
	(0.0301)	(0.0244)	(0.0288)	(0.0291)	(0.0279)	(0.0255)
Regional controls	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year × month FE	YES	YES	YES	YES	YES	YES
R^2	0.0627	0.0582	0.0638	0.0614	0.0511	0.0511
N	3,135,330	929,434	1,173,392	2,891,372	1,226,741	2,838,023
Coefficient test	2.3117**		3.0509***		4.1274***	
Panel B: *Relative* DPI_t						
Relative DPI_t	0.0093***	0.0077***	0.0117***	0.0084***	0.0122***	0.0080***
	(0.0010)	(0.0012)	(0.0014)	(0.0009)	(0.0015)	(0.0008)
$Ln(CreditPay_{t-1})$	0.0894***	0.0988***	0.1022***	0.0870***	0.0982***	0.0831***
	(0.0057)	(0.0066)	(0.0068)	(0.0056)	(0.0066)	(0.0052)
$Ln(Consumption_{t-2})$	0.1790***	0.1605***	0.1741***	0.1763***	0.1515***	0.1580***
	(0.0302)	(0.0244)	(0.0288)	(0.0291)	(0.0279)	(0.0255)
Regional controls	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year × month FE	YES	YES	YES	YES	YES	YES
R^2	0.0623	0.0578	0.0632	0.0610	0.0504	0.0508
N	3,135,330	929,434	1,173,392	2,891,372	1,226,741	2,838,023
Coefficient test	1.0762		1.9828**		2.4706**	

***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Standard errors clustered at the City-Year×month level are shown in parentheses.

financial development, the marginal effect of digital wealth management on consumption appears to be more pronounced. One potential explanation is that as digital finance matures, its impact on consumption becomes more saturated. Hence, in cities with underdeveloped digital finance, where the transition is still ongoing, the marginal effect of digital wealth management on consumption remains relatively stronger.

4. Robustness checks

In this section, we employ instrumental variable regression to address potential endogeneity concerns that may arise from the relationship between digital platform investment and consumption. This approach helps ensure the validity and reliability of our findings by accounting for any confounding factors that may affect both variables simultaneously.

4.1. Endogeneity

To address concerns regarding potential endogeneity in the relationship between digital wealth management and residents' consumption, we employ an instrumental variable approach. It allows us to establish a causal relationship by mitigating the potential biases arising from residents' self-selection into digital platform investment.

In our instrumental variable regression, we utilize the logarithm of the average investment position of all other residents in the same city within the sample range in month t as the instrumental variable. Regional characteristics, such as the level of financial development and the popularity of digital finance, can significantly influence residents' decision to invest in digital platforms. Consequently, the digital platform investment of different residents within the same city becomes positively correlated, satisfying the correlation requirements for instrumental variables.

Furthermore, the monthly consumption expenditure and the extent to which Alipay is used for consumption are self-selected by each resident. These variables are determined by each resident and are not directly affected by the digital platform investment of other residents within the same city, which satisfies the exclusive requirements for instrumental variables.

Table 5 presents the results of the two-stage least squares (2SLS) regression. In Columns (1)–(3) of Panel A, we examine the endogenous variable, the indicator of whether resident i participates in Ant Fortune in month t, the logarithm of resident i's investment position on Ant Fortune in month t, and the relative investment position of resident i in month t, respectively. To test the validity of the instrumental variable regression, Panel B reports the results of the first stage of the IV estimation. The coefficient is found to be significantly positive, and the F-value of the first-stage regression exceeds 10. This indicates that the IV estimation is not compromised by the problem of weak instrumental variables.

We then examine the second stage of the instrumental variable regression, shown in Panel A of Table 5. After addressing endogeneity, our main results remain significantly positive. It suggests in Column (2) that a 1% increase in digital platform investment leads to a 0.2101% increase in consumption, thus supporting the positive effects of digital wealth management on residents' consumption.

Table 5
Instrumental variable regression results.

Dependent variable	$Ln(Consumption_t)$		
	(1)	(2)	(3)
Panel A: Second stage regression			
$I(DPI_t > 0)$	1.5433**		
	(0.7880)		
$Ln(DPI_t)$		0.2101**	
		(0.1070)	
Relative DPI_t			0.7389*
			(0.3773)
$Ln(CreditPay_{t-1})$	0.0807***	0.0845***	0.0765***
	(0.0088)	(0.0075)	(0.0106)
$Ln(Consumption_{t-2})$	0.1590***	0.1668***	0.1588***
	(0.0337)	(0.0314)	(0.0338)
Regional controls	YES	YES	YES
Individual FE	YES	YES	YES
Year × *month FE*	YES	YES	YES
R^2	0.0618	0.0618	0.0599
N	4,064,764	4,064,764	4,064,764
Panel B: First stage regression			
Explained variable	$I(DPI_t > 0)$	$Ln(DPI_t)$	*Relative* DPI_t
IV	0.0290***	0.2131***	0.0606*
	(0.0063)	(0.0445)	(0.0350)
Personal controls	YES	YES	YES
Regional controls	YES	YES	YES
Individual FE	YES	YES	YES
Year × *month FE*	YES	YES	YES
R^2	0.0049	0.0023	0.0008
$F - value$	26.247	30.842	20.619
N	4,064,764	4,064,764	4,064,764

***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Standard errors clustered at the City-Year×month level are shown in parentheses.

4.2. Total consumption or Alipay consumption increases?

One may be concerned that the consumption increase captured in our sample may be due to either the increase in total consumption, or the increase in the proportion of consumption using Alipay. To address this question, we conducted a robustness test to ascertain the source of consumption increase.

In our robustness test, we assume that the average amount of each payment is primarily influenced by personal characteristics such as income, age, and risk attitude, and has little to do with the choice of mobile payment application (e.g., Alipay or WeChat Pay). We posit that the disparity in the amount of cash consumption, WeChat Pay consumption, and Alipay consumption of the same individual mainly stems from differences in the number of payments made, rather than variations in the average consumption per payment.

In light of this assumption, if residents do not consume more but use Alipay more frequently for their consumption, we would expect to observe an increase in both monthly consumption and the number of monthly payments on Alipay, without a significant variation in the average consumption per payment. Conversely, if we observe an increase in both the total consumption and the average consumption per payment on Alipay, it indicates an increment in residents' total consumption rather than just consumption on Alipay.

To test the hypothesis, we construct a variable, average consumption per payment $Ln(Consumption/NumPay_t)$ as the ratio of total consumption on Alipay to the number of payments on Alipay. Table 6 reports the impact of digital platform investment on $Ln(Consumption/NumPay_t)$. The variables of interests in column (1) to (3) are $I(DPI_t > 0)$, $Ln(DPI_t)$ and $Relative\ DPI_t$ respectively. Individual fixed effects are used in all estimations.

The results show that participation in digital platform investment significantly enhances the average consumption per payment. As column (2) shows, a 1% increase in the digital platform investment position is associated with a 0.0015% increase in average consumption.

While investment on Ant Fortune may prompt individuals to switch from other payment channels to Alipay, our findings demonstrate that digital platform investment participation still exerts a positive and significant impact on total consumption even after controlling possible payment channel switching. Thus, we conclude that the observed increase in total consumption is not solely driven by a shift in payment channels but is, in fact, influenced by the positive association between digital platform investment participation and consumption.

4.3. Investment participation due to payment activity?

One concern may also arise that individuals who invest in Ant Fortune are active users of Alipay. Therefore, we conduct a robustness check examining user activity. We propose two measurements of user activity to investigate this alternative explanation further.

The first measurement of user activity is based on investment behavior. We calculate the cumulative investment months for each resident within the sample period. The median cumulative investment month among the 184,762 individuals is seven months. Thus, we define an individual as an active user if he or she has invested for more than seven months during our study period.

The second measurement of user activity is based on consumption behavior. We find the average number of monthly payments made by each individual and its median is 31.33. An individual is classified as an active user if his or her average number of monthly payments exceeds 31.33, while those below this threshold are categorized as inactive users.

Panel A of Table 7 uses the cumulative investment month as the criterion for user activity, while Panel B uses the average number of

Table 6
Robustness check of average consumption per payment.

Dependent variable	$Ln(Consumption/NumPay_t)$		
	(1)	(2)	(3)
$I(DPI_t > 0)$	0.0244***		
	(0.0067)		
$Ln(DPI_t)$		0.0015**	
		(0.0007)	
$Relative\ DPI_t$			0.0018**
			(0.0008)
$Ln(CreditPay_{t-1})$	0.0321***	0.0322***	0.0323***
	(0.0034)	(0.0034)	(0.0034)
$Ln(Consumption/NumPay_{t-2})$	0.1100***	0.1101***	0.1101***
	(0.0226)	(0.0226)	(0.02265)
Regional controls	YES	YES	YES
Individual FE	YES	YES	YES
Year × month FE	YES	YES	YES
R^2	0.0190	0.0190	0.0190
N	4,064,764	4,064,764	4,064,764

***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Standard errors clustered at the City-Year×month level are shown in parentheses.

monthly payments as the criterion. In each panel, columns (1) and (2) examine the impact of the position of digital platform investment, while columns (3) and (4) consider the impact of the relative position of digital platform investment.

The results demonstrate that regardless of whether a user is considered active or inactive, his or her participation in digital platform investment positively influences monthly consumption. These findings help exclude the alternative explanation that the positive correlation between digital platform investment and consumption growth is solely driven by users' preference for using Alipay. Furthermore, if the alternative explanation were accurate, we would anticipate a greater impact of digital platform investment on consumption in the active-user sub-sample. However, the results contradict this expectation. Instead, they indicate that the marginal effect of digital platform investment participation on consumption is higher in the inactive-user group, implying that the baseline results are not driven solely by user activity.

4.4. Additional tests

We perform a series of robustness tests in this section. First, to address concerns regarding potential reverse causality between digital platform investment and consumption, we conduct a robustness test by incorporating a one-month lag in our measurement of digital platform investment. By considering the lagged digital platform investment measurement, we aim to mitigate any potential issues related to the concurrent influence of investment and consumption. This approach helps to establish a temporal ordering between investment and consumption, providing further insights into the relationship between the two variables.

The results are presented in Columns (1) to (3) of Table 8, with $I(DPI_{t-1} > 0)$, $Ln(DPI_{t-1})$ and $Relative\ DPI_{t-1}$ respectively. All estimations of digital platform investment demonstrate a positive effect at a 1% significance level, indicating an association between digital platform investment and consumption.

Second, in columns (1) to (3) of Table 9, we present the results from a restricted sample that excludes individuals who have never invested on the digital platform throughout the sample period. Conversely, in columns (4) and (5) of Table 9, we report the findings from the investment sample, which only includes individuals with investment activity. Our results consistently support the major conclusions derived from the baseline regression. Despite the differences in sample composition, the estimated coefficients consistently validate the key findings.

Table 7
Robustness check of user activity.

Dependent variable: $Ln(Consumption_t)$	Whether a user active or not			
	Inactive	Active	Inactive	Active
	(1)	(2)	(3)	(4)
Panel A: cumulative investment month as activity measurement				
$Ln(DPI_t)$	0.0230***	0.0138***		
	(0.0020)	(0.0015)		
$Relative\ DPI_t$			0.0145***	0.0077***
			(0.0013)	(0.0010)
$Ln(CreditPay_{t-1})$	0.0960***	0.0860***	0.0963***	0.0865***
	(0.0058)	(0.0058)	(0.0058)	(0.0058)
$Ln(Consumption_{t-2})$	0.1761***	0.1742***	0.1764***	0.1749***
	(0.0285)	(0.0297)	(0.0286)	(0.0298)
Regional controls	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Year × month FE	YES	YES	YES	YES
R^2	0.0637	0.0611	0.0632	0.0606
N	2,033,746	2,031,018	2,033,746	2,031,018
Coefficient test	3.6800***		4.1460***	
Panel B: average number of monthly payments as activity measurement				
$Ln(DPI_t)$	0.0206***	0.0098***		
	(0.0014)	(0.0010)		
$Relative\ DPI_t$			0.0121***	0.0056***
			(0.0012)	(0.0007)
$Ln(CreditPay_{t-1})$	0.1067***	0.0683***	0.1072***	0.0685***
	(0.0065)	(0.0047)	(0.0066)	(0.0047)
$Ln(Consumption_{t-2})$	0.1623***	0.2056***	0.1628***	0.2060***
	(0.0283)	(0.0295)	(0.0283)	(0.0295)
Regional controls	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Year × month FE	YES	YES	YES	YES
R^2	0.0582	0.0750	0.0576	0.0747
N	2,030,622	2,034,142	2,030,622	2,034,142
Coefficient test	6.2773***		4.6788***	

***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Standard errors clustered at the City-Year×month level are shown in parentheses.

Table 8
Robustness tests of lagged digital wealth management.

Dependent variable	$Ln(Consumption_t)$		
	(1)	(2)	(3)
$I(DPI_{t-1} > 0)$	0.1180***		
	(0.0076)		
$Ln(DPI_{t-1})$		0.0128***	
		(0.0010)	
$Relative\ DPI_{t-1}$			0.0096***
			(0.0005)
$Ln(CreditPay_{t-1})$	0.0909***	0.0913***	0.0916***
	(0.0057)	(0.0058)	(0.0058)
$Ln(Consumption_{t-2})$	0.1746***	0.1754***	0.1758***
	(0.0290)	(0.0291)	(0.0291)
Regional controls	YES	YES	YES
Individual FE	YES	YES	YES
Year × month FE	YES	YES	YES
R^2	0.0626	0.0622	0.0620
N	4,064,764	4,064,764	4,064,764

***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Standard errors clustered at the City-Year×month level are shown in parentheses.

Table 9
Robustness check of restricted samples.

Dependent variable: $Ln(Consumption_t)$	Excluding users without DPI records			investment sample	
	(1)	(2)	(3)	(4)	(5)
$I(DPI_t > 0)$	0.1482***				
	(0.0132)				
$Ln(DPI_t)$		0.0144***		0.0108***	
		(0.0012)		(0.0009)	
$Relative\ DPI_t$			0.0090***		0.0050***
			(0.0009)		(0.0006)
$Ln(CreditPay_{t-1})$	0.0889***	0.0895***	0.0898***	0.0630***	0.0630***
	(0.0057)	(0.0058)	(0.0058)	(0.0043)	(0.0043)
$Ln(Consumption_{t-2})$	0.1775***	0.1788***	0.1792***	0.0773***	0.0774***
	(0.0299)	(0.0301)	(0.0301)	(0.0143)	(0.0143)
Regional controls	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
Year × month FE	YES	YES	YES	YES	YES
R^2	0.0655	0.0645	0.0640	0.0183	0.0181
N	3,127,762	3,127,762	3,127,762	1,641,846	1,641,846

***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Standard errors clustered at the City-Year×month level are shown in parentheses.

5. Mechanisms

In this section, we delve into the potential mechanisms through which digital wealth management facilitates consumption. We begin by highlighting two crucial mechanisms: the wealth effect of investment return and the risk diversification offered by digital wealth management. Subsequently, we examine the relationship between the wealth effect and risk diversification. By exploring these mechanisms, we aim to shed light on how digital wealth management contributes to the growth of individuals' consumption.

5.1. *The wealth effect of investment return*

After residents participate in digital wealth management on Ant Fortune, their investment positions have the potential to generate investment returns, thereby increasing their disposable income and promoting consumption. To investigate the existence of the wealth effect, Table 10 examines the relationship between investment returns and residents' consumption, while controlling various investment position indicators. Additionally, residents who do not participate in digital wealth management in month t are excluded from the regression sample in Table 10. This exclusion is necessary to ensure sufficient variation in investment returns.

We estimate the model using the investment sample of residents with digital platform investment in month *t* and present the results in columns (1) and (2). The results show a significantly positive estimated coefficient for investment position, indicating its impact on consumption. However, the estimated coefficient for investment returns is found to be insignificant, which may not support the existence of the wealth effect.

Table 10
Wealth effect of investment return on consumption.

Dependent variable: $Ln(Consumption_t)$	DPI investors (1)	DPI investors (2)	Low position (3)	High position (4)	Low position (5)	High position (6)
Investment return	0.0018	0.0017	0.0184***	0.0025***	0.0187***	0.0024***
	(0.0012)	(0.0011)	(0.0061)	(0.0008)	(0.0062)	(0.0008)
$Ln(DPI_t)$	0.0107***		0.0240***	0.0107***		
	(0.0010)		(0.0030)	(0.0021)		
Relative DPI_t		0.0048***			0.0447***	0.0034***
		(0.0007)			(0.0093)	(0.0008)
$Ln(CreditPay_{t-1})$	0.0630***	0.0630***	0.0705***	0.0465***	0.0705***	0.0465***
	(0.0043)	(0.0043)	(0.0153)	(0.0037)	(0.0052)	(0.0037)
$Ln(Consumption_{t-2})$	0.0773***	0.0774***	0.0728***	0.0493***	0.0729***	0.0493***
	(0.0143)	(0.0143)	(0.0052)	(0.0131)	(0.0153)	(0.0131)
Regional controls	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year × month FE	YES	YES	YES	YES	YES	YES
R^2	0.0183	0.0181	0.0195	0.0086	0.0193	0.0087
N	1,641,846	1,641,846	821,018	820,828	821,018	820,828
Coefficient test of Investment return	/	/	2.5844***		2.6074***	

***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Standard errors clustered at the City-Year×month level are shown in parentheses.

To explore whether the results in columns (1) and (2) are due to the absence of a wealth effect or differing sensitivities to investment returns across different investor groups, we further divide the DPI investors into low-position and high-position groups monthly, based on the median in the logarithm of investment. Investors with an investment position greater than the sample median in month t are classified as high-position investors. Columns (3)–(6) present the heterogeneous impact of investment returns on residents' consumption among different investor groups.

The results indicate that the estimated coefficient for investment returns is significantly positive in both groups. Moreover, comparing columns (3) and (4), it becomes evident that if the same 100-*yuan* investment return is realized, investors in the lower-position group experience a greater proportion of consumption increase compared to investors in the higher-position group. This finding suggests that the wealth effect is more pronounced for new investors engaging in digital wealth management.

These results not only confirm the existence of the wealth effect but also highlight the crucial role of investment opportunities in driving residents' consumption.

5.2. The risk diversification of digital wealth management

In addition to the wealth effect, another underlying mechanism may be the risk diversification of digital wealth management. The inherent risks associated with the investment can be mitigated through a diversified investment portfolio. This diversification not only smoothens out risks but also significantly enhances consumption.

To ascertain the possible risk diversification mechanism, we employ the Herfindahl-Hirschman Index (HHI) to gauge the degree of investment diversification of a particular resident *i* in a specific month *t*. Specifically, we first identify resident *i*'s investment position in various wealth management products in month *t*. These products may include monetary funds, short-term debt funds, bond funds, index funds, hybrid funds, equity funds, QDII funds, pension funds, and FOF funds. We then calculate the sum of the squares of the proportions of different wealth management products in the total investment position to derive the HHI, i.e., $HHI_{i,t} = \sum_j \left(\frac{investment\ position_{i,t,j}}{Total\ investment\ position_{i,t}}\right)^2$. If the HHI of resident *i* in month *t* is closer to 0, the more diversified the investment portfolio, the smoother the investment risk.

Table 11 incorporates the Herfindahl-Hirschman Index (HHI) into the baseline regression to examine the risk diversification channel. Since the HHI can only be calculated for residents with digital platform investment, Table 11 uses the subsample of DPI investors.

Columns (1) and (2) pool all DPI investors together, assuming a homogeneous impact of HHI on consumption for all investors. The estimated coefficients of HHI in columns (1) and (2) are significantly negative, indicating that diversification leads to a higher increase in consumption. This finding confirms the significant influence of risk diversification on the inclusive effect of digital wealth management. As shown in column (1), if the HHI of DPI investors decreases by one standard deviation, their monthly consumption is expected to increase by 0.0152% (0.2 × 0.0758).

Columns (3)–(6) further divide the DPI investors into low- and high-postion groups to capture the heterogeneous impact of HHI on residents' consumption among different investors. We find that the effect of diversification on consumption is more pronounced in the subsample of investors with lower investments. One plausible explanation is that investors who are new in digital wealth management tend to be more sensitive to risk, making diversification of investments more essential for them.

Table 11
The risk diversification of digital wealth management.

Dependent variable: $Ln(Consumption_t)$	DPI investors (1)	DPI investors (2)	Low position (3)	High position (4)	Low position (5)	High position (6)
HHI_t	−0.0758***	−0.0905***	−0.1116***	−0.0126***	−0.1401***	−0.0151***
	(0.0090)	(0.0095)	(0.0146)	(0.0126)	(0.0140)	(0.0127)
$Ln(DPI_t)$	0.0095***		0.0184***	0.0110***		
	(0.0009)		(0.0031)	(0.0020)		
$Relative\ DPI_t$		0.0043***			0.0349***	0.0035***
		(0.0006)			(0.0092)	(0.0007)
$Ln(CreditPay_{t-1})$	0.0630***	0.0630***	0.0705***	0.0465***	0.0705***	0.0465***
	(0.0043)	(0.0043)	(0.0052)	(0.0037)	(0.0052)	(0.0037)
$Ln(Consumption_{t-2})$	0.0773***	0.0773***	0.0727***	0.0493***	0.0728***	0.0493***
	(0.0143)	(0.0143)	(0.0153)	(0.0131)	(0.0153)	(0.0131)
Regional controls	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year × month FE	YES	YES	YES	YES	YES	YES
R^2	0.0184	0.0182	0.0196	0.0086	0.0195	0.0086
N	1,641,846	1,641,846	821,018	820,828	821,018	820,828
Coefficient test of HHI_t	/	/	−5.1335***		−6.6130***	

***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Standard errors clustered at the City-Year×month level are shown in parentheses.

5.3. The relation between wealth effect and risk diversification

We have demonstrated that wealth effect and risk diversification may potentially be the mechanism through which digital wealth management enhances consumption, but the relationship of the wealth effect and risk diversification has yet to be investigated. We decompose investment returns based on the risks of wealth management products. Specifically, we categorize five types of wealth management products as low-risk investments, including monetary, short-term debt, bond, index, and pension. In contrast, the other four types of products are defined as high-risk investments, encompassing hybrid, stock, QDII, and FOF. To investigate the heterogeneous wealth effect across different risk groups and degrees of diversification, we calculate the low-risk return and high-risk return for each resident in a given month. We then incorporate these returns, along with the HHI, into the baseline regression and present the results in Table 12.

Columns (1) and (4) of Table 12 examine the heterogeneous wealth effect across different risk groups, assuming that the source and magnitude of the wealth effect are independent of risk diversification. The estimated coefficient of low-risk return is significantly positive, while the coefficient of high-risk return is insignificant. This suggests that the wealth effect primarily stems from low-risk

Table 12
Investment risk, diversification and consumption.

Dependent variable: $Ln(Consumption_t)$	DPI investors (1)	High-HHI (2)	Low-HHI (3)	DPI investors (4)	High-HHI (5)	Low-HHI (6)
$Ln(DPI_t)$	0.0091***	0.0070***	0.0159***			
	(0.0009)	(0.0010)	(0.0032)			
$Relative\ DPI_t$				0.0016***	0.0017***	0.0013
				(0.0004)	(0.0004)	(0.0008)
$Low-risk\ ret_t$	0.0046*	0.0086***	0.0048	0.0079***	0.0116***	0.0062**
	(0.0025)	(0.0029)	(0.0031)	(0.0025)	(0.0029)	(0.0031)
$High-risk\ ret_t$	0.0023	0.0028	0.0037**	0.0020	0.0028	0.0034**
	(0.0019)	(0.0018)	(0.0017)	(0.0018)	(0.0018)	(0.0017)
HHI_t	−0.0762***	−0.5676***	−0.0339	−0.0948***	−0.6776***	−0.0362
	(0.0090)	(0.1165)	(0.0239)	(0.0093)	(0.1169)	(0.0237)
$Ln(CreditPay_{t-1})$	0.0630***	0.0584***	0.0537***	0.0630***	0.0584***	0.0538***
	(0.0043)	(0.0046)	(0.0041)	(0.0043)	(0.0046)	(0.0041)
$Ln(Consumption_{t-2})$	0.0773***	0.0662***	0.0371***	0.0774***	0.0663***	0.0372***
	(0.0143)	(0.0138)	(0.0142)	(0.0143)	(0.0138)	(0.0142)
Regional controls	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year × month FE	YES	YES	YES	YES	YES	YES
R^2	0.0184	0.0145	0.0089	0.0182	0.0144	0.0088
N	1,641,846	1,168,670	473,176	1,641,846	1,168,670	473,176

Low-risk funds include currency-type fund, short-term bond fund, pension-type fund, bond-type fund, and index-type fund. High-risk funds include blend-type fund, stock-type fund, fund of funds (fof) and QDII-type fund. ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Standard errors clustered at the City-Year×month level are shown in parentheses.

investments. To further investigate the heterogeneous wealth effect across different degrees of investment diversification, Columns (2) and (3), as well as columns (5) and (6) divide the DPI investors into low-HHI and high-HHI groups based on the average HHI. It allows us to examine the impact of investment diversification together with the wealth effect.[10] We find that the wealth effect of low-risk return is significantly positive in the high-HHI group. Conversely, the wealth effect of high-risk return is significantly positive in the low-HHI group. This suggests that when investment is less diversified, the stable returns of low-risk investments play a crucial role in driving the wealth effect. On the other hand, people are more inclined to diversify when they invest in higher-risk funds, making higher-risk investments an additional contributor to the wealth effect.

These results highlight that the source and magnitude of the wealth effect depend on the degree of risk diversification, underscoring the significance of risk diversification in promoting the wealth effect.

6. Further discussion: digital platform investment and consumption upgrading

In this section, we turn our focus to the impact of digital platform investment on the structure of consumption. Specifically, we analyze the effects on e-commerce subsistence consumption and non-subsistence consumption, both in logarithms. The results are presented in Table 13. Panel A reports the results in the full sample, while Panel B and Panel C present the results in subsamples categorized by individual income and the level of financial development in the city where individuals reside.

It shows that residents' participation in digital platform investment has an asymmetric impact on subsistence consumption and non-subsistence consumption. Residents' digital platform investment promotes their non-subsistence consumption, indicating a potential effect of consumption upgrading. However, the increase in subsistence consumption is primarily in traditionally financially under-developed areas and among low-income residents. This can be attributed to the wealth effect and the income elasticity of consumption. Subsistence consumption generally has a lower income elasticity, while non-subsistence consumption exhibits a higher income elasticity. The returns from digital platform investment have a greater impact on increasing consumption of non-subsistence goods, contributing to consumption upgrading.

Moreover, the results reveal that both subsistence and non-subsistence consumption experience greater increase for residents living in financially underdeveloped cities compared to those in financially developed cities. Similarly, the increase of subsistence consumption and non-subsistence consumption resulting from digital platform investment participation is more pronounced for low-income residents than for high-income residents.

Overall, the participation in digital wealth management not only stimulates consumption but also facilitates consumption upgrading, particularly benefiting low-income residents in traditionally financially underdeveloped areas.

7. Conclusion

With the continuous growth of China's economy, there is an increasing demand for wealth management among residents. The emergence of digital wealth management platforms has provided convenient access for residents to engage in financial management. By lowering the thresholds of entry of financial management, these platforms have enabled low-income residents, who were previously excluded from traditional financial management, to participate in financial activities.

This paper examines the inclusive effect of digital wealth management on residents' consumption, using unique microdata from Ant Fortune's fund transactions and Alipay's consumption. Our baseline results indicate that digital platform investment promotes residents' consumption. Our main result still holds after we address potential endogeneity and in various robustness specifications.

To further investigate the inclusive effect of digital wealth management, we explore its heterogeneous impact on residents' consumption across different residents and cities. We find that digital wealth management has a stronger impact on consumption among low-income residents and in cities with underdeveloped finance. This suggests that the low entry barriers and high cost-efficiency of digital platform wealth management have a significant effect on residents who were previously excluded from traditional wealth management due to their low income or limited access to financial services in underdeveloped cities.

Additionally, we identify two potential mechanisms underlying the inclusive effect: wealth effect and risk diversification. The wealth effect stems from the potential investment returns that increase residents' disposable income and therefore promote consumption. The risk diversification effect highlights the importance of diversified investment portfolios in smoothing out risks and enhancing consumption. We further decompose the wealth effects based on different risk types of wealth management products, emphasizing that high-risk investments contribute to the wealth effect only when investors diversify their risks.

Our findings not only validate the inclusive effect of digital platform finance on consumer growth, in line with the theoretical predictions of Gong, Yu, and Zhang (2020), but also shed light on the significance of risk diversification. Financial institutions, including digital wealth management platforms, should focus on innovating financial service models, reducing thresholds and transaction costs, and expanding the coverage of financial services to reach vulnerable groups such as low-income residents and those in remote areas. More importantly, financial institutions should also give attention to financial product innovation and strive to provide investors with a wide range of asset management products with varying risks to facilitate risk diversification and promote inclusive growth.

[10] If the HHI of investor i is greater than the sample average in month t, she will be categorized as a high-HHI investor, and vice versa.

Table 13
Digital platform investment and consumption upgrading.

Panel A: Full sample (N = 4,064,764)				
Dependent variable	$Ln(Subsistence\ Consumption_t)$	$Ln(Nonsubsistence\ Consumptioni_t)$	$Ln(Subsistence\ Consumption_t)$	$Ln(Nonsubsistence\ Consumptioni_t)$
	(1)	(2)	(3)	(4)
$Ln(DPI_t)$	0.0104***	0.0106***		
	(0.0011)	(0.0010)		
$Relative\ DPI_t$			0.0025***	0.0030***
			(0.0005)	(0.0005)
$Ln(CreditPay_{t-1})$	0.0520***	0.0494***	0.0523***	0.0497***
	(0.0037)	(0.0030)	(0.0037)	(0.0030)
$Ln(Consumption_{t-2})$	0.0755***	0.0631***	0.0759***	0.0635***
	(0.0121)	(0.0092)	(0.0122)	(0.0092)
Regional controls	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Year × month FE	YES	YES	YES	YES
R^2	0.006	0.0046	0.0059	0.0045

Panel B: Individual Income				
Dependent variable	Low income (N = 3,135,330)		High income (N = 929,434)	
	$Ln(Subsistence\ Consumption_t)$	$Ln(Nonsubsistence\ Consumptioni_t)$	$Ln(Subsistence\ Consumption_t)$	$Ln(Nonsubsistence\ Consumptioni_t)$
$Ln(DPI_t)$	0.0106***	0.0112***	0.01***	0.0087***
	(0.0012)	(0.0011)	(0.0012)	(0.0015)
$Ln(CreditPay_{t-1})$	0.0497***	0.0464***	0.0606***	0.0591***
	(0.0036)	(0.0028)	(0.0046)	(0.0038)
$Ln(Consumption_{t-2})$	0.0775***	0.0306***	0.0654***	0.0589***
	(0.0128)	(0.0095)	(0.01)	(0.008)
Regional controls	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Year × month FE	YES	YES	YES	YES
R^2	0.0062	0.0046	0.0052	0.0044

Panel C: Regional finance development				
Dependent variable	Underdeveloped city (N = 1,173,392)		Developed city (N = 2,891,372)	
	$Ln(Subsistence\ Consumption_t)$	$Ln(Nonsubsistence\ Consumptioni_t)$	$Ln(Subsistence\ Consumption_t)$	$Ln(Nonsubsistence\ Consumptioni_t)$
$Ln(DPI_t)$	0.0127***	0.0119***	0.0096***	0.0101***
	(0.0016)	(0.0014)	(0.0011)	(0.0011)
$Ln(CreditPay_{t-1})$	0.0553***	0.0524***	0.0508***	0.0483***
	(0.0045)	(0.0035)	(0.0035)	(0.0029)
$Ln(Consumption_{t-2})$	0.0694***	0.0577***	0.0788***	0.0661***
	(0.0118)	(0.0089)	(0.0123)	(0.0093)
Regional controls	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Year × month FE	YES	YES	YES	YES
R^2	0.0065	0.0051	0.0059	0.0045

***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Standard errors clustered at the city level are shown in parentheses.

Data availability

The authors do not have permission to share data.

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