INTERNATIONAL JOURNAL OF ECONOMICS AND FINANCE STUDIES
Vol: 16 **No:** 03 **Year:** 2024 **ISSN:** 1309-8055 (Online) (**pp.** 442-461) **Doi:** 10.34109/ijefs.202416321
Received: 11.07.2024 | **Accepted:** 20.10.2024 | **Published Online:** 30.10.2024

-RESEARCH ARTICLE-

THE ROLE OF DIGITAL FINANCE IN SHAPING HOUSEHOLD CONSUMPTION IN CHINA

Jiankun Zhang

PhD, International College of Digital Innovation,
Chiang Mai University, Chiang Mai, Thailand 50200
Email: jiankun_z@cmu.ac.th
ORCID ID: https://orcid.org/0000-0001-8084-1835

Nathee Naktnasukanjn (Corresponding Author)

Dr/Assistant Professor, International College of Digital Innovation,
Chiang Mai University, Chiang Mai, Thailand, 50200
Email: nathee@cmuic.net
ORCID ID: https://orcid.org/0009-0007-8844-3656

Anukul Tamprasirt

Dr/Assistant Professor, International College of Digital Innovation,
Chiang Mai University, Chiang Mai, Thailand, 50200
Email: anukul@innova.or.th
ORCID ID: https://orcid.org/0009-0005-5424-1170

Piyachat Udomwong
Dr/Assistant Professor, International College of Digital Innovation,
Chiang Mai University, Chiang Mai, Thailand, 50200
Email: piyachat.u@cmu.ac.th
ORCID ID: https://orcid.org/0000-0002-3915-6411

—Abstract—
This study investigates the influence of digital finance on consumer behaviour, with particular attention to its effect on domestic consumption trends in China. Utilising extensive provincial panel data spanning the period from 2012 to 2022, the research

Citation (APA): Zhang, J., Naktnasukanjn, N., Tamprasirt, A., Udomwong, P., (2024). The Role of Digital Finance in Shaping Household Consumption in China. *International Journal of Economics and Finance Studies*, 16(03), 442-461. doi: 10.34109/ijefs.202416321

employs both quantitative and qualitative methodologies to examine core attributes of digital finance, including its breadth of coverage, usage dimensions, and level of digitalisation. The findings indicate that digital finance significantly enhances household consumption by increasing income levels, mitigating income volatility, and easing liquidity constraints. Notably, the effects of digital financial services differ considerably across regions and demographic groups, with more pronounced benefits observed among higher-income populations and in provinces characterised by more sophisticated financial infrastructure and elevated levels of human capital. These outcomes highlight the critical role of expanding digital financial services and strengthening financial systems as strategic approaches to stimulate household expenditure and foster long-term economic development. The study provides valuable insights for both governmental authorities and private sector entities, suggesting that targeted policy interventions can harness the potential of digital finance to unlock consumer demand, narrow financial disparities, and support inclusive economic progress. Furthermore, it offers a foundational framework for future academic inquiry into the sustained and structural impact of digital finance on economic performance and financial development.

Keywords: Household Consumption, Financial Inclusion, Liquidity Limitations, Digital Finance and Income Uncertainty

INTRODUCTION

Digital finance has emerged as a globally significant phenomenon, attracting growing scholarly and policy interest due to its profound implications for both economic structures and societal dynamics. In recent years, China has witnessed substantial advancement in digital finance, which has become deeply integrated across diverse sectors. This widespread adoption positions it as a vital catalyst for economic restructuring and the enhancement of consumption patterns (Liu et al., 2021). The proliferation of digital financial tools—such as mobile payment systems, internet-based wealth management, online lending platforms, and digital currencies—has substantially reshaped consumer behaviours and expenditure trends (Gruin & and Knaack, 2020; Xu, 2020). Given the country's extensive engagement with digital finance, China offers a robust empirical foundation for assessing its influence on household consumption (Hasan et al., 2020).

This paper focuses on an in-depth exploration of how the expansion of digital financial services influences the consumption behaviours of Chinese residents, guided by the following research questions:

- To what extent does digital finance enhance household consumption?
- What are the underlying mechanisms through which digital finance impacts consumption?

Vol: 16 **No:** 03 **Year:** 2024 **ISSN:** 1309-8055 (Online) (**pp.** 442-461) **Doi:** 10.34109/ijefs.202416321

To address these research questions, this study draws upon several theoretical frameworks to analyse household consumption in China.

Income Hypothesis: Income level is the main factor determining consumption capacity. Digital finance can augment the resident's income and consumption ability by providing more services and instruments of financial investment (Li & Ma, 2021). Liquidity Constraint Theory: This theory suggests that individuals facing limited access to liquid assets may experience restricted consumption. Digital finance mitigates such constraints by facilitating convenient access to credit and lending platforms, thereby encouraging consumer expenditure (Li et al., 2022). Precautionary Savings Theory: Faced with economic uncertainty, individuals often reduce current consumption to increase savings as a buffer.

This investigation utilises data drawn from multiple sources, including financial institutions, the China Statistical Yearbook, and publicly available data from the People's Bank of China. Employing a mixed-methods approach that combines both quantitative and qualitative techniques, the study conducts a comprehensive assessment of how digital financial instruments—particularly virtual currencies—affect consumer spending behaviours.

LITERATURE REVIEW

The Income Hypothesis's Effect on Domestic Spending

The income hypothesis suggests that consumption is strongly influenced by an individual's income level. A substantial body of research supports the view that income distribution has a direct effect on consumption levels (Demir et al., 2022; Straub, 2019). For example, a more balanced distribution of income is often associated with a marked increase in aggregate consumption (Uzar, 2020). In the Chinese context, the persistently low consumption rate has frequently been linked to structural imbalances in income distribution (Li et al., 2019; Wang et al., 2024). Azizur and Carl (2023) observe that heightened income inequality results in disparities in consumption, whereby rising income inequality suppresses overall household spending.

Impact of Liquidity Constraint on Household Consumption

Credit constraints limit households' ability to maintain stable consumption patterns over time, as access to borrowing is restricted. Households experiencing such constraints are often unable to smooth current consumption by relying on expected future income, which leads to lower present spending and an increase in precautionary savings (Yu et al., 2022). Empirical evidence indicates that the advancement of financial markets, which alleviates liquidity constraints, contributes to growth in consumption levels (Mukherjee et al., 2021). Credit rationing is particularly prevalent in regions with underdeveloped financial infrastructures, significantly curtailing

Vol: 16 **No:** 03 **Year:** 2024 **ISSN:** 1309-8055 (Online) (**pp.** 442-461) **Doi:** 10.34109/ijefs.202416321

individuals' consumption capacity (Petry, 2020). Digital finance serves as a mechanism to mitigate these limitations by providing more accessible credit services that facilitate increased spending (Yu et al., 2022). Studies further demonstrate that the easing of credit constraints enabled by digital financial platforms leads to a measurable rise in average household consumption (Li et al., 2019).

Impact of Precautionary Savings on Household Consumption

The precautionary savings theory, initially proposed by Friedman (1957), posits that an increase in income uncertainty leads households to allocate more resources toward future consumption, thereby elevating savings (Drakopoulos, 2021). This behavioural response typically results in a decline in current consumption levels (Wang et al., 2023). Households experiencing insecurity due to deficiencies in social security systems or unstable income sources tend to exhibit stronger precautionary saving behaviour, which negatively impacts their immediate spending (Garriga et al., 2023). Cipriani and Fioroni (2021) suggest that improving social security mechanisms can reduce the need for precautionary savings and, in turn, stimulate greater consumption.

Table 1: Factors Affecting Household Consumption: A Comparative Table

Factor	Description	Key Findings	Research
Income Hypothesis	Suggests that permanent income, not current income levels, should be used to assess expenditure.	Equitable income distribution promotes overall consumption; income disparity reduces consumption levels.	Wang et al. (2023); Uzar (2020); Li et al. (2019); Azizur and Carl (2023)
Liquidity Constraints	Households face consumption limitations when they lack sufficient liquid funds.	Financial market development and digital financial services can encourage consumer growth and ease liquidity limitations.	Petry (2020); Cavoli et al. (2020); Li et al. (2020)
Precautionary Savings	Households save more when faced with greater income uncertainty to ensure future consumption stability.	Improved social security can reduce precautionary savings and increase consumption; inadequate social security leads to higher savings and lower consumption.	Drakopoulos (2021); Garriga et al. (2023); Cipriani and Fioroni (2021); Broadway and Haisken-DeNew (2019); Gu et al. (2020)
Payment Environment Optimization	Enhances payment convenience and security, altering consumption behaviour and habits.	Digital finance increases consumption frequency and volume, raising overall consumption levels.	Xun et al. (2020); Liu et al (2023)
Income Distribution	Examines the impact of income distribution on consumption levels.	Equitable income distribution promotes overall consumption; higher income disparity reduces overall consumption levels.	Uzar (2020); Li et al. (2019); Azizur and Carl (2023)

Vol: 16 **No:** 03 **Year:** 2024 **ISSN:** 1309-8055 (Online) (**pp.** 442-461) **Doi:** 10.34109/ijefs.202416321

Social Security	Addresses social security systems' effects on family consumption.	Robust social security reduces future uncertainties, decreasing savings and increasing consumption; inadequate social security leads to higher savings and lower consumption.	Cipriani and Fioroni (2021); Broadway and Haisken-DeNew (2019); Gu et al. (2020)
Credit Services	Explores the role of expanding credit services in alleviating liquidity constraints.	Expanding credit services can promote consumption, particularly among low-income earners.	Janzen and Carter (2019); Mian et al. (2020); Riley (2024)

Enhanced social welfare provisions help to mitigate perceived future risks, encouraging increased present expenditure and reducing the necessity to save (Broadway & Haisken-DeNew, 2019).

Conversely, limited access to social protection often leads to heightened saving behaviour and diminished consumption, particularly among lower-income groups (Gu et al., 2020). The literature review has outlined several key theories and hypotheses concerning household consumption behaviour. Collectively, these studies underscore the complexity of consumption dynamics, which are shaped by income distribution patterns, the level of financial market development, and the effectiveness of social security systems. The relevant determinants and supporting empirical findings are summarised in Table 1.

Despite the extensive body of literature exploring the influence of digital finance on household consumption, several research gaps persist. Existing studies predominantly assess the general impact of digital finance on consumption, with limited exploration into its specific dimensions—such as the scope, depth, and breadth of digitalisation. Much of the existing scholarship focuses on urban populations, while rural areas remain under-researched, despite significant discrepancies in financial literacy, infrastructural development, and consumer environments between these settings. Theoretically, by identifying the specific mechanisms through which digital finance stimulates consumption, this research enriches the academic discourse surrounding consumer behaviour and financial innovation. Practically, the findings provide valuable insights for policymakers and businesses, enabling more effective utilisation of digital finance tools to formulate strategic interventions, enhance consumer engagement, and support resilient and inclusive economic growth.

Research Hypotheses

Based on the insights derived from the literature review, the following research hypotheses are proposed to investigate the influence of digital banking expansion on residents' consumption levels, as illustrated in Figure 1.

Vol: 16 **No:** 03 **Year:** 2024 **ISSN:** 1309-8055 (Online) (**pp.** 442-461) **Doi:** 10.34109/ijefs.202416321

First Hypothesis (H1): *The growth of online banking raises citizens' income levels, thereby promoting consumption. Digital finance enhances residents' income levels through entrepreneurship and economic growth while providing a variety of wealth management methods to increase residents' property income, thereby boosting consumption levels.*

Second Hypothesis (H2): *The growth of digital finance reduces residents' uncertainties, increasing consumption willingness. The expansion of digital finance enriches family wealth management methods, and diversified financial management models reduce income uncertainties. The development of digital insurance increases insurance consumption and purchasing insurance can reduce property losses caused by sudden life events, thereby enhancing residents' consumption willingness.*

Third Hypothesis (H3): *The evolution of online banking liquidity constraints, promoting residents' consumption. Digital finance promotes a competitive supply of consumer credit from traditional financial institutions, expanding residents' budget space. Furthermore, the wealth management models of digital finance make bonds, funds, etc., easy to cash in, making consumers' wealth more easily used for consumption, thereby boosting consumption levels.*

The interrelationship among these three hypotheses is depicted in Figure 1.

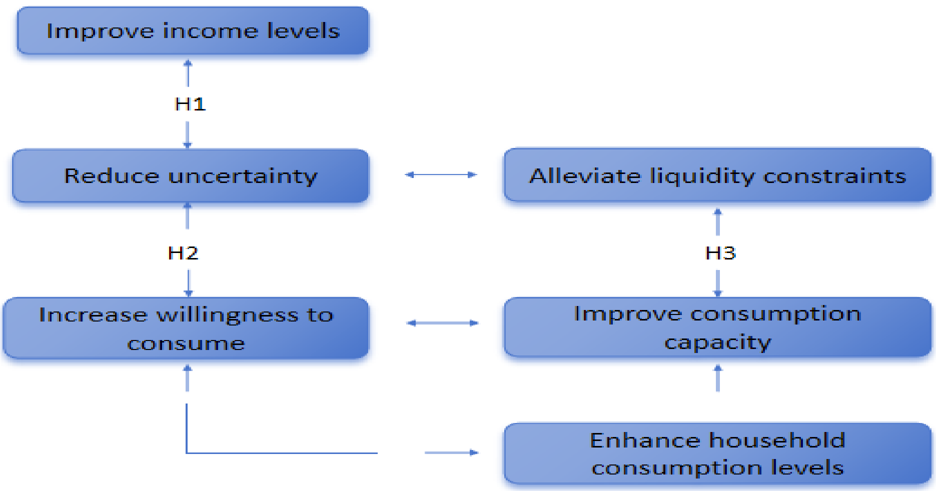

Figure 1: Hypothesis Analysis

METHODOLOGY

Data Collection

To gain a comprehensive understanding of the impact of digital finance on household consumption, the sample selection process involved selecting households from across the nation. To further explore regional variations, the study incorporated representative provinces and cities from the eastern, central, and western regions of the country. This approach facilitated an examination of the geographical differences in the effects of digital banking. The research analysed data spanning the past decade (2012–2022) to investigate the process and long-term effects of digital finance growth on consumption patterns. The sample size included thousands of households, with each region representing at least one thousand households to ensure statistical accuracy.

Data was collected from official statistics provided by the Provincial Statistical Bureau and the National Bureau of Statistics, alongside academic resources such as The Digital Finance Research Centre at Peking University. In addition, direct surveys were conducted with selected households. Both categorical data (e.g., average income levels, total consumer expenditure, and digital finance usage) and textual data (e.g., satisfaction with digital finance services and anticipated future income levels) were gathered. The data underwent pre-processing, which included addressing missing values and outliers to ensure completeness and accuracy for further analysis. Descriptive statistical methods were applied to summarise basic characteristics of the sample, including income levels, consumption expenditure, and digital finance utilisation. Subsequently, a regression model was used to examine the effect of digital banking development on household spending, adjusting for other influencing factors. To ensure the reliability of the results, robustness tests, such as the use of instrumental variables, were conducted.

Figure 2 illustrates the entire research process. It begins with nationwide sampling, covering the eastern, central, and western regions (2012-2022), followed by data collection from the China Family Panel Studies. Preliminary empirical tests were then conducted, with the data subsequently analysed using STATA software, focusing on the relationship between the development of digital finance (independent variable) and household consumption (dependent variable), considering five key influencing factors.

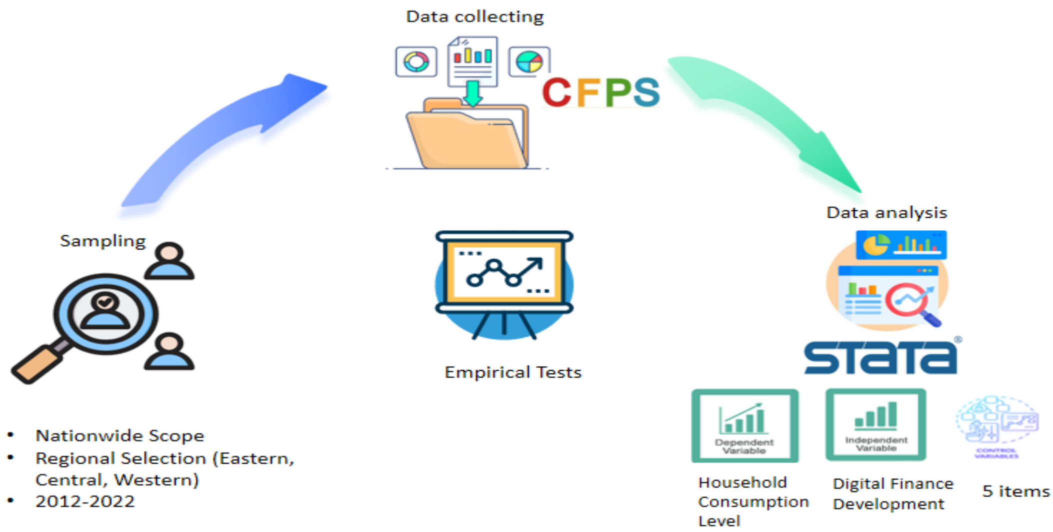

Figure 2: Data and Sample Gathering

Vol: 16 **No:** 03 **Year:** 2024 **ISSN:** 1309-8055 (Online) (**pp.** 442-461) **Doi:** 10.34109/ijefs.202416321

Variables Description

The level of household consumption, which reflects overall spending on goods and services, serves as the dependent variable in this study, as outlined in Table 2. These variable captures both the consumption capacity and behaviour of households. The independent variable is the growth of digital finance, which measures the development of digital finance across different regions and time periods. This is typically assessed using digital finance indices or coverage rates. A description of the variables can be found in Table 2.

Table 2: Variable Description

Household Consumption Level	Total amount spent by households on goods and services, indicating their purchasing power and behaviours.
Digital Finance Development	Evaluates the degree of progress made in digital finance across different locations and time periods, typically assessed using digital finance indices or coverage rates.
Household Income Level	Indicates the disposable income of households, usually measured by data on disposable income per person.
Uncertainty in Income	Assesses the stability of household income, often measured by income volatility or unemployment rates.
Level of Social Security	Reflects the completeness of social security services available to households, typically measured by social security coverage rates or welfare expenditure as a percentage of GDP.
Liquidity Constraints	Represents the ease or difficulty households face in obtaining credit and financing, usually measured by credit availability or borrowing rates.
Payment Environment	Measures the convenience and security of using digital payment methods by households, often assessed by the penetration rate of mobile payments or the volume of electronic payment transactions.

Data Analysis

A formulation for the basic regression model used to look at the connection between consumer spending and the growth of digital finance is as follows:

The formula is $Cons_i=\alpha+\beta 1DFD_i+\beta 2IL_i+\beta 3IU_i+\beta 4SSL_i+\beta 5LC_i+\beta 6PE_i +E_i$

The development of digital finance is denoted as DFD, income level as IL, income uncertainty as IU, payment environment as PE, liquidity constraints as LC, and social security level as SSL, with α representing the constant term. Household consumption, reflecting purchasing power and spending habits, is the total expenditure on goods and services. In the model, α is the intercept and β1–β6 are coefficients. β1 captures the effect of digital finance on household spending; β2–β6 reflect the influences of income level, income uncertainty, social security, liquidity constraints, and the payment environment. Ei denotes the error term.

Vol: 16 **No:** 03 **Year:** 2024 **ISSN:** 1309-8055 (Online) (**pp.** 442-461) **Doi:** 10.34109/ijefs.202416321

RESULTS AND DISCUSSION

Description of Statistics

A statistical summary of the variables discussed in this chapter is presented in Table 3. The regression analysis results are based on descriptive statistics for three variables: consumption for development, happiness, and survival, derived from a sample of 341, as shown in Table 3. Survival consumption, averaging 0.414 (41.4% of total consumption), displays moderate variability. Development consumption averages 0.088 (8.8%), indicating lower variability, while enjoyment consumption averages 0.681 (68.1%) with moderate variability. This suggests that survival consumption takes precedence, in line with economic theory, reflecting individual preferences and constraints. Heterogeneity in consumption is influenced by factors such as income, age, family size, and personal preferences. Considering the above descriptive statistical findings, a key inference emerges: the consumption structure of Chinese households follows a clear trend. The share allocated to basic needs (survival) decreases, while the allocation for development and enjoyment-related consumption increases.

Table 3: Statistical Description

Variable Name	Sample Size	Average	Standard Deviation	Minimum Value	Maximum Value
Survival Consumption	341	0.414	0.040	0.251	0.502
Development Consumption	341	0.088	0.010	0.049	0.107
Enjoyment Consumption	341	0.681	0.051	0.501	0.804

Baseline Regression

The model assesses the intricate impacts of digital finance development by analysing the consumption structure of the population as the dependent variable. The detailed results of this regression analysis are presented in Table 4.

Table 4: Digital Finances and Consumption Level

Dependent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Digital Finance	0.031**	0.026**	0.018**	0.013***	0.010**	0.012***
	(2.145)	(2.298)	(2.405)	(3.408)	(2.382)	(3.303)
GDP Per Capita		0.094**	0.217***	0.114***	0.103**	0.101**
		(2.358)	(4.528)	(3.048)	(2.330)	(2.527)
Financial Development		0.034*	0.125***	0.058**	0.052	0.032
		(1.977)	(4.523)	(2.255)	(1.512)	(1.141)
Urbanization			0.259***	0.382***	0.373***	0.410***
			(4.226)	(10.415)	(10.570)	(9.008)
Human Capital			0.008	0.021	0.015	-0.003
			(0.446)	(1.212)	(0.781)	(-0.180)
Education Expenditure				-0.034**	-0.021	-0.049***
				(-2.233)	(-1.348)	(-3.676)
Medical Expenditures				0.058**	0.062**	0.043**
				(2.625)	(2.741)	(2.636)
Social Security Expenditures				-0.016	-0.012	-0.032*

				(-0.901)	(-0.604)	(-1.893)
Elderly Dependence Ratio					0.018	-0.033*
					(0.796)	(-1.724)
Ratio of Child Dependency					-0.079**	-0.088**
					(-2.292)	(-2.522)
Disposable Income Per Capita						0.083***
						(6.699)
Province-Fixed Impacts	Yes	yes	yes	yes	yes	yes
Year-Fixed Impacts	Yes	yes	yes	yes	yes	yes
Obs.	341	341	341	341	341	341
R^2	0.040	0.046	0.205	0.389	0.412	0.519

Note: *The t statistics are in parenthesis, and the symbols "***", "**", and "*" denote significance at the 1%, 5%, and 10% levels, respectively.*

A positive correlation is observed between the expansion of digital finance and the diversity of consumption patterns among individuals, as indicated by the regression analysis. Specifically, a one-unit increase in digital finance development results in a 0.012-unit increase in the consumption structure, after accounting for relevant factors. In practical terms, the consumption structure increases by 1.2% for every 10% growth in digital finance development. This highlights the significant role that digital banking plays in shaping consumer spending behaviour. The model is then evaluated using the household spending structure as the dependent variable to assess the impact of digital finance growth on this structure. The regression outcomes are presented in Table 5.

Table 5: Structure of Digital Finance and Consumption

Dependent Variable Consumption Structure	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Coverage Breadth	0.008***					
	(2.904)					
Utilize Depth		0.015***				
		(4.040)				
Amount of Digitalization			0.003*			
			(1.850)			
Index of Payment				0.009*		
				(1.712)		
Index of Insurance					0.003*	
					(1.722)	
Index of Credit						0.015***
Degree of Coverage						(3.699)
Control Variables	Yes	Yes	Yes	yes	yes	yes
Province Fixed Effects	Yes	Yes	Yes	yes	yes	yes
Year Fixed Effects	Yes	Yes	Yes	yes	yes	yes
Obs.	341	341	341	341	341	341
R^2	0.515	0.526	0.506	0.509	0.507	0.526

Vol: 16 **No:** 03 **Year:** 2024 **ISSN:** 1309-8055 (Online) (**pp.** 442-461) **Doi:** 10.34109/ijefs.202416321

The regression analysis results show that various aspects of digital finance significantly influence household spending patterns. Key findings include:

- Model 1: The coverage of digital banking has a positive and significant effect ($p < 0.01$) on household expenditure patterns. Greater access to digital financial services encourages more varied and sophisticated consumption.
- Model 2: The depth of usage also shows a positive and significant impact ($p < 0.01$), suggesting that frequent interactions with digital finance services improve household consumption diversity and intensity.
- Model 3: The digitalisation of financial services has a positive but marginal effect ($p < 0.1$), indicating that digital technology enhances household expenditure, though less so than coverage and usage.
- Model 4: The payment index shows a positive but marginal effect ($p < 0.1$), highlighting that improved payment systems, such as mobile payments, promote more frequent consumption by offering convenience and security.
- Model 5: The insurance index has a significant positive effect ($p < 0.01$), suggesting that digital insurance services reduce financial uncertainty and allow for more consumption.
- Model 6: The credit index demonstrates a strong positive relationship ($p < 0.01$), indicating that digital credit services enable larger and more frequent purchases by improving access to credit.

These findings suggest that the growth of digital finance, in terms of coverage, usage, digitalisation, payment systems, insurance, and credit service, enhances household consumption patterns. Expanding digital finance could lead to more sophisticated and varied spending habits, benefiting both households and the broader economy.

Robustness Assessments

Several robustness tests were conducted using various models and instrumental variables to ensure the reliability and consistency of the results regarding the impact of digital finance growth on household consumption structure. These tests were designed to verify the robustness and dependability of the methodology. Below is a summary of the findings from these robustness checks.

Table 6: Robustness Checks

Consumption Structure as the Dependent Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**
	Fixed Effects+IV	Fixed Effects+IV+GMM	IV1 (Post Office) with Fixed Effects	Fixed Effects + IV2 (Telephone)
Digital Finance	0.003***	0.001**	0.583**	0.115***
	(3.326)	(2.092)	(2.203)	(4.450)
Control Variables	Yes	Yes	Yes	Yes

Vol: 16 **No:** 03 **Year:** 2024 **ISSN:** 1309-8055 (Online) (**pp.** 442-461) **Doi:** 10.34109/ijefs.202416321

Province Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Unrecognizable Test	0.000	0.000	0.006	0.058
Instrumental Weakness Variables Test	23.936	23.936	10.681	13.797
Test for Overidentification	0.410	0.410		
Obs.	341	341	341	341
R^2	0.290	0.288	0.256	0.283

As shown in Table 6, robustness tests using fixed effects and instrumental variables (IV) were conducted to address endogeneity in Model 1. Digital finance shows a strong positive effect on household spending (0.003, $p < 0.01$). The F-statistic (23.936) suggests valid instruments, with the unrecognisable test ($p = 0.05$) indicating significant correlation, and a p-value of 0.000 confirming instrument relevance. The overidentification test ($p = 0.410$) supports instrument validity. In Model 2, results using GMM confirm digital finance improves consumption structure (0.001, $p < 0.05$), with similar test results reinforcing robustness.

Model 3 uses the post office as the instrumental variable. The positive coefficient for digital finance (0.583, $p < 0.05$) confirms its significant impact on household expenditure composition. The weak instrumental variables F-statistic of 10.681 suggests moderately strong instruments, and the unrecognisable test p-value of 0.006 supports the instruments' relevance. The R^2 value of 0.256 indicates that a substantial portion of the variation in household spending structure is explained by this model. Model 4 employs the telephone as the instrumental variable. The coefficient for digital finance (0.115, $p < 0.01$) remains large and significant, indicating a strong positive effect on household consumption structure.

The F-statistic of 13.797 for weak instrumental variables suggests strong instruments. The unrecognisable test p-value of 0.058, though slightly higher than in previous models, still indicates instrument relevance. This model also explains a significant proportion of the variance in family spending structure, with an R^2 value of 0.283. The use of various instrumental variables and methods (IV, GMM) reinforces the reliability of these findings. The strong F-statistics confirm the strength of the instruments, while the unrecognisable and overidentification tests validate their relevance and validity. The R^2 values across models further support the robustness of the results, indicating that a significant amount of the variation in household consumption structure is explained by the models.

Analysis of Heterogeneity

China's vast size and large population create significant regional disparities, with variations in natural geographical conditions and economic development levels. These disparities lead to differences in earnings, consumption patterns, and economic

Vol: 16 No: 03 Year: 2024 ISSN: 1309-8055 (Online) (pp. 442-461) Doi: 10.34109/ijefs.202416321

behaviour among residents. Additionally, regional differences in basic education, transportation, and network infrastructure contribute to unequal access to resources, further affecting consumer behaviour. Given these variations, it is crucial to examine the heterogeneous effects of digital finance growth across different regions, income groups, human capital levels, and consumption types.

Heterogeneity Test 1：Digital Finance and Different Regions

Using various estimation methods (Fixed Effects, Fixed Effects + IV + GMM, Fixed Effects + IV2), the heterogeneity test investigates how digital finance development impacts household spending patterns across China's East, Central, and West regions.

Table 7: Digital Finance and Different Regions

Structure of Consumption as a Dependent Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	Fixed Effects			Fixed Effects+IV+GMM			Fixed Effects+IV2		
	East	Central	West	East	Central	West	East	Central	West
Digital Finance	0.030**	0.011***	0.006**	0.073**	0.071*	0.036***	0.443**	0.302**	0.254*
	(2.659)	(4.335)	(2.323)	(2.046)	(1.707)	(3.222)	(2.506)	(2.292)	(1.746)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unidentifiable Test				0.056	0.026	0.001	0.014	0.047	0.000
Weak Instrumental Variables Test				10.926	11.009	10.603	10.228	14.131	12.375
Overidentification Test				0.496	0.163	0.864			
Obs.	121	88	132	121	88	132	121	88	132
R^2	0.244	0.359	0.173	0.194	0.387	0.234	0.472	0.362	0.270

Table 7 presents the results, showing regional variations in the impact of digital finance on household spending patterns. All digital finance coefficients are positive and significant, though their magnitude and statistical significance differ by region and model.

Eastern Region

- Fixed Effects (Model 1): Coefficient of 0.030, significant at 5% ($p < 0.05$), indicating a positive impact.
- Fixed Effects + IV + GMM (Model 2): Coefficient of 0.073, significant at 5% ($p < 0.05$), suggesting a larger impact.

Vol: 16 **No:** 03 **Year:** 2024 **ISSN:** 1309-8055 (Online) (**pp.** 442-461) **Doi:** 10.34109/ijefs.202416321

- Fixed Effects + IV2 (Model 3): Coefficient of 0.443, significant at 5% ($p < 0.05$), showing a substantial effect.
- Instruments are valid, with strong F-statistics and p-values < 0.05.

Central Region

- Fixed Effects (Model 1): Coefficient of 0.011, highly significant at 1% ($p < 0.01$), indicating a positive effect.
- Fixed Effects + IV + GMM (Model 2): Coefficient of 0.071, significant at 10% ($p < 0.1$), consistent positive impact.
- Fixed Effects + IV2 (Model 3): Coefficient of 0.302, significant at 5% ($p < 0.05$), indicating a larger impact.
- Instruments are relevant and strong, with valid results from overidentification tests.

Western Region

- Fixed Effects (Model 1): Coefficient of 0.006, significant at 5% ($p < 0.05$), showing a positive but smaller effect.
- Fixed Effects + IV + GMM (Model 2): Coefficient of 0.036, highly significant at 1% ($p < 0.01$), suggesting a larger contribution.
- Fixed Effects + IV2 (Model 3): Coefficient of 0.254, significant at 10% ($p < 0.1$), indicating a significant impact.
- Instruments are valid, with strong F-statistics and overidentification tests confirming their relevance.

The heterogeneity test shows that digital finance positively impacts household spending across regions, with the Eastern region most affected. The robustness of these findings is supported by multiple instrumental variables and estimation techniques, confirming the importance of considering regional factors when analysing the effects of digital finance on household consumption.

Heterogeneity Test 2: Various Income Groups and Digital Finance

The results of the heterogeneity test, employing various estimation methods, shed light on how the growth of digital finance has influenced household expenditure patterns across low- and high-income groups. The findings highlight significant differences in the impact of digital finance on household consumption patterns between high- and low-income groups, as well as variations across different estimation methods, as shown in Table 8.

Table 8: Digital Finance and Different Income Groups

Dependent Variable Consumption Structure	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
	Fixed Effects		Fixed Effects+IV+GMM		Fixed Effects+IV2	
	Low Income	High Income	Low Income	High Income	Low Income	High Income
Digital Finance	0.009***	0.028**	0.007***	0.012***	0.255***	0.458***

Vol: 16 **No:** 03 **Year:** 2024 **ISSN:** 1309-8055 (Online) (**pp.** 442-461) **Doi:** 10.34109/ijefs.202416321

	(3.477)	(2.290)	(2.635)	(5.531)	(3.159)	(3.999)
Control Variables	yes	Yes	Yes	yes	yes	yes
Province Fixed Effects	yes	Yes	Yes	yes	yes	yes
Year Fixed Effects	yes	Yes	Yes	yes	yes	yes
Unrecognizable Test			0.001	0.013	0.071	0.036
Weak Instrumental Variables Test			10.190	15.832	20.025	20.881
Overidentification Test			0.315	0.897		
Obs.	225	116	225	116	225	116
R^2	0.105	0.205	0.451	0.468	0.550	0.489

Low-Income Group

Fixed Effects (Model 1): Digital finance positively impacts low-income families' consumption patterns, as evidenced by the coefficient of 0.009, which is highly significant ($p < 0.01$). The model explains 10.5% of the variance in consumption structure, with an R^2 value of 0.105.

Model 2: In the Fixed Effects + IV + GMM model, digital finance has a slightly smaller coefficient (0.007), but it remains highly significant ($p < 0.01$). This indicates a consistent positive effect, even after accounting for endogeneity. The strength of the instruments is confirmed by the F-statistic of 10.190 for weak instrumental variables. The unrecognisable test p-value of 0.001 further supports the relevance of the instruments. The model explains a significant portion of the variation, with an R^2 value of 0.451.

Fixed Effects + IV2 (Model 3): In the Fixed Effects + IV2 model, digital finance shows a notably higher coefficient (0.25) and is highly significant ($p < 0.01$), indicating that the second instrumental variable has a strong positive impact. The weak instrumental variables test reveals robust instruments with an F-statistic of 20.025. Although slightly higher, the unrecognisable test p-value of 0.071 still confirms the instruments' relevance. The model accounts for nearly half of the variance in consumption structure, as indicated by the R^2 value of 0.550.

High-Income Group

Fixed Effects (Model 1): Digital finance has a more substantial positive impact on high-income families' household consumption structure, with a coefficient of 0.028, significant at the 5% level ($p < 0.05$). The model explains 20.5% of the variance, as indicated by the R^2 value of 0.205.

Model 2: Using Fixed Effects + IV + GMM, digital finance maintains a consistently positive effect, with a highly significant coefficient of 0.012 ($p < 0.01$). The F-statistic of 15.832 indicates strong instruments, while the unrecognisable test p-value of 0.013

Vol: 16 **No:** 03 **Year:** 2024 **ISSN:** 1309-8055 (Online) (**pp.** 442-461) **Doi:** 10.34109/ijefs.202416321

confirms their relevance. The model accounts for a substantial portion of the variation, with an R^2 value of 0.468.

Fixed Effects + IV2 (Model 3): The second instrumental variable reveals a notably strong positive impact, with a substantially larger digital finance coefficient of 0.458, which is highly significant ($p < 0.01$). The F-statistic of 20.881 confirms the robustness of the instruments, while the unrecognisable test p-value of 0.036 supports their relevance. The model explains over half the variance in consumption structure, as indicated by an R^2 value of 0.489.

The heterogeneity test findings indicate that digital finance development has a positive effect on household expenditure composition in both low- and high-income groups. However, the impact is generally more pronounced and statistically significant among high-income households. The consistent use of various instrumental variables and estimation techniques reinforces the robustness of these results. Instrument strength and relevance are validated by the unrecognisable and weak instrument tests. R^2 values across models confirm that a substantial proportion of the variation in household expenditure is explained, further supporting the reliability of the conclusions. These results highlight the income-based disparities in the benefits of digital finance, suggesting that such initiatives may yield greater advantages for higher-income families.

Heterogeneity Test 3: Digital Finance and Different Levels of Human Capital

Using a range of estimation approaches, the heterogeneity test results provide insight on how household spending habits at both low and high human capital levels have been impacted by the emergence of digital banking. Three models provide a summary of the findings. As shown in Table 9, the results reveal significant differences in the impact of digital finance on household consumption structure between families with high and low levels of human capital, as well as across different estimation methods.

Table 9: Digital Finance and Different Levels of Human Capital

Dependent Variable Consumption Structure	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
	Fixed Effects		Fixed Effects+IV+GMM		Fixed Effects+IV2	
	Low Human Capital	High Human Capital	Low Human Capital	High Human Capital	Low Human Capital	High Human Capital
Digital Finance	0.004**	0.016**	0.029***	0.106***	0.141**	0.124**
	(1.780)	(1.758)	(2.623)	(2.593)	(2.104)	(2.499)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Unrecognizable Test			0.000	0.043	0.022	0.046

Vol: 16 No: 03 Year: 2024 ISSN: 1309-8055 (Online) (pp. 442-461) Doi: 10.34109/ijefs.202416321

Weak Instrumental Variables Test			19.518	13.262	21.405	20.348
Overidentification Test			0.638	0.613		
Obs.	176	165	176	165	176	165
R^2	0.212	0.217	0.424	0.455	0.327	0.765

Low Human Capital Group

Fixed Effects (Model 1): Digital finance exerts a modest yet positive influence on household consumption structure among families with low human capital, as reflected by the coefficient of 0.004, which is significant at the 5% level ($p < 0.05$).

Model 2: Using Fixed Effects + IV + GMM, the impact of digital finance on households with low human capital becomes more pronounced, with the coefficient rising to 0.029 and remaining highly significant ($p < 0.01$). The instruments are strong, as evidenced by the weak instrumental variables test's F-statistic of 19.518. Their significance is further validated by the unrecognisable test p-value of 0.000. The model explains a substantial portion of the variation in consumption structure, as reflected in the R^2 value of 0.424.

Fixed Effects + IV2 (Model 3): With the second instrumental variable, the coefficient for digital finance rises to 0.141, indicating a notable positive effect that is significant at the 5% level ($p < 0.05$). The instruments are strong, as shown by the weak instrumental variables test's F-statistic of 21.405. The unrecognisable test p-value of 0.022 further supports the instruments' validity.

High Human Capital

In Model 1, digital finance has a stronger positive effect for high human capital households, with a coefficient of 0.016 ($p < 0.05$). The model explains 21.7% of the variance ($R^2 = 0.217$).

Model 2: In Model 2, digital finance has a much stronger effect, with a coefficient of 0.106 ($p < 0.01$). The instruments are strong ($F = 13.262$; $p = 0.043$). The model explains 45.5% of the variance ($R^2 = 0.455$).

Model 3: In Model 3 (Fixed Effects + IV2) shows a strong positive effect of digital finance (coefficient = 0.124, $p < 0.05$). The instruments are robust ($F = 20.348$; $p = 0.046$). The model explains 76.5% of the variance ($R^2 = 0.765$).

Overall, digital finance positively influences consumption patterns in both low and high human capital groups, with stronger effects in higher-capital households. The results are robust across models and instruments, as supported by the relevant F- and p-values. High R^2 values confirm strong explanatory power, highlighting the greater benefits of digital finance among households with more human capital.

CONCLUSION

This study investigates the impact of digital finance growth on the consumption patterns of Chinese households, demonstrating that digital finance encourages consumer spending by enhancing credit access, stabilising income, and reducing financial uncertainty. The analysis identifies three key factors through which digital finance drives consumption: the breadth of financial services, the extent of digital transformation, and the utilisation of digital monetary tools. Households engaging with a wider range of digital financial services exhibit greater consumption diversification. Increased involvement in financial technologies, lower transaction costs, and higher online engagement are positively linked with elevated spending. The study also highlights regional and demographic disparities. These findings suggest that while digital finance fosters overall consumption growth, targeted policies are needed to address regional imbalances in financial development. The research offers valuable insights for policymakers, business leaders, and managers. By tailoring digital finance policies, authorities can stimulate consumption, mitigate financial inequalities, and promote long-term economic development. Future studies could investigate the prolonged effects of digital finance on economic growth and explore other mechanisms through which it influences consumer behaviour. This research provides a robust foundation for implementing digital finance strategies aimed at fostering economic progress.

REFERENCES

Azizur, R. K., & Carl, R. (2023). Income and inequality in China: composition, distribution and growth of household income, 1988 to 1995. In *People's Republic of China, Volumes I and II* (pp. Vol2: 61-Vol62: 94). Routledge. https://doi.org/10.4324/9781315194646-33

Broadway, B., & Haisken-DeNew, J. P. (2019). Keep calm and consume? Subjective uncertainty and precautionary savings. *Journal of Economics and Finance*, *43*(3), 481-505. https://doi.org/10.1007/s12197-018-9451-0

Cavoli, T., Gopalan, S., & Rajan, R. S. (2020). Does Financial Inclusion Amplify Output Volatility in Emerging and Developing Economies? *Open Economies Review*, *31*(4), 901-930. https://doi.org/10.1007/s11079-019-09568-0

Cipriani, G. P., & Fioroni, T. (2021). Endogenous demographic change, retirement, and social security. *Macroeconomic Dynamics*, *25*(3), 609-631. https://doi.org/10.1017/S1365100519000269

Demir, A., Vanesa, P.-C., Yener, A., & and Murinde, V. (2022). Fintech, financial inclusion and income inequality: a quantile regression approach. *The European Journal of Finance*, *28*(1), 86-107. https://doi.org/10.1080/1351847X.2020.1772335

Drakopoulos, S. A. (2021). Theories of consumption. https://mpra.ub.uni-muenchen.de/id/eprint/108215

Garriga, C., Hedlund, A., Tang, Y., & Wang, P. (2023). Rural-Urban Migration, Structural Transformation, and Housing Markets in China. *American Economic Journal: Macroeconomics*, *15*(2), 413-440. https://doi.org/10.1257/mac.20160142

Gruin, J., & and Knaack, P. (2020). Not Just Another Shadow Bank: Chinese Authoritarian Capitalism and the 'Developmental' Promise of Digital Financial Innovation. *New Political Economy*, *25*(3), 370-387. https://doi.org/10.1080/13563467.2018.1562437

Gu, X., Tam, P. S., Li, G., & Zhao, Q. (2020). An alternative explanation for high saving in China: Rising inequality. *International Review of Economics & Finance*, *69*, 1082-1094. https://doi.org/10.1016/j.iref.2018.12.004

Hasan, M. M., Yajuan, L., & Khan, S. (2020). Promoting China's Inclusive Finance Through Digital Financial Services. *Global Business Review*, *23*(4), 984-1006. https://doi.org/10.1177/0972150919895348

Janzen, S. A., & Carter, M. R. (2019). After the drought: The impact of microinsurance on consumption smoothing and asset protection. *American Journal of Agricultural Economics*, *101*(3), 651-671. https://doi.org/10.1093/ajae/aay061

Li, J., Wu, Y., & Xiao, J. J. (2020). The impact of digital finance on household consumption: Evidence from China. *Economic Modelling*, *86*, 317-326. https://doi.org/10.1016/j.econmod.2019.09.027

Li, J., Zhang, J., Zhang, D., & Ji, Q. (2019). Does gender inequality affect household green consumption behaviour in China? *Energy Policy*, *135*, 111071. https://doi.org/10.1016/j.enpol.2019.111071

Li, K., Mengmeng, H., & Huo, J. (2022). Digital inclusive finance and asset allocation of Chinese residents: Evidence from the China Household Finance Survey. *Plos one*, *17*(5), e0267055. https://doi.org/10.1371/journal.pone.0267055

Li, T., & Ma, J. (2021). Does digital finance benefit the income of rural residents? A case study on China. *Quant. Financ. Econ*, *5*(4), 664-688. https://doi.org/10.3934/QFE.2021030

Liu, Y., Luan, L., Wu, W., Zhang, Z., & Hsu, Y. (2021). Can digital financial inclusion promote China's economic growth? *International Review of Financial Analysis*, *78*, 101889. https://doi.org/10.1016/j.irfa.2021.101889

Mian, A., Sufi, A., & Verner, E. (2020). How does credit supply expansion affect the real economy? the productive capacity and household demand channels. *The Journal of Finance*, *75*(2), 949-994. https://doi.org/10.1111/jofi.12869

Mukherjee, P., Sahana, R. C., & and Bhattacharya, P. (2021). Does financial liberalization lead to financial development? Evidence from emerging economies. *The Journal of International Trade & Economic Development*, *30*(8), 1263-1287. https://doi.org/10.1080/09638199.2021.1948589

Petry, J. (2020). Financialization with Chinese characteristics? Exchanges, control and capital markets in authoritarian capitalism. *Economy and Society*, *49*(2), 213-238. https://doi.org/10.1080/03085147.2020.1718913

Vol: 16 **No:** 03 **Year:** 2024 **ISSN:** 1309-8055 (Online) (**pp.** 442-461) **Doi:** 10.34109/ijefs.202416321

Riley, E. (2024). Resisting social pressure in the household using mobile money: Experimental evidence on microenterprise investment in Uganda. *American Economic Review*, *114*(5), 1415-1447. https://doi.org/10.1257/aer.20220717

Straub, L. (2019). *Consumption, savings, and the distribution of permanent income.* Harvard University. https://scholar.harvard.edu/files/straub/files/cons_ineq_rates.pdf

Uzar, U. (2020). Is income inequality a driver for renewable energy consumption? *Journal of Cleaner Production*, *255*, 120287. https://doi.org/10.1016/j.jclepro.2020.120287

Wang, G., Hao, Y., & Ma, J. (2024). Family Income Level, Income Structure, and Dietary Imbalance of Elderly Households in Rural China. *Foods*, *13*(2), 190. https://doi.org/10.3390/foods13020190

Wang, W., He, T., & Li, Z. (2023). Digital inclusive finance, economic growth and innovative development. *Kybernetes*, *52*(9), 3064-3084. https://doi.org/10.1108/K-09-2021-0866

Xu, P. (2020). Chinese travellers' adoption of mobile payment applications of WeChat pay and Alipay in New Zealand hotels. https://openrepository.aut.ac.nz/server/api/core/bitstreams/d88696f8-6405-4f30-982e-086b6c17f47e/content

Xun, Z., Guanghua, W., Jiajia, Z., & Zongyue, H. (2020). Digital economy, financial inclusion and inclusive growth. *China Economist*, *15*(3), 92-105. https://doi.org/10.19602/j.chinaeconomist.2020.05.07

Yu, C., Jia, N., Li, W., & Wu, R. (2022). Digital inclusive finance and rural consumption structure – evidence from Peking University digital inclusive financial index and China household finance survey. *China Agricultural Economic Review*, *14*(1), 165-183. https://doi.org/10.1108/CAER-10-2020-0255