THE IMPACT OF DIGITAL FINANCE ON HOUSEHOLD CONSUMPTION BEHAVIOR, EVIDENCE FROM CHINESE HOUSEHOLD EXPENDITURE DATA

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by

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ABSTRACT

This study examines the impact of digital finance on household consumption behavior in China using panel data from the China Family Panel Studies (2012–2020) and the Digital Financial Inclusion Index developed by Peking University. Employing a fixed-effects regression model, the research finds that digital finance significantly increases overall household consumption and shifts expenditure patterns toward discretionary spending. The analysis reveals that this effect is more pronounced among urban, high-income, and high-asset households. Additionally, the study identifies the level of digitization as a key driver, particularly influencing essential categories such as food. These findings offer empirical insights into how financial technology shapes consumption behavior and highlight implications for inclusive economic policy in digitally transforming societies.

BIOGRAPHICAL SKETCH

Emilie (Shiyuan) Fu is a Master of Science student at the Dyson School of Applied Economics and Management at Cornell University with a focus on Management. She received a Bachelor of Arts degree from University of Southern California where she studied Economics and Journalism. Her interests lie in technology and innovation, business strategy, marketing, and applied economics.

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I am grateful for the many resources provided by the Graduate School at Cornell University, which nurtured this research. These include the wealth of academic support, a diligent and supportive cohort of fellow researchers, and the exceptional faculty—many of whom have engaged me in some of the most intellectually stimulating conversations I have ever experienced.

Finally, I extend my heartfelt thanks to my parents and family for their unwavering support and continuous investment in my personal and academic growth. Their enduring faith in me has been the most significant source of motivation behind all of my efforts, including this research.

Beyond the findings of this paper, one of the most important lessons I have learned is that the boundaries of human knowledge are ever-expanding—pushed forward by the relentless pursuit of research. Learning is a lifelong journey, and I am proud to carry forward the values I have gained through this project: curiosity, persistence, meticulousness, and more, as I embark on the next chapter of my academic and professional path.

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1 Introduction

Financial technology has been evolving quickly and digitizing every aspect of household finance in recent years. Various financial innovations have altogether established a digitalized channel to better connect providers and recipients of financial services in the market and enable them to carry out transactions in a faster and more efficient manner. This is the reason why we observe activities central to household finance such as payments and consumption, borrowing and lending, and investment are increasingly taking place on digital platforms. It has significantly reduced the friction and inconvenience people used to experience when accessing financial services and therefore stimulated a significant growth in consumption.

While the positive impact of fintech adoption on household consumption at an aggregate level is material from previous research studies, it is still unclear whether and how the consumption pattern has shifted due to the effect of improving digital financial inclusion. These considerations raise the question of which consumption categories are influenced the most by fintech development and what household or individual characteristics are driving the change in consumption behavior across various aspects that digital finance has improved upon including payment, wealth management, level of digitalization, and many more.

This research addresses these questions in the context of China's digital financial inclusion evolution from 2011 to 2020, which provides an auspicious study context for several reasons. First, improving financial inclusion has been an important policy objective of the Chinese government over the past decade. With a focus on democratizing access to financial services across the country's mass population, China has seen a tremendous expansion on the accessibility and coverage of digital finance, benefitting especially historically disadvantaged groups and regions. This policy background with ample data made available allows the paper to capture a period of significant growth with variations across 25 provinces and almost 10 years. Furthermore, the policy context has also fostered the rapid growth of Chinese fintech conglomerates such as the Ant Group and Tencent which developed and are currently operating world's leading mobile payment platforms (Alipay and WeChat pay respectively). These innovative digital financial goods and services made available are so deeply integrated into

Chinese people's daily lives that they are one step ahead of their international peers in terms of living a digitalized society. This, again, allows this study to carry practical significance and valuable implications for global markets following a similar digital transformation journey.

The study starts from the following theoretical motivations. While existing studies have shown that FinTech can relieve consumers from liquidity constraints and thus increase consumption demand by promoting efficient resource allocation and smoothing intertemporal consumption (Yi and Zhou, 2018), the study also factors in China's unique FinTech history and evolution. First, popular mobile payment and online banking features in China have greatly lowered the cost of payment associated with traditional transaction methods such as bringing physical cash and swiping cards. Studies have found that online payments are considered "senseless payments" because people are less aware of their declining account balances compared to when using cash. As a result, they tend to spend more (Hou et al., 2021) (Ul et al., 2017) (Hu et al., 2023) (Li et al., 2023). In contrast, traditional payment methods usually involve physically taking cash out of a wallet, which often makes people more reluctant to spend. Moreover, the seamless integration of these payment tools into Alibaba's online marketplace Taobao (the Internet conglomerate's another branch for online shopping) has further incentivized users to spend more by providing better access to a variety of goods and merchants online and offering a central marketplace to find good deals and bargains. These considerations motivate the study to examine if there is an upward trend in Chinese households' expenditure structure and if heterogeneity effects exist among various consumption categories across households under the influence of digital finance development.

To answer these questions, the paper gathers and analyzes household financial data from the China Family Panel Studies (CFPS) together with digital finance indexes studied by Peking University based on a massive Alipay usage dataset. The paper uses a fixed effect model to estimate the causal impact of digital finance on household consumption expenditure and consumption structure based on the panel dataset while taking into account time, household, and province fixed effects. The paper first uses the panel data at provincial level to conduct the baseline regression. Second, the paper conducts heterogeneity analysis based on several household characteristics such as urban and urban gap, income and asset level difference, and

financial knowledge disparity. Last but not least, the paper examines the effects of disaggregated indexes on consumption across various categories.

This study has several contributions to the existing literature. While existing studies have explored how digital finance influences household spending across various consumption categories, they often lack a comprehensive analysis grounded in a clear and consistent classification of these categories, as available in detailed household expenditure data. This gap motivates the paper to examine household consumption behavior from both a macro perspective—assessing the overall impact of FinTech on total household spending—and a micro perspective, which investigates emerging shifts and trends in specific consumption patterns. The goal is to offer a comprehensive understanding of how household consumption behavior is evolving in the context of digital financial development. Second, the paper also examines the effects of digital financial indexes at a disaggregated level to gauge the main driver of this change in consumption pattern.

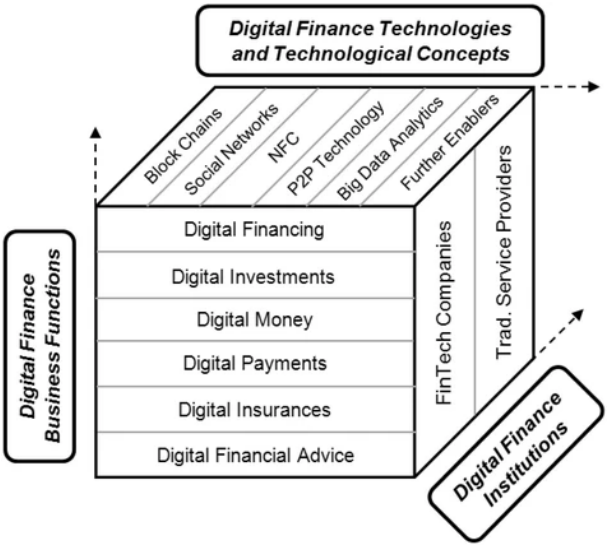
The paper proceeds as follows. Section 2 lays out the theoretical analysis combined with the literature review of household consumption behavior change under the influence of digital finance. Section 3 describes the data, model, and research methodology. Section 4 presents the analytical findings with the description and interpretation of main results. Section 5 concludes the paper with findings, implications, and further considerations. Section 6 lists the literature references.

2 Literature Review & Theoretical Analysis

2.1 Development and Impact of Digital Finance

In a paper that discusses the current and future of digital finance development, Gomber et al. (2017) propose the concept of Digital Finance Cube to provide a comprehensive overview of key players and innovations in the FinTech evolution, a model that has high level of generalizability and flexibility (see Figure 1 below). This framework lays the foundation for this paper's further exploration and analysis of FinTech's influence on consumption behavior under the large framework.

Figure 1: The Digital Finance Cube and Its Dimensions



With its rapid development in the recent decade, digital finance is considered by many as a new venue of huge potential to provide greater financial inclusion and expansion of basic services to underserved groups (Rizzo, 2014) (Pazarbasioglu et al., 2020). The research of Wang et al. (2020) proves that financial sector efficiency positively correlates with digital finance improvements, while the effect has significant differences across various Chinese provinces. Mu et al. (2022) finds that digital finance enhances corporate environment, social, and governance (ESG) by mitigating financing constraints. The research of Xie et al. (2018) and Zhang et al. (2018) finds that digital finance development has greatly promoted entrepreneurship and innovation. Similarly, Beck et al. (2018) finds that mobile payment innovations could boost

entrepreneurial performance of small businesses by improving entrepreneurship execution and reducing the degree of asymmetric information.

On the other hand, the potential risks associated with FinTech development are also brought up by researchers. In a recent paper that broadly discusses the impact of digital finance on financial inclusion, the author provides cautionary insights on FinTech's claimed benefits on historically excluded groups by pointing out the fundamental difference between financial inclusion and financial data inclusion, difference between availability and accessibility of financial services, as well as lack of trust, awareness, and education toward digital technologies among poor communities (Ozili, 2018). Yue et al. (2021) find that while the widespread use of digital finance increases credit market participation and stimulates household borrowing and consumption, it also increases the risk of falling into a debt trap. Panos and Wilson (2020) discuss how digital finance platforms such as mobile apps can damage people's financial well-being by triggering impulsive consumer behavior, especially among groups with low financial literacy.

2.2 Factors Influencing Consumption and Consumption Pattern

There are several key factors that are considered to have a strong influence on consumption at household and personal level. First, income, income expectations, and future price expectations are considered as an important determinant of consumption. According to the Permanent Income Hypothesis, families change their consumption behavior only in response to their preferences and expectations about lifetime income and prices, but not in response to transitory or predictable fluctuations. While it is widely seen as a canonical theory in household consumption behavior, later findings pose a challenge to the hypothesis by showing a changing marginal propensity to consume out of transitory income shocks and out of liquidity. Baker & Yannelis (2017), Parker (1999), Hsieh (2003), Stephens (2003), Kueng (2018) demonstrate that households exhibit a significant degree of excess sensitivity in their consumption patterns to the transitory income shock, violating the permanent income hypothesis. Flavin (1984) shows that liquidity constraints are an important part of the observed excess sensitivity of consumption to current income. Wealth and asset holding conditions are another important factor. Alp & Seven (2019) demonstrates that consumption is positively associated with income, credit, and housing wealth, and is negatively associated with interest rate and equity market wealth. Last but not

least, macroeconomics factors and business cycles that influence all the above-mentioned factors and people's expectations on the economy also play an important role in shaping household consumption (Gross et al., 2020).

2.3 Digital Finance Development and Its Impact on Consumption and Consumption Pattern

The study is related to the following existing literature that studies the impact of digital finance development on household consumption. First, it is related to the studies on digital finance development and consumption from a micro-household perspective where existing research shows that digital inclusive finance can promote household consumption, while heterogeneity effects exist across various regions and household characteristics (Li et al., 2021). Yi and Zhou (2018) further explores and tests the mechanism of digital finance development to promote household consumption through two channels: easing the liquidity constraints and facilitating the payment of households. From previous literature on household consumption and digital finance separately, researchers have demonstrated that the digitalized channel has greatly boosted the efficiency in the financial service sector and reduced asymmetric information among service providers and recipients. In the meantime, various business functions (such as payment, insurance, financing) summarized in the Digital Finance Cube are considered to be closely related to household consumption in a almost mechanical way — Digital financial goods and services made available under these business functions expand the availability and accessibility of traditional financial systems and thus enhance the possibility, easiness, and frequency of financial activities and transactions central to household consumption. This brings the paper to the first hypothesis:

Hypothesis 1: Household consumption increases with the development of digital finance.

Furthermore, while existing research has attempted to explore household spending on different consumption categories under the influence of digital finance, there is not a thorough study on household consumption behavior to date based on a clear classification criteria of various categories as disclosed in rich household expenditure data. The research of Li et al. (2021) finds that consumption expenditure of rural households is significantly influenced by digital finance in

several categories including food, clothing, medical care, transportation, and education. He and Song (2020) further explores various consumption categories and concludes that development of digital finance mainly promotes consumption growth among urban households, especially on basic consumption expenditure of food and clothing. Hu et al. (2023) takes one step further in exploring consumption structure and finds that digital finance allows households to achieve consumption upgrading by using the proportion of household expenditure on different consumption categories. These studies motivate this paper to study household consumption behavior from both an aggregated perspective (influence of FinTech on overall household expenditure) and a disaggregated perspective focusing on shifts and new trends in household consumption patterns. The goal is to provide a holistic view on the evolution of household consumption behavior with the development of digital finance. More specifically, this study dives into consumption behavior by subdividing the consumption basket into essential and discretionary categories based on a classification proposed by the economist Ralph Hawtrey (Scitovsky, 1975). His definition of defensive and creative products among various consumption choices lays the foundation for the construction of essential and discretionary consumption in the paper:

"Hawtrey distinguished 'two broad classes of objects of consumption: on the one hand those products which are intended to prevent or remedy pains, injuries or distress, and on the other those which are intended to supply some positive gratification or satisfaction'. He called them defensive and creative products (Scitovsky 1986)."

According to this definition, defensive products yield merely negative satisfaction of minimizing pain, discomfort, and efforts. Once a pain is completely eliminated, there is no more need to be satisfied from that quarter. Therefore, one's needs for them is satiable and these products' ability to give satisfaction is correspondingly limited. When the consumer does realize this fact sometimes, their demand declines with the scope for satisfaction. This explains the low and declining income elasticity of demand for necessities, which are always defensive products (Scitovsky, 1975). Creative products, on the other hand, intend to provide positive satisfaction from some form of stimulation.

Other popular classifications on the consumption basket are broadly compatible with the distinction between defensive and creative products. Dhar and Wertenbroch (2000) examine the consumer choice between hedonic and utilitarian goods where they define hedonic goods as ones whose consumption is featured by an affective and sensory experience of aesthetic pleasure and utilitarian goods as ones whose consumption is more instrumental, cognitively driven, and goal oriented. This definition builds onto Hawtrey's classification and other similar findings on product characteristics. Bazerman, Tenbrunsel, and Wade-Benzoni (1998) recognize affective preferences ("wants") and cognitive or reasoned preferences ("shoulds") that underlie consumer choice. Wants category is reflected in preferences that are emotional, affective, impulsive, and "hot headed", whereas shoulds category is characterized by rational, cognitive, thoughtful, and "cool headed" preferences.

Based on these criteria, this research constructs the two following consumption categories that are broadly compatible with the aforementioned classification rules: essential and discretionary consumption. The paper defines essential categories as necessary and crucial household expenditures that aim to fulfill basic living needs, which is characterized by low and declining income elasticity of demand due to limited satisfaction drawn from each category. Discretionary consumption, on the other hand, serves to satisfy creative, stimulating, and affective needs that go beyond physiological and safety aspects. This is sometimes revealed in preferences that are emotional, affective, impulsive, and "hot headed" as outlined in the want/should distinction. What has not been evaluated previously, however, is how household consumption choice between essential and discretionary goods is influenced by FinTech development.

This study aims to investigate and weigh household consumption choices between the two categories under the influence of financial technology advancements. On one hand, since essential expenditures is an indispensable component in maintaining household operations regardless of all the new possibilities and channels made available by digital finance, will FinTech development have a significant impact on household expenditure serving essential needs? It is equally important to consider whether FinTech has heightened convenience and efficiency in accessing essential and discretionary goods for consumers to the same extent, and whether these financial innovations are designed in a way that leans towards serving "defensive"

or “creative” needs in the first place. As a shift from basic and safety needs to more advanced level of fulfillment is closely related to people’s and the society’s living standards and economic growth (with the rapid development of FinTech as the byproduct and a clear evidence of this societal and economical advancement in the first place), the study expects a similar shift in actual household expenditure pattern to reflect people’s increasing preference on discretionary consumption supported by improving financial wellbeing in terms of a higher willingness and ability to pay for high-quality goods and services beyond fulfilling survival needs.

Furthermore, existing research have shown some evidence that FinTech development may elevate certain risky consumption behaviors (such as falling into debt trap and impulsive purchases) that will instead hurt financial well-being especially among vulnerable communities. This is more closely related to excess expenditure on discretionary categories in nature, because they are not necessary to people’s health, safety, and financial well-being conditions. While the definition on financial well-being varies case by case and household by household, it is commonly agreed that a household whose basic living needs cannot be met can barely be called in a good financial situation; On the other hand, households with lavish expenditure on discretionary categories can have either good or bad implications on their financial well-being. Meanwhile, the popularity of e-commerce businesses in China led by leading online shopping platforms such as Taobao and JD.com together with the emergence of live streaming in recent years continues to revolutionize the consumer market and influence people’s spending habits. They triggered impulsive behavior by providing expanding access to services and products while making the transaction and payment process easy and seamless. There are a few existing studies that discusses how Taobao and similar shopping platforms anchors strategically promote consumer impulsive buying behavior to survive the intense e-commerce competition and maximize businesses’ own profits (Huang et al., 2024) (Akram et al., 2018) (Gao et al., 2022). This e-commerce craze among Chinese consumers, again, has motivated this paper to explore whether Chinese households have exhibited a shifting consumption pattern toward unnecessary and even luxury categories. All these considerations lead the study to posit a second hypothesis:

Hypothesis 2: Among all the choices in the consumption basket, households have an increasing tendency to spend more on discretionary categories than essential counterparts.

3 Methods

3.1 Data

The household finance data comes from the five waves of household survey results collected by the China Family Panel Studies (CFPS) which provides a thorough panel dataset on the economic well-being of Chinese households over the past decade. The CFPS sample is drawn from 25 provinces, cities, or autonomous regions in China that covers 95% of the total Chinese population and therefore can be considered as a nationally representative sample. This paper uses the panel data composed of survey samples in 2012, 2014, 2016, 2018, and 2020.

To measure and quantify financial development across the 25 regions tracked, the paper uses the Digital FInancial Inclusion Index (DFII) studied and published by the Institute of Digital Finance at Peking University through its continuous collaboration with Alipay to gather the company's massive usage and activity data across the country.

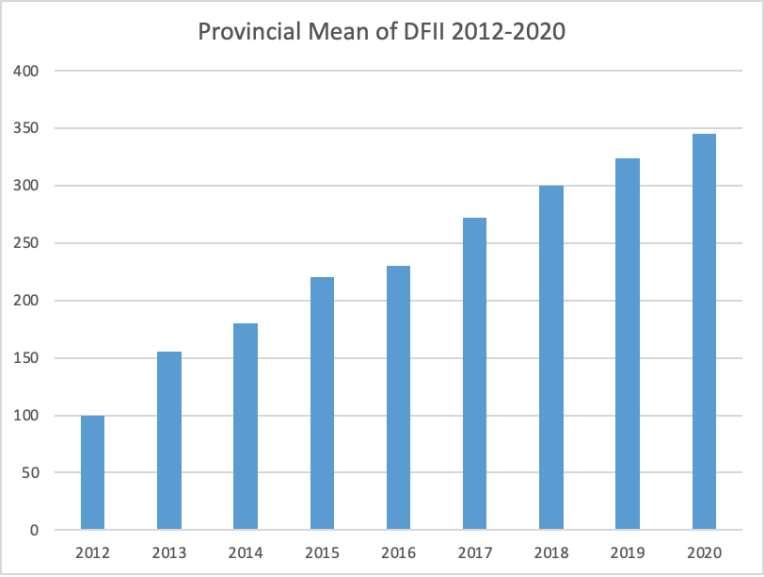
The research builds a comprehensive and objective indicator system of digital financial inclusion that takes into account three dimensions of financial services—breadth of coverage, depth of use, and level of digitization. The breadth of coverage is reflected by the e-account coverage ratio. An example indicator is the number of internet payment accounts owned by the local population. The depth of digital finance usage is calculated by the actual use of internet financial services which are further classified into payment services, monetary fund services, credit services, insurance services, investment services, and credit investigation services. Different categories under this dimension correspond to the various Digital Finance Business Functions proposed in the Digital Finance Cube model, but specifically apply to Alipay’s usage data. The usage measured in the study can be further broken down into the number of actual users, the number of transactions per capita, and the average transaction amount per capita. Level of digitalization captures mobility, affordability, credit, and convenience of the usage.

There are key design principles that ensure the quality and integrity of the data. As disclosed by the system’s three dimensions and detailed subdimensions, the index system takes both breadth and depth into account and also reflects the multilevel and diversity of financial services.

Moreover, it puts an emphasis on both vertical (across time) and horizontal (across regions) comparability of the index, which provides a good foundation for constructing a fixed-effect model. Last but not least, this study ensures that the data comes from reliable and accurate sources through formal collaboration with Alipay and continuous tracking and building onto previous years' results. Besides, the calculations[1] carefully follow the principles of mathematics, statistics, and economics by the research team at Peking University to ensure the objectivity of evaluation results.

From the raw data, we observe a steady growing trend in both DFII and disaggregated indexes across the survey period. Figure 2 displays the increasing trend of the aggregate index (DFII) averaged across provinces from 2012 to 2020. The index grew from an average of 99.69 in 2012 to 345.04 in 2020, indicating a strong improvement in digital financial inclusion in most regions of China that are covered by the research.

Figure 2: Provincial Mean of DFII from 2012 to 2020



Looking at the time trend from a disaggregated level in Figure 3 that further breaks DFII into coverage breadth, usage depth, and digitization level, we observe a similar growing trend across all three dimensions over the years. While the baseline values of all the indexes were close to

[1] Detailed index calculation methodology: https://en.idf.pku.edu.cn/docs/20190610145822397835.pdf.

each other in 2012, the improvement in level of digitization is the most prominent that surpasses all three other indexes in each single year following 2012. This indicates that compared to depth of usage and breadth of coverage, the provinces have seen a significant improvement in the mobility, affordability, credit, and convenience of the usage. The aggregate index and coverage breadth lines resemble a similar upward trend with relatively steady growth rates over the years. Depth of usage, on the other hand, has seen a faster growing rate from 2014 to 2017 and increased at a decreasing rate after that.

Figure 3: Provincial Mean of Indexes from 2012 to 2020

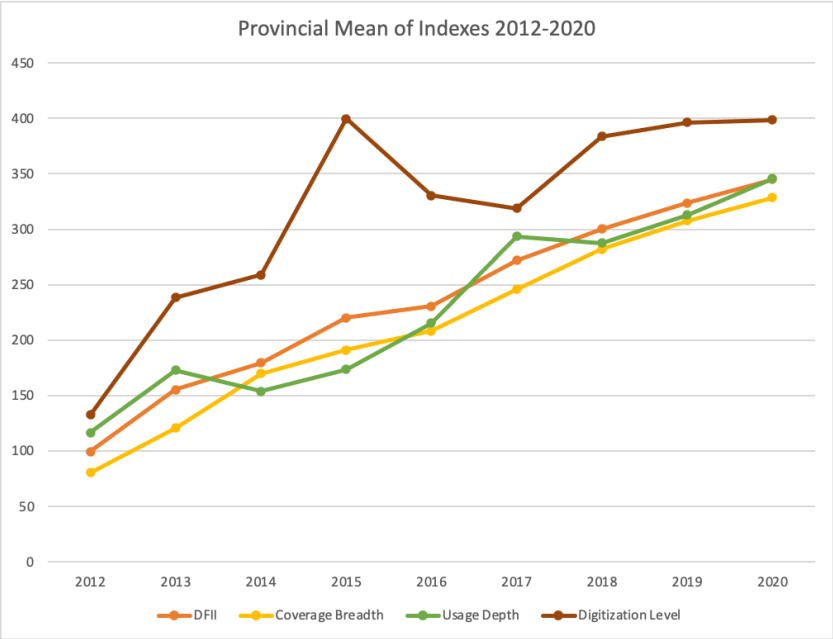
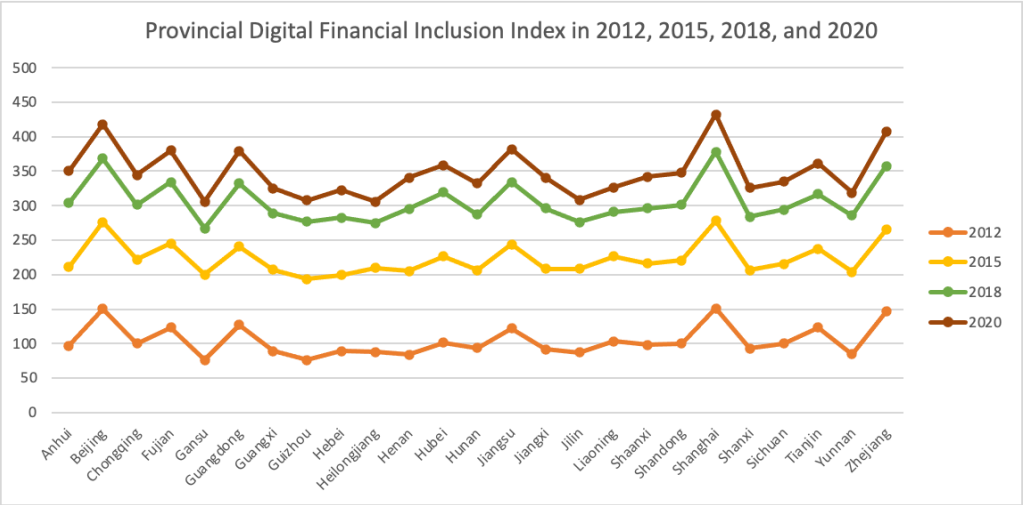


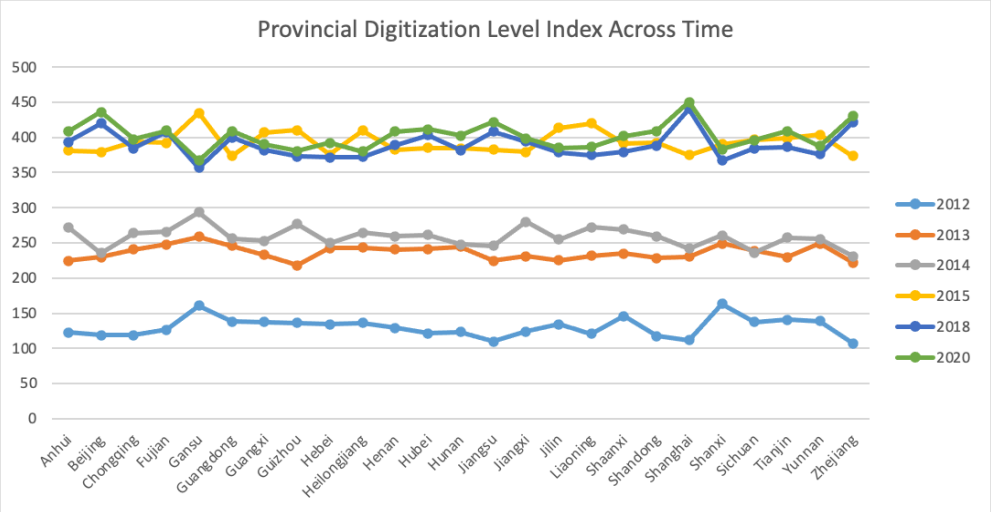
Figure 4 displays the aggregate indexes across the 25 provinces, while each trend line represents the results of a certain wave year. Comparing the aggregate index across the provinces from the waves of 2012, 2015, 2018, and 2020, the difference between each year observed from the overall trend narrows down with time, indicating that DFII is increasing at a decreasing rate. Furthermore, as the overall shape of trend lines resemble each other, the ranking of DFII among provinces remains similar across the years. For instance, the top 3 regions with the highest aggregate indexes are Shanghai, Beijing, and Zhejiang, which remain unchanged in the four years captured.

Figure 4: Provincial DFII in 2012, 2015, 2018, and 2020



Compared to the aggregate index, the provincial index of digitization level shown in Figure 5 has a much faster increasing rate during the first half of the survey period (2012 to 2015) and becomes steady at an average index around 400 in later waves. The digitization level index has experienced two huge jumps from 2012 to 2013 and 2014 to 2015, each almost doubling the previous year's result. This corresponds to the overall FinTech development in China. Starting from 2012, the country entered a new development stage of financial inclusion marked by innovative internet finance that has witnessed a significant adoption of new financial internet products such as Yu'ebao, mobile wallets, and QR code payment. Notably, the successful launch of Yu'ebao in June 2013 has significantly boosted the society's awareness of FinTech services, including mobile payment. The distribution of digital red envelopes on WeChat Pay during the Chinese New Year in 2014 has further attracted hundreds of millions of new users and raised people's enthusiasm for mobile payment. This is also a period with very few FinTech regulations imposed by the government due to the potential benefits of FinTech products in providing better financial access and thus promoting financial inclusion in China. The tolerant financial regulation is considered to provide the window for FinTech companies to experiment with their innovation (Huang, 2020).

Figure 5: Provincial Digitization Level Index over Time



The DFII data is then matched with province-level household financials to reflect local financial technology advancements over the five waves of survey period. Furthermore, this paper also uses the Gross Regional Product Per Capita data from the National Bureau of Statistics of China to factor in regional economic development from a macro perspective in the study.

3.2 Variables

The dependent variables used in this study are total consumption and ratio of consumption on discretionary categories to total consumption which reflects the aggregate consumption level of households and proportion of spending on essential and discretionary categories to the total amount, respectively. The survey data collected by CFPS has kept detailed breakdowns of consumption that span across various categories such as food, clothing, daily commodities, education, rent, transportation, and many more. This study further divides it into two classifications: essential and discretionary consumption. Essential consumption is defined as expenditure on basic goods and services that are essential to survival and maintaining a minimum living standard. Discretionary consumption, on the other hand, goes beyond basic items and involves the purchase of things that are not strictly necessary for survival. This category includes luxury items, entertainment, travel, and other indulgences that contribute to a more comfortable or enjoyable lifestyle. As previously mentioned, the definition mainly builds

onto Hawtrey's classification of defensive and creative products in subdividing the consumption basket.

Based on the CFPS household consumption data, essential or defensive consumption refers to the spending in the following specific categories: food excluding eating out, basic communication, local transportation, water and electricity, clothing, daily commodities and necessities, and rent. Discretionary or creative consumption includes all other categories that fall outside the definition of essential purchases such as eating out expenditure, education, tourism, lottery, and fitness.

The following control variables are also included in the models: total family income, total assets, age of the household head, years of schooling received by the household head, gender of the household head, and Gross Regional Product Per Capita for each geographic area.

Table 1: List of Variables with Description

Variable Name	Description
pce	Total Household Consumption
pce_ess	Total Essential Consumption
pce_disc	Total Discretionary Consumption
disc	Discretionary Consumption Ratio
index_aggregate	Aggregate Index - DFII
digitization_level	Level of Digitization
usage_depth	Depth of Usage
coverage_breadth	Breadth of Coverage
fincome1	Total Annual Family Income
total_asset	Total Annual Family Assets
age	Age of Household Head
edu	Schooling Years of Household Head
gender	Gender of Household Head
GRP numeric	Gross Regional Product Per Capita

Table 2: Summary Statistics of Variables

	N	Mean	SD
pce	52196	52976.995	70436.903
pce ess	42595	28078.206	33730.809
pce disc	40107	20008.5	48369.082
disc	40107	.334	0.229
index aggregate	57335	221.609	88.416
digitization level	57335	291.358	100.512
usage depth	57335	214.398	89.141
coverage breadth	57335	204.458	88.718
fincome1	54833	71833.399	168054.254
total asset	55440	599320.51	1500515.583
age	51717	49.867	14.758
edu	50640	7.537	4.722
gender	51607	.522	0.500
GRP numeric	57335	103.108	59.299

Figure 6 and 7 reflect the change in average household essential and discretionary consumption over the survey period. Essential consumption has shown a steady increase over the years, while discretionary consumption experienced a significant growth from 2014 to 2016, and its growth rate gradually slowed down from 2016 to 2020. Discretionary consumption ratio slightly fluctuated between 0.32 and 0.35 from 2012 to 2020, showing an upward trend from 2014 to 2018.

Figure 6: Essential and Discretionary Consumption from 2012 to 2020

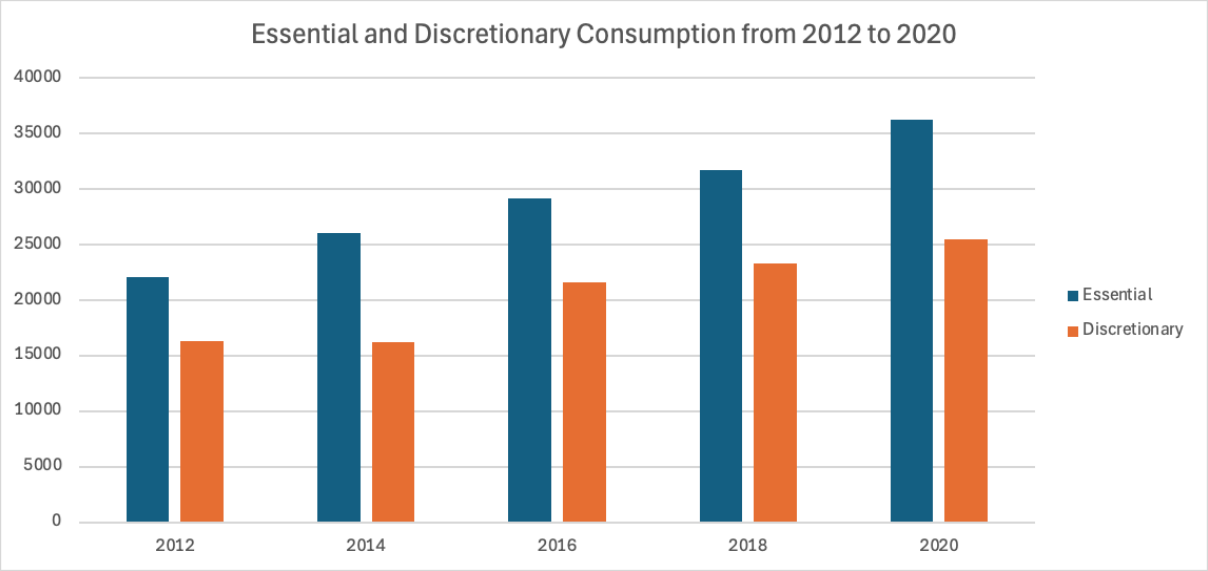
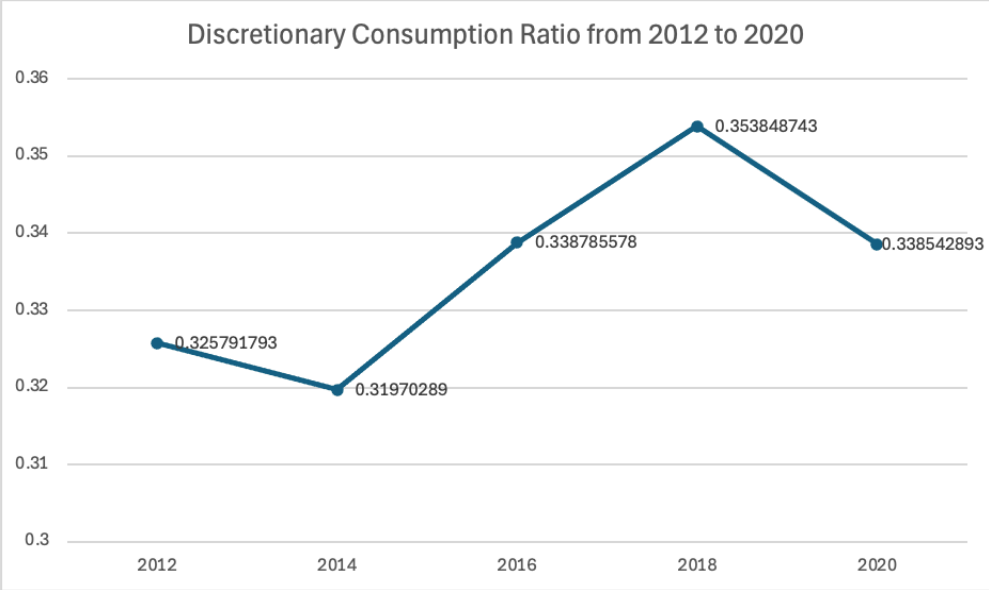


Figure 7: Discretionary Consumption Ratio Change from 2012 to 2020



3.3 Models

The paper uses an ordinary least squares (OLS) regression to construct the baseline model. The model is shown as follows:

$$Consumption_{ijt} = \alpha_0 + \alpha_1 DFII_{jt} + \alpha_2 Control_{ijt} + fixed\ effects + \varepsilon_{ijt}$$

$$Discretionary\ Consumption\ Ratio_{ijt} = \alpha_0 + \alpha_1 DFII_{jt} + \alpha_2 Control_{ijt} + fixed\ effects + \varepsilon_{ijt}$$

Consumption and discretionary consumption ratio are the core dependent variables. Control represents control variables including total family income, family asset, age, education and gender of household head, and provincial economy indicator. Fixed effects include time, household, and province fixed effects. The subscripts i, j, and t are the relevant indicators in household i, province or region j, and time t.

4 Results

4.1 Basic Regression

Table 3: The Effect of Aggregate DFII on Total Household Consumption

	(1)	(2)	(3)	(4)
VARIABLES	ln_pce	ln_pce	pce	pce
index_aggregate	0.00224***	0.00221***	293.6***	254.9***
	(0.000465)	(0.000492)	(34.81)	(35.43)
ln_income	0.122***	0.122***	5,596***	5,604***
	(0.00539)	(0.00540)	(316.5)	(316.3)
ln_asset	0.0837***	0.0837***	5,347***	5,317***
	(0.00400)	(0.00400)	(248.8)	(249.0)
age	0.0120***	0.0120***	597.5***	610.7***
	(0.00266)	(0.00266)	(167.5)	(167.6)
age2	-0.000234***	-0.000234***	-11.19***	-11.35***
	(2.92e-05)	(2.92e-05)	(1.825)	(1.825)
edu	0.0107***	0.0107***	565.6***	562.6***
	(0.00208)	(0.00208)	(138.9)	(139.0)
gender	0.0121	0.0121	-245.3	-215.8
	(0.0122)	(0.0122)	(827.9)	(828.5)
GRP_numeric		-2.21e-05		-26.03***
		(9.28e-05)		(7.463)
Constant	7.576***	7.586***	-143,434***	-131,991***
	(0.137)	(0.144)	(9,754)	(10,033)
Observations	43,773	43,773	43,800	43,800
R-squared	0.686	0.686	0.574	0.575

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

According to the baseline regression results, total household consumption has significantly increased with DFII at a 1% significance level. The first two columns of the following table take the natural log of total consumption as the dependent variable, while column (3) and (4) uses the winsorized absolute value of consumption that has eliminated the top and bottom 1% of the samples. Based on results from column (2) and (4) that takes into account regional economic growth conditions, the aggregate digital financial index has positive parameters of 0.00221 and 254.9 respectively, indicating that a point increase in DFII is associated with 0.22% increase in total household consumption or 254.9 RMB in absolute terms, holding all other variables constant. Because the aggregate index has a standard deviation of 88.416, the results also tell us

that when it increases by one standard deviation, the total household consumption will go up by 19.54% or 22,547 RMB. This conforms to previous findings on the positive correlation between digital finance development and overall household consumption, which is achieved through easing households' liquidity constraint and facilitating the payment of households.

In addition, the family income and asset are two strongly significant variables that affect consumption level as expected — A percentage increase in total household income and asset leads to 0.12% and 0.084% increase in total household consumption. There is also positive comovement observed between consumption and household head's age and education level. This meets the expectations as income and asset levels are expected to be positively correlated with one's age and years of education received.

In the second regression model shown in Table 4, consumption is broken down into essential and discretionary categories. The discretionary consumption ratio is calculated as dividing discretionary consumption by total consumption. The net values of essential and discretionary consumption (column 1, 2, 4, 5) as well as the discretionary consumption ratio (column 3, 6) are used as the dependent variables in the model to further gauge changes in household expenditure patterns. The first three columns in Table 4 report the natural log values of consumption without winsorization, and the last three columns remove consumption outliers using winsorization at a 1% level.

The results have shown a similar upward trend in net consumption across essential and discretionary categories. The aggregate DFII has positive parameters of 0.00166 and 0.00255 in column (1) and (2) respectively, which means the improvement of one standard deviation in the index is associated with a 14.68% increase in net expenditure on essential categories and 22.55% increase in discretionary expenditure when holding all variables constant. This tells us that households prefer to raise expenditure on discretionary items over their essential counterparts by a 7.87% margin with advancements made possible by financial technology. A similar (and even more significant) trend and correlation is observed in the last three columns with winsorized values of consumption.

The positive parameter of 0.000389 of DFII on discretionary consumption ratio at a 10% significance level is a more explicit and straightforward evidence of this shift in consumption pattern, as shown in column (3). As discretionary and essential consumption ratios are mirror statistics to each other due to the way they are calculated, the positive sign shown in column (3) indicates that compared to essential categories, discretionary expenditure is taking a greater proportion in households' overall expenditure and budget. When DFII increases by one standard deviation, the discretionary consumption ratio also goes up by 0.034, while the essential consumption ratio decreases by the same amount simultaneously. When households' income and asset level improves, discretionary consumption also takes a greater share in the overall expenditure as shown by the positive parameters of 0.0073 and 0.00633 in column (3). The age and education level of household heads are also positively correlated with discretionary consumption ratio at a 5% significance level.

Table 4: The Effect of Aggregate DFII on Total Essential and Discretionary Consumption

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln_pce_ess	ln_pce_disc	disc	pce_ess	pce_disc	disc
index_aggregate	0.00166***	0.00255**	0.000389*	128.2***	122.6***	0.000487**
	(0.000549)	(0.00124)	(0.000210)	(30.44)	(28.09)	(0.000210)
ln_income	0.0949***	0.141***	0.00730***	2,331***	2,161***	0.00584***
	(0.00497)	(0.0112)	(0.00173)	(181.7)	(241.2)	(0.00172)
ln_asset	0.0673***	0.107***	0.00633***	2,503***	2,057***	0.00607***
	(0.00428)	(0.00950)	(0.00147)	(199.1)	(178.2)	(0.00146)
age	0.00700**	0.0173***	0.00219**	203.6	486.6***	0.00147
	(0.00313)	(0.00656)	(0.00109)	(150.4)	(135.0)	(0.00109)
age2	-0.000156***	-0.000328***	-3.56e-05***	-4.163**	-7.366***	-2.78e-05**
	(3.37e-05)	(6.88e-05)	(1.13e-05)	(1.787)	(1.389)	(1.13e-05)
edu	0.00731***	0.0192***	0.00183**	148.5	467.9***	0.00175**
	(0.00238)	(0.00484)	(0.000839)	(140.7)	(110.1)	(0.000835)
gender	0.0240*	0.0218	0.000501	376.9	-6.889	-0.00329
	(0.0138)	(0.0289)	(0.00505)	(662.0)	(689.9)	(0.00504)
GRP_numeric	3.29e-05	-0.000275	-5.69e-05	-9.197	-18.41***	-4.54e-05
	(0.000101)	(0.000225)	(3.86e-05)	(6.279)	(6.638)	(3.89e-05)
Constant	7.713***	5.500***	0.0762	-53,930***	-61,396***	0.0908
	(0.156)	(0.354)	(0.0594)	(8,121)	(7,909)	(0.0593)
Observations	34,752	32,475	32,673	34,788	32,698	32,698
R-squared	0.672	0.581	0.439	0.482	0.497	0.436

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.2 Heterogeneity Analysis

The paper also conducts the following heterogeneity analysis to test the effect size of digital finance on consumption based on various household characteristics.

Table 5 reports different effects on rural and urban households while controlling for all other factors. The baseline coefficients of the aggregate index represent the effect size among rural households, while coefficients of the interaction term further reflect the difference in rural and urban households. Looking at essential consumption in column (1), while both rural and urban households increase their spending on essential categories significantly with DFII increase, urban households spend even more — With one standard deviation increase in DFII, urban households increase essential consumption by 15.03%, while rural households' essential consumption only go up by 11.94%. Column (2) and (3) of discretionary consumption tell us that DFII has no significant impact on rural households' discretionary consumption, while the positive effect remains effective among urban households as shown by the significant coefficients of 0.000561 in column (2). The increase in discretionary consumption equates roughly 22.38% when the standard deviation of aggregate index increases by one. Similarly, while we do not observe rural households shift consumption patterns toward discretionary categories, urban households have seen a significant increase in discretionary consumption ratio at 5% level, indicating that the main driver of household consumption pattern shift towards discretionary categories exists among urban households.

Table 5: Effect on Rural and Urban Households

VARIABLES	(1) ln_pce_ess	(2) ln_pce_disc	(3) disc
index_aggregate	0.00135**	0.00197	0.000305
	(0.000559)	(0.00126)	(0.000214)
1.urban12#c.index_aggregate	0.000374***	0.000561***	6.93e-05**
	(8.52e-05)	(0.000196)	(3.31e-05)
Control	Yes	Yes	Yes
Observations	34,572	32,303	32,502
R-squared	0.672	0.581	0.438

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 and 7 report the effects on households with different income and asset levels. The paper defines households with above-median income or assets in the first wave year of the survey (2012) as high-income or high-asset households, and vice versa. Taking the first-year household condition as a fixed benchmark, the paper aims to reduce potential endogeneity brought by digital finance improvement throughout the study period.

Across different income levels, results show that digital finance does not seem to have a significant impact on either net consumption expenditure or consumption structure of low-income households across essential and discretionary categories. On the contrary, its positive impact on consumption among high-income households is highly significant at a 1% confidence level across both essential and discretionary categories. The results tell us that one standard deviation increase in aggregate index is associated with 11.49% increase in essential expenditure and 23.87% increase in discretionary expenditure among high-income households, holding all other factors constant. With the percentage increase doubled in discretionary expenditure, it indicates that high-income households allocate their budget more towards discretionary categories under the influence of digital finance. The positive parameter on the discretionary consumption ratio is a more explicit piece of evidence of this shift in consumption structure among high-income households.

Table 6: Effect on Low- and High-income Households

VARIABLES	(1) ln_pce_ess	(2) ln_pce_disc	(3) disc
index_aggregate	0.000759	0.00165	0.000317
	(0.000577)	(0.00130)	(0.000220)
1.high_income#c.index_aggregate	0.000583***	0.00100***	0.000116***
	(9.01e-05)	(0.000206)	(3.44e-05)
Control	Yes	Yes	Yes
Observations	32,487	30,342	30,524
R-squared	0.670	0.580	0.436

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The heterogeneity effect on households with different asset levels has shown a similar pattern that the change in net expenditure and consumption pattern is mainly driven by high-asset households. Results in Table 7 show that under the influence of digital finance, low-asset households raise their consumption expenditure on essential categories significantly but not on discretionary categories. The effect of digital finance improvement on consumption across all categories is stronger and more significant among high-asset households. Across essential categories, one standard deviation increase in DFII is associated with approximately 2% more increase in essential consumption among high-asset households compared to households with below-median assets. Furthermore, high-asset households show a significant tendency to raise discretionary consumption more than essential consumption by a margin of 0.08%, also indicated by the positive discretionary consumption ratio that is significant at a 1% confidence level. Results in Table 6 and 7 combined indicate that households with high income and asset levels are the driving force of consumption pattern shift towards discretionary expenditure.

Table 7: Effect on Low- and High-asset Households

VARIABLES	(1) ln_pce_ess	(2) ln_pce_disc	(3) disc
index_aggregate	0.00136**	0.00183	0.000247
	(0.000569)	(0.00128)	(0.000216)
1.high_asset#c.index_aggregate	0.000226***	0.000569***	9.97e-05***
	(8.64e-05)	(0.000195)	(3.29e-05)
Control	Yes	Yes	Yes
Observations	34,464	32,205	32,401
R-squared	0.671	0.581	0.439

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the 2014 survey, the questionnaire asks specific questions about households' financial knowledge. For those who think their financial knowledge is above the average level, the paper identifies them as households with high self-reported financial knowledge, and vice versa. Results from Table 8 tell us that DFII increase has significant impact on households' consumption pattern among those with low self-reported financial knowledge level, while there is no significant difference observed between the two financial knowledge levels. For households with low self-reported financial knowledge, a standard deviation increase in DFII leads to a 14.85% increase in essential consumption and a 22.81% increase in discretionary consumption, holding all other variables constant. The parameter on discretionary consumption ratio is also statistically significant at a 90% confidence level, indicating that when digital finance improves over time, households shift consumption expenditure toward discretionary categories. While the parameters on all the interaction terms are not statistically significant, it indicates that the effect of digital financial inclusion on household consumption patterns has no significant difference across households with low and high financial knowledge reported.

Table 8: Effect on Households with Low and High Self-reported Financial Knowledge

VARIABLES	(1) ln_pce_ess	(2) ln_pce_disc	(3) disc
index_aggregate	0.00168***	0.00258**	0.000390*
	(0.000549)	(0.00124)	(0.000210)
1.knowledge_high#c.index_aggregate	-0.000146	0.000999	0.000173
	(0.000287)	(0.000737)	(0.000123)
Control	Yes	Yes	Yes
Observations	34,757	32,479	32,678
R-squared	0.672	0.581	0.438

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.3 Disaggregated Indexes Analysis

The paper further examines the effects of the disaggregated index—level of digitization—on household consumption. Though the aggregate index is measured across three dimensions — usage depth, coverage depth, and digitization level, this paper is more interested in investigating the impact of digitalization of financial services on household consumption behavior as compared to the other two dimensions. As the measurement of actual digital financial service usage is related to household consumption level in an almost mechanical way, we expect the regression results to be more precise and less influenced by potential endogeneity issues using only the digitization level as the key variable of interest.

According to results in Table 9, the level of digitization has a strong positive influence on the overall household consumption and expenditure on essential categories. The positive coefficients in column (1) and (2) tell us that a one-unit increase in digitization level is associated with increases in total household consumption and essential expenditures by 0.08% and 0.097% respectively. While we know ‘digitization level’ has a standard deviation of 100.51, it indicates that when the level of digitization increases by one standard deviation, total household consumption will increase by 7.99%, and total essential consumption will go up by 9.76%. On the other hand, its impact on discretionary consumption is not statistically significant even at a 10% level.

Table 9: The Effect of Digitization Level on Consumption

VARIABLES	(1) ln_pce	(2) ln_pce_ess	(3) ln_pce_disc	(4) disc
digitization_level	0.000795***	0.000971***	0.000295	-4.15e-05
	(0.000193)	(0.000213)	(0.000461)	(7.83e-05)
Control	Yes	Yes	Yes	Yes
Observations	43,796	34,757	32,479	32,678
R-squared	0.686	0.672	0.581	0.438

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Further breaking down the essential expenditure by categories as shown in Table 10, the rise in digitization level has a significant effect on boosting essential food expenditure. The regression results show that essential food consumption will go up by approximately 13.57% with a one standard deviation increase in digitization level. This is related to the rising popularity of online grocery shopping in China in the recent decade. With the booming e-commerce industry and the ease of digital payment methods, China has seen new forms of online retail for groceries and fresh goods that can be delivered direct to the house or office door. According to Statista, the penetration rate of fresh food e-commerce in China has increased from 0.36% in 2013 to 7.63% in 2020, and the gross merchandise value has reached 364.13 billion yuan in 2020, achieving more than 2700% growth compared to the business in 2013.

Table 10: The Effect of Disaggregated Indexes on Detailed Consumption Categories

VARIABLES	(1) ln_food	(2) ln_comm	(3) ln_utility	(4) ln_transp	(5) ln_commodity	(6) ln_dress	(7) ln_rent
digitization_level	0.00135***	-0.000663**	-0.000831***	-0.000330	-1.65e-05	-0.000574*	0.000662*
	(0.000352)	(0.000259)	(0.000304)	(0.000392)	(0.000288)	(0.000302)	(0.000387)
usage_depth	0.000377	-0.000852**	-0.00110**	-0.000478	-0.00133***	0.000668	-0.00105*
	(0.000553)	(0.000421)	(0.000449)	(0.000618)	(0.000460)	(0.000511)	(0.000629)
coverage_breadth	-0.00377***	0.00538***	0.000679	0.00351***	0.00418***	0.000176	0.00216**
	(0.000950)	(0.000743)	(0.000864)	(0.00113)	(0.000788)	(0.000852)	(0.000964)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,282	45,038	31,295	34,617	45,240	43,170	45,487
R-squared	0.563	0.649	0.688	0.621	0.581	0.651	0.548

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5 Conclusion

In this paper, we show that digital finance has significant effects on stimulating household consumption across essential and discretionary categories. This is consistent with previous findings and theories that consumption expenditures rise with better digital financial inclusion through alleviating household liquidity constraints while providing greater payment convenience and better investment efficiency. This paper also finds that there exists a shift in household consumption pattern from essential to discretionary categories. First, results show that households tend to increase their expenditure towards discretionary items more than their essential counterparts. Second, we observe that the proportion of discretionary expenditures gets larger in household budgets under the influence of digital finance.

The paper also examines the heterogeneity effects of digital finance based on different household characteristics. Several significant factors contribute to this shift in household consumption behavior: urban and rural gap and differences in household financial well being indicated by total income and asset level. Results show that households living in urban areas and with a higher income and asset level are more likely to raise their overall expenditure on both essential and discretionary categories, and they have also displayed a higher discretionary consumption ratio.

One major shortcoming of the paper is the limited investigation and discussion on detailed consumption categories due to data constraints. Ideally, the paper should also explore various discretionary categories and come up with a more detailed classification rule to investigate change in consumption structure further. Since the consumption expenditure data is not very consistent across different waves of survey studies, it poses challenges to dig deeper into discretionary consumption. Moreover, since the CFPS study is still ongoing, continued research can track the new release of household expenditure and digital financial index data to monitor the change further. With COVID-19 hitting the Chinese and global economy in early 2020, it will be interesting to investigate its impact on household consumption patterns. Are households getting more reserved in consumption and investment given the pandemic uncertainty? Which households are more vulnerable to such a change, and are these similar or different groups of people who benefit the most from digital finance improvement as discussed in this paper?

Deepening our understanding on how household consumption behavior evolves in shifting economical and digital landscape remains an exciting topic for further research.

6 References

Akram, U., Hui, P., Khan, M., Yan, C., & Akram, Z. (2018). Factors Affecting Online Impulse Buying: Evidence from Chinese Social Commerce Environment. *Sustainability*, *10*(2), 352. https://doi.org/10.3390/su10020352

Alp, E., & Seven, U. (2019). The dynamics of household final consumption: The role of wealth channel. *Central Bank Review*, *19*(1), 21–32. https://doi.org/10.1016/j.cbrev.2019.03.002

Baker, S. R., & Yannelis, C. (2017). Income changes and consumption: Evidence from the 2013 federal government shutdown. *Review of Economic Dynamics*, *23*, 99–124. https://doi.org/10.1016/j.red.2016.09.005

Bazerman, M. H., Tenbrunsel, A. E., & Wade-Benzoni, K. (1998). Negotiating with Yourself and Losing: Making Decisions with Competing Internal Preferences. *The Academy of Management Review*, *23*(2), 225. https://doi.org/10.2307/259372

Dhar, R., & Wertenbroch, K. (2000). Consumer choice between hedonic and utilitarian goods. *Journal of Marketing Research*, *37*(1), 60–71.

Gao, H., Chen, X., Gao, H., & Yu, B. (2022). Understanding Chinese Consumers' Livestreaming Impulsive Buying: An Stimulus-Organism-Response Perspective and the Mediating Role of Emotions and Zhong Yong Tendency. *Frontiers in Psychology*, *13*(881294). https://doi.org/10.3389/fpsyg.2022.881294

Gomber, P., Koch, J.-A., & Siering, M. (2017). Digital Finance and fintech: Current Research and Future Research Directions. *Journal of Business Economics*, *87*(5), 537–580. https://doi.org/10.1007/s11573-017-0852-x

Gross, T., Notowidigdo, M. J., & Wang, J. (2020). The Marginal Propensity to Consume over the Business Cycle. *American Economic Journal: Macroeconomics*, *12*(2), 351–384. https://doi.org/10.1257/mac.20160287

Hou, L., Hsueh, S.-C., & Zhang, S. (2021). Digital Payments and Households' Consumption: A Mental Accounting Interpretation. *Emerging Markets Finance and Trade*, *57*(7), 2079–2093. https://doi.org/10.1080/1540496x.2021.1887727

Hu, D., Zhai, C., & Zhao, S. (2023). Does digital finance promote household consumption upgrading? An analysis based on data from the China family panel studies. *Economic Modelling*, *125*, 106377–106377. https://doi.org/10.1016/j.econmod.2023.106377

Huang, Q., Dastane, O., Cham, T.-H., & Cheah, J.-H. (2024). Is “she” more impulsive (to pleasure) than “him” during livestream e-commerce shopping?. *Journal of Retailing and Consumer Services*, *78*, 103707. https://doi.org/10.1016/j.jretconser.2024.103707

Huang, Y. (2020). *ADBI Working Paper Series FINTECH DEVELOPMENT IN THE PEOPLE'S REPUBLIC OF CHINA AND ITS MACROECONOMIC IMPLICATIONS Asian Development Bank Institute*. https://www.adb.org/sites/default/files/publication/629396/adbi-wp1169.pdf

Li, J., Luo, S., & Zhou, G. (2023). Electronic payment, natural environment and household consumption: Evidence from China household finance survey. *International Review of Financial Analysis*, *85*, 102472. https://doi.org/10.1016/j.irfa.2022.102472

Li, J., Wu, Y., & Xiao, J. J. (2019). 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

Ma, Y. (2024a, December 20). *Gross merchandise volume of fresh food e-commerce in China from 2013 to 2023*. Statista. https://www-statista-com.proxy.library.cornell.edu/statistics/1026889/china-fresh-food-ecommerce-gross-merchandise-volume/

Ma, Y. (2024b, December 20). *Penetration rate of fresh food e-commerce in China from 2013 to 2023*. Statista. https://www-statista-com.proxy.library.cornell.edu/statistics/1194968/china-online-penetration-rate-of-fresh-ecommerce/

Mu, W., Liu, K., Tao, Y., & Ye, Y. (2022). Digital Finance and Corporate ESG. *Finance Research Letters*, *51*, 103426. https://doi.org/10.1016/j.frl.2022.103426

Ozili, P. K. (2018). Impact of digital finance on financial inclusion and stability. *Borsa Istanbul Review*, *18*(4), 329–340. Sciencedirect. https://doi.org/10.1016/j.bir.2017.12.003

Pazarbasioglu, C., Mora, A., Uttamchandani, M., Natarajan, H., Feyen, E., & Saal, M. (2020). *Digital Financial Services*. https://pubdocs.worldbank.org/en/230281588169110691/Digital-Financial-Services.pdf

Rizzo, M. (2014, April 10). *Digital Finance: Empowering the Poor via New Technologies*. World Bank.

https://www.worldbank.org/en/news/feature/2014/04/10/digital-finance-empowering-poor-new-technologies

Scitovsky, T. (1975). INCOME AND HAPPINESS. *Acta Oeconomica*, *15*(1), 45–53. JSTOR. https://doi.org/10.2307/40728373

Ul, B., F., R., Mehraj, A., Ahmad, A., & Assad, S. (2017). A Compendious Study of Online Payment Systems: past Developments, Present Impact, and Future Considerations. *International Journal of Advanced Computer Science and Applications*, *8*(5). https://doi.org/10.14569/ijacsa.2017.080532

Wang, Q., Yang, J., Chiu, Y., & Lin, T. (2020). The impact of digital finance on financial efficiency. *Managerial and Decision Economics*, *41*(7), 1225–1236. https://doi.org/10.1002/mde.3168

Yue, P., Korkmaz, A. G., Yin, Z., & Zhou, H. (2021). The rise of digital finance: Financial inclusion or debt trap? *Finance Research Letters*, *47*, 102604. https://doi.org/10.1016/j.frl.2021.102604