Received: 08 Sep. 2025 | Revised: 09 Sep. 2025 | Accepted: 11 Sep. 2025 | Published online: 15 Oct. 2025

RESEARCH ARTICLE

Journal of Global Humanities and Social Sciences
2025,Vol. 6(6)245-265
DOI: 10.61360/BoniGHSS252018880603

FinTech's Role in Shaping Household Debt Structure: Evidence from the Housing Market in China

Yu Feng[1], Xin Ge[2,*] & Jiawei You[1]

[1] *School of Finance, Shanghai University of International Business and Economics, China*

[2] *Research Institute of Social Development, Southwestern University of Finance and Economics, China*

Abstract: The issue of high household housing debt is a pressing concern requiring immediate attention. Drawing on insights from behavioral economics, particularly the concept of scarcity mentality, this study investigates the potential role of digital finance in amplifying household housing debt through the manipulation of funds across mental accounts, influenced by the tube effect. Empirical analysis utilizing the Beijing University Digital Inclusive Finance Index for prefecture-level cities and data from the China Household Finance Survey (CHFS) confirms a significant association between digital finance expansion and increased likelihood of households acquiring housing debt, larger debt amounts, and elevated risk of excessive debt burden. Notably, these effects vary significantly across urban-rural divides, city classifications, and income brackets. Additionally, a spatial diffusion effect of digital finance on housing debt levels is observed, with cities with advanced digital finance infrastructure impacting surrounding areas. Importantly, household financial literacy emerges as a key mitigating factor against excessive housing debt induced by digital finance growth. The study's implications suggest the need for enhanced regulatory measures in digital finance, establishment of a comprehensive housing consumption financial framework, regional coordination in housing debt management, and promotion of household financial education.

Keywords: digital finance, housing debt, over debt, China

1. Introduction

Housing serves as the cornerstone of individuals' livelihoods and signifies their personal identity and social standing in China. Following the discontinuation of the housing welfare distribution system in 1998, housing prices have consistently surged. Consequently, it has become commonplace for households to resort to borrowing for property acquisition or construction, leading to a rapid escalation in housing debt levels. A joint report by Southwest University of Finance and Economics and Ant Financial Services Group in 2019, titled "China Household Finance Survey Special Topic - Research on China Residents' Leverage and Household Consumption Credit", revealed a substantial increase in household housing loan balances by 16.8 trillion yuan from 2013 to 2019. During this period, the proportion of household debt surged from 21.3% to 55.6%. The exponential growth of housing debt has emerged as a significant risk factor, akin to a "gray rhino", within China's financial system (Wang et al., 2023; Biehl, 2018). Therefore, conducting a comprehensive analysis of the determinants influencing the heightened levels of housing debt in the household sector is imperative to mitigate systemic financial risks and uphold stability within the housing market.

The Chinese government has implemented various measures to address household housing debt, such as differentiated credit policies and loans from housing provident funds across different regions. Despite some progress over the years, these policies have limited coverage. Rural residents and low-income families face challenges due to significant credit constraints, leading to unresolved

Corresponding Author: Xin Ge
Research Institute of Social Development, Southwestern University of Finance and Economics, China

issues regarding the mismatch between housing debt demand and the high cost of financing and limited capital availability (Landvoigt, 2017). These groups lack traditional credit collateral, making it difficult to access funds. Moreover, the mobility of capital, coupled with its tendency to favor the affluent, results in a concentration of credit resources among the higher social strata (Leyshon & Thrift, 2007). Therefore, prioritizing the reduction of capital costs and enhancing its accessibility are crucial steps in addressing the housing debt capital supply-demand imbalance in China's household sector (Zou, 2014).

In recent years, the emergence of digital finance has offered a solution to this issue. In 2016, the People's Bank of China disseminated the "G20 Principles for Innovative Financial Inclusion", advocating the utilization of digital technologies to advance financial inclusion and broaden the ecosystem of digital financial services. Subsequently, the "2019 Government Work Report" emphasized the need to deepen research and development and the application of big data and artificial intelligence. It also highlighted the acceleration of the "Internet Plus" approach across various sectors to bolster the digital economy. The Fintech Development Plan (2019-2021) issued by the People's Bank of China in 2019 outlined the strategic blueprint for digital finance development. Against the backdrop of advancing big data, cloud computing, and other emerging technologies, digital finance experienced rapid growth at a pivotal juncture. Illustrated in Figure 1, the average digital financial inclusion index of prefecture-level cities in China surged from 49.3987 to 232.8683 between 2011 and 2018, reflecting a mean annual growth rate of 26%.

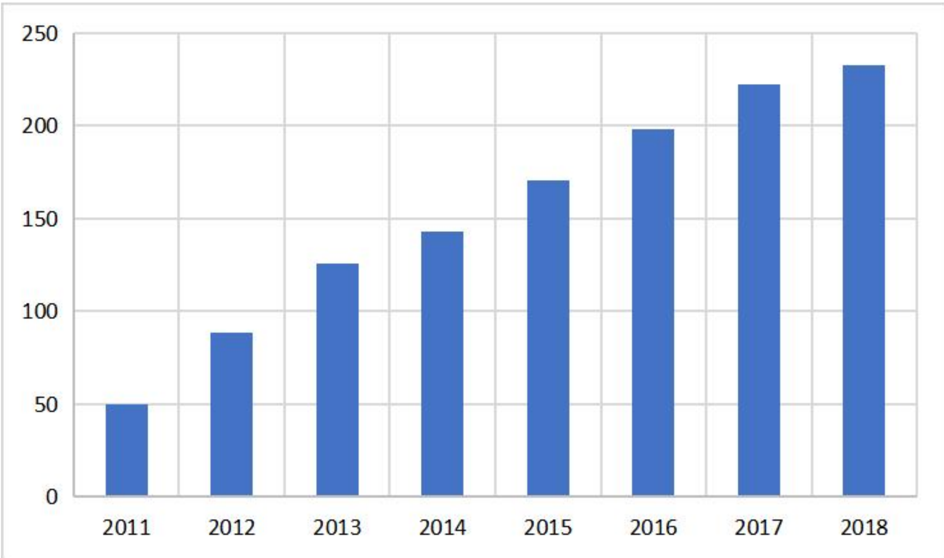

Figure 1. 2011-2018 China's Digital Financial Inclusion Index

Compared to traditional financial services, digital finance is distinguished by its low entry barriers, high convenience, and extensive reach. This can effectively reduce financial exclusion, improve financial accessibility, and enhance the efficiency of financial resource allocation. Particularly, network credit has transcended spatial constraints, facilitating rapid connections between capital suppliers and demanders. In the realm of housing, the evolution of digital finance impacts household housing debt by diversifying funding sources and bolstering debt willingness. Initially, in terms of housing fund procurement, digital financial instruments like housing loans and inclusive financial products for housing rentals have emerged. Notably, innovative financial products such as "down payment loans" combining digital finance and housing have surfaced since 2014 in the commercial housing sector. For instance, products like Ping and "Haofang Mortgage" address inadequate down payments by offering installment plans and short-term bridge loans. Unlike traditional bank mortgages, these loans are funded by P2P platform investors, allowing borrowers to access up to 2 million yuan. However, the increased use of these funds has heightened risks in the housing market. To curb the excessive financialization of real estate, regulatory measures have been implemented to restrict the use of digital finance in housing. Despite this, under governmental pressure and the growing disparity between housing demand and capital, various digital financial products have proliferated in the real estate market. Two primary forms have emerged: first, provident fund network loans, such as "Pleasant Loan", "You My Loan" and "Citic Bank Miaomiaodai" which extend loans based on residents' housing provident fund contributions.

These loans, ranging from 200,000 to 300,000 yuan, can be utilized for property purchases and construction. Second, through consumer loans, business loans, and other mortgage, banks and private lenders collaborate with real estate developers to offer digital consumer and operating loans that are effectively channeled into the housing market. In 2020, the People's Bank of China issued an Urgent Notice to major commercial banks to investigate the flow of online consumer loans into real estate, estimating a capital influx of one trillion yuan. Subsequently, local banking and insurance regulatory bodies have imposed fines for violations related to bank loan activities, involving institutions like Bank of Chongqing, Agricultural Bank of China, and China Minsheng Bank. In the housing rental sector, digital inclusive financial products like China Construction Bank's "special rental loan" and Industrial Bank's "Business Start-up Plan" directly stimulate household rental debt by offering borrowing avenues and financial backing. Furthermore, in terms of debt willingness, digital finance significantly boosts individual financial literacy, empowering families to leverage finances for housing. The advancement of digital finance also enhances families' social trust, encouraging them to embrace debt. This prompts an inquiry into whether digital finance can address family housing financial challenges, potentially increasing the likelihood of household housing debt. Consequently, the expansion of digital finance may amplify household housing debt levels, potentially leading to excessive debt burdens for families.

Currently, there is a gap in the literature regarding the impact of digital finance on household housing debt. Existing research can be categorized into two main areas: the first pertains to digital finance, focusing on its definition, measurement, and economic advantages. The inception of digital finance was rooted in the concept of inclusive finance. Traditional financial systems often exclude groups facing significant liquidity constraints, such as those in remote areas and low-income households, from accessing financial services. Digital finance's inclusive nature aims to counteract this financial exclusion by providing common and equitable financial services to the majority of vulnerable groups (Dev, 2006; Jiao & Sun, 2021). Building upon this notion, Yan et al (2024) suggested that financial institutions engage in promoting inclusive finance to eliminate barriers to financial services and enhance resource allocation efficiency. Through the evolution of financial technology (fintech), individuals' financing costs have decreased, and financial institutions have bolstered their risk management capabilities by improving access thresholds, scale, and speed, thereby advancing financial inclusion (Wang & Wang, 2022). Simultaneously, the convergence of digital technologies like the Internet of Things, big data, and artificial intelligence with financial services has propelled the evolution of digital finance. To gauge the actual level of digital finance development in a country or region, some scholars have attempted to devise quantitative index systems. Sarma (2012) pioneered the evaluation of inclusive finance development based on bank service penetration, service availability, and actual usage efficiency. Other scholars have employed index synthesis methods, such as the analytic hierarchy process, entropy method, and coefficient of variation method, to assess the extent of inclusive finance development (Deng & Liu, 2022; Lu et al., 2022; Zhang & Jia, 2025). Nevertheless, these assessments have overlooked the integration of Internet technology into the financial system. Addressing this gap, Guo et al. (2024) formulated an index system for digital inclusive finance from an Internet finance perspective, evaluating indicators at provincial, prefecture-city, and county levels. As digital finance becomes increasingly quantifiable, scholars are delving into its economic benefits. At a macro level, studies have revealed that digital finance can reduce the income disparity between urban and rural areas and enhance regional economic development (Chen et al., 2024; Hao et al., 2023). On a micro level, existing research predominantly explores the positive impacts of digital finance on household income, consumption, and wealth (Yang et al., 2024).

Research on family housing debt focuses on the formation and effects of such debt. Internal family characteristics and the external macroeconomic environment are key factors influencing housing debt. Studies indicate that demographic factors like the education level and health status of the household head are closely linked to housing debt (Chen et al., 2018). Wu et al. (2019) observed a positive relationship between household income and housing debt levels, considering household credit constraints. Moreover, income inequality accelerates housing debt growth (Zhang, 2015). Households with high financial literacy and ample social capital are more inclined to hold housing debt, preferring formal or private borrowing channels (Wu et al., 2024). While these studies highlight the impact of household characteristics on housing debt, they often overlook changes in the macroeconomic environment, hindering the identification of systemic financial risks stemming from household housing debt. Zhao et al. (2021) reveal that increasing housing prices directly contribute to household debt, with mortgage and wealth effects being primary influencing mechanisms. Yi & Zhang (2021) demonstrate that the advancement of digital inclusive finance can effectively lower household asset-liability ratios. Regarding the impact of housing debt, some scholars note a crowding-out effect on household consumption, leading to reduced family spending (Zhang et al., 2023; Zhang & Zhang, 2019), diminishing family life quality and resident happiness (Pan et al., 2024; Liu et al., 2020), and potentially trapping families in poverty (Zakaria et al., 2017). Excessive housing debt is a significant factor contributing to systemic financial risks (Chen & Li, 2019).

In conclusion, scholars globally have made significant contributions to the research on digital finance and household housing debt, forming the basis for this study. However, to the best of our knowledge, no scholars have explored the impact of digital finance on household housing debt. Therefore, this paper's innovative contributions lie in several key areas: firstly, examining how digital finance, by easing liquidity constraints, may stimulate household housing debt growth through various channels, offering insights for government decision-making on addressing residents' housing fund challenges. Secondly, investigating the diverse effects of digital finance on housing debt within the context of urban-rural dual financial structures, city levels, and different income brackets to establish a theoretical framework for regulating digital finance development. Thirdly, analyzing the spatial implications of digital finance on housing debt at a macro level to provide empirical support for mitigating systemic financial risks. Lastly, uncovering the impact of digital finance on excessive household housing debt and offering practical insights for averting financial risks in the household sector.

2. Theoretical Analysis and Research Hypothesis

2.1 Digital finance, liquidity constraints and household housing consumption

Housing has both investment and consumption dual attributes. As a durable good, families can realize the advance consumption of housing through the way of "own capital + debt". According to Attanasio (1994), we expand the optimal intertemporal consumption model. In the model, digital finance can alleviate liquidity constraints by expanding household borrowing channels, thus satisfying household housing consumption.

The maximization effect function is reseted as follows:

$$V = maxE_t \sum_{t=0}^{\infty} \beta U(C_t) \quad (1)$$

$$C_t = H_t + N_t \quad (2)$$

Where, E represents expectation, $U(C_t)$ is a utility function, and $U(C_t)'\geq 0$, $U(C_t)''\leq 0$. β is the subjective discount factor, and C_t represents the total consumption in t period, as shown in Formula (2). This paper is mainly divided into housing consumption H_t and non-housing consumption N_t. The constraint equation of Formula (1) is as follows:

$$A_{t+1} = (1 + r_{t+1})(A_t + Y_t - H_t - N_t) \quad (3)$$

In Equation (3), A_t represents real assets, Y_t represents labor income, and r_{t+1} represents the real interest rate on assets from period t to period t + 1. According to Hall (1988), formula (3) can be converted to the following Euler equation:

$$\acute{U}(H_t + N_t) = \beta E_t(1 + r_{1+t})U(H_{t+1} + N_{t+1}) \quad (4)$$

Equation (4) indicates that in period t, the optimal consumption choice is when the marginal utility of the adjacent two periods of consumption reaches balance. The utility function $U(\cdot)$ is assumed to be a relative risk-averse utility function, and the interest rate is assumed to be constant and there is no uncertainty. Therefore, the optimal consumption level in period t is set as follows:

$$H(t) + N(t) = \left[1 - \frac{\beta^{\delta}(1+r)^{\delta}}{1+r}\right]\left[(1+r)(A_{t-1} - H_{t-1} - N_{t-1}) + \sum_{\tau=t}^{\infty}(\frac{1}{(1+r)}^{\tau-t} Y_{\tau}\right] \quad (5)$$

In Equation (5), δ represents the interest rate elasticity of consumption across time, and indicates that the optimal consumption level is jointly determined by asset stock, current income, future income and interest rate. However, Equation (5) contains perfect competitive market and deterministic conditions, which are inconsistent with the reality. Deaton (1992) found that liquidity constraint and precautionary savings had a significant impact on residents' asset holding motivation. On this basis, Carroll (2001) combined the liquidity constraint hypothesis and precautionary savings and proposed the buffer inventory model. The constraint conditions were further extended as follows:

$$A_{t+1} = (1 + r_{t+1})(A_t + Y_t - H_t - N_t + Z_t) \geq 0 \quad (6)$$

Where, $Z_t \geq 0$ is the borrowing limit, and the smaller the value of Z is, the stronger the liquidity constraint of households is. When Z is 0, the liquidity constraint of households is the strongest, and the Euler equation is as follows:

$$\acute{U}(H_t + N_t) = \beta E_t(1 + r_{1+t})U(H_{t+1} + N_{t+1}) + \lambda_t(D) \quad (7)$$

In equation (7), λ_t is the shadow price of liquidity constraint, and *D* is the development level of digital finance. The above formula shows that when households are constrained by liquidity in the current period, they will naturally reduce consumption, including housing consumption; The development of digital finance broadens the borrowing channels of families, reduces the threshold for families to enter the financial market, and can effectively alleviate the current liquidity constraints of families, thus meeting their housing needs.

2.2. Digital finance, social trust and household housing consumption

In fact, the assumption of complete markets in the theory of classical economics and point of the contrast between the real market environment, the uncertainty of the factors on the market will also have great influence on family consumption decisions, for example, compare consumption, herding effect, social trust, and individual cognitive psychological factors can cause consumer savings income marginal effect is greater than the marginal effect of consumption, This leads to "exhausted consumption" under debt. Among them, Adam Smith mentioned in the Theory of Moral Sentiments that all economic activities of man are influenced by moral and social habits. Social trust is the lubricant of social and economic operation. A large number of economists believe that social trust can alleviate information asymmetry in the market, help consumers overcome perceived risks in transaction activities, and then stimulate their consumption, borrowing and other economic behaviors (Chen & Wu, 2023). Digital finance, based on online real-name authentication, fingerprint identification and other biological technologies, can significantly enhance the social trust of families, and thus stimulate the willingness of households to borrow housing debt, especially from private channels. Based on this, this paper extends the maximization effect function as:

$$V = maxE_t \sum_{t=0}^{\infty} \beta \left[U(C_t, L_t) + \gamma(X_t - \theta\overline{X_t}\right] \quad (8)$$

Where, X_t represents the housing effect under social trust, $\overline{X_t}$ represents its mean value; $0 \leq \gamma \leq 1$, represents the degree of influence of $\overline{X_t}$ on consumption. When $Xt > \overline{X_t}$, the family gains extra utility. This means that when $\overline{X_t}$ increases, household housing consumption also increases. Due to budget constraints, the increase of $\overline{X_t}$ will inevitably lead households to meet their needs with external financing, and the larger γ is, the more likely it is to lead to excessive housing debt.

Based on the above analysis, hypotheses of this paper are listed as follows:

H1: The development of digital finance will increase the likelihood that households will have housing debt.

H2: The development of digital finance will increase the scale of household housing debt.

H3: Digital finance will increase the probability that households have excessive housing debt.

3. Research Design

3.1. Econometric model

This paper first analyzes the influence of the development degree of digital finance on whether households have housing debt. Then, this paper investigates how the development level of digital finance affects the scale of household housing debt. Besides, if digital finance can stimulate the growth of household housing debt, can it also lead to excessive household housing debt? In order to figure out these questions, we construct the following model:

$$Y^{*}_{i,j,t} = \alpha_0 + \alpha_1 Index_{i,j,t} + \alpha_2 X_{i,j,t} + \sigma_i + \theta_j + \varepsilon_{i,j,t} | \varepsilon_{i,j,t} \sim N(0, \delta^2)$$

$$Y_{i,j,t} = \begin{cases} 1, & Y^{*}_{i,j,t} > 0 \\ 0, & Y^{*}_{i,j,t} \leqq 0 \end{cases} \tag{9}$$

$$Debt_{i,j,t} = \beta_0 + \beta_1 Index_{i,j,t} + \beta_3 X_{i,j,t} ++ \sigma_i + \theta_j + \varepsilon_{i,j,t} \tag{10}$$

$$Over_{i,j,t} = \alpha_0 + \alpha_1 Index_{i,j,t} + \alpha_2 X_{i,j,t} + \sigma_i + \theta_j + \varepsilon_{i,j,t} \tag{11}$$

Where, subscripts i、j、t represent the individual family, the city where the family is located and the survey year respectively. The explained variable Y is a dummy variable, and the assigned value of household housing debt is 1; otherwise, it is 0. $Debt_{i,j,t}$ is the size of household housing debt. $Over_{i,j,t}$ is a dummy variable, and the value of excessive housing debt in households is 1; otherwise, it is 0. $Index_{i,j,t}$ is the core explanatory variable of this paper, which is used to measure the development level of digital finance in prefecture-level. $X_{i,j,t}$ represents control variable. σ_i represents individual fixed effect, θ_j represents city fixed effect, $\varepsilon_{i,j,t}$ represents residual term. It should be noted that in the subsequent empirical process, this paper will use clustering standard errors at the household level to deal with intra-group autocorrelation.

3.2. Variable selection and assignment

3.2.1. Dependent variable

The dependent variables in this paper are "households have housing debt", "the size of housing debt", and "households have excessive housing debt". Among them, "households have housing debt" is derived from a related questions in survey: 'Has your family borrowed money to buy and build a house?', 'Has your family borrowed money from relatives and friends or private financial institutions to buy and build a house?', 'Has your family borrowed money for housing?'. The dependent variable "the size of housing debt" is derived from questions: 'How much is the outstanding mortgage?', 'Total amount borrowed from friends and relatives to buy a house', 'total amount of borrowing from other financial institutions for the purchase and construction of the house'. "Household have excessive housing debt" is constructed according to the CBRC's "Guidelines on Risk Management of Commercial Banks' Real Estate Loans", which stipulates that a household's asset-liability ratio exceeding 55% is considered as excessive debt.

3.2.2 Core independent variables

The core independent variable in this paper is the development degree of digital finance at the prefecture-level. We use the digital financial inclusion index of prefecture-level constructed by Guo et al. (2020) as a measurement index. The index is composed of digital financial services data provided by Ant Financial, and consists of three dimensions, covering three levels of province, city and county from 2011 to 2019, we use city-level indexes.

3.2.3 Control Variables

Referring to private studies (Białowolski, 2019), control variables include individual characteristics, family characteristics and regional characteristics. The Individual characteristics are gender, age, household status, education level, marital status and self-rated health status. Family characteristics are net asset, income, number of houses owned, dependency ratio of elderly population, dependency ratio of young population, and family size. Regional features are the average commercial housing sales price and per capita gross regional product.

3.3. Data sources and descriptive statistics

3.3.1. Data sources

In this paper, China Household Finance Survey (CHFS) and the data of Peking University China Digital Inclusive Finance Development Index at the prefecture-level are combined and used as the panel data set for the empirical study. Among them, CHFS data were obtained from southwestern University of Finance and Economics for follow-up survey in 2013, 2015 and 2017. The total sample covers 29 provinces (including autonomous regions and municipalities directly under the Central Government), 355 counties and 1,428 villages. The data coverage is broad and representative. The micro family data used in this paper mainly come from the family and individual questionnaire module.

Before the empirical study, we preprocessed the data as follows: (1) the regression sample only retained the households with self-owned housing rights, and the heads of households were 18-65 years old; (2) In order to avoid the interference of outliers on the research results, the continuous variables such as household income and household net asset are winsorized at the upper and lower 1% level. (3) Delete samples with missing data or invalid values. Finally, there are 31,766 sample observations were obtained.

3.3.2. Descriptive statistics

The definition and descriptive statistical analysis of the main variables are shown in Table 1. The sample size of housing debt in this paper is 5,254 households, accounting for 13.50% of the total sample. The mean and standard deviation of the full sample housing debt scale were 2.549 and 0.342 respectively. The maximum value and minimum value are 450 and 0 respectively, indicating that the housing debt scale varies greatly among different families. The sample mean value of excessive debt is 0.051, and the standard deviation is 0.220, indicating that there is no excessive housing debt in Chinese households as a whole. In terms of family characteristics, the mean value and standard deviation of net asset are 104.794 and 205.161, indicating that the range of variation of family net worth is large. The mean of family income was 85,700 yuan, and the standard deviation was 19.026, which means there was a great difference in the income of different families. From the perspective of whether households have housing debt or excessive housing debt, and the scale of household housing debt, there are great differences in the housing debt situation of Chinese households.

Table 1. Descriptive analysis

Variables	Definition	Mean	Standard deviation	Minimum	Maximum
Has housing debt	Dummy variable, the family has housing debt takes 1, otherwise takes 0	0.135	0.342	0	1
Scale of housing debt	Total household housing debt (ten thousand yuan)	2.549	12.852	0	450
Excessive housing debt	Dummy variable, household has excessive housing debt takes 1; otherwise takes 0	0.051	0.220	0	1
Digital finance	Development index of China digital Inclusive Finance at prefecture-level	188.607	40.231	87.771	285.432
Age	The age of the head of household in the year surveyed	43.904	11.047	18	60
Gender	Dummy variable, 1 for male, otherwise takes 0	0.657	0.475	0	1
Residence	Dummy variable, non-farm hukou status takes 1, otherwise takes 0	0.260	0.438	0	1
Education	Dummy variable, 1 for bachelor degree or above, otherwise takes 0	0.105	0.306	0	1
Marriage	Dummy variable, married or cohabiting takes 1, otherwise takes 0	0.829	0.377	0	1
Health	Dummy variable, very healthy or healthy takes 1, otherwise takes 0	0.319	0.466	1	5
Work	Dummy variable, household-head has work takes 1, otherwise takes 0	0.773	0.419	0	1
Net assets	Total housing Assets and Financial assets - Total household liabilities (ten thousand yuan)	104.794	205.161	0	3000
Income	Including salary, operation, property, transfer and other income (ten thousand yuan)	8.570	19.026	0	500
Old	Number of persons aged 65 and above/number of persons aged 16-64	0.099	0.273	0	5
Young	Number of persons aged 15 and below/number of persons aged 16-64	0.203	0.306	0	4
House number	The number of houses owned by households	1.218	0.512	0	6
Family size	Total Household Population	1.587	1.273	1	18
House price	Commodity housing Price in provinces and cities (including autonomous regions) (Ten thousand yuan/square meter)	0.743	0.471	0.363	3.412
GDP per capita	Per capita GDP of the province or city (including autonomous region) in which household is located (ten thousand yuan)	17.253	1.280	13.610	19.540

Note: Mean value, standard deviation, maximum and minimum values are reported in the table. The continuous variables reported in the table are all numerical characteristics before logarithm.

4. Empirical Analysis

4.1. Baseline regression

4.1.1. The impact of digital finance on whether households have housing debt

Table 2 reports empirical results of the impact of the development level of digital finance on household housing debt. In order to ensure the robustness of regression results, this paper adopts the stepwise regression method to introduce individual characteristic variables, family characteristic variables and regional characteristic variables successively. The result in column (1) shows that the digital finance coefficient is 0.311, which means that digital finance significantly increases the possibility of households having housing debt, that is, the probability of households having housing debt increases by 0.331 percentage points with each increase in the development level of digital finance by one unit. In columns (2) and (3), the coefficients and significance of digital financial variables are still robust after household and regional control variables are successively added. This means that the development of digital finance has stimulated the probability that households have housing debt. This is because, on the one hand, the development of digital finance has improved the financial awareness of residents, prompting households to choose to obtain housing in the way of debt; At the same time, the development of digital finance has improved the social trust of families, making them more "dare" to take on debt. On the other hand, cities with a higher degree of digital inclusive finance have a more complete financial system and more diversified capital channels, making it more accessible for families to obtain housing funds.

Table 2. The regression results of weather household has housing debt

	Has housing debt		
	(1)	(2)	(3)
Digital finance	0.311***	0.298***	0.298***
	(0.000)	(0.000)	(0.000)
Gender	0.011***	0.008**	0.005*
	(0.004)	(0.004)	(0.004)
Age	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.002)
Age squared	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Health	0.009***	0.010***	0.011***
	(0.002)	(0.002)	(0.002)
work	0.022***	0.019***	0.019***
	(0.005)	(0.005)	(0.005)
Education	0.075***	0.067***	0.064***
	(0.006)	(0.006)	(0.006)
Marriage	0.020***	0.015***	0.017***
	(0.005)	(0.005)	(0.006)
Residence	0.024***	0.020***	0.019***
	(0.004)	(0.004)	(0.005)
Income		0.004***	0.004***
		(0.000)	(0.000)
Family size		0.006***	0.005**
		(0.002)	(0.002)
Net assets		-0.001	-0.001
		(0.000)	(0.000)
House number		0.042***	0.042***
		(0.003)	(0.003)
Old		-0.060***	-0.061***
		(0.008)	(0.009)
Young		0.009	0.007
		(0.006)	(0.007)
GDP per capita			-0.014**
			(0.007)
House price			-0.009
			(0.016)
Fixed effect	Yes	Yes	Yes
City control	Yes	Yes	Yes
N	31,766	31,766	31,766
Pseudo R^2	0.261	0.270	0.271

Note: *, ** and *** represent significance at the confidence levels of 10%, 5% and 1%, respectively. The values in brackets are cluster standard errors.

4.1.2. The impact of digital finance on the scale of housing debt

The above analysis shows that digital finance significantly increases the likelihood that households have housing debt. But, whether the higher the development level of digital finance, the larger the scale of household housing debt? To explore this problem, this part carries out empirical test based on model (2), and the results are shown in Table 3. Among them, only individual control variables are introduced into the results in column (1), and regression results after adding all control variables are listed in column (3). The results showed that the level of financial development can significantly stimulate the housing debt, 1% rise in digital level of financial development, family housing debt rise 0.3% at the same time, it because that the region with high financial development degree has more money to borrow, and the channels more diversified, so that the households can obtain more housing fund support. About the control variables, if household-heads have high level of health and in the working status, the households have larger housing debt scale. This is because, based on the human capital theory, both health and work income can increase an individual's resource endowment, improve his debt paying ability, and thus bear more housing debt. However, the coefficient of marital status and urban household registration are significantly 1.188 and 0.369 respectively, which is because the housing demand of married families is more robust than that of unmarried families, especially the housing debt scale of families with improved housing demand is higher. Urban households face higher housing price pressure, their housing debt scale is significantly higher than rural households. In terms of household characteristics, household income and net assets are significantly positive, which is because it is less difficult for high-income and high-net-assets families to obtain loans and their capital scale is large, leading to higher housing debt scale. The coefficient of the number of houses is 0.659, which means that families with more houses will bear more housing debt. The dependency ratio is -1.364 for the elderly and 0.706 for the young, meaning that households are more willing to take on housing debt for the next generation than the elderly. In terms of regional characteristics, the housing price coefficient is 0.503, which is because in regions with higher the housing price, households always have more money to borrow, which leads to large housing debt.

Table 3. The regression results of the housing debt

	Scale of housing debt		
	(1)	(2)	(3)
Digital finance	2.487**	2.455***	2.450**
	(0.003)	(0.003)	(0.005)
Gender	0.014	-0.018	-0.017
	(0.157)	(0.162)	(0.180)
Age	-0.082*	-0.105**	-0.141***
	(0.047)	(0.046)	(0.052)
Age squared	-0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Health	0.100**	0.247***	0.290***
	(0.081)	(0.084)	(0.094)
Work	1.006***	0.786***	0.883***
	(0.139)	(0.139)	(0.152)
Education	5.380***	4.409***	4.421***
	(0.454)	(0.452)	(0.486)
Marriage	1.370***	1.063***	1.188***
	(0.195)	(0.190)	(0.209)
Residence	0.964***	0.394**	0.369*
	(0.172)	(0.195)	(0.215)
Income		0.051***	0.052***
		(0.011)	(0.012)
Family size		-0.272***	-0.283***
		(0.064)	(0.082)
Net assets		0.005***	0.006***
		(0.001)	(0.001)
House number		0.641***	0.659***
		(0.229)	(0.248)
Old		-1.304***	-1.364***
		(0.173)	(0.188)
Young		0.656***	0.706***
		(0.223)	(0.259)
GDP per capita			-0.084
			(0.225)
House price			0.503**
			(0.032)
Fixed effect	Yes	Yes	Yes
City control	Yes	Yes	Yes
N	31,766	31,766	31,766
R^2	0.156	0.274	0.275

4.1.3. The impact of digital finance on the excessive housing debt

Table 4 reports the empirical results of the development level of digital finance and whether households have excessive housing debt. In the column (3), digital financial coefficient is 0.084, shows that the development of digital financial significantly increased the possibility of a family have excessive housing debt, namely digital financial development level increases 1 unit, the probability of excessive housing debt has increased by 8.6%, this may be because, on the one hand, the cities where the degree of digital finance is high, have better financing environment and various capital channels, households have more choices and more sufficient capital to borrow, which is more likely to cause excessive housing debt. On the other hand, cities with high levels of digital finance tend to have higher housing prices, so the social status symbol of housing is stronger, families are more likely to go into excessive debt in pursuit of social areas. About the control variables, the gender coefficient of household-head is 0.010, which means that families with male heads are more prone to excessive housing debt. This is because compared with women, men have stronger risk appetite (Gao et al., 2017), which is more likely to cause excessive housing debt of families. In terms of the age of the household-head, the result shows an inverted U-shaped characteristic. With the change of the age, the possibility of having excessive housing debt increases firstly, and then gets decrease. The coefficient of health degree and working status of individuals is -0.002 and -0.048 respectively, indicating that household-heads with higher health degree and better working status are also more rational in financing structure. Individual marital status has no significant effect on excessive housing debt. The coefficient of total income and net assets are -0.001, which indicates that households with higher income level and net assets have stronger ability to pay and weaker willingness to take debt. Households with more houses are more likely to have excessive housing debt. In terms of family population structure, the dependency ratio of the elderly and the dependency ratio of the young are -0.026 and 0.008 respectively, which means that families are more willing to take on debt for the next generation. In terms of regional characteristics, GDP per capita significantly increases the likelihood of households having excessive housing debt, but housing price has no significant effect.

Table 4. The impact of digital finance on the excessive housing debt

	Excessive housing debt		
	（1）	（2）	（3）
Digital finance	0.087***	0.084***	0.084***
	(0.000)	(0.000)	(0.000)
Gender	0.014***	0.009***	0.010***
	(0.003)	(0.003)	(0.003)
Age	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Age squared	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Health	-0.004***	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)
Work	-0.046***	-0.045***	-0.048***
	(0.004)	(0.004)	(0.004)
Health	0.015***	0.017***	0.016***
	(0.004)	(0.004)	(0.005)
Marriage	-0.002	-0.003	-0.006
	(0.003)	(0.003)	(0.004)
Residence	-0.012***	-0.012***	-0.011***
	(0.003)	(0.003)	(0.003)
Income		-0.001***	-0.001***
		(0.000)	(0.000)
Family size		0.018***	0.017***
		(0.001)	(0.001)
Net assets		-0.001***	-0.001***
		(0.000)	(0.000)
House number		0.008***	0.008***
		(0.002)	(0.002)
Old		-0.028***	-0.026***
		(0.004)	(0.004)
Young		0.009**	0.008*
		(0.004)	(0.005)
GDP per capita			0.016***
			(0.004)
House price			0.003
			(0.011)
Fixed effect	Yes	Yes	Yes
City control	Yes	Yes	Yes
N	31,766	31,766	31,766
Adjusted R^2	0.215	0.224	0.224

4.2. Results of heterogeneity analysis

4.2.1. Urban- rural structure

Since financial system presents an obvious urban-rural dual structure in China, the impact of digital finance on housing debt may be affected by the differences between urban and rural areas. Accordingly, this paper divides the sample into urban and rural sub-samples for regression according to the location of household survey. The results are shown in Table 5. The coefficient of housing debt in rural areas is significantly 0.287, while the coefficient of housing debt scale in urban households is significantly 0.013, indicating that the improvement of digital finance development level can improve the probability of housing debt in rural households and stimulate the housing debt scale in urban households. This is because, for rural families, digital finance mainly through the popularization of financial knowledge to enhance the family debt awareness, and then increase the possibility of housing debt; For urban households, the development of digital finance can enrich their borrowing channels and ease liquidity constraints, thus stimulating the scale of household housing debt. At the same time, as urban households face higher housing costs, they will naturally assume a higher level of housing debt. In terms of excessive housing debt, the coefficients of both urban and rural households are significantly positive, which means that the development of digital finance has a stimulating effect on excessive housing debt of both in urban and rural regions.

Table 5. The regression results of the housing debt by urban-rural structure

	Has housing debt		The scale of housing debt		Excessive housing debt	
	Urban	Rural	Urban	Rural	Urban	Rural
Digital finance	0.260	0.287***	0.013**	0.011	0.090***	0.081***
	(0.000)	(0.001)	（0.005）	（0.009）	（0.000）	（0.000）
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City control	Yes	Yes	Yes	Yes	Yes	Yes
N	17,990	13,776	18,128	13,638	18,289	13,477
Pseudo R^2(R^2)	0.157	0.198	0.168	0.177	0.126	0.125

4.2.2. Different levels of cities

Because the financial development degrees are difference among cities, we divide sample into three types of cities according to both the state administrative hierarchy and the “The City Ranking from Premier Business”. The results are shown in Table 6. The coefficient of housing debt in second - and third-tier cities are 0.268 and 0.270 respectively, and the coefficient of housing debt size are 2.533 and 2.500, which means that compared with first-tier cities with higher financial development, the stimulus effect of digital finance on housing debt is more significant in second - and third-tier cities. Reason is mainly manifested in the following two points: firstly, a line of second - and third-tier cities, compared to the city itself more developed financial service system, the residents' awareness of financial literacy and liabilities is relatively high, therefore the marginal effect of digital financial in the first-tier cities is low, the development of digital financial liquidity constraints for second - and third-tier cities family relief and financial knowledge popularization effect more significant; Second, households in first-tier cities have higher housing costs. By calculating the housing costs of households in different cities in 2017, the average housing costs of households in first-tier cities are 3.25-million-yuan, 960,000 yuan in second-tier cities and 460,000 yuan in third-tier cities. The housing costs in first-tier cities are much higher than those in second tier and third-tier cities. However, the capital brought by digital finance is "a drop in the bucket" compared with the purchase cost in first tier cities, and the stimulus effect is relatively low. In terms of excessive housing debt, the results show that the coefficients of excessive housing debt in second - and third-tier cities are 0.088 and 0.098, which means that cities with higher housing debt probability and debt scale are more likely to have excessive housing debt of families.

Table 6. The regression results of the housing debt by cities’ level

	Has housing debt			The scale of housing debt			Excessive housing debt		
	First tier	Second tier	Third tier	First tier	Second tier	Third tier	First tier	Second tier	Third tier
Digital finance	0.274	0.268***	0.270*	2.524	2.533***	2.500**	0.090	0.088***	0.098***
	（0.000）	（0.000）	（0.000）	(0.024)	(0.008)	(0.002)	(0.001)	(0.000)	(0.000)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,575	6,357	21,834	3,575	6,357	21,834	3,757	6,483	21,526
Pseudo R2(R2)	0.184	0.174	0.139	0.178	0.167	0.165	0.118	0.122	0.119

4.2.3. Family income

In this paper, we divide the sample into high-income, middle-income and low-income groups according to the 1/3 and 2/3 subpoints of total household income. The regression results are shown in Table 7. The coefficient of housing debt of middle- and low-income households is 0.267 and 0.280 respectively. The coefficient of the scale of housing debt was 2.473 and 2.540, respectively. On the whole, the development level of digital finance has significantly increased the probability of housing debt and the size of housing debt in middle- and low-income households. This because, compared with high-income households, the development of digital finance can provide more access to capital for middle and low-income families, which are more constrained by liquidity, and thus promote their housing debt. However, the coefficient of excessive housing debt of low-income and high-income households is 0.098 and 0.081 respectively. This means that households with excessive housing debt are polarized compared to middle-income households. This may be because low-income families are more prone to irrational housing debt due to their lack of personal knowledge. However, high-income families have higher housing costs due to their higher requirements on the number and quality of housing. At the same time, because high-income households are affected by higher expected income and higher available credit, they are more likely to choose to bear a higher housing debt burden in the current period.

Table 7. The regression results of the housing debt by family income

	Has housing debt			The scale of housing debt			Excessive housing debt		
	Low	Middle	High	Low	Middle	High	Low	Middle	High
Digital finance	0.280***	0.267***	0.201	2.540**	2.473***	2.430	0.098***	0.090	0.081*
	(0.000)	(0.005)	(0.000)	（0.003）	（0.005）	（0.012)	(0.000)	(0.001)	(0.000)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10,210	10,783	10,773	10,210	10,783	10,773	10,610	10,893	10,263
Pseudo $R^2(R^2)$	0.192	0.135	0.110	0.144	0.135	0.161	0.153	0.111	0.110

4.3. Results of endogeneity testing

In this subsection, we adopt two methods to do the endogeneity test: solving endogeneity problem and using provincial data.

The baseline regression in this paper is likely to cause endogeneity problems due to omitted variables, mutual causation and measurement errors. Based on the practice of Bartik (2009), we constructed “Bartik Instrument” (the product of the digital financial inclusion index with one lag and the first-order difference in time of the digital financial index), and then used it as an instrumental variable for regression estimation. The results are shown in Table 8. Digital finance significantly increases the possibility of households having housing debt, the scale of housing debt and the probability of excessive housing debt, which is consistent with the previous result.

Table 8. The regression results by using instrumental variable

	Has housing debt	The scale of housing debt	Excessive housing debt
	(1)	(2)	(3)
Digital finance	0.280**	2.311**	0.087***
	(0.000)	(0.009)	(0.000)
Control variables	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes
City control	Yes	Yes	Yes
N	31,766	31,766	31,766
Pseudo R^2(R^2)	0.252	0.273	0.223

The core explanatory variable of this paper is the digital financial inclusion index at prefecture-level. In order to verify the robustness of the regression results, we use the digital financial inclusion index at the provincial level for regression. The results are shown in Table 9. The digital financial Inclusion index at the provincial level significantly increases the probability of households having housing debt, increases the scale of housing debt and causes excessive housing debt of households, which is consistent with the baseline regression results above and robust.

Table 9. The regression results by using provincial level data

	Has housing debt	The scale of housing debt	Excessive housing debt
	(1)	(2)	(3)
Digital finance	0.282***	2.533***	0.097***
	(0.065)	(0.493)	(0.008)
Control variables	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes
City control	Yes	Yes	Yes
N	31,766	31,766	31,766
Pseudo R^2(R^2)	0.157	0.174	0.220

5. Discussion

In this paper, the research shows that the development of digital finance has a positive impact on the household housing debt and the scale of housing debt. Does this influence have a spatial effect among cities? Will household financial literacy effectively alleviate household excessive housing debt caused by digital finance? To explore the above questions, we carry out further analysis as follows.

5.1. Spatial spillover effects of digital finance on the scale of housing debt

5.1.1. Econometric Model

By observing the distribution of digital inclusive financial index of prefecture-level cities in 2013, 2015 and 2017, we find the development degree of digital finance has obvious spatial characteristics over time, and it is mainly concentrated in the Yangtze River Delta, Pearl River Delta, Beijing-Tianjin-Hebei and inland developed urban agglomerations. Will the development level of digital finance have a spatial spillover effect on the scale of household housing debt at macro level? To some extent, cities with high digital finance level have an impact on the scale of housing debt in their surrounding cities. Accordingly, we use the method of spatial econometrics to analyze. It is worth noting that this paper uses the mean of housing debt scale of different urban households in different years as a measure index of housing debt scale of the city. In terms of spatial weight, adjacency and economic weight matrices are selected. Where, the adjacency space weight matrix W_1 is calculated by urban latitude and longitude, and its element $W_{i,j}$ represents the space element i and j are adjacent to each other, which is 1; otherwise, it is zero. The economic spatial weight matrix W_2 selects the difference of gross domestic product level as the measure index.

We construct the spatial linear regression model following Anselin (1988):

$$Debt = \rho W * Debt + \beta index + \vartheta X + \mu \quad (12)$$

Where, $Debt$ represents the average size of household housing debt at prefecture-level, W is the weight matrix of N × N related to spatial regression, and index is the digital financial inclusion index of each city. The coefficient β shows the spatial correlation between the development degree of digital finance and household housing debt. X is the control variable, including urban housing price, population, and banking competition degree, while μ is a random item.

5.1.2. Empirical analysis

We examine the spatial correlation between digital finance and household housing debt size through Moran's I. The results are shown in Table 10. For adjacency weight and economic spatial weight, both p-values are less than 0.05, indicating that there is a significant spatial correlation between digital financial development level and the scale of housing debt.

Table 10. The testing of spatial correction

Year	Weight of adjacent space			Weight of economic spatial		
	I	Z	P	I	Z	P
2013	0.009	1.787	0.037	0.003	0.932	0.016
2015	0.013	2.258	0.012	0.016	2.249	0.012
2017	0.009	1.868	0.031	0.013	1.989	0.023

The results of spatial regression are shown in Table 11. In Column (1) and Column (2), the results show that under the weight of adjacent space and economic space, the digital finance coefficients are 0.049 and 0.048 respectively, which means that when the development level of digital finance increases by one unit, the average scale of housing debt in urban increases by 4.9 and 4.8 percentage points. This is because there is a “pass-through” effect between geographically close and economically connected cities, with housing prices and debt affecting their “sister” cities. From columns (3) to (6), results demonstrate that the spatial feature is still significant after the replacement of the data from 2015 and 2017, indicating that the results are robust.

Table 11. The results of spatial regression

	2013		2015		2017	
	Weight of adjacent space	Weight of economic spatial	Weight of adjacent space	Weight of economic spatial	Weight of adjacent space	Weight of economic spatial
	(1)	(2)	(3)	(4)	(5)	(6)
Digital finance	0.049^{***}	0.048^{***}	0.059^{***}	0.060^{***}	0.040^{***}	0.042^{***}
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
N	160	160	167	167	167	167
Sigma	1.52		1.36		1.44	

5.2 The mediating effect of financial literacy

5.2.1. Econometric Model

In order to investigate whether financial literacy can alleviate the stimulating effect of digital finance on household excessive housing debt, this paper constructed the following regression model:

$$Over_{i,j,t} = \omega_0 + \omega_1 Index_{i,j,t} + \omega_2 Finance_{i,j,t} + \omega_3 Index_{i,j,t} * Finance_{i,j,t} + \omega_4 X_{i,j,t} + \sigma_i + \theta_j + \varepsilon_{i,j,t} \quad (13)$$

Where, $Over_{i,j,t}$ is a dummy variable, the excess household debt is 1, otherwise it is 0, the definition of the value is according to the CBRC "Guidelines for Risk Management of Real Estate Loans for Commercial Banks": the household asset-liability ratio exceeds 55% is considered as excessive household debt. $Finance_{i,j,t}$ represents the degree of family financial literacy. Since the assessment of family financial literacy in The CHFS questionnaire covers multiple aspects, and the question setting is inconsistent every year. Therefore, based on the questionnaire questions of each year, we use principal component analysis to synthesize the dimensionality reduction of multiple variables, and calculates the financial literacy value of each family according to the variance contribution rate of each principal component.

5.2.2. Empirical analysis

Table 12 shows that household financial literacy has a moderating effect between digital finance and household excessive housing debt. The results in column (1) show that the development level of digital finance significantly increases the possibility of households having excessive housing debt. In the results in Column (2), the coefficient of financial literacy is significantly -0.024, which means that the probability of excessive housing debt will be reduced by 2.4 percentage points if the family's financial literacy increases by 1 unit, which means that the higher the family's financial literacy is, the less likely it is to produce excessive housing debt. The results in Column (3) show that the interaction coefficient between financial literacy and digital finance is -0.088, indicating that financial literacy can effectively alleviate the possibility of households having housing debt brought about by the development of digital finance, that is, the moderating effect exists.

Table 12. The results of mediating effect

	Excessive housing debt		
	（1）	（2）	（3）
Digital finance	0.091***	0.090***	0.090***
	(0.000)	(0.001)	(0.001)
Financial literacy		-0.024***	-0.022***
		(0.003)	(0.003)
Digital finance × Financial literacy			-0.088***
			(0.000)
Control variables	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes
City control	Yes	Yes	Yes
N	31,766	31,766	31,766
R^2	0.323	0.304	0.325

6. Conclusion

This paper systematically analyzes the impact of digital finance on household housing debt by using The China Digital Financial Inclusion Index of Peking University and the panel data of CHFS in 2013, 2015 and 2017. The research shows that the development of digital finance significantly increases the possibility of households having housing debt, stimulates the scale of household housing debt and increases the probability of households having excessive housing debt; Besides, the impact of digital finance on household housing debt has obvious heterogeneity between urban and rural areas, different cities and households with different incomes. Specifically, the development level of digital finance has enhanced the willingness of rural households to buy houses in debt, and stimulated the scale of housing debt of urban households. At the same time, the development of digital finance will cause the probability of excessive housing debt of urban and rural families; Digital finance has increased the willingness of middle - and low-income families and families in second - and third-tier cities to take on housing debt, increased the scale of household housing debt and led to excessive housing debt. At the same time, the development of digital finance has increased the probability and scale of housing debt of middle- and low-income families, but it is more likely to cause excessive housing debt of high- and low-income families. Thirdly, through further discussion, we find that, from a macro point of view, digital finance has a significant spatial spillover effect on household housing debt scale, and cities with a higher degree of digital finance development also have a stimulating effect on household housing debt scale in their surrounding areas. In addition, family financial literacy can effectively alleviate the possibility of excessive housing debt caused by digital finance.

Acknowledgement

This research was funded by: Shanghai University of International Business and Economics Youth Fund Project (24QN019)

Conflict of Interest

The authors declare that they have no conflicts of interest to this work.

References

Anselin, L. (1988). Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geographical Analysis, 20*(1), 1-17. https://doi.org/10.1111/j.1538-4632.1988.tb00159.x

Attanasio, O. (1994). *Personal saving in the United States. International Comparisons of Household Saving*, University of Chicago Press.

Bartik, T. J. (2009). What proportion of children stay in the same location as adults, and how does this vary across location and groups? Upjohn Institute Working Paper 09-145. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research. https://doi.org/10.17848/wp09-145.

Białowolski, P. (2019). Economic sentiment as a driver for household financial behavior. *Journal of Behavioral and Experimental Economics, 80*, 59-66. https://doi.org/10.1016/j.socec.2019.03.006

Biehl, A. M. (2018). The first-time homebuyer tax incentives: Did they work? *Journal of Housing research, 27*(1), 1-15. https://doi.org/10.1080/10835547.2018.12092138

Carroll, C. D. (2001). A theory of the consumption function, with and without liquidity constraints. *Journal of Economic Perspectives, 15*(3), 23-45. https://doi.org/10.1257/jep.15.3.23

Chen, J., Hardin III, W., & Hu, M. (2018). Housing, wealth, income and consumption: China and homeownership heterogeneity. *Real Estate Economics, 48*(2), 373-405. https://doi.org/10.1111/1540-6229.12245

Chen, S., & Li, W. (2019). Local government debt and regional economic growth in China. *China Political Economy, 2*(2), 330-353. https://doi.org/10.1108/CPE-10-2019-0028

Chen, X., & Wu, C. (2023). Subnational social trust and the internationalization of emerging market firms. *Journal of Business Research, 158.* https://doi.org/10.1016/j.jbusres.2023.113661

Chen, Z., Gong, Y., Meng, Q., Hu, X., & Ding, Y. (2024). Can digital finance boost regional innovation? From the perspective of resource mismatch in China. *Technology Analysis & Strategic Management, 1-14.* https://doi.org/10.1080/09537325.2024.2426046

Deaton, A. (1992). Household saving in LDCs: Credit markets, insurance and welfare. *The Scandinavian Journal Economics, 94*(2), 253-273. https://doi.org/10.2307/3440451

Deng, J., & Liu, Y. (2022). Does digital finance reduce the employment in the finance industry? Evidence from China. Finance Research Letters, 48. https://doi.org/10.1016/j.frl.2022.102994.

Dev, S. M. (2006). Financial Inclusion: Issues and challenges. *Economic and Political Weekly, 41*(41), 4310-4313. http://www.jstor.org/stable/4418799

Guo, F., Wang, J., Wang, F., Kong, T., Zhang, X., & Cheng, Z. (2020). Measuring China's digital financial inclusion: Index compilation and spatial characteristics. *China Economic Quarterly, 19*(4), 1401-1418. https://doi.org/10.13821/j.cnki.ceq.2020.03.12

Guo, Z., Wang, Y., & Bai, M. (2024). A study of the impact of digital inclusive finance on the real economy: Evidence from China. *International Journal of Business & Economics, 9*(1), 26-47. https://doi.org/10.58885/ijbe.v09i1.26.zg

Hall, R. E. (1988). The relation between price and marginal cost in U.S. industry. *Journal of Political Economy, 96*(5). https://doi.org/10.1086/261570

Hao, J., Peng, M., & He, W. (2023). Digital finance development and bank liquidity creation. International Review of Financial Analysis, 90. https://doi.org/10.1016/j.irfa.2023.102839

Jiao, S., & Sun, Q. (2021). Digital economic development and its impact on economic growth in China: Research based on the perspective of sustainability. *Sustainability, 13*(18), 10245. https://doi.org/10.3390/su131810245

Landvoigt, T. (2017). Housing demand during the boom: The role of expectations and credit constraints. *The Review of Financial Studies, 30*(6), 1865-1902. https://doi.org/10.1093/rfs/hhx026

Leyshon, A., & Thrift, N. (2007). The capitalization of almost everything: The future of finance and capitalism. Theory, culture & society. https://doi.org/10.1177/0263276407084699

Liu, Z., Zhong, X., Zhang, T., & Li, W. (2020). Household debt and happiness: Evidence from the China household finance survey. *Applied Economics Letters, 27*(3), 199-205. https://doi.org/10.1080/13504851.2019.1610706

Lu, X., Lai, Y., & Zhang, Y. (2022). Digital financial inclusion and investment diversification:

Evidence from China. *Accounting & Finance, 63*(S2), 2781-2799. https://doi.org/10.1111/acfi.13043

Pan, Z., Liu, Y., & Liu, Y. (2024). Uncovering the pathways between house prices and depressive symptoms in Chinese cities: A nationally representative study. *Housing Studies, 39*(4), 901-924. https://doi.org/10.1080/02673037.2022.2092599

Sarma, M. (2012). Index of financial inclusion-A measure of financial sector inclusiveness. Berlin working paper on money, finance, trade and development, centre for international trade and development, School of International Studies. India: Jawaharlal Nehru University, No.7, 1-34.

Wang, H., Sun, K. K., & Xu, S. (2023). Does housing boom boost corporate financialization? Evidence from China. *Emerging Market Finance and Trade, 59*(6), 1655-1667. https://doi.org/10.1080/1540496X.2022.2138702

Wang, X., & Wang, X. (2022). Digital financial inclusion and household risk sharing: Evidence from China's digital finance revolution. *China Economic Quarterly International, 2*(4), 334-348. https://doi.org/10.1016/j.ceqi.2022.11.006

Wu, L., & Zhang, Y. (2024). Social credit system construction and corporate debt dilemmas. Finance Research Letters, 60. https://doi.org/10.1016/j.frl.2023.104855

Wu, L., Bian, Y., & Zhang, W. (2019). Housing ownership and housing wealth: new evidence in transitional China. *Housing Studies, 34*(3), 448-468. https://doi.org/10.1080/02673037.2018.1458291

Yan, G., Cifuentes-Faura, J., & Liu, X. (2024). How digital inclusive finance affects the health of the migrant population-evidence from China migrants dynamic survey. *Applied Economics, 57*(40), 6305-6317. https://doi.org/10.1080/00036846.2024.2383331

Yang, Y., Lin, Z., Xu, Z., & Liu, S. (2024). The impact of digital finance on regional economic resilience. *Pacific-Basin Finance Journal, 85*. https://doi.org/10.1016/j.pacfin.2024.102353

Zakaria, R., Jaafar, N., & Ishak, N. (2017). Household debt decision: poverty or psychology? *International Journal of Business and Society, 18*(3), 515-532. https://doi.org/10.33736/ijbs.3143.2017

Zhang, C. (2015). Income inequality and access to housing: Evidence from China. *China Economic Review, 36*, 261-271. https://doi.org/10.1016/j.chieco.2015.10.003

Zhang, C., & Zhang, F. (2019). Effects of housing wealth on subjective well-being in urban China. *Journal of Housing and the Built Environment, 34*, 965-985. https://doi.org/10.1007/s10901-019-09651-5

Zhang, Y. & Jia, D. (2025). The impact of inclusive finance and education investment on new quality productivity: The nonlinear mediating effect of education development. *Finance Research Letters, 77*. https://doi.org/10.1016/j.frl.2025.107065

Zhao K., Hao, Y., & Wu, W. (2022). Asymmetric effect on monetary policy on housing price from short-term and long-term perspectives. *Journal of Advanced Computational Intelligence and Intelligent Informatics, 26*(4), 581-589. https://doi.org/10.20965/jaciii.2022.p0581

Zheng, H., Qian, J., Liu, G., Wu, Y., Delang, C. O., & He, H. (2023). Housing prices and household consumption: A threshold effect model analysis in central and western China. *Humanities and Social Sciences Communications, 10*. https://doi.org/10.1057/s41599-023-02258-w

Zou, Y. (2014). Contradictions in China's affordable housing policy: Goals vs. structure. *Habitat International, 41*, 8-16. https://doi.org/10.1016/j.habitatint.2013.06.001

How to Cite: Feng, Y., Ge, X. & You, J. (2025). FinTech's Role in Shaping Household Debt Structure: Evidence from the Housing Market in China. *Journal of Global Humanities and Social Sciences*, *6*(6), 245-265
https://doi.org/ 10.61360/BoniGHSS252018880603