# Can Digital Payment Stimulate Household Consumption Growth Persistently? An Inconsistent Time Preference Perspective

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# Can Digital Payment Stimulate Household Consumption Growth Persistently? An Inconsistent Time Preference Perspective

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## Abstract

This study investigates whether digital payments can sustainably stimulate household consumption by integrating insights from behavioral economics and intertemporal choice theory. We develop a multi-period model incorporating quasi-hyperbolic discounting to capture the time-inconsistent preferences triggered by frictionless digital transactions. The model predicts that digital payments enhance short-run consumption through reduced payment pain and higher present bias, but weaken long-run consumption growth as self-control deteriorates. Using panel data from the 2013–2019 China Household Finance Survey, we find strong empirical support: digital payments significantly increase consumption and consumption growth immediately after adoption, but these effects decline with prolonged use. Heterogeneity tests show stronger impacts among low self-control households, hedonic consumption categories, rural users, and households with optimistic income expectations.

**Keywords:** Digital Payment; Household Consumption; Inconsistent Time Preference; Self-Control;

**JEL:** D10, D15, D91, G50

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# 1. Introduction

Digital payments, including mobile and online payment systems, have become a central component of modern household transactions. By reducing transaction frictions and making purchases more immediate and convenient, these technologies may reshape not only how households pay, but also how much they spend and how they allocate expenditure across categories. A growing literature shows that payment instruments influence consumer behavior by altering the psychological experience of spending. Earlier studies find that non-cash payment methods reduce the salience of payment, weaken the "pain of paying," and can increase expenditure by separating payment from consumption in time (Prelec and Loewenstein, 1998; Lee and Tsai, 2014). Related work also shows that payment formats can redirect attention during transactions and affect the accuracy of expenditure recall (Chatterjee and Rose, 2012; Soman, 2001; Srivastava and Raghubir, 2002). More recent studies on digital payments emphasize standard channels such as lower transaction costs, reduced shopping time, and improved convenience (Yi and Zhou, 2018; Zhang et al., 2020). However, most existing research focuses on the contemporaneous or short-run effects of payment adoption, while giving much less attention to whether these effects persist, attenuate, or change in composition as households accumulate experience with digital payment systems.

This paper asks a broader question: how does digital payment adoption affect household consumption over time? In particular, does digital payment use generate only a short-run increase in spending, or does it also produce lasting changes in consumption growth and expenditure structure? We argue that answering this question requires moving beyond standard transaction-cost explanations to consider behavioral mechanisms, especially present bias, time-inconsistent preferences, and household self-control. In this sense, digital payments may not merely facilitate spending; they may also alter the intertemporal decision environment in which household consumption choices are made.

China provides an especially suitable setting for examining this issue. As one of

the world's most developed digital payment markets, China offers both large-scale adoption and substantial household-level variation in usage intensity and duration. This makes it possible to study not only whether digital payments raise household spending, but also whether their effects differ between first-time adoption and continued use.

Figures 1–3 provide preliminary motivation for this inquiry. The descriptive evidence suggests that digital payments may affect not only the level of household consumption, but also its growth trajectory and composition. First, household expenditure appears to rise alongside the expansion of digital payment use, with particularly strong increases in more discretionary categories such as entertainment, travel, and education. This pattern is consistent with the view that lower payment friction and greater transaction convenience stimulate spending. Second, when we examine the first difference of consumption, the sharpest increase occurs in the initial year of adoption, followed by a gradual moderation in subsequent periods. This suggests that digital payment adoption may trigger an immediate behavioral response—potentially through reduced payment salience or stronger present-biased spending—that weakens as households gain experience. Third, the composition of spending also appears to shift over time: the share of hedonic expenditure rises, while the share of basic living expenditure declines. Taken together, these patterns suggest that digital payments may influence both the intensity and the structure of household consumption, and that these effects may evolve dynamically rather than remain constant over time.

To explain these patterns, we develop a behavioral framework that embeds digital payment use in a multi-period consumption–saving model. The model incorporates quasi-hyperbolic discounting to allow for time-inconsistent preferences and self-control problems. In our setting, digital payments do not create present bias per se; rather, by making transactions more immediate and less psychologically salient, they can amplify the behavioral consequences of existing present-biased preferences. As a result, digital payment adoption increases current consumption and raises consumption growth in the short run. Over time, however, as households accumulate experience and become more aware of the consequences of overspending, the initial stimulatory effect is predicted to

weaken. The model therefore implies that digital payments may generate a front-loaded increase in consumption, followed by slower consumption growth as self-control responses emerge. In addition, the model incorporates the role of unexpected income changes and income expectations, which help explain why the consumption effects of digital payments may persist for some households but fade for others.[1]

We test these predictions using four waves of the China Household Finance Survey (2013–2019), which provide nationally representative household-level information on consumption, digital payment use, income, demographic characteristics, and financial behavior. Our empirical strategy exploits the panel structure of the data to distinguish between short-run and longer-run digital payment effects. Specifically, we estimate fixed-effects regressions that separately identify first-time digital payment users and continuing users, allowing us to compare the immediate effect of adoption with the effect of sustained use. To better understand the underlying mechanisms, we further examine heterogeneity across consumption categories, self-control proxies, income expectation profiles, and urban–rural households. We also strengthen the empirical design through instrumental-variable specifications based on city-level digital payment coverage and its interaction with local education levels. This combined approach enables us to study digital payments not simply as a payment technology, but as a behavioral and financial innovation with dynamic implications for household consumption.

Our analysis yields three main findings. First, digital payment adoption significantly increases household consumption in the short run, and it also raises consumption growth most clearly at the time of initial adoption. In the growth regressions, first-time digital payment use is associated with a robust and economically meaningful increase in two-year household consumption growth, even after controlling for rich household characteristics and city-level conditions. By contrast, the effect of continued digital payment use is smaller and becomes statistically weak in the most

[1] Other models have been used to describe self-control problems, such as the planner-doer model (Thaler and Shefrin, 1981; Fudenberg and Levine, 2006), the inherent conflict between "want" and "should" urges (Bazerman et al., 1998; Milkman et al., 2008), visceral factors and cue-conditioned impulsivity (Loewenstein, 1996; Bernheim and Rangel, 2004).

demanding specifications. This pattern indicates that digital payments generate a strong initial spending response, but the growth effect is not equally persistent over time. More broadly, the evidence suggests that digital payments influence household expenditure not only through lower transaction costs and convenience, but also through behavioral channels related to the reduced salience of payment (Prelec and Loewenstein, 1998; Lee and Tsai, 2014).

Second, the effect of digital payments on consumption is dynamic rather than permanent. While adoption is associated with a clear short-run increase in consumption growth, this effect attenuates as households accumulate experience with digital payment systems. This result is consistent with the behavioral mechanism proposed in our model: digital payments initially amplify present-biased consumption, but households gradually adjust by moderating borrowing, reallocating liquid assets, and strengthening spending discipline. The attenuation of the growth effect is therefore not evidence that digital payments cease to matter; rather, it suggests that the initial behavioral impulse weakens over time as self-control responses emerge. At the same time, we find that the positive effect of digital payments is more likely to persist among households with more optimistic income expectations and more favorable anticipated economic conditions. This finding contributes to the literature by offering a behavioral-finance explanation for why fintech-induced spending surges may fade over time, whereas much of the existing literature implicitly treats the effect of payment innovation as contemporaneous or constant (Yi and Zhou, 2018; Zhang et al., 2020).

Third, the effects of digital payments are heterogeneous across both expenditure categories and household types. Hedonic spending responds much more strongly than essential consumption, indicating that digital payments disproportionately affect categories in which immediacy, convenience, and impulse play a larger role. The response is also stronger among rural households, households with weaker self-control, and households with more optimistic income expectations. These patterns suggest that the impact of digital payment adoption depends jointly on psychological traits and socioeconomic conditions, and that aggregate estimates may mask substantial

heterogeneity in how financial digitization shapes household behavior.

These findings contribute to several strands of literature. First, the paper extends the literature on payment methods and consumer behavior. Existing studies show that payment instruments affect spending by reducing the "pain of paying," separating payment from consumption in time, redirecting attention during transactions, and weakening expenditure recall (Prelec and Loewenstein, 1998; Lee and Tsai, 2014; Chatterjee and Rose, 2012; Soman, 2001; Srivastava and Raghubir, 2002). However, most of this literature focuses on cash, debit cards, and credit cards. By examining digital payments, we extend this line of inquiry to a payment technology that is now central to household finance, while emphasizing its dynamic implications for intertemporal consumption rather than only its contemporaneous effect on spending.

Second, the paper contributes to the growing literature on digital payments and household consumption, particularly in China. Existing studies largely emphasize mechanisms such as lower transaction costs, reduced shopping time, improved convenience, and enhanced financial access (Yi and Zhou, 2018; Zhang et al., 2020). While these channels are clearly important, they do not fully explain why the effect of digital payments is strongest at adoption, why the growth effect weakens with prolonged use, or why the response differs so sharply across expenditure categories and household groups. Our analysis complements this literature by showing that digital payments also operate through behavioral channels, especially present bias, self-control, and expectations about future income.

Third, the paper contributes to the broader literature on self-control and household finance. Self-control has been studied in relation to temptation (Bucciol, 2012; Huang et al., 2015), health (Grafova, 2007), poverty (Pascaline and Jonathan, 2013; Bernheim et al., 2015), borrowing and consumption (Wertenbroch et al., 2001; DellaVigna and Malmendier, 2006), and responses to shocks (Callen, 2015). A central insight of this literature is that time-inconsistent preferences can generate overspending and under-saving. Yet relatively little attention has been paid to the role of payment technologies in shaping the decision environment in which these choices are made. Our results

suggest that payment methods are not behaviorally neutral: by changing the immediacy and salience of transactions, digital payments can intensify present-biased spending in the short run while also inducing gradual self-correction over time.

Finally, the paper also speaks to the literature on income dynamics and consumption adjustment. Standard consumption theory emphasizes the role of income in determining expenditure (Keynes, 1936; Modigliani and Brumberg, 1954; Friedman, 1957), while empirical evidence shows that predictable changes in income and expenditure are often smoothed and incorporated into household planning (Browning and Collado, 2001; Hsieh, 2003; Adamopoulou and Zizza, 2015). By contrast, unexpected income shocks can have substantial effects on current consumption (Stephens, 2001; Souleles, 1999; Parker et al., 2013; Kaplan and Violante, 2014; Hastings and Shapiro, 2018). In the context of digital payments, this issue is especially relevant because payment technologies may affect not only spending behavior directly, but also the way households perceive, anticipate, and respond to future resources. For this reason, our framework incorporates income expectations, allowing us to examine how anticipated economic conditions interact with digital payment adoption to shape short-run spending responses and longer-run consumption growth.

The remainder of this paper is organized as follows. In Section 2, we establish the theoretical framework by constructing an intertemporal consumption-saving model from a self-control perspective. We then formulate several hypotheses and test them in Section 3 by empirical analysis. In Section 4, we delve into the topic of self-control and examine the underlying mechanisms. In Section 5, we explore the heterogeneity among different characteristics. In Section 6, we perform an instrumental variable analysis to address the endogeneity concerns, and finally, we conclude in Section 7.

## 2. Theoretical Analysis and Hypothesis

### 2.1 Inconsistent time preference with digital payment

Based on the prospect theory value function, Thaler (1985) proposes the mental accounting theory and incorporates the mental price of products into the total utility function, which depends on the feelings and thoughts of spending. And if the mental price is relatively higher than the actual pay of the product, it will increase the transaction utility of spending and promote transaction realized. Research shows that payment methods influence consumers' cognitive processing and product evaluation (Feinberg, 1986; Prelec and Loewenstein, 1998; Raghubir and Srivastava, 2008). Studies focus mainly on traditional payment tools. Self-control also matters: consumers with stronger self-control prioritise cost information, lowering perceived value, reducing purchase desire, and strengthening mental budget constraints (Trudel and Murray, 2013).

As discussed in Hou et al. (2021), we believe that digital payment would weaken the pain of paying and magnify the pleasure of buying compared with other traditional payments, which directly increases the mental price and transaction utility. On the one hand, digital payment uses digital currency without physical cash outflows, making the payment process faster and less vivid. Consumers would pay more attention to owning instead of paying, which enhances the feelings of pleasure and evaluate the spending with a higher mental price. On the other hand, digital payment can connect to several available funds on the digital platform. It is more convenient to pay by using QR codes, no password input, and smartphone Apps, facilitating the payment process. So, we think digital payment would improve the mental price of spending and sometimes overvalue the present utility. It would lead to inconsistent time preference and self-control problems, e.g., present-bias issues. Consumers would like to overspend now and save less for the future, which is not optimal for rational people with consistent time preferences.

## 2.2 Setup of intertemporal consumption-saving model

Strotz (1955) shows that when individuals discount future utility inconsistently, they continually re-optimise consumption, creating self-control problems. Laibson (1997) models this using hyperbolic discounting, demonstrating that present-biased consumers rely on commitment devices and that financial innovations worsen self-control by increasing liquidity. This motivates our view that digital payments, as a modern financial innovation, similarly amplify present bias by making spending easier and more immediate.

We build a classic intertemporal consumption-saving model with a quasi-hyperbolic discount function. A household wishes to maximize their utility function at period *t* as follows:

$$U_t = u_t + \beta_t \sum_{\tau=1}^{T-t} \delta^\tau u_{t+\tau} \tag{2.1}$$

where $\beta_t$ is the additional discount factor to capture the inconsistent time preference at period *t*, where $\beta_t$ is the "self-control factor". It varies over periods and differs from the constant exponential discount factor $\delta$. In this setup, household's awareness of their self-control would affect the degree of their present bias. Adopting some methods, such as XXXX will improve self-control problems if it is fully known (O'Donoghue and Rabin, 2001). Ali (2011) believes people can learn by doing and improve their awareness of self-control problems by choosing more appropriate methods.

When $\beta_t \in (0, 1)$, there is present bias, which means the discount rate would be relatively higher over short horizons than over long horizons[2]. When $\beta_t = 1$, time preference is consistent and the discount rate is constant over future periods. So, we use the varying self-control factor to capture the time-preference effect caused by the usage of digital payment on households' consumption.

We assume the household's life cycle is four discrete periods (T=4). In the first three periods ($t$ = 1, 2, 3), the household maximizes the utility function at the present

[2] At period t, the future utility in period t+1 will discount with $\beta_t\delta$, but at period t+1, the future utility in period t+2 will discount with $\delta$. The discount rate is different and shows "present impatience" and "long-run patience".

moment and decides how much to consume and save. And the utility is only determined by consumption. In the last period ($t = 4$), all the savings and income would be used for consumption resulting in zero savings. There is no initial wealth. The saving rate is denoted as $r$, which is constant. Because the consumption plan would be dynamic over periods, we need to distinguish the consumption, income, and saving in different periods. For example, at period $t$, we denote present consumption as ${C_t}^t$ and future consumption as ${C_{t+j}}^t$. The upper subscript $t$ means that the decision-making problem and consumption plan are made on period $t$, while the lower subscripts $t$ and $t+j$ indicate which period to consume. Similarly, we denote the income flows (${Y_t}^t$, ${Y_{t+j}}^t$) and savings flows (${S_t}^t$, ${S_{t+j}}^t$), where $t \leq t+j \leq 4$.

We also consider two channels through which digital payments will affect a household's consumption. First, is the time preference effect. Digital payments might lead to an inconsistent time preference and enhance the present bias, which overvalues the present utility thus encouraging overspending. The second is the unexpected income change effect. On the one hand, digital payments might decrease the transaction cost, stimulate some consumers' spending desire and make them work harder to earn more money. On the other hand, applying digital payments would influence work efficiency and effectiveness in some industries, bringing about unexpected income changes for the workers.

To demonstrate these two influencing channels in the model, we assume that the household only consumes with cash payments in the first period ($t = 1$). To highlight the present bias caused by digital payments, we simply set the time preference to be consistent in period one, and the self-control factor $\beta_1$ equals one. Then, in the second period ($t = 2$), the household starts using digital payments to consume, leading to present bias issues with the self-control factor $\beta_2$ smaller than one. In the following two periods, the household persists with using digital payments and accumulates the usage experiences, but the self-control factors $\beta_3$ and $\beta_4$ vary depending on their awareness of self-control problems and self-control abilities. In addition, when using

digital payments, the present income and expected future income would change over periods and generate unexpected income changes, e.g., the expected income ${Y_{t+1}}^{t}$ would be different from the actual income ${Y_{t+1}}^{t+1}$. Further, we define the consumption change in the second period as the short-run effect of digital payment and the last two periods as the long-run effect. Then we can compare the variation of digital payment's impact on consumption over time.

## 2.3 Dynamic utility maximization over periods

In the first period, the household only uses cash payments to consume with the self-control factor $\beta_1$ equal to one. The decision-making problem is to maximize the total utility subject to budget constraints:

$$maxU_1 = u\left({C_1}^1\right) + \delta u\left({C_2}^1\right) + \delta^2 u\left({C_3}^1\right) + \delta^3 u\left({C_4}^1\right) \tag{2.2}$$

$$\text{s.t.} \quad {C_1}^1 = {Y_1}^1 - {S_1}^1$$

$${C_2}^1 = (1+r){S_1}^1 + {Y_2}^1 - {S_2}^1$$

$${C_3}^1 = (1+r){S_2}^1 + {Y_3}^1 - {S_3}^1$$

$${C_4}^1 = (1+r){S_3}^1 + {Y_4}^1$$

Combining the four constraints gives rise to a modified intertemporal budget constraint:

$$\sum_{j=0}^{3} \frac{{C_{1+j}}^1}{(1+r)^j} = \sum_{j=0}^{3} \frac{{Y_{1+j}}^1}{(1+r)^j} \tag{2.3}$$

The optimality condition, or Euler equation, is:

$$u'\left({C_t}^1\right) = \delta(1+r)u'\left({C_{t+1}}^1\right) \tag{2.4}$$

Assume the utility function is the log utility function, i.e., $u(C) = ln\,(C)$. The first-order condition can be written as:

$${C_{t+1}}^1 = \delta(1+r){C_t}^1, \qquad \text{t=1, 2, 3} \tag{2.5}$$

Now take this and plug it into the intertemporal budget constraint:

$${C_t}^1 = \frac{[\delta(1+r)]^{t-1}}{1+\delta+\delta^2+\delta^3} \sum_{j=0}^{3} \frac{{Y_{1+j}}^1}{(1+r)^j}, \qquad \text{t=1, 2, 3, 4} \tag{2.6}$$

Simplify the equation (2.6) by denoting: $\mathrm{W}^1 = \sum_{j=0}^{3} \frac{{Y_{1+j}}^1}{(1+r)^j}$, $\mathrm{k} = 1 + \delta + \delta^2 + \delta^3$,

then the consumption plan in period one is:

$$C_t{}^1 = [\delta(1+r)]^{t-1} * \frac{\mathrm{W}^1}{k}, \qquad \text{t=1, 2, 3, 4} \tag{2.7}$$

So using cash payment with consistent time preferences, the expected consumption growth rate in each period is constant:

$$\frac{C_{t+1}{}^1 - C_t{}^1}{C_t{}^1} = \delta(1+r) - 1 \tag{2.8}$$

If the household keeps using cash payments instead of digital payments, and the actual future income is expected correctly, the actual future consumption would follow the optimal plan in period one, as equation (2.7) shows, and its growth rate is constantly equal to $\delta(1+r) - 1$.

**In the second period**, the household starts using digital payments, which brings about present bias and unexpected income change effects. The self-control factor $\beta_2$ is smaller than one. Similarly, to maximize the total utility subject to budget constraints:

$$maxU_2 = u(C_2{}^2) + \beta_2\, \delta u(C_3{}^2) + \beta_2 \delta^2 u(C_4{}^2) \tag{2.9}$$

$$\text{s.t.} \quad C_2{}^2 = (1+r)S_1{}^1 + Y_2{}^2 - S_2{}^2$$

$$C_3{}^2 = (1+r)S_2{}^2 + Y_3{}^2 - S_3{}^2$$

$$C_4{}^2 = (1+r)S_3{}^2 + Y_4{}^2$$

The consumption ($C_1{}^1$), saving ($S_1{}^1$) and income ($Y_1{}^1$) in the first period are determined. Combining the constraints leads to the intertemporal budget constraint and plugging $\mathrm{W}^1$ into it:

$$C_1{}^1 + \frac{C_2{}^2}{1+r} + \frac{C_3{}^2}{(1+r)^2} + \frac{C_4{}^2}{(1+r)^3} = \mathrm{W}^1 + \frac{Y_2{}^2 - Y_2{}^1}{1+r} + \frac{Y_3{}^2 - Y_3{}^1}{(1+r)^2} + \frac{Y_4{}^2 - Y_4{}^1}{(1+r)^3} \tag{2.10}$$

To simplify the unexpected income change in the second period, we denote $M^2 = \frac{Y_2{}^2 - Y_2{}^1}{1+r} + \frac{Y_3{}^2 - Y_3{}^1}{(1+r)^2} + \frac{Y_4{}^2 - Y_4{}^1}{(1+r)^3}$.

The optimality conditions are:

$$u'(C_2{}^2) = \beta_2 \delta(1+r) u'(C_3{}^2)$$

$$u'(C_3{}^2) = \delta(1+r) u'(C_4{}^2) \tag{2.11}$$

Based on the log utility function, $u(C) = ln\,(C)$, the first-order condition can be written as:

$$C_3{}^2 = \beta_2\delta(1+r)C_2{}^2,\ \ C_4{}^2 = \delta(1+r)C_3{}^2 \tag{2.12}$$

Take this and plug it into the intertemporal budget constraint:

$$\begin{cases} C_2{}^2 = \frac{1+r}{1+\beta_2\delta+\beta_2\delta^2} * \frac{k-1}{k} * \mathrm{W}^1 + \frac{1+r}{1+\beta_2\delta+\beta_2\delta^2} * M^2 \\ C_3{}^2 = \beta_2\delta(1+r)C_2{}^2 \\ C_4{}^2 = \delta(1+r)C_3{}^2 \end{cases} \tag{2.13}$$

The equation (2.13) shows that the actual consumption in the second period is different from its expected level in the first period because of the inconsistent time preference ($\beta_2$) and unexpected income change ($M^2$). If the present bias is more severe, indicating the self-control factor ($\beta_2$) is smaller, the actual consumption in period two will increase a lot, and this will also happen if the unexpected income change is positive and more significant.

Moreover, the second-period consumption's actual growth rate ($\frac{C_2{}^2 - C_1{}^1}{C_1{}^1}$) could be different from the constant level ($\delta(1+r)-1$) using cash payments. For example, when $M^2 > (\beta_2 - 1)\delta^2(1+\delta)\frac{\mathrm{W}^1}{k}$, the second period's actual growth rate will be higher than the previous constant level $\delta(1+r)-1$. Considering the actual situation that the unexpected income change caused by digital payment would be weak and slow, we assume $M^2$ equal to 0, and get the second period's actual growth rate higher than the expected constant level, which means the time preference effect of digital payment will promote consumption and its growth rate in the short run.

**Hypothesis 1: Digital payment promotes consumption and its growth rate in the short run, under the dominant effect of the inconsistent time preference.**

In the third period, the household keeps using the digital payment, and the self-control factor $\beta_3$ depends on the awareness of self-control problems and self-control ability. After long-term usage of digital payment, if the household learns more about his present bias issues and adopts some measures to strengthen self-control, the factor $\beta_3$ will be larger than before and close to one; otherwise, the factor $\beta_3$ will be stable or smaller. Also, some unexpected income changes still might exist in the third period. To maximize the total utility subject to budget constraints:

$$maxU_3 = u\left({C_3}^3\right) + \beta_3\delta u\left({C_4}^3\right) \tag{2.14}$$

$$\text{s.t.} \qquad {C_3}^3 = (1+r){S_2}^2 + {Y_3}^3 - {S_3}^3$$

$${C_4}^3 = (1+r){S_3}^3 + {Y_4}^3$$

The consumption $({C_1}^1,\ {C_2}^2)$, saving $({S_1}^1,\ {S_2}^2)$ and income $({Y_1}^1,\ {Y_2}^2)$ in the first and second periods are determined. Combining the constraints leads to the intertemporal budget constraint, plugging $\mathrm{W}^1$ and $M^2$ into it:

$${C_1}^1 + \frac{{C_2}^2}{1+r} + \frac{{C_3}^3}{(1+r)^2} + \frac{{C_4}^3}{(1+r)^3} = \mathrm{W}^1 + \mathrm{M}^2 + \frac{{Y_3}^3 - {Y_3}^2}{(1+r)^2} + \frac{{Y_4}^3 - {Y_4}^2}{(1+r)^3} \tag{2.15}$$

To simplify the unexpected income change in the third period, we denote $M^3 = \frac{{Y_3}^3 - {Y_3}^2}{(1+r)^2} + \frac{{Y_4}^3 - {Y_4}^2}{(1+r)^3}$.

The optimality conditions are:

$$u'\left({C_3}^3\right) = \beta_3\delta(1+r)u'\left({C_4}^3\right) \tag{2.16}$$

$${C_4}^3 = \beta_3\delta(1+r){C_3}^3$$

Take this and plug it into the intertemporal budget constraint:

$$\begin{cases} {C_3}^3 = \frac{\beta_2\delta(1+\delta)(1+r)^2}{(1+\beta_2\delta+\beta_2\delta^2)(1+\beta_3\delta)} * \frac{k-1}{k} * \mathrm{W}^1 + \frac{\beta_2\delta(1+\delta)(1+r)^2}{(1+\beta_2\delta+\beta_2\delta^2)(1+\beta_3\delta)} * \mathrm{M}^2 + \frac{(1+r)^2}{1+\beta_3\delta} * M^3 \\ {C_4}^3 = \beta_3\delta(1+r){C_3}^3 \end{cases} \tag{2.17}$$

The equation (2.17) shows that the actual consumption in the third period varies from its expected level in the previous period because of the inconsistent time preference ($\beta_3$) and unexpected income change ($M^3$). And we can get similar inference that worse self-control and higher unexpected income change would increase the actual third-period consumption.

And the actual third-period consumption growth rate $\frac{{C_3}^3 - {C_2}^2}{{C_2}^2} = \frac{\beta_2\delta(1+\delta)(1+r)}{1+\beta_3\delta} + \frac{(1+r)^2M^3}{(1+\beta_3\delta){C_2}^2} - 1$. When $M^3 > \frac{(1-\beta_2)\delta+(\beta_3-\beta_2)\delta^2}{(1+r)} * {C_2}^2$, the actual growth rate will be higher than the constant level $(\delta(1+r)-1)$; otherwise, the growth rate will be lower. As long as the unexpected income change effect is large enough to be dominant, the consumption will keep growth on a high level constantly. But if the income effect is weak, the consumption growth rate will decline in the long run, under the dominant inconsistent time preference effect. For example, if the unexpected income changes $M^3$

in third period is not large enough $M^3 < \frac{(1-\beta_2)\delta+(\beta_3-\beta_2)\delta^2}{(1+r)} * {C_2}^2$, and the self-control ability does not have significant improvement ($\beta_3 = \beta_2$), the actual growth rate will decrease a lot under the time preference effect. And when the unexpected income change is zero and $M^2 = M^3 = 0$, if $\beta_3 \geq \beta_2 + \frac{\beta_2 - 1}{\delta}$, self-control is improved after learning by using, the actual growth rate would be lower than the constant level, showing that the improvement of self-control ability accelerate the declining process of consumption change rate.

**Hypothesis 2: The consumption growth rate will decline in the long run, under the dominant time inconsistent preference effect.**

In the last period, the household still uses digital payment. All the savings and income would be used for consumption with no savings. To denote the unexpected income change in the last period, we use $M^4 = \frac{{Y_4}^4 - {Y_4}^3}{(1+r)^3}$, and get the consumption function:

$${C_4}^4 = \frac{\beta_2\beta_3\delta^2(1+\delta)(1+r)^3}{(1+\beta_2\delta+\beta_2\delta^2)(1+\beta_3\delta)}\left(\frac{k-1}{k}\mathrm{W}^1 + \mathrm{M}^2\right) + \frac{\beta_3\delta(1+r)^3}{1+\beta_3\delta}M^3 + (1+r)^3M^4 \quad (2.18)$$

Similarly, the unexpected income change $M^4$ will determine the value of actual consumption. The actual consumption growth rate $\frac{{C_4}^4 - {C_3}^3}{{C_3}^3} = \beta_3\delta(1+r) - 1 + \frac{(1+r)^3}{{C_3}^3}M^4$, when $M^4 > \frac{(1-\beta_3)\delta}{(1+r)^2}{C_3}^3$, the actual consumption growth rate will be higher than the constant level. If $M^4 = 0$, $\frac{{C_4}^4 - {C_3}^3}{{C_3}^3} = \beta_3\delta(1+r) - 1$, $\beta_3 \in (0, 1]$, the actual consumption growth rate will be no more than the constant level ($\delta(1+r) - 1$), indicating a declining growth rate in the last period without significant positive unexpected income change.

To be more specific, we discuss households' consumption changes under all situations, considering both the time preference effect and the unexpected income change effect. And the detail is presented in the Appendix C.

# 3. Empirical Analysis

In this paper, we investigate the effect of digital payment on household consumption from the level to the change and verify the hypothesis by empirical regressions.

## 3.1 Data and Variables

### A. Data

Our sample is derived from the China Household Finance Survey (CHFS) conducted in 2013, 2015, 2017, and 2019, which includes households from 29 provinces in China and was obtained through stratified cluster sampling. The CHFS data is comparable to the US Survey of Consumer Finance (SCF) and provides a wealth of information about household demographics, payment methods, income, expenses, assets, and liabilities. With approximately 50% of households tracked in each wave, we have created an unbalanced panel data set for our regression analysis.

Firstly, we eliminate the households that have only one year of data, as the change in consumption is one of the main dependent variables. Then, we exclude households that start using digital payment but discontinue it midway. These families may have experienced significant influences that interfere with their payment choices and consumption, and it would be better to exclude them from the baseline sample and discuss them further in the Appendix if they are motivated by extreme self-control issues.

### B. Variables

Table 1 shows all variables' descriptions. The key independent variable is the household's experience of using digital payment. We first define digital payment as computer payment (including E-bank, Alipay, etc.) and mobile terminal payment using a cell phone or pad. In the questionnaire, households are asked about their choices of payment methods for shopping (including online shopping), which are multiple-choice questions and differently designed in each wave. So we try to make it consistent, and the detailed process is presented in the Appendix A. Then, we count the years of using digital payment and construct two dummy variables, DP_SR and DP_LR. If it is the

first year the household adopts digital payment to consume, DP_SR equals one; otherwise, it equals 0. Also, if the household has used digital payment for more than one year, DP_LR equals one; otherwise, it equals 0. We use these two variables to capture the differential effects of digital payment on consumption in the short and long term.

Our dependent variable is the consumption expenditure of a family. We focus on the following categories of consumption. The first is *total_consumption*, i.e., the total consumption of a household in a year (RMB yuan). The second is *life_consumption*, i.e., the household's essential living expenditures in a year (RMB yuan), including food, clothes, rent, utilities, daily necessities, durable goods, local transportation, communication, and medical expenses. The last is *hedonic_consumption*, i.e., the household's hedonic goods and services in one year (RMB yuan), including education, entertainment, travel, health and fitness, housekeeping, and hairdressing expenditures. Moreover, we use the CPI in 2010 to adjust consumption for inflation, making every year's consumption comparable. And in the regressions, we take the logarithmic form of consumption as the measurement of consumption level, then take the first-order difference of the log of consumption as the measurement of consumption growth.

We select three sets of control variables: the household head's demographics, the household's characteristics, and the city's characteristics. The detailed definitions are presented in Table 1.

Table 2 presents the summary statistics of all variables. To avoid the influence of extreme values, we winsorize the upper and bottom 1% of all variables related to consumption, income, liabilities, and assets.

## 3.2 Baseline Regression Analysis

### *A. Specification*

Based on the unbalanced panel data, we construct the following model to investigate how digital payment affects household consumption:

$$\mathrm{Y}_{ijt} = \alpha_0 + \alpha_1 DP_SR_{it} + \alpha_2 DP_LR_{it} + \alpha_3 X_{it} + \alpha_4 Z_{jt} + \mu_t + \tau_i + \varepsilon_{ijt} \quad (3.1)$$

where $\mathrm{Y}_{ijt}$ indicates three measurements of household i's consumption in year t, including $\log \mathrm{C}_{ijt}$ (the log of consumption), $\Delta \log \mathrm{C}_{ijt}$ (the first-order difference of the log of consumption), and $\frac{\mathrm{C}_{kijt}}{\mathrm{C}_{ijt}}$ (the ratio of specific consumption to total consumption). $DP_SR_{it}$ and $DP_LR_{it}$ are the key independent variables implying household i's adoption experience of digital payment in year t. $X_{it}$ includes the household head's demographics and the family characteristics. $Z_{jt}$ refers to the city characteristics. Also, we control for the year ($\mu_t$) and household ($\tau_i$) fixed effects. The standard errors are clustered at household level. And we run the fixed effect regression with the unbalanced panel data.

**B. Baseline regression results**

We first estimate the impact of digital payment adoption on households' total consumption, using the log of annual total consumption as the dependent variable. Table 3 reports a sequence of specifications with progressively richer controls and fixed effects; column (3) is our benchmark, which includes the full set of household-level controls, household fixed effects, and city×year fixed effects. The benchmark estimates indicate a robust positive association between digital payment use and consumption levels. In column (3), the coefficient on DP_SR is 0.1011, implying that households in their first year of adoption spend about 10.11% more than non-users. The coefficient on DP_LR is 0.1367, implying that households with more than one year of DP experience spend about 13.67% more than non-users. These effects are precisely estimated and remain stable across alternative fixed-effects structures (columns (2) and (4)), supporting our first hypothesis that digital payments raise consumption levels.

We then examine whether digital payments affect consumption growth, measured as the first difference of log total consumption. Table 4 reports the corresponding fixed-effects estimates under the same sequence of specifications as Table 3; column (3) is our benchmark, which includes the full set of household controls, household fixed effects, and city×year fixed effects.

Two results stand out. First, the short-run effect is large and precisely estimated: in column (3), the coefficient on DP_SR is 0.0682 (s.e. 0.0192), indicating that households experience a statistically significant increase in consumption growth in the first year of DP adoption. Second, the long-run effect is muted: the coefficient on DP_LR becomes small and statistically insignificant in the benchmark specification (−0.0257, s.e. 0.0315), and remains close to zero under alternative fixed-effects structures (columns (2) and (4)). Taken together, the evidence suggests that digital payments generate an adoption-year spike in consumption growth, but this acceleration does not persist with longer usage.

This "front-loaded" pattern complements the level results in Table 3. While DP adoption is associated with a permanently higher consumption level, the growth evidence indicates that the increase is concentrated around the adoption period rather than reflecting a sustained upward shift in the consumption growth path. This is consistent with the model's intertemporal-choice mechanism: frictionless transactions reduce payment salience and can strengthen present-oriented spending immediately after adoption; with experience, households may update beliefs about their own spending tendencies and adopt self-regulation (e.g., tighter liquidity management or borrowing restraint), so that consumption growth gradually returns toward the trajectory of non-users even though the level remains elevated.

**C. Consumption categories**

We next examine whether the consumption response to digital payment adoption differs across spending categories. Guided by the behavioral mechanism in our model, we distinguish life consumption from hedonic consumption. Digital payment would weaken the pain of paying and magnify the pleasure of buying compared with traditional payments, directly increasing the mental price and transaction utility (Hou et al., 2021). Digital payments reduce payment salience and transaction frictions, which should matter more for discretionary, affect-driven purchases—i.e., hedonic goods and services—than for routine necessities. In addition, digital payment platforms typically

bundle multiple funding sources (e.g., bank cards and credit lines), making liquidity more readily accessible at the point of purchase and thereby facilitating flexible spending, especially for hedonic items that are more likely to be impulse-driven.

Table 5 reports the category-specific results using the benchmark specification with household fixed effects and city×year fixed effects. Columns (1)–(2) show that digital payment adoption raises both life and hedonic consumption levels, but the magnitudes differ substantially. In the first adoption year, DP_SR is 0.0700 for life consumption and 0.2585 for hedonic consumption, implying roughly a 7.0% increase in essentials versus a 25.9% increase in hedonic spending. The pattern persists for longer experience: DP_LR remains small for life consumption (0.0285) but large for hedonic consumption (0.2522). This asymmetric response supports the view that digital payments primarily operate through behavioral channels that are more salient for discretionary spending.

Columns (3)–(4) turn to consumption growth. Digital payment adoption increases growth in the first year for both categories, again with a stronger effect for hedonic consumption: DP_SR is 0.0356 for life consumption growth and 0.1272 for hedonic consumption growth. Strikingly, for households with more than one year of experience, growth declines sharply—especially for hedonic spending. The coefficient on DP_LR is −0.1331 for life consumption growth and −0.5128 for hedonic consumption growth. This dynamic pattern is consistent with the "front-loaded" adoption response documented for total consumption: initial spending accelerates after adoption, but growth subsequently attenuates, with a particularly pronounced reversal for hedonic purchases—precisely the category most sensitive to present bias and self-control concerns.

Finally, columns (5)–(6) show that digital payments reshape consumption composition. In the first adoption year, DP_SR reduces the life consumption share by 1.95 percentage points (−0.0195) and increases the hedonic share by 1.04 percentage points (0.0104). With longer DP experience, the life share declines further (−0.0582) while the hedonic share remains higher (0.0136). Overall, Table 5 indicates that digital payment adoption is associated not only with higher spending levels, but also with a

reallocation toward hedonic categories, consistent with the consumption-structure patterns in Figure 3.

# 4. Mechanism

## 4.1 Behavioral Channel: Present Bias and Liquidity-Enabled Spending

A central mechanism in our framework is that digital payments (DP) reshape consumption by lowering transaction frictions and attenuating the "pain of paying," thereby weakening the salience of out-of-pocket spending at the moment of purchase (Prelec & Loewenstein, 1998; Soman, 2001). When payments become less salient, consumers perceive a lower psychological cost of spending, which can increase purchase propensity—especially for discretionary goods whose utility is tightly linked to affect, pleasure, and immediacy (Thaler, 1999; Raghubir & Srivastava, 2008; Hou et al., 2021). At the same time, models of quasi-hyperbolic discounting imply that households with time-inconsistent (present-biased) preferences are particularly vulnerable to temptation when commitment is weak and gratification is immediate, so the same payment-technology shock may generate heterogeneous responses depending on underlying self-control problems and available liquidity (Laibson, 1997; O'Donoghue & Rabin, 1999).

To operationalize heterogeneity in self-control, we proxy present bias using pre-existing credit-card borrowing and repayment behaviors. A large behavioral and household-finance literature documents that present-biased individuals are more likely to borrow on credit cards to fund immediate consumption and to procrastinate repayment or revolve balances despite predictable future costs (Angeletos et al., 2001; Meier & Sprenger, 2010; Barboza, 2018; Grodzicki & Koulayev, 2021). In our setting, the "present bias" indicator is constructed from credit-card behaviors observed prior to DP adoption (e.g., delayed repayment, revolving credit, cash advances, installment use, and "consume first" motives). This design aligns with evidence that time preferences are relatively persistent over medium horizons and helps mitigate reverse causality

concerns whereby DP adoption itself would mechanically generate the behaviors used to define present bias (Dohmen et al., 2006; Meier & Sprenger, 2010). Separately, we include a credit-card holder indicator to capture baseline participation in consumer finance and liquidity access, which may complement DP convenience through a financing margin.

Table 6 implements this idea by estimating the benchmark consumption regressions and augmenting them with interaction terms between DP adoption status and (i) present bias and (ii) credit-card ownership. The coefficients on DP_SR and DP_LR represent DP effects for the reference group (households without present bias and without a credit card), while the interaction terms allow the DP effect to differ for present-biased households and for credit-card holders. Consistent with the baseline results, DP is associated with higher consumption levels: the main DP coefficients are positive for total consumption, and DP is also positively related to category consumption levels in several specifications. In contrast, for growth outcomes, the longer-run DP effect is weaker and often negative, with a particularly pronounced deceleration for hedonic consumption growth. This "level-up, growth-down" pattern is consistent with a payment-technology shock that initially relaxes frictions and expands feasible spending, but then attenuates as households update budgets, rebuild buffers, or internalize the implications of easier spending (Laibson, 1997; O'Donoghue & Rabin, 1999).

The interaction results point to two distinct margins. First, present-biased households exhibit an attenuated DP-induced expansion, especially in the short run. The interaction *DP_SR* × *present bia*s is negative and statistically significant in the total-consumption and hedonic-consumption level regressions, and significantly negative in the consumption growth regression. This indicates that, upon first adopting DP, households with stronger self-control problems increase consumption less than otherwise comparable households. One coherent interpretation—consistent with models in which present bias interacts with costly borrowing and weak commitment—is that present-biased households encounter binding constraints more quickly (e.g., rapid exhaustion of informal budgets or earlier repayment pressure), which induces

faster correction once the spending environment becomes more frictionless (Angeletos et al., 2001; Heidhues & Kőszegi, 2008). A complementary behavioral interpretation is that DP usage may reveal overspending risks sooner for present-biased households, prompting earlier adoption of compensating rules or tighter budgeting, consistent with broader commitment and self-regulation arguments (Laibson, 1997; Thaler, 1999). In the long run, the present-bias interactions are generally weaker and sometimes heterogeneous across consumption categories, which is consistent with differences in adjustment speed rather than a uniform amplification effect.

Second, credit-card ownership amplifies DP effects, consistent with liquidity–convenience complementarity. The interactions *DP_SR* × *creditcard* and *DP_LR* × *creditcard* are positive and statistically significant for consumption levels and for consumption growth, with particularly strong effects in hedonic categories. This pattern is consistent with a mechanism in which DP reduces transaction frictions and increases payment convenience, while credit-card access relaxes short-run liquidity constraints and expands the feasible set of purchases; together they generate larger spending responses, especially for discretionary consumption that is more sensitive to both liquidity and payment salience (Gross & Souleles, 2002; Agarwal et al., 2015; Prelec & Loewenstein, 1998; Soman, 2001). In short, Table 6 supports a behavioral channel in which DP affects consumption through reduced payment salience, but the magnitude and persistence of the response depend on the household's self-control profile and credit access: present-biased households show muted short-run DP effects consistent with faster constraint binding or earlier correction, whereas credit-card holders exhibit amplified DP effects consistent with liquidity–convenience complementarity.

### 4.2 Self-Control Adjustments: Borrowing and Liquidity Management

The baseline results in Table 3 and Table 4 show a clear intertemporal pattern: digital payment adoption is associated with a higher consumption level, while the consumption growth effect is concentrated in the short run and fades in the long run. A natural interpretation—consistent with behavioral models of present bias and self-control—is

that digital payment initially relaxes transaction frictions and expands effective liquidity, but households subsequently adopt commitment-like adjustments to curb overspending. Two widely discussed self-regulation margins are (i) tightening the growth of consumption-related borrowing and (ii) managing liquid resources that are easiest to spend (e.g., deposits and platform balances). The evidence in Tables 7 and 8 aligns with these "self-control adjustment" predictions.

### *A. Borrowing adjustment*

Table 7 investigates whether digital payment use changes households' consumption-related borrowing and, crucially, whether this response differs by behavioral traits and liquidity access. Column (1) shows that first-year digital payment adoption (*DP_SR*) is associated with a significant increase in consumer loans, and the long-run indicator (*DP_LR*) is also positive and highly significant, indicating that digital payment is correlated with higher borrowing levels in the pooled sample. However, the dynamics are more revealing: in column (2), the coefficient on *DP_LR* is negative and significant for consumer loan growth, suggesting that while experienced users may have higher borrowing stocks, they restrain further expansion of borrowing over time. This pattern is consistent with a "catch-up then discipline" trajectory: borrowing rises with adoption but the growth of borrowing is later curtailed as households become more aware of overspending risks and actively manage credit exposure.

The heterogeneity patterns sharpen the self-control interpretation. Columns (1)–(2) interact digital payment with a present-bias proxy. The interaction terms are significantly negative for borrowing levels: *DP_SR*×*presentbias* and *DP_LR*×*presentbias* are both negative and highly significant, implying that present-biased households do not translate digital payment adoption into larger borrowing stocks to the same extent as the reference group. Rather than contradicting a behavioral story, this is consistent with the idea that present-biased households face stronger self-control concerns and may respond by limiting formal borrowing (or actively deleveraging) once digital payment makes their spending tendencies more salient. In contrast, columns (3)–(4) show that credit card holders exhibit a markedly stronger "liquidity expansion" response: *DP_SR*×*credit_card* and *DP_LR*×*credit_card* are large, positive, and highly significant for both borrowing levels and borrowing growth. This is exactly what one would expect if credit card availability amplifies the ability to finance current consumption when the payment environment becomes more frictionless. Finally, columns (5)–(6) include both present-bias and credit card interactions simultaneously; the key coefficients remain qualitatively similar, indicating that the present-bias and credit-card channels capture distinct aspects of household behavior rather than being purely redundant proxies.

***B. Liquidity management adjustment***

Table 8 examines whether households adjust their liquid asset positions in ways consistent with self-control. Columns (1)–(3) show that both *DP_SR* and *DP_LR* are significantly positively associated with liquid assets, implying that digital payment users hold substantially more liquid balances—consistent with the mechanics of digital payment itself, which typically relies on readily spendable accounts (bank deposits, platform balances, and related instruments). Turning to dynamics, column (4) indicates that *DP_SR* is also associated with significantly higher liquid asset growth, consistent with an initial reallocation into payment-ready liquidity when adopting digital payment. By contrast, the long-run indicator *DP_LR* is not significantly related to liquid asset growth, which is consistent with a stabilization stage once households have completed the initial portfolio adjustment.

Heterogeneity again points to behavioral discipline. In columns (1) and (3), the interaction *DP_LR*×*presentbias* is negative and statistically significant, indicating that among present-biased households, long-run digital payment use is associated with lower liquid asset holdings relative to the reference group. This is consistent with a self-control interpretation: present-biased households may intentionally reduce the most "spendable" resources (liquid balances) as a commitment device to limit temptation, reallocating away from easy-to-tap liquidity once they recognize that digital payment increases spending salience and convenience. Notably, the credit-card interactions in columns (2), (3), (5), and (6) are generally statistically weak for liquid assets and liquid asset growth, suggesting that the credit-card channel primarily operates through credit-financed spending/borrowing (Table 12) rather than through systematic changes in liquid asset accumulation. Importantly, when both interaction sets are included (columns (3) and (6)), the negative *DP_LR*×*presentbias* term remains, reinforcing the conclusion that present bias is linked to disciplining liquidity, especially in the longer run.

Taken together, Tables 7 and 8 support a coherent self-control adjustment narrative.

Digital payment adoption is associated with higher borrowing and larger liquid balances—consistent with expanded short-run spending capacity and reduced transaction frictions. Yet, as households accumulate experience, the evidence points to restraint along two margins: borrowing growth slows (Table 7, DP_LR in the growth equation) and present-biased households in particular exhibit patterns consistent with "commitment-like" behavior—most notably, lower long-run liquid asset holdings relative to otherwise similar households (Table 8, DP_LR×presentbias). These responses are precisely the types of endogenous adjustments emphasized in behavioral models where agents anticipate or learn about self-control problems and adopt financial constraints (through credit tightening or liquidity management) to mitigate overconsumption.

# 5. Heterogeneity

## 5.1 Heterogeneity by region: Opportunity-Set Expansion

Table 9 evaluates whether digital payment (DP) use has differential effects in rural versus urban areas, which speaks directly to an opportunity-set expansion channel. In settings where local offline product variety, merchant density, and financial access are more limited—features typically more pronounced in rural areas—DP can relax search and transaction frictions, broaden access to online goods and services, and reduce effective constraints on consumption. The regression interacts DP adoption with a rural indicator to test whether the consumption response is stronger where the baseline opportunity set is narrower.

The results show a clear level effect for urban households (the reference group). For urban residents, first-year adoption (*DP_SR*) is associated with higher total consumption and life consumption, and a particularly large increase in hedonic consumption (columns (1)–(3)). Long-term use (*DP_LR*) also remains strongly positive for consumption levels in urban areas, again with the largest magnitude for hedonic

spending. This pattern is consistent with DP reducing payment frictions and amplifying discretionary purchases that are more sensitive to convenience and impulse channels.

More importantly for the opportunity-set expansion mechanism, the rural interaction terms indicate substantially stronger marginal effects of DP in rural areas—especially for growth outcomes. In columns (1)–(2), *DP_SR×rural* is positive and highly significant for total and life consumption levels, implying that rural households experience an additional consumption increase upon adoption beyond the urban effect. While the incremental effect for hedonic levels (column (3)) is positive but not statistically significant, the growth regressions provide stronger evidence of opportunity-set expansion: *DP_SR×rural* is positive and highly significant for total growth, life growth, and hedonic growth (columns (4)–(6)). Quantitatively, the incremental rural effect on growth is sizable, indicating that once rural households adopt DP, their consumption growth accelerates markedly relative to urban adopters. This is consistent with a "catch-up" dynamic: DP adoption in rural areas may unlock new purchase margins (online retail, delivery-enabled services, broader brand access) that were previously difficult or costly to reach, generating a larger short-run expansion in consumption.

By contrast, the interactions for long-run DP use are generally small and statistically weak (*DP_LR×rural* is insignificant across columns), suggesting that the rural–urban gap is primarily an adoption-stage phenomenon rather than a persistent differential trend. This pattern fits the opportunity-set story: much of the expansion occurs when households first connect to the broader digital marketplace and learn to use DP-enabled channels; once the new opportunity set is incorporated into routine behavior, additional rural-specific gains diminish.

Taken together, it supports the interpretation that DP adoption delivers larger marginal benefits where the pre-existing opportunity set is more constrained. Rural households start from a lower consumption base (the coefficient of *rural* is negative for consumption levels in Columns 1-3), but DP adoption partially offsets this disadvantage

through stronger first-year effects—most notably through significantly higher growth in both essential (life) and discretionary (hedonic) consumption.

### 5.2 Heterogeneity by age: Life Cycle Horizon and Precaution

Life-cycle models predict that responses to liquidity-convenience shocks depend on horizon, income risk, and precautionary motives. Older households typically have shorter planning horizons, higher health-risk exposure, and stronger precautionary spending considerations, which may shift the composition of spending and attenuate sustained discretionary growth.

Table 10 implements this by interacting DP with *divide* (whether head age ≥ 60). For households with head age below 60, *DP_SR* raises total consumption (0.0892) and hedonic consumption (0.2230) and increases total consumption growth (0.0661) and hedonic growth (0.1440), consistent with an adoption-related spending impulse. For households with head age 60+, the level effects are even larger: the total-consumption adoption effect becomes 0.0892 + 0.1248 ≈ 0.214, and the hedonic-consumption adoption effect becomes 0.2230 + 0.2256 ≈ 0.449. This suggests a substantial level shift in spending associated with adoption among older households.

However, the dynamic responses differ sharply. For the senior group, the adoption-related growth effects are weaker and in several cases negative once we add the interaction: life-consumption growth is 0.0166 − 0.1535 ≈ −0.137, and hedonic-consumption growth is 0.1440 − 0.4850 ≈ −0.341. This pattern is consistent with an "immediate re-optimization" story: adoption raises convenience and may trigger an initial portfolio/spending reallocation (levels), but senior households do not sustain faster growth—likely reflecting stronger precautionary motives and tighter self-regulation after the initial adjustment.

The shares reinforce the composition channel. *DP_SR* reduces the life-consumption share for <60 (−0.0220) and the reduction is much larger for 60+ (additional −0.0636), while the hedonic share rises (0.0088, with an additional 0.0125 for 60+). In other words, senior households exhibit a stronger reallocation away from

basic categories and toward discretionary categories at adoption, but not a persistent acceleration in growth—consistent with horizon/precaution forces restraining sustained expansion.

### 5.3 Heterogeneity by education: Self-Control Capacity

Education is often interpreted as a proxy for cognitive skills, financial literacy, and the ability to plan intertemporally—traits that can mitigate impulsive responses to reduced "pain of paying" and help households adopt commitment strategies more effectively (Becker & Mulligan, 1997; evidence linking education/cognition to patience and planning is also consistent with a broad behavioral finance literature).

Table 11 shows that higher education systematically dampens the marginal effect of digital payment on consumption outcomes. The interaction *DP_SR*×*education* is negative and significant for total consumption (−0.0100), life consumption (−0.0209), and hedonic consumption (−0.0255), and it is also negative for life-consumption growth (−0.0359). Similarly, *DP_LR*×*education* is negative for life consumption (−0.0169), for life-consumption share (−0.0073), and mildly positive for hedonic share (0.0026). Interpreting these coefficients as semi-elasticities, the marginal DP effect declines with education, implying that more educated households exhibit a weaker consumption surge upon adoption and a faster reversion of growth—consistent with stronger self-control capacity and better budgeting discipline under payment convenience.

Importantly, this is not saying educated households are "unaffected" by DP—*DP_SR* and *DP_LR* remain positive and significant in several columns—but the incremental sensitivity is lower. That is exactly what a self-control-capacity interpretation predicts: digital payment reduces friction for everyone, but the magnitude of behavioral over-response is smaller among households with greater planning ability.

### 5.4 Heterogeneity by income expectation

A key implication of life-cycle/permanent-income models is that the consumption response to a payment/credit innovation should depend on households' expected future

resources and their precautionary saving motive. When expected earning capacity improves (a more optimistic outlook), households can sustain higher consumption growth for longer; when future income is perceived as risky or declining (stronger precautionary motive), households should shift spending toward necessities and compress growth—especially for discretionary ("hedonic") items. This logic is consistent with canonical intertemporal choice models in which consumption responds to expected lifetime resources rather than contemporaneous income alone (Friedman, 1957; Hall, 1978; Deaton, 1992), as well as precautionary-saving frameworks where improved outlook or lower uncertainty raises current consumption (Carroll, 1997).

*A. Health condition*

Table 12 uses *better health* of the household head as an indicator for improved expected earning capacity. The baseline DP effects (for households without health improvement) show the familiar "front-loaded" pattern: first-year DP adoption raises consumption growth (*DP_SR* is positive for total growth), while long-run DP use is associated with slower growth (*DP_LR* is negative for total growth and strongly negative for life and hedonic growth). Importantly, the interaction terms indicate that improved health attenuates this long-run slowdown—most clearly for hedonic spending. The coefficient on *DP_LR* × *better health* is positive and statistically significant for hedonic consumption growth (0.1578), meaning that among households with improving health prospects, the long-run DP–growth relationship becomes less negative (or even partially reversed) for hedonic consumption. Consistent with this, *DP_LR* × *better health* is also positive for the hedonic consumption share (0.0127), suggesting that a more favorable outlook allows households to maintain (or expand) discretionary spending rather than retrenching into necessities. By contrast, *DP_SR* × *better health* effects are generally small and statistically weak, implying that income-expectation heterogeneity matters more for persistence of DP effects than for the initial "adoption shock."

*B. Family Structure*

Table 13 provides a complementary, conceptually symmetric test using the household's elderly composition (elder) as a proxy for a more pessimistic long-run budget environment. A larger elderly burden typically increases expected future non-discretionary expenditures (healthcare, care responsibilities) and may reduce expected labor income growth, which would strengthen precautionary motives and make sustained discretionary expansion less likely (Deaton, 1992; Carroll, 1997). Consistent with that prediction, Table 8 shows that elderly households have lower consumption levels across categories (negative elder in columns 1–3), and—more importantly for the mechanism—the interactions DP_SR × elder and DP_LR × elder are negative for total consumption growth (column 4), with particularly large negative coefficients for hedonic consumption growth (column 6). At the same time, the share regressions show positive interactions for the life consumption share (column 7), implying that when elderly burden is higher, DP adoption is associated with a relative shift toward necessities (or, at minimum, away from discretionary expansion), consistent with precautionary re-optimization under a tighter perceived long-run constraint. In other words, the "expectations" mechanism appears not only in stronger-outlook households (better health dampens the long-run retrenchment), but also in weaker-outlook households (elderly burden amplifies the DP-related growth slowdown, especially for hedonic spending).

Taken together, Tables 12 and 13 support an "income-expectation / precautionary" mechanism: DP adoption can raise spending immediately, but whether the effect persists depends on households' perceived future resources. Optimistic households (improving health) sustain DP-enabled hedonic growth and tilt toward discretionary items, whereas households with stronger precautionary motives (higher elderly burden) exhibit a more pronounced long-run retrenchment—lower growth and a reallocation toward essential consumption.

## 6. Endogeneity concerns

A central empirical challenge in estimating the causal effect of digital payment (DP) adoption on household consumption is endogeneity of DP use. Households do not adopt DP randomly: adoption may be correlated with unobserved traits—such as financial sophistication, self-control, consumption preferences, or expectations about future income—that also directly affect consumption. Moreover, reverse causality is plausible: households with rising consumption needs (or a preference for hedonic spending) may be more likely to start using DP. Finally, time-varying local shocks (e.g., local fintech promotion, changes in payment infrastructure, or city-level business-cycle conditions) could jointly influence both DP adoption and consumption, biasing fixed-effects estimates even after controlling for household and time effects.

To address these concerns, we implement an instrumental variables (IV) approach that leverages plausibly exogenous variation in DP adoption at the city level. Specifically, we use two instruments: (i) the annual DP adoption ratio in a city, capturing the local diffusion intensity and peer/network exposure; and (ii) the interaction between the city DP adoption ratio and the average education level of adults in that city, capturing differential diffusion capacity through learning and technology absorption. The identifying idea is that these city-level diffusion measures shift an individual household's propensity to adopt DP, while being less likely to affect that household's consumption directly once we condition on household fixed effects, year dummies, and the standard covariates.

The first-stage results in Tables 14–15 indicate that the instruments strongly predict DP adoption status (DP_SR and DP_LR). In Table 14, the city DP adoption ratio loads positively on DP_SR and negatively on DP_LR, and the interaction with city education is also highly significant, consistent with diffusion and learning mechanisms. Instrument strength is further supported by the Kleibergen–Paap Wald F statistics: 100.559 in Table 14 and 18.624 in Table 15, both well above the conventional weak-IV thresholds and the reported "10% maximal IV size" benchmark (7.03). This substantially mitigates concerns that the IV estimates are driven by weak identification.

Table 14 reports the IV estimates for CPI-deflated log consumption levels (total, life/basic, and hedonic). The second-stage coefficients show that DP_LR is positively associated with consumption levels, with statistically significant effects at the 10% level for both total and life consumption (0.1185 and 0.1019, respectively). The effect on hedonic consumption is positive and precisely estimated (0.8451), indicating a particularly strong link between sustained DP use and discretionary spending. In contrast, the coefficient on DP_SR is positive but imprecisely estimated for total and life consumption, while large and significant for hedonic consumption (1.0971). Taken together, the IV results reinforce the baseline pattern that DP adoption is associated with higher consumption levels—especially for hedonic categories—while also suggesting that some of the short-run level effects for total/life may be more sensitive once endogenous selection is purged.

Table 15 turns to consumption dynamics (first differences of CPI-deflated log consumption). Two features stand out. First, DP_SR has a positive and significant effect on total consumption growth (0.6416), and a very large effect on hedonic growth (2.4832), consistent with a short-run adoption boost—particularly in discretionary spending. Second, DP_LR has strongly negative effects on growth across all categories (−1.7285 total; −1.3712 life; −7.1146 hedonic), implying that after the initial adoption phase, consumption growth falls back sharply. This dynamic profile is consistent with your behavioral interpretation: DP adoption may initially loosen perceived payment frictions and expand short-run spending, but over time households adjust—either through learning about self-control problems, tighter budgeting, or active liquidity/borrowing management—so that growth decelerates, with the strongest reversal in hedonic consumption.

Conceptually, the IV results support a causal narrative that DP adoption shifts both the level and the intertemporal profile of spending: a front-loaded increase (especially hedonic), followed by slower growth as households adjust. This aligns well with mechanisms emphasized in the behavioral and household-finance literature—such as reduced "pain of paying," present bias, and subsequent self-regulation—while also

being consistent with a life-cycle view in which households revise their spending plan once the novelty/credit-liquidity channel is internalized.

That said, the IV strategy rests on the exclusion restriction: conditional on household fixed effects, year effects, and controls, city-level DP diffusion should not directly affect household consumption except through DP adoption. The most natural threat is that city diffusion may proxy for broader local changes (e-commerce penetration, fintech credit expansion, or pro-consumption policies) that influence consumption directly. Your fixed effects structure already absorbs time-invariant household heterogeneity and common year shocks, but to further bolster credibility, it is useful to emphasize (and, if feasible, implement) additional safeguards—e.g., controlling for time-varying city economic conditions more fully, or showing robustness to alternative instrument constructions (lagged diffusion, leave-one-out city adoption, or excluding the household's own adoption from the city ratio).

Overall, Tables 14–15 indicate that the baseline findings are not driven by endogenous DP adoption. The instruments are highly relevant and sufficiently strong, and the second-stage estimates preserve the main qualitative conclusions: DP adoption increases consumption—especially hedonic spending—and the impact on growth is short-run positive but long-run negative, consistent with an "initial spending impulse followed by adjustment/self-control" mechanism.

## 7. Conclusion

The COVID-19 pandemic disrupted household demand and intensified the policy imperative to restore consumption. Digital payments are frequently cited as a promising lever because they reduce transaction frictions and expand access to modern retail and financial services. Yet an open question is whether digital payment adoption can sustain consumption growth over time, rather than simply generating a short-lived spending impulse. This paper addresses that question by combining a behavioral intertemporal framework with household panel evidence from China.

On the theory side, we embed digital payment use into a classic self-control setting with quasi-hyperbolic discounting, which captures time-inconsistent (present-biased) preferences. The model clarifies two channels through which digital payments affect consumption choices. First, digital payments can exacerbate present bias by lowering the "pain of paying," thereby shifting consumption toward the present and inducing an initially higher growth rate. Second, digital payments may also generate unexpected income and opportunity effects—for example, via reduced search and transaction costs, improved matching, and expanded market access—that support consumption in a more durable way. The interaction of these forces yields testable predictions about the level and growth of consumption, as well as heterogeneity by self-control capacity and economic outlook.

Empirically, using CHFS data from 2013–2019, we document three core findings. First, digital payment adoption is associated with higher consumption levels, with the strongest effects concentrated in hedonic consumption, consistent with a payment-friction and behavioral spending channel. Second, the dynamics are distinctly non-linear: digital payments are linked to a short-run acceleration in consumption growth, but the growth effect becomes weak or negative in the long run, particularly for hedonic spending. This pattern is consistent with an "impulse-and-adjustment" mechanism—initially, reduced payment salience and expanded liquidity facilitate spending; subsequently, households revise behavior and slow growth as they recognize self-control risks or face tighter intertemporal constraints. Third, the heterogeneity evidence supports this interpretation. Households with greater self-control capacity (proxied by education) exhibit weaker present-bias-driven responses, while households facing tighter horizons and stronger precautionary motives (older heads and households with larger elderly burdens) display more conservative long-run growth, especially in discretionary categories. In parallel, the results indicate that sustaining long-run growth depends importantly on income expectations and economic conditions: improved health status (as a proxy for earning capacity and outlook) is associated with more favorable long-run dynamics, whereas family structures implying higher future

obligations are linked to weaker growth responses.

We further examine how households adjust when attempting to stabilize consumption paths. Consistent with self-regulation, digital payment use is associated with systematic changes in household balance-sheet behavior—particularly in borrowing and liquidity management—suggesting that households respond to overspending risks by tightening effective liquidity (e.g., slowing consumer loan growth) and re-optimizing liquid asset positions. Finally, rural–urban heterogeneity indicates that digital payments have a comparatively larger role in rural areas, consistent with an opportunity-set expansion mechanism whereby digital platforms broaden access to goods, services, and financial tools in otherwise thinner markets.

Overall, this study contributes to the consumption and digital-finance literature by highlighting that digital payments are not a mechanical engine of persistent consumption growth. Their short-run stimulus can be substantial, but it is behaviorally fragile if driven primarily by present bias. Durable consumption growth is more likely to arise from channels that raise expected permanent resources and improve economic fundamentals—income growth, labor-market prospects, and productivity gains linked to the digital economy—rather than from payment convenience alone. From a policy perspective, the results suggest a two-pronged approach: promote digital payment infrastructure to reduce frictions and expand market access (especially in rural areas), while also strengthening consumer protection and financial capability to mitigate self-control problems and prevent unstable, debt-fueled spending.

This paper has limitations. CHFS consumption measures rely on self-reported survey responses and may contain reporting error. The annual frequency of consumption and adoption indicators may obscure higher-frequency dynamics and introduce measurement noise, particularly when household digital payment use is intermittent across waves. Future work could leverage higher-frequency transaction data, examine platform-level design features that shape payment salience and credit access, and test external validity in countries where traditional payment habits and consumer credit institutions differ substantially.

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## Tables and Figures

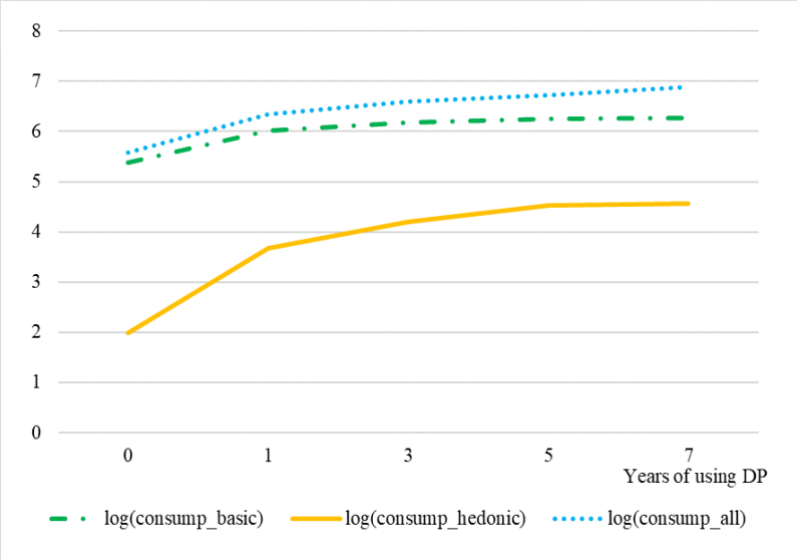



**Figure 1 Household consumption (level)**

Notes: This figure plots household consumption levels against the number of years since a household began using digital payments (DP). Basic consumption includes food, clothing, rent, utilities, daily necessities, durable goods, local transportation, communication, and medical expenditures. Hedonic consumption includes education, entertainment, travel, health and fitness, housekeeping, and personal care (e.g., hairdressing). All consumption measures are expressed in natural logarithms and are shown separately for basic, hedonic, and total consumption. Consumption is deflated to constant prices (CPI-adjusted). Years since adoption are coded as 0, 1, 3, 5, and 7.

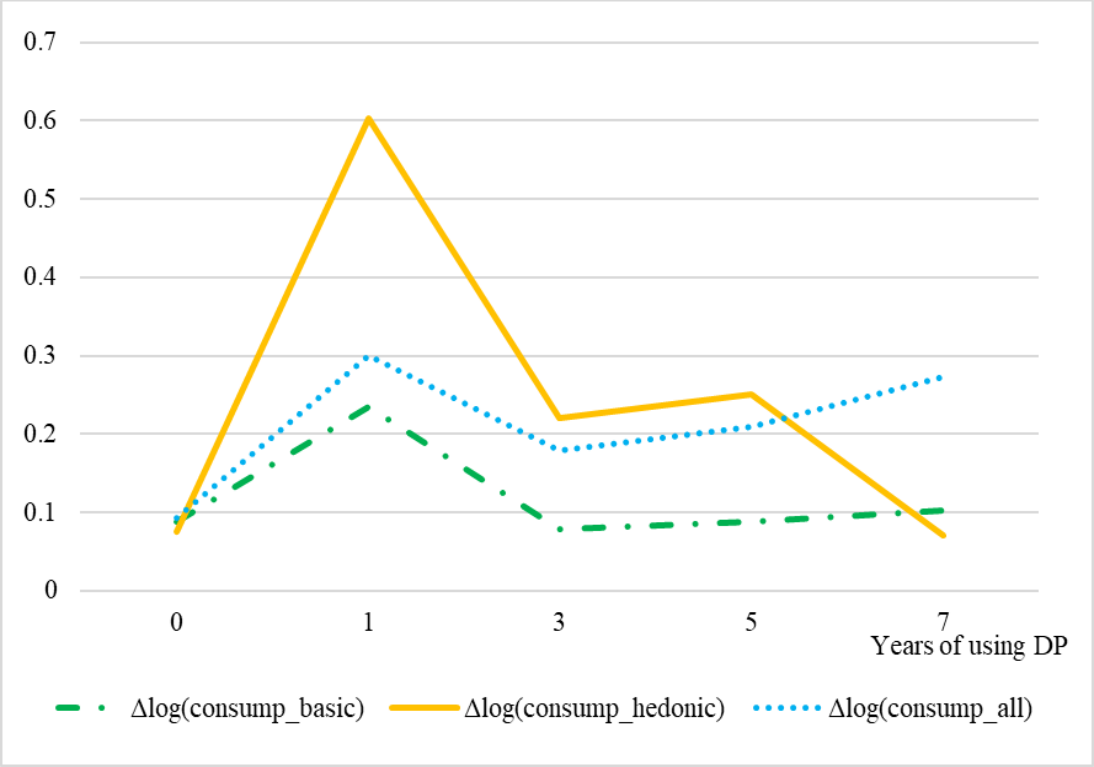



**Figure 2 Household consumption growth**

This figure plots the household consumption growth against the number of years since a household began using digital payments (DP). The series are defined as first differences of the log consumption measures, shown separately for basic, hedonic, and total consumption. Δlog(consumption), is computed between consecutive survey waves for the same household. Definitions of the consumption categories follow Figure 1.

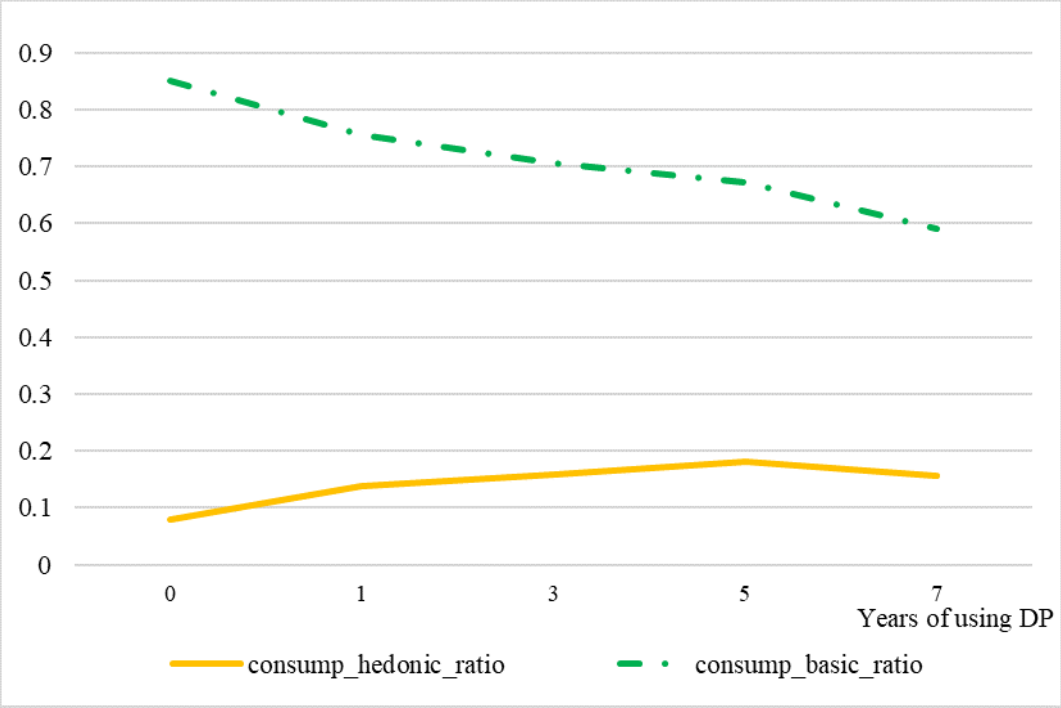



**Figure 3 Household consumption structure**

This figure plots the composition of household consumption against the number of years since a household began using digital payments (DP). It shows the shares of basic and hedonic consumption in total household consumption, defined as basic/total consumption, and hedonic/total consumption, respectively. Category definitions follow Figure 1.

## Table 1 Variable definition

| Variable | Definition |
|---|---|
| **Key independent variables** | |
| DP_SR | Indicator equal to 1 if the household adopts digital payments in the current year (i.e., first-year user), and 0 otherwise. |
| DP_LR | Indicator equal to 1 if the household has used digital payments for more than one year, and 0 otherwise. |
| **Dependent variables** | |
| Total consumption | A household's total annual consumption (RMB). |
| Life consumption | A household's annual life (essential) consumption (RMB), including food, clothing, rent, utilities, daily necessities, durable goods, local transportation, communication, and medical expenditures. |
| Hedonic consumption | A household's annual hedonic consumption (RMB), including education, entertainment, travel, health and fitness, housekeeping, and personal care (e.g., hairdressing). |
| Total growth | Total consumption growth, measured by first difference of log total consumption. |
| Life growth | Basic consumption growth, measured by first difference of log life consumption. |
| Hedonic growth | Hedonic consumption growth, measured by first difference of log hedonic consumption. |
| Life share | Share of basic consumption in total consumption, life /total consumption. |
| Hedonic share | Share of hedonic consumption in total consumption, hedonic/total consumption. |
| **Control variables** | |
| age | The age of the household head. |
| gender | Indicator equal to 1 if the household head is male, and 0 otherwise. |
| education | Education category of the household head (1–9): 1 = no schooling; 2 = primary school; 3 = junior high school; 4 = high school; 5 = technical/secondary school; 6 = junior college/senior vocational school; 7 = university; 8 = master's degree; 9 = Ph.D. |
| marry | Indicator equal to 1 if the household head is married or remarried, and 0 otherwise. |
| Family size | Number of household members. |
| total income | Total household income (in 2010 constant RMB), including labor income, agricultural income, business/operational income (e.g., manufacturing), transfer income, and investment income. The income value is deflated to 2010 prices using the CPI before taking logs. |
| total asset | Total household assets (in 2010 constant RMB). Total assets include both financial and non-financial assets. Financial assets comprise social security accounts, cash, deposits, stocks, and other financial assets. Non-financial assets include business assets, land, and housing. The asset value is deflated to 2010 prices using the CPI before taking |

| | |
|---|---|
| | logs. |
| Kid ratio | Share of minors (under age 18) in the household. |
| Worker ratio | Share of employed members in the household. |
| Financial invest | Indicator equal to 1 if a household holds risky financial assets, and 0 otherwise. |
| Risk lover | Indicator equal to 1 if a household reports a preference for risky investments, and 0 otherwise. |
| House invest | Indicator equal to 1 if a household owns additional housing beyond the primary residence, and 0 otherwise. |
| Loan to asset ratio | Household debt-to-asset ratio. |
| Credit card | Indicator equal to 1 if a household owns at least one credit card, and 0 otherwise. |
| Rural | Indicator equal to 1 if a household resides in a rural area, and 0 otherwise. |
| log(gdppc_city) | Logarithm of city-level GDP per capita in year $t$. |
| **Other variables** | |
| Consumer loan | Total consumption-related borrowing (RMB), including non-mortgage consumer loans, education loans, and credit card debt. |
| Liquid assets | Liquid financial assets excluding cash (RMB), including demand deposits, balances in internet wealth management products, balances held in third-party payment platforms, and cash balances in financial investment accounts. |
| Illiquid asset ratio | Share of illiquid assets in total assets. |
| Better health | Indicator equal to 1 if the household head's health status improves, and 0 otherwise. |
| Divide | Indicator equal to 1 if the household head's age is above 60, and 0 otherwise. |
| Elder ratio | Share of elderly members in the household. |

## Table 2 Summary Statistics

| Variables | Observation | Mean | Sd | Min | Max |
|---|---|---|---|---|---|
| **Key independent variables** | | | | | |
| DP_SR | 91440 | 0.1374 | 0.3442 | 0 | 1 |
| DP_LR | 91440 | 0.0853 | 0.2794 | 0 | 1 |
| **Dependent variables** | | | | | |
| Total consumption | 91440 | 472.5646 | 501.3189 | 33.9335 | 3430.661 |
| Life consumption | 91440 | 335.8860 | 271.1947 | 29.7254 | 1659.365 |
| Hedonic consumption | 91440 | 54.9799 | 105.7631 | 0 | 681.7545 |
| Log_total | 91440 | 5.7744 | 0.8788 | 3.5534 | 8.1408 |
| Log_life | 91440 | 5.5332 | 0.7840 | 3.4251 | 7.4148 |
| Log_hedonic | 91440 | 2.4178 | 1.9690 | 0 | 6.5261 |
| Total growth | 63554 | 0.1316 | 0.8248 | -4.5874 | 4.5722 |
| Life growth | 63554 | 0.1038 | 0.7307 | -3.9897 | 3.9897 |
| Hedonic growth | 63554 | 0.1699 | 1.9541 | -6.5261 | 6.5261 |
| Life share | 91440 | 0.8237 | 0.2026 | 0.1565 | 1 |
| Hedonic share | 91440 | 0.0939 | 0.1345 | 0 | 0.6210 |
| **Control variables** | | | | | |
| age | 91431 | 56.5395 | 13.8321 | 14 | 102 |
| gender | 91437 | 0.7843 | 0.4113 | 0 | 1 |
| education | 91374 | 3.2107 | 1.5770 | 1 | 9 |
| marry | 91400 | 0.8596 | 0.3474 | 0 | 1 |
| Family size | 91440 | 3.3966 | 1.6721 | 1 | 20 |
| Total income | 91440 | 607.2304 | 728.3309 | 0.7549 | 4981.825 |
| Total asset | 91440 | 7112.751 | 12532.76 | 14.2163 | 82747.21 |
| Kid ratio | 91440 | 0.1186 | 0.1652 | 0 | 1 |
| Worker ratio | 91440 | 0.4811 | 0.3350 | 0 | 1 |
| Financial invest | 91440 | 0.1403 | 0.3473 | 0 | 1 |
| Risk lover | 91440 | 0.0784 | 0.2688 | 0 | 1 |
| House invest | 91440 | 0.1489 | 0.3560 | 0 | 1 |
| Loan to asset ratio | 91440 | 0.1204 | 0.4247 | 0 | 3.2242 |
| Credit card | 91440 | 0.1790 | 0.3834 | 0 | 1 |
| Rural | 91440 | 0.3905 | 0.4879 | 0 | 1 |
| log(gdppc_city) | 91440 | 6.0739 | 1.4921 | 2.8241 | 11.7033 |
| **Other variables** | | | | | |
| Consumer loan | 91,440 | 0.2788 | 1.0998 | 0 | 5.8117 |
| Consumer loan growth | 63,554 | 0.0222 | 1.3335 | -5.8117 | 5.8117 |
| Liquid asset | 91,440 | 2.5495 | 2.5801 | 0 | 8.2194 |
| Liquid asset growth | 63,554 | 0.3140 | 2.7243 | -8.2194 | 8.2194 |
| Illiquid asset ratio | 91440 | 0.9374 | 0.1216 | 0 | 1 |
| Better health | 57132 | 0.3917 | 0.4881 | 0 | 1 |

| | | | | | |
|---|---|---|---|---|---|
| Divide | 91440 | 0.4060 | 0.4911 | 0 | 1 |
| Elder ratio | 91440 | 0.2579 | 0.3696 | 0 | 1 |

**Table 3 Digital payment and household total consumption**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | Dependent variable: Log of total consumption | | | |
| DP_SR | 0.2106*** | 0.1023*** | 0.1011*** | 0.1003*** |
| | (0.0088) | (0.0084) | (0.0086) | (0.0085) |
| DP_LR | 0.3211*** | 0.1395*** | 0.1367*** | 0.1367*** |
| | (0.0133) | (0.0129) | (0.0135) | (0.0130) |
| age | | -0.0042*** | -0.0041*** | -0.0044*** |
| | | (0.0005) | (0.0005) | (0.0005) |
| gender | | 0.0178* | 0.0184** | 0.0198** |
| | | (0.0092) | (0.0093) | (0.0093) |
| education | | 0.0228*** | 0.0211*** | 0.0223*** |
| | | (0.0042) | (0.0042) | (0.0042) |
| marry | | 0.0747*** | 0.0800*** | 0.0757*** |
| | | (0.0126) | (0.0126) | (0.0126) |
| Family size | | 0.0970*** | 0.0995*** | 0.0981*** |
| | | (0.0031) | (0.0031) | (0.0032) |
| Log (total income) | | 0.0641*** | 0.0630*** | 0.0642*** |
| | | (0.0031) | (0.0031) | (0.0031) |
| Log (total asset) | | 0.0777*** | 0.0757*** | 0.0770*** |
| | | (0.0026) | (0.0026) | (0.0026) |
| kid_ratio | | 0.1164*** | 0.1065*** | 0.1100*** |
| | | (0.0294) | (0.0293) | (0.0297) |
| worker_ratio | | -0.0121 | -0.0152 | -0.0117 |
| | | (0.0112) | (0.0113) | (0.0113) |
| Financial invest | | 0.0659*** | 0.0634*** | 0.0656*** |
| | | (0.0087) | (0.0088) | (0.0088) |
| risk_lover | | 0.0315*** | 0.0274** | 0.0298** |
| | | (0.0116) | (0.0116) | (0.0117) |
| house_invest | | 0.0764*** | 0.0729*** | 0.0752*** |
| | | (0.0085) | (0.0086) | (0.0086) |
| Loan to asset ratio | | 0.1036*** | 0.0999*** | 0.1037*** |
| | | (0.0074) | (0.0074) | (0.0075) |
| rural | | -0.1157*** | -0.0827** | -0.1150*** |
| | | (0.0304) | (0.0324) | (0.0304) |
| Log(gdppc_city) | | | | 0.0511** |
| | | | | (0.0236) |
| Constant | 5.7181*** | 4.5335*** | 4.5345*** | 4.2367*** |
| | (0.0022) | (0.0451) | (0.0457) | (0.1505) |

| | | | | |
|---|---|---|---|---|
| Household FE | Y | Y | Y | Y |
| City FE | N | Y | N | Y |
| Year FE | Y | Y | N | Y |
| City×Year FE | N | N | Y | N |
| Observations | 91,440 | 90,868 | 90,774 | 89,784 |
| R-squared | 0.722 | 0.747 | 0.752 | 0.747 |

Notes: This table reports household fixed-effects estimates of the relationship between digital payment adoption and household total consumption. The dependent variable is the logarithm of annual total consumption, *total consumption. DP_SR* is an indicator equal to 1 if the household adopts digital payments in the first year (first-year user) and 0 otherwise; *DP_LR* is an indicator equal to 1 if the household has used digital payments for more than one year and 0 otherwise. All specifications include household fixed effects. Column (1) includes year fixed effects. Column (2) adds city fixed effects and year fixed effects. Column (3) is the benchmark specification and replaces separate city and year fixed effects with city×year fixed effects to control for time-varying city-level shocks; it also retains household fixed effects. Column (4) includes city fixed effects and year fixed effects and additionally controls for city-level economic conditions using *log(gdppc_city)*. Control variables include the household head's *age, gender, education*, and marital status, household size, *total income, total asset, kid ratio, worker ratio*, indicators for holding risky financial assets (*financial invest)* and risk preference (*risk_lover*), housing investment (*house_invest*), *loan-to-asset ratio*, and rural residence. Standard errors are clustered at household level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 4 Digital payment and total consumption growth**

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Dependent variable: total consumption growth | | | |
| DP_SR | 0.1634*** | 0.0717*** | 0.0682*** | 0.0716*** |
| | (0.0188) | (0.0189) | (0.0192) | (0.0190) |
| DP_LR | 0.1474*** | 0.0027 | -0.0257 | 0.0028 |
| | (0.0302) | (0.0306) | (0.0315) | (0.0307) |
| age | | -0.0010 | -0.0010 | -0.0011 |
| | | (0.0010) | (0.0010) | (0.0010) |
| gender | | 0.0208 | 0.0167 | 0.0256 |
| | | (0.0202) | (0.0203) | (0.0203) |
| education | | 0.0032 | 0.0026 | 0.0034 |
| | | (0.0095) | (0.0096) | (0.0095) |
| marry | | 0.0841*** | 0.0962*** | 0.0861*** |
| | | (0.0288) | (0.0289) | (0.0290) |
| Family size | | 0.0624*** | 0.0651*** | 0.0638*** |
| | | (0.0067) | (0.0067) | (0.0068) |
| Log (total income) | | 0.0885*** | 0.0864*** | 0.0880*** |
| | | (0.0072) | (0.0072) | (0.0072) |
| Log (total asset) | | 0.0847*** | 0.0830*** | 0.0844*** |
| | | (0.0059) | (0.0060) | (0.0059) |
| kid_ratio | | 0.2310*** | 0.2209*** | 0.2163*** |
| | | (0.0667) | (0.0663) | (0.0673) |
| worker_ratio | | 0.0387 | 0.0346 | 0.0355 |
| | | (0.0253) | (0.0254) | (0.0255) |
| Financial invest | | 0.0915*** | 0.0898*** | 0.0924*** |
| | | (0.0215) | (0.0217) | (0.0216) |
| risk_lover | | 0.0267 | 0.0181 | 0.0260 |
| | | (0.0279) | (0.0279) | (0.0283) |
| house_invest | | 0.1045*** | 0.0977*** | 0.1029*** |
| | | (0.0196) | (0.0197) | (0.0197) |
| Loan to asset ratio | | 0.1235*** | 0.1229*** | 0.1263*** |
| | | (0.0160) | (0.0161) | (0.0162) |
| rural | | 0.0502 | 0.0603 | 0.0514 |
| | | (0.0714) | (0.0772) | (0.0714) |
| Log(gdppc_city) | | | | -0.0426 |
| | | | | (0.0501) |
| Constant | 0.0896*** | -1.4195*** | -1.4002*** | -1.1586*** |
| | (0.0049) | (0.1021) | (0.1041) | (0.3154) |
| Household FE | Y | Y | Y | Y |
| City FE | N | Y | N | Y |
| Year FE | Y | Y | N | Y |
| City×Year FE | N | N | Y | N |
| Observations | 50,805 | 50,633 | 50,576 | 49,999 |
| R-squared | 0.219 | 0.244 | 0.264 | 0.244 |

Notes: This table reports estimates of the effect of digital payment usage on household consumption growth. The dependent variable is *total consumption growth*, defined as the first difference of CPI-deflated log total consumption. *DP_SR* equals 1 if the household adopts digital payments in the first year (first-year user) and 0 otherwise; *DP_LR* equals 1 if the household has used digital payments for more than one year and 0 otherwise. Columns (2)–(4) include a common set of household characteristics and balance-sheet controls: the household head's *age, gender, education*, and marital status; *family size*; log CPI-deflated income (*total income*) and assets (*total asset*); *kid ratio; worker ratio*; participation in risky financial accounts (*financial invest*); risk preference (*risk_lover*); housing investment (*house_invest*); *loan-to-asset ratio*; and an indicator for rural residence (*rural*). Column (1) reports the bivariate specification with DP indicators only. Column (2) adds the full set of controls. Column (3) is the benchmark specification. Column (4) additionally controls for city-level economic conditions using (*lgdppc_city*). Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 5 Consumption categories and structure**

| VARIABLES | (1) Life consumption | (2) Hedonic consumption | (3) Life consumption growth | (4) Hedonic consumption growth | (5) Life share | (6) Hedonic share |
|---|---|---|---|---|---|---|
| DP_SR | 0.0700*** | 0.2585*** | 0.0356** | 0.1272*** | -0.0195*** | 0.0104*** |
| | (0.0075) | (0.0221) | (0.0168) | (0.0480) | (0.0030) | (0.0018) |
| DP_LR | 0.0285** | 0.2522*** | -0.1331*** | -0.5128*** | -0.0582*** | 0.0136*** |
| | (0.0115) | (0.0340) | (0.0269) | (0.0770) | (0.0048) | (0.0029) |
| age | -0.0032*** | -0.0108*** | -0.0006 | -0.0066*** | 0.0007*** | -0.0006*** |
| | (0.0004) | (0.0011) | (0.0009) | (0.0023) | (0.0001) | (0.0001) |
| gender | 0.0103 | -0.0016 | -0.0036 | 0.0799 | -0.0055* | -0.0012 |
| | (0.0083) | (0.0233) | (0.0180) | (0.0497) | (0.0030) | (0.0019) |
| education | 0.0130*** | 0.0289*** | -0.0012 | -0.0442* | -0.0048*** | 0.0012 |
| | (0.0038) | (0.0107) | (0.0085) | (0.0228) | (0.0014) | (0.0009) |
| marry | 0.0863*** | -0.0588** | 0.1039*** | -0.1088* | 0.0034 | -0.0085*** |
| | (0.0115) | (0.0282) | (0.0261) | (0.0638) | (0.0037) | (0.0023) |
| Family size | 0.0827*** | 0.2270*** | 0.0565*** | 0.1451*** | -0.0117*** | 0.0115*** |
| | (0.0028) | (0.0080) | (0.0060) | (0.0162) | (0.0010) | (0.0006) |
| Log (total income) | 0.0563*** | 0.0533*** | 0.0745*** | 0.0973*** | -0.0042*** | -0.0009 |
| | (0.0027) | (0.0071) | (0.0062) | (0.0158) | (0.0010) | (0.0006) |
| Log (total asset) | 0.0543*** | 0.0987*** | 0.0622*** | 0.1186*** | -0.0120*** | 0.0028*** |
| | (0.0024) | (0.0060) | (0.0055) | (0.0135) | (0.0008) | (0.0005) |
| kid_ratio | 0.1149*** | 1.0396*** | 0.1249** | 1.4336*** | -0.0160 | 0.0083 |
| | (0.0260) | (0.0763) | (0.0588) | (0.1609) | (0.0097) | (0.0066) |
| worker_ratio | -0.0029 | -0.0495** | 0.0237 | 0.1020* | 0.0053 | -0.0096*** |
| | (0.0102) | (0.0249) | (0.0230) | (0.0545) | (0.0034) | (0.0019) |
| Financial invest | 0.0471*** | 0.2420*** | 0.0539*** | 0.3881*** | -0.0146*** | 0.0125*** |
| | (0.0075) | (0.0239) | (0.0183) | (0.0558) | (0.0033) | (0.0021) |
| risk_lover | 0.0218** | 0.1254*** | 0.0164 | 0.1421** | -0.0067* | 0.0074*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.0102) | (0.0290) | (0.0240) | (0.0694) | (0.0041) | (0.0024) |
| house_invest | 0.0369*** | 0.0688*** | 0.0452*** | 0.0935* | -0.0197*** | -0.0013 |
| | (0.0074) | (0.0211) | (0.0169) | (0.0481) | (0.0029) | (0.0017) |
| Loan to asset ratio | 0.0700*** | 0.0355** | 0.1011*** | 0.0426 | -0.0128*** | 0.0018 |
| | (0.0069) | (0.0157) | (0.0146) | (0.0337) | (0.0021) | (0.0013) |
| rural | -0.0574* | -0.1530** | 0.0688 | -0.0436 | 0.0090 | -0.0067 |
| | (0.0310) | (0.0748) | (0.0679) | (0.1729) | (0.0106) | (0.0058) |
| Constant | 4.5374*** | 0.9883*** | -1.1284*** | -1.5206*** | 0.9693*** | 0.0769*** |
| | (0.0419) | (0.1096) | (0.0939) | (0.2409) | (0.0141) | (0.0088) |
| Household FE | Y | Y | Y | Y | Y | Y |
| City×Year FE | Y | Y | Y | Y | Y | Y |
| Observations | 90,774 | 90,774 | 50,576 | 50,576 | 90,771 | 90,771 |
| R-squared | 0.750 | 0.702 | 0.265 | 0.248 | 0.502 | 0.583 |

Notes: This table examines whether the effects of digital payments differ across consumption categories. Columns (1)–(2) use CPI-deflated log consumption levels for **life consumption** and **hedonic consumption**. Columns (3)–(4) use life consumption growth and *hedonic consumption growth* Columns (5)–(6) use consumption composition measures: **life_share** and **hedonic_share**, defined as the shares of basic and service/hedonic consumption in total consumption, respectively. **DP_SR** equals 1 if the household adopts digital payments in the first year (first-year user) and 0 otherwise; **DP_LR** equals 1 if the household has used digital payments for more than one year and 0 otherwise. All regressions include the full set of household controls listed in the baseline specification (household head demographics, household size, CPI-deflated log income and assets, household composition ratios, risk-taking measures, housing investment, leverage, and rural residence). Unless otherwise noted, the fixed-effects structure follows the benchmark specification in column 3 of Table 3. All regressions include household fixed effects and city×year fixed effects; standard errors are clustered at the household level. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 6 Behavioral channel: Present bias & credit card**

| VARIABLES | (1) Total consumption | (2) Life consumption | (3) Hedonic consumption | (4) Consumption growth | (5) Life consumption growth | (6) Hedonic consumption growth |
|---|---|---|---|---|---|---|
| DP_SR | 0.0880*** | 0.0437** | 0.0511*** | 0.2225*** | 0.0232 | 0.0823 |
| | (0.0105) | (0.0217) | (0.0093) | (0.0261) | (0.0194) | (0.0561) |
| DP_LR | 0.1178*** | -0.0778** | -0.0159 | 0.1171*** | -0.1863*** | -0.6618*** |
| | (0.0180) | (0.0372) | (0.0156) | (0.0438) | (0.0324) | (0.0934) |
| DP_SR×present bias | -0.0599** | 0.0235 | -0.0598** | -0.2146*** | 0.0049 | 0.0503 |
| | (0.0302) | (0.0768) | (0.0241) | (0.0759) | (0.0588) | (0.1909) |
| DP_LR×present bias | -0.0453 | 0.0863 | -0.0742*** | 0.0164 | 0.0084 | 0.4264* |
| | (0.0352) | (0.0974) | (0.0278) | (0.0856) | (0.0728) | (0.2245) |
| DP_SR×creditcard | 0.0700*** | 0.0672* | 0.0326** | 0.1871*** | -0.0162 | 0.2183** |
| | (0.0154) | (0.0368) | (0.0131) | (0.0397) | (0.0312) | (0.0964) |
| DP_LR×creditcard | 0.0946*** | 0.0755* | 0.0480*** | 0.2447*** | 0.0068 | 0.3111*** |
| | (0.0183) | (0.0400) | (0.0151) | (0.0460) | (0.0323) | (0.1033) |
| Constant | 4.5955*** | -1.3978*** | 4.6069*** | 1.0337*** | -1.1432*** | -1.5275*** |
| | (0.0513) | (0.1129) | (0.0474) | (0.1221) | (0.1019) | (0.2618) |
| Control | Y | Y | Y | Y | Y | Y |
| Household FE | Y | Y | Y | Y | Y | Y |
| City×Year FE | Y | Y | Y | Y | Y | Y |
| Observations | 70,367 | 45,024 | 70,367 | 70,367 | 45,024 | 45,024 |
| R-squared | 0.789 | 0.279 | 0.784 | 0.752 | 0.267 | 0.280 |

**Notes:** This table reports heterogeneity estimates of the effect of digital payment (DP) use on household consumption outcomes. Columns (1)–(3)

use CPI-deflated log consumption levels for **total consumption**, **life consumption**, and **hedonic consumption**, respectively. Columns (4)–(6) use CPI-deflated consumption growth, defined as the first difference of log consumption, , for the corresponding categories. **DP_SR** is an indicator equal to 1 if the household adopts digital payments in the first year (first-year user) and 0 otherwise; **DP_LR** is an indicator equal to 1 if the household has used digital payments for more than one year and 0 otherwise. **present bias** is an indicator (or index) constructed from pre-DP credit-card usage/repayment behaviors that signal time-inconsistent preferences (e.g., procrastinated repayment, installment payment, cash advance/revolving borrowing, or stated "consume-in-advance" use). **creditcard** is an indicator equal to 1 if the household owns at least one credit card. The interaction terms allow the DP effects to vary by present-bias status and by credit-card ownership. The coefficient on DP_SR (DP_LR) captures the DP effect for households without present-bias indicators and without a credit card; the corresponding effects for other groups are obtained by adding the relevant interaction coefficients. All regressions include the baseline set of household controls and fixed effects as in the benchmark specification. All regressions include household fixed effects and city×year fixed effects; standard errors are clustered at the household level. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 7 Self-Control : Borrowing**

| VARIABLES | (1) Consumer loan | (2) Consumer loan growth | (3) Consumer loan | (4) Consumer loan growth | (5) Consumer loan | (6) Consumer loan growth |
|---|---|---|---|---|---|---|
| DP_SR | 0.1285*** | -0.0002 | -0.0571*** | -0.1840*** | -0.0181 | -0.1869*** |
| | (0.0169) | (0.0352) | (0.0185) | (0.0399) | (0.0185) | (0.0398) |
| DP_LR | 0.3154*** | -0.1171* | -0.0131 | -0.2572*** | 0.0804** | -0.2752*** |
| | (0.0282) | (0.0649) | (0.0324) | (0.0704) | (0.0322) | (0.0698) |
| DP_SR*presentbias_card | -0.3206*** | 0.2954 | | | -0.5308*** | 0.0003 |
| | (0.0923) | (0.2050) | | | (0.0954) | (0.2046) |
| DP_LR*presentbias_card | -0.9453*** | 0.1593 | | | -1.0425*** | 0.2130 |
| | (0.1074) | (0.2695) | | | (0.1132) | (0.2821) |
| DP_SR*credit_card | | | 0.6246*** | 0.8827*** | 0.6219*** | 0.8973*** |
| | | | (0.0379) | (0.0812) | (0.0386) | (0.0824) |
| DP_LR*credit_card | | | 0.6762*** | 0.7115*** | 0.7820*** | 0.6910*** |
| | | | (0.0462) | (0.1006) | (0.0465) | (0.1017) |
| Constant | 0.0026 | -0.4012** | 0.0195 | -0.3838** | 0.0400 | -0.3845** |
| | (0.0758) | (0.1600) | (0.0884) | (0.1763) | (0.0880) | (0.1763) |
| Control | Y | Y | Y | Y | Y | Y |
| Household FE | Y | Y | Y | Y | Y | Y |
| City×Year FE | Y | Y | Y | Y | Y | Y |
| Observations | 90,774 | 50,576 | 70,367 | 45,024 | 70,367 | 45,024 |
| R-squared | 0.532 | 0.221 | 0.578 | 0.244 | 0.581 | 0.244 |

Notes: This table investigates whether digital payment (DP) use affects households' consumption-related borrowing and whether the effect varies with present bias and credit card status. The dependent variables are shown in the column headings. Consumption loan measures a household's consumption-related loans (as defined in the variable appendix), and Consumption loan growth is the first difference of the log of consumption loans, constructed consistently with the benchmark growth outcomes. DP_SR equals 1 if the

household adopts digital payments in the first year (first-year user) and 0 otherwise; DP_LR equals 1 if the household has used digital payments for more than one year and 0 otherwise.

Columns (1)–(2) interact DP use with present bias, an indicator capturing strong present bias (inconsistent time preference) inferred from pre-DP credit-card usage behaviors (e.g., revolving credit, installment repayment, cash advance, or procrastinated repayment; see appendix for details). Columns (3)–(4) interact DP use with credit_card, an indicator equal to 1 if the household holds at least one credit card and 0 otherwise. Columns (5)–(6) include both sets of interactions simultaneously (horse-race specification). The coefficients on DP_SR and DP_LR capture the DP effects for the reference group (presentbias = 0 and/or credit_card = 0, depending on the column); the corresponding effects for present-biased households or credit-card holders are obtained by adding the relevant interaction coefficients. All specifications include the baseline set of controls, household fixed effects and city×year fixed effects. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 8 Self-Control : Liquidity Management**

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Liquid asset | | | Liquid asset growth | | |
| DP_SR | 0.7342*** | 0.7182*** | 0.7281*** | 0.5613*** | 0.6224*** | 0.6072*** |
| | (0.0326) | (0.0375) | (0.0378) | (0.0713) | (0.0790) | (0.0795) |
| DP_LR | 0.9385*** | 0.9451*** | 0.9721*** | -0.0028 | 0.1343 | 0.1050 |
| | (0.0513) | (0.0632) | (0.0642) | (0.1203) | (0.1341) | (0.1372) |
| DP_SR*presentbias | -0.1180 | | -0.0831 | 0.3286 | | 0.4479 |
| | (0.1083) | | (0.1168) | (0.2782) | | (0.2934) |
| DP_LR*presentbias | -0.3897*** | | -0.2884** | 0.2919 | | 0.4361 |
| | (0.1221) | | (0.1298) | (0.3146) | | (0.3307) |
| DP_SR*credit_card | | 0.0804 | 0.0631 | | -0.0572 | -0.1045 |
| | | (0.0540) | (0.0583) | | (0.1350) | (0.1408) |
| DP_LR*credit_card | | -0.0389 | -0.0022 | | -0.1366 | -0.1475 |
| | | (0.0644) | (0.0655) | | (0.1450) | (0.1469) |
| Constant | -0.7367*** | -0.6868*** | -0.6834*** | -3.2948*** | -3.2993*** | -3.3138*** |
| | (0.1479) | (0.1691) | (0.1691) | (0.3222) | (0.3482) | (0.3483) |
| Control | Y | Y | Y | Y | Y | Y |
| Household FE | Y | Y | Y | Y | Y | Y |
| City×Year FE | Y | Y | Y | Y | Y | Y |
| Observations | 90,774 | 70,367 | 70,367 | 50,576 | 45,024 | 45,024 |
| R-squared | 0.668 | 0.699 | 0.700 | 0.228 | 0.257 | 0.257 |

**Notes:** This table examines whether DP use is associated with changes in households' liquidity position and whether such effects differ by present bias and credit card status. The dependent variables are shown in the column headings. **Liquid asset** is the log of households' CPI-deflated liquid assets (as defined in the variable appendix), and **Liquid asset growth** is the first difference of the log of liquid assets. **DP_SR** equals 1 if the household adopts digital payments in the first year and 0 otherwise; **DP_LR** equals 1 if the household has used digital payments for more than one year and 0 otherwise.

Columns (1) and (4) report heterogeneity by **presentbias** through interaction terms **DP_SR×presentbias** and **DP_LR×presentbias**. Columns (2) and (5) report heterogeneity by credit card status through interaction terms **DP_SR×credit_card** and **DP_LR×credit_card**. Columns (3) and (6) include both sets of interactions simultaneously. The coefficients on **DP_SR** and **DP_LR** capture the DP effects for the reference group (presentbias = 0 and/or credit_card = 0); the corresponding effects for present-biased households or credit-card holders are obtained by adding the relevant interaction coefficients. All specifications include the baseline set of controls, household fixed effects, and city×year fixed effects. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 9 Heterogeneity by region**

| VARIABLES | (1) Total consumption | (2) Life consumption | (3) Hedonic consumption | (4) Total growth | (5) Life growth | (6) Hedonic growth |
|---|---|---|---|---|---|---|
| DP_SR | 0.0840*** | 0.0518*** | 0.2460*** | 0.0258 | -0.0023 | 0.0370 |
| | (0.0094) | (0.0081) | (0.0254) | (0.0218) | (0.0188) | (0.0574) |
| rural | -0.0888*** | -0.0635** | -0.1602** | 0.0475 | 0.0598 | -0.0707 |
| | (0.0324) | (0.0310) | (0.0751) | (0.0773) | (0.0680) | (0.1737) |
| DP_SR*rural | 0.0596*** | 0.0641*** | 0.0391 | 0.1172*** | 0.1060*** | 0.2499*** |
| | (0.0172) | (0.0151) | (0.0430) | (0.0355) | (0.0314) | (0.0893) |
| DP_LR | 0.1272*** | 0.0203* | 0.2338*** | -0.0528 | -0.1443*** | -0.5696*** |
| | (0.0143) | (0.0121) | (0.0368) | (0.0344) | (0.0290) | (0.0859) |
| DP_LR*rural | 0.0021 | -0.0123 | 0.0891 | 0.0453 | -0.0248 | 0.0916 |
| | (0.0315) | (0.0275) | (0.0799) | (0.0646) | (0.0558) | (0.1640) |
| Constant | 4.5374*** | 4.5407*** | 0.9900*** | -1.3943*** | -1.1243*** | -1.5081*** |
| | (0.0457) | (0.0419) | (0.1096) | (0.1041) | (0.0938) | (0.2408) |
| Observations | 90,774 | 90,774 | 90,774 | 50,576 | 50,576 | 50,576 |
| R-squared | 0.752 | 0.750 | 0.702 | 0.265 | 0.265 | 0.249 |

**Notes:** This table examines whether the effects of digital payment (DP) use on household consumption differ between rural and urban areas. Columns (1)–(3) report CPI-deflated log consumption levels for **Total consumption**, **Life (basic) consumption**, and **Hedonic consumption**. Columns (4)–(6) report consumption growth, defined as the first difference of CPI-deflated log consumption, for the corresponding categories: **Total growth**, **Life growth**, and **Hedonic growth**.

**DP_SR** equals 1 if the household adopts digital payments in the first year (first-year user) and 0 otherwise; **DP_LR** equals 1 if the household has used digital payments for more than one year and 0 otherwise. **rural** is an indicator equal to 1 if the household resides in a rural area and 0 otherwise. Interaction terms (**DP_SR×rural** and **DP_LR×rural**) allow the DP effects to differ between rural and urban households. The coefficients on **DP_SR** and **DP_LR** capture the DP effects for urban households (**rural = 0**); the corresponding effects for rural households (**rural = 1**) are obtained by adding the relevant interaction coefficients. All specifications include the baseline set of controls and fixed effects as in the benchmark specification (household fixed effects and city×year fixed effects). Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 10 Heterogeneity by household head age**

| VARIABLES | (1) Total consumption | (2) Life consumption | (3) Hedonic consumption | (4) Consumption growth | (5) Life consumption growth | (6) Hedonic consumption growth | (7) Life consumption share | (8) Hedonic consumption share |
|---|---|---|---|---|---|---|---|---|
| DP_SR | 0.0892*** | 0.0527*** | 0.2230*** | 0.0661*** | 0.0166 | 0.1440*** | -0.0220*** | 0.0088*** |
| | (0.0094) | (0.0082) | (0.0243) | (0.0212) | (0.0185) | (0.0530) | (0.0034) | (0.0021) |
| DP_SR*divide | 0.1248*** | 0.0059 | 0.2256*** | -0.0252 | -0.1535*** | -0.4850*** | -0.0636*** | 0.0125*** |
| | (0.0141) | (0.0120) | (0.0355) | (0.0331) | (0.0282) | (0.0802) | (0.0050) | (0.0031) |
| DP_LR | 0.0512*** | 0.0731*** | 0.1546*** | 0.0088 | 0.0766** | -0.0670 | 0.0103* | 0.0067** |
| | (0.0164) | (0.0142) | (0.0422) | (0.0373) | (0.0322) | (0.0951) | (0.0058) | (0.0034) |
| DP_LR*divide | 0.0585** | 0.1281*** | 0.1008 | -0.0089 | 0.0926** | -0.1495 | 0.0365*** | 0.0040 |
| | (0.0259) | (0.0204) | (0.0656) | (0.0543) | (0.0445) | (0.1439) | (0.0102) | (0.0059) |
| Constant | 4.5476*** | 4.5587*** | 1.0235*** | -1.3994*** | -1.1077*** | -1.5443*** | 0.9734*** | 0.0784*** |
| | (0.0459) | (0.0421) | (0.1103) | (0.1050) | (0.0945) | (0.2428) | (0.0141) | (0.0088) |
| Control | Y | Y | Y | Y | Y | Y | Y | Y |
| Household FE | Y | Y | Y | Y | Y | Y | Y | Y |
| City×Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 90,774 | 90,774 | 90,774 | 50,576 | 50,576 | 50,576 | 90,771 | 90,771 |
| R-squared | 0.752 | 0.751 | 0.703 | 0.264 | 0.265 | 0.248 | 0.502 | 0.583 |

**Notes:** This table examines whether the effects of digital payment use on household consumption differ by the household head's age. The dependent variables are shown in the column headings. Columns (1)–(3) report CPI-deflated log consumption levels for Total consumption, Life (basic) consumption, and Hedonic consumption. Columns (4)–(6) report consumption growth, defined as the first difference of CPI-deflated log consumption, for the corresponding categories: Consumption growth, Life consumption growth, and Hedonic consumption growth. Columns (7)–(8) report consumption shares: Life consumption share =Life consumption/Total consumption and Hedonic consumption share =Hedonic consumption/Total consumption. These two shares do not sum to one because total consumption includes additional consumption categories beyond life and hedonic consumption.

DP_SR equals 1 if the household adopts digital payments in the first year (first-year user) and 0 otherwise; DP_LR equals 1 if the household has used digital payments for more than one year and 0 otherwise. divide is an indicator equal to 1 if the household head is aged 60 or above and 0 otherwise. Interaction terms (DP_SR×divide and DP_LR×divide) allow the DP effects to differ for older households. The coefficients on DP_SR and DP_LR capture the DP effects for households with head age below 60; the corresponding effects for households with head age 60 or above are obtained by adding the interaction coefficients. All specifications include the baseline set of controls, household fixed effects, and city×year fixed effects. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 11 Heterogeneity by education**

| VARIABLES | (1) Total consumption | (2) Life consumption | (3) Hedonic consumption | (4) Consumption growth | (5) Life consumption growth | (6) Hedonic consumption growth | (7) Life consumption share | (8) Hedonic consumption share |
|---|---|---|---|---|---|---|---|---|
| DP_SR | 0.1381*** | 0.1450*** | 0.3507*** | 0.1141*** | 0.1557*** | 0.1972* | -0.0025 | 0.0067 |
| | (0.0191) | (0.0167) | (0.0488) | (0.0442) | (0.0384) | (0.1107) | (0.0068) | (0.0042) |
| DP_LR | 0.1226*** | 0.0867*** | 0.2981*** | -0.0595 | -0.0636 | -0.4231*** | -0.0294*** | 0.0029 |
| | (0.0288) | (0.0245) | (0.0733) | (0.0650) | (0.0552) | (0.1591) | (0.0105) | (0.0064) |
| DP_SR*education | -0.0100** | -0.0209*** | -0.0255** | -0.0135 | -0.0359*** | -0.0211 | -0.0048*** | 0.0011 |
| | (0.0046) | (0.0039) | (0.0117) | (0.0116) | (0.0098) | (0.0291) | (0.0017) | (0.0011) |
| DP_LR*education | 0.0011 | -0.0169*** | -0.0151 | 0.0060 | -0.0228* | -0.0253 | -0.0073*** | 0.0026* |
| | (0.0060) | (0.0049) | (0.0150) | (0.0146) | (0.0121) | (0.0351) | (0.0022) | (0.0014) |
| Constant | 4.5328*** | 4.5255*** | 0.9762*** | -1.4014*** | -1.1452*** | -1.5346*** | 0.9651*** | 0.0782*** |
| | (0.0458) | (0.0421) | (0.1102) | (0.1044) | (0.0943) | (0.2418) | (0.0141) | (0.0088) |
| Control | Y | Y | Y | Y | Y | Y | Y | Y |
| Household FE | Y | Y | Y | Y | Y | Y | Y | Y |
| City×Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 90,774 | 90,774 | 90,774 | 50,576 | 50,576 | 50,576 | 90,771 | 90,771 |
| R-squared | 0.752 | 0.750 | 0.702 | 0.264 | 0.265 | 0.248 | 0.502 | 0.583 |

**Notes:** This table examines whether the effects of digital payment (DP) use on household consumption vary with the household head's educational attainment. The dependent variables are shown in the column headings. Columns (1)–(3) report CPI-deflated log consumption levels for **Total consumption**, **Life consumption**, and **Hedonic consumption**. Columns (4)–(6) report consumption growth, defined as the first difference of CPI-deflated log consumption, for the corresponding categories: **Consumption growth**, **Life consumption growth**, and **Hedonic consumption growth**. Columns (7)–(8) report consumption shares: **Life consumption share** and **Hedonic consumption share**. These two shares do **not** sum to one because total consumption includes additional categories beyond life and hedonic consumption.

**DP_SR** equals 1 if the household adopts digital payments in the first year (first-year user) and 0 otherwise; **DP_LR** equals 1 if the household has used digital payments for more than one year and 0 otherwise. **education** measures the household head's educational attainment (coded as an ordered categorical variable; see variable appendix for coding). Interaction terms (**DP_SR×education** and **DP_LR×education**) allow DP effects to vary

with education. All specifications include the baseline set of controls, household fixed effects, and city×year fixed effects as indicated in the table. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 12 Heterogeneity by health condition**

| VARIABLES | (1) Total consumption | (2) Life consumption | (3) Hedonic consumption | (4) Consumption growth | (5) Life consumption growth | (6) Hedonic consumption growth | (7) Life consumption share | (8) Hedonic consumption share |
|---|---|---|---|---|---|---|---|---|
| DP_SR | 0.1086*** | 0.0762*** | 0.2425*** | 0.0544** | 0.0212 | 0.1381** | -0.0190*** | 0.0051* |
| | (0.0140) | (0.0125) | (0.0352) | (0.0232) | (0.0205) | (0.0595) | (0.0050) | (0.0030) |
| DP_LR | 0.1615*** | 0.0085 | 0.1097* | -0.0671* | -0.1996*** | -0.6030*** | -0.0793*** | -0.0108** |
| | (0.0230) | (0.0200) | (0.0560) | (0.0369) | (0.0321) | (0.0927) | (0.0085) | (0.0050) |
| DP_SR× better health | -0.0006 | -0.0229 | -0.0174 | 0.0234 | 0.0036 | 0.0154 | -0.0120* | 0.0020 |
| | (0.0197) | (0.0173) | (0.0504) | (0.0325) | (0.0287) | (0.0863) | (0.0072) | (0.0044) |
| DP_LR×better health | -0.0168 | -0.0066 | 0.0531 | 0.0233 | 0.0229 | 0.1578** | 0.0021 | 0.0127*** |
| | (0.0186) | (0.0151) | (0.0458) | (0.0311) | (0.0251) | (0.0775) | (0.0077) | (0.0047) |
| Constant | 4.5277*** | 4.5128*** | 0.8850*** | -1.4643*** | -1.2014*** | -1.6873*** | 0.9623*** | 0.0647*** |
| | (0.0699) | (0.0652) | (0.1626) | (0.1180) | (0.1080) | (0.2738) | (0.0221) | (0.0128) |
| Control | Y | Y | Y | Y | Y | Y | Y | Y |
| Household FE | Y | Y | Y | Y | Y | Y | Y | Y |
| City×Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 43,113 | 43,113 | 43,113 | 43,113 | 43,113 | 43,113 | 43,111 | 43,111 |
| R-squared | 0.790 | 0.782 | 0.755 | 0.282 | 0.267 | 0.282 | 0.562 | 0.649 |

Notes: This table examines whether the effects of digital payment (DP) use on household consumption vary with changes in the household head's health status. Columns (1)–(3) report results for CPI-deflated log consumption levels: Total consumption, Life (basic) consumption, and Hedonic consumption. Columns (4)–(6) report results for consumption growth, defined as the first difference of CPI-deflated log consumption, for the corresponding categories: Consumption growth, Life consumption growth, and Hedonic consumption growth. Columns (7)–(8) report consumption shares: Life consumption share =Life consumption/Total consumption and Hedonic consumption share=Hedonic consumption/Total consumption. These two shares do not sum to one because total consumption includes additional categories beyond life and hedonic consumption. DP_SR equals

1 if the household adopts digital payments in the first year (first-year user) and 0 otherwise; DP_LR equals 1 if the household has used digital payments for more than one year and 0 otherwise. *health_better* equals 1 if the household head becomes healthier relative to the previous survey wave and 0 otherwise; we interpret improved health as a proxy for stronger expected earning capacity and a more favorable future outlook. Interaction terms (DP_SR×*health_better* and DP_LR×*health_better*) allow DP effects to differ by health improvement status. All specifications include the baseline set of controls, household fixed effects, and city×year fixed effects. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 13 Heterogeneity by family structure**

| VARIABLES | (1) Total consumption | (2) Life consumption | (3) Hedonic consumption | (4) Consumption growth | (5) Life consumption growth | (6) Hedonic consumption growth | (7) Life consumption share | (8) Hedonic consumption share |
|---|---|---|---|---|---|---|---|---|
| DP_SR | 0.0959*** | 0.0598*** | 0.2565*** | 0.0820*** | 0.0389** | 0.1620*** | -0.0218*** | 0.0089*** |
| | (0.0095) | (0.0082) | (0.0246) | (0.0214) | (0.0187) | (0.0536) | (0.0034) | (0.0021) |
| elder | -0.1022*** | -0.0742*** | -0.1570*** | -0.0675* | -0.0144 | 0.0230 | 0.0195*** | -0.0164*** |
| | (0.0161) | (0.0147) | (0.0359) | (0.0359) | (0.0320) | (0.0789) | (0.0047) | (0.0027) |
| DP_SR*elder | -0.0046 | 0.0447* | -0.0512 | -0.1259* | -0.0293 | -0.2408 | 0.0261*** | 0.0046 |
| | (0.0293) | (0.0244) | (0.0737) | (0.0650) | (0.0545) | (0.1719) | (0.0099) | (0.0059) |
| DP_LR | 0.1258*** | 0.0121 | 0.2470*** | -0.0067 | -0.1318*** | -0.4547*** | -0.0607*** | 0.0118*** |
| | (0.0145) | (0.0124) | (0.0366) | (0.0341) | (0.0289) | (0.0829) | (0.0052) | (0.0032) |
| DP_LR*elder | 0.0023 | 0.0810** | -0.1156 | -0.2225** | -0.0168 | -0.4920* | 0.0430** | -0.0025 |
| | (0.0473) | (0.0364) | (0.1210) | (0.1104) | (0.0871) | (0.2847) | (0.0175) | (0.0115) |
| Constant | 4.5583*** | 4.5545*** | 1.0254*** | -1.3794*** | -1.1239*** | -1.5266*** | 0.9646*** | 0.0807*** |
| | (0.0457) | (0.0420) | (0.1098) | (0.1045) | (0.0945) | (0.2416) | (0.0141) | (0.0088) |
| Control | Y | Y | Y | Y | Y | Y | Y | Y |
| Household FE | Y | Y | Y | Y | Y | Y | Y | Y |
| City×Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 90,774 | 90,774 | 90,774 | 50,576 | 50,576 | 50,576 | 90,771 | 90,771 |
| R-squared | 0.752 | 0.750 | 0.703 | 0.265 | 0.265 | 0.249 | 0.502 | 0.583 |

**Notes:** This table examines whether the effects of digital payment (DP) use on household consumption vary with family structure, proxied by the presence/share of elderly household members. The dependent variables are shown in the column headings. Columns (1)–(3) report CPI-deflated log consumption levels for **Total consumption**, **Life consumption**, and **Hedonic consumption**. Columns (4)–(6) report consumption growth, defined as the first difference of CPI-deflated log consumption, for the corresponding categories: **Consumption growth**, **Life consumption growth**, and **Hedonic consumption growth**. Columns (7)–(8) report consumption shares: **Life consumption share** and **Hedonic consumption share**. These two shares do **not** sum to one because total consumption includes additional categories beyond life and hedonic consumption.

**DP_SR** equals 1 if the household adopts digital payments in the first year (first-year user) and 0 otherwise; **DP_LR** equals 1 if the household has used digital payments for more than one year and 0 otherwise. **elder** measures the elderly share of household members. Interaction terms (**DP_SR×elder** and **DP_LR×elder**) allow DP effects to differ by elderly composition. The coefficients on **DP_SR** and **DP_LR** capture the DP effects for households with **elder = 0** (reference group); for households with higher elderly composition, the corresponding DP effects are obtained by adding the interaction coefficients. All specifications include the baseline set of controls, household fixed effects, and city×year fixed effects. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 14 IV regression on consumption level**

| | Total consumption | Life consumption | Hedonic consumption | DP_SR | DP_LR |
|---|---|---|---|---|---|
| | Second stage | | | First stage | |
| DP_SR | 0.0838 | 0.1226 | 1.0971*** | | |
| | (0.1101) | (0.0992) | (0.2664) | | |
| DP_LR | 0.1185* | 0.1019* | 0.8451*** | | |
| | (0.0685) | (0.0610) | (0.1786) | | |
| DP adoption ratio in a city | | | | 1.1115*** | -0.8918*** |
| | | | | (0.0839) | (0.0531) |
| DP adoption ratio in a city * average education level of adults in a city | | | | -0.2136*** | 0.3463*** |
| | | | | (0.0213) | (0.0140) |
| Controls | Y | Y | Y | Y | Y |
| Year dummies | Y | Y | Y | Y | Y |
| Household dummies | Y | Y | Y | Y | Y |
| Kleibergen-Paap Wald rk F statistic：100.559 > 10% maximal IV size: 7.03 | | | | | |

The table shows the IV regressions of digital payment on consumption levels. The first instrumental variable is the annual coverage ratio of households using digital payment at the city level. The second instrumental variable is the product of the average education level of adults and the digital payment coverage ratio at the city level. The results prove our main results are consistent and robust. Also, we control all the control variables and do the fixed effect regressions. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively. Standard errors clustered to the city level are in parentheses.

**Table 15 IV regression on consumption change**

| | Total growth | Life growth | Hedonic growth | DP_SR | DP_LR |
|---|---|---|---|---|---|
| | Second stage | | | First stage | |
| DP_SR | 0.6416** | 0.3891 | 2.4832*** | | |
| | (0.3102) | (0.2619) | (0.8859) | | |
| DP_LR | -1.7285*** | -1.3712*** | -7.1146*** | | |
| | (0.5338) | (0.4397) | (1.6009) | | |
| DP adoption ratio in a city | | | | 0.6217*** | -0.3160*** |
| | | | | (0.1103) | (0.0617) |
| DP adoption ratio in a city * average education level of adults in a city | | | | -0.0352 | 0.1318*** |
| | | | | (0.0287) | (0.0167) |
| Controls | Y | Y | Y | Y | Y |
| Year dummies | Y | Y | Y | Y | Y |
| Household dummies | Y | Y | Y | Y | Y |
| Kleibergen-Paap Wald rk F statistic：18.624 > 10% maximal IV size: 7.03 | | | | | |

The table shows the IV regressions of digital payment on consumption changes. The first instrumental variable is the annual coverage ratio of households using digital payment at the city level. The second instrumental variable is the product of the average education level of adults and the digital payment coverage ratio at the city level. The results prove our main results are consistent and robust. Also, we control all the control variables and do the fixed effect regressions. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively. Standard errors clustered to the city level are in parentheses.

# Appendix A

**Table A.1 The baseline regressions with households who start using digital payment but stop midway**

This table presents the baseline regressions with households who start using digital payment but stop midway. To check the robustness of baseline results, we add the households who start using digital payment but quit midway into the regression sample. The results prove the robustness of our main results.

| | log(consump_all) | Δlog(consump_all) |
|---|---|---|
| DP_SR | 0.0877*** | 0.0535*** |
| | (0.0098) | (0.0198) |
| DP_LR | 0.0535*** | -0.0830*** |
| | (0.0103) | (0.0221) |
| Controls | Y | Y |
| Year dummies | Y | Y |
| Household dummies | Y | Y |
| Constant | 4.4514*** | 1.3965** |
| | (0.2682) | (0.5727) |
| Observation | 90987 | 57591 |
| Within R^2 | 0.137 | 0.086 |

# Appendix B

**Table B.1 Questions about digital payment from CHFS questionnaires**

This table shows the detailed questions about digital payment in CHFS questionnaires.

| year | Question from the CHFS Questionnaires | digital payment definition |
|---|---|---|
| 2013 | **[e2021]** Which of the following payment methods are generally used in your household's online shopping?<br>1. Online banking<br>2. Alipay App<br>3. Credit card<br>4. Tenpay<br>5. find someone to pay<br>6. cash on delivery<br>7. others | The household uses digital payment if the choice is option 1, 2 or 4; otherwise, the household does not use digital payment. |
| 2015 | **[**d2107**]** Which of the following banking services are generally used ?<br>1. Bank/Credit Union branch counter<br>2. Onling banking<br>3. Phone banking<br>4. Village inclusive financial service point<br>5. Mobile banking<br>6. Self-service banking<br>7. others<br>**[**d2122**]** What is the main purpose of using online banking for your family?<br>1. Inter-account and inter-bank transfer and remittance services<br>2. Transfer money to Alipay, Tenpay and other payment platforms<br>3. Online shopping electronic payment<br>4. Account inquiry and management services<br>5. Credit card repayment and inquiry services<br>6. Pay telephone bills, water, electricity, gas bills, cable TV bills, etc.<br>7. Others<br>**[**d2126**]** What is the main purpose of using | The household adopts digital payment to consume if the online or mobile banking is generally used (the choice option for **[**d2107**]** is 2 or 5) and the mian purpose is to transfer money to digital payment platforms or online shopping (the choice option for **[**d2122**]** is 2 or 3; the choice option for **[**d2126**]** is 2 or 3); otherwise, the household does not use digital payment to consume. |

| | | |
|---|---|---|
| | mobile banking for your family?<br>1. Inter-account and inter-bank transfer and remittance services<br>2. Transfer money to Alipay, Tenpay and other payment platforms<br>3. Online shopping electronic payment<br>4. Account inquiry and management services<br>5. Credit card repayment and inquiry services<br>6. Pay telephone bills, water, electricity, gas bills, cable TV bills, etc.<br>7. Others | |
| 2017 | **[e2001a]** Which of the following payment methods are generally used in your household's shopping (including online shopping)? (You can choose more than one answer)<br>1. Cash<br>2. Cards (including bank cards, credit cards, etc.)<br>3. Computer payment (including E-bank, Alipay, etc.)<br>4. Mobile terminal payment using cell phone or pad (including Alipay App, WeChat Pay, mobile banking, Apple Pay, etc.)<br>7777. Others (Please specify) | The household uses digital payment if the choice is option 3 or 4; otherwise, the household does not use digital payment. |
| 2019 | **[d7106d]** Now, have your family opened an third-party payment account, including Alipay, Wechat pay, Jingdong online banking wallet, Baidu wallet and etc.?<br>1. yes 2. no | The household uses digital payment to consume if the choice is option 1; otherwise, the household does not use digital payment. |

# Appendix C

**Table C.1 Households' consumption changes under different situations (1)**

This table shows several situations under cash payment and different effects of digital payment. The first situation is the households keep using cash payment in the whole period. The second situation is the households use cash payment in the first period and start to use digital payment from the second period. Also, we assume the households are only affected by the unexpected income changes effect of using digital payment. Then we calculate the actual consumption level and its growth rate in each period, which is easy to see the unexpected income changes effect of using digital payment versus using cash payment.

| | First situation | Second situation |
|---|---|---|
| Actual consumption level: | | |
| First period | $\frac{W^1}{k}$ | $\frac{W^1}{k}$ |
| Second period | $\delta(1+r)\frac{W^1}{k}$ | $\delta(1+r)\frac{W^1}{k}+\frac{1+r}{1+\delta+\delta^2}*M^2$ |
| Third period | $\delta^2(1+r)^2\frac{W^1}{k}$ | $\delta^2(1+r)^2\frac{W^1}{k}+\frac{\delta(1+r)^2}{1+\delta+\delta^2}*M^2+\frac{(1+r)^2}{1+\delta}*M^3$ |
| Last period | $\delta^3(1+r)^3\frac{W^1}{k}$ | $\delta^3(1+r)^3\frac{W^1}{k}+\frac{\delta^2(1+r)^3}{1+\delta+\delta^2}*M^2+\frac{\delta(1+r)^3}{1+\delta}*M^3+(1+r)^3*M^4$ |
| Actual consumption growth rate: | | |
| Second period | $\delta(1+r)-1$ | $[\delta(1+r)-1]+\frac{1+r}{1+\delta+\delta^2}*\frac{kM^2}{W^1}$ |
| Third period | $\delta(1+r)-1$ | $[\delta(1+r)-1]+\frac{\frac{(1+r)^2}{1+\delta}*M^3}{[\delta(1+r)\frac{W^1}{k}+\frac{1+r}{1+\delta+\delta^2}*M^2]}$ |
| Last period | $\delta(1+r)-1$ | $[\delta(1+r)-1]+\frac{(1+r)^3*M^4}{[\delta^2(1+r)^2\frac{W^1}{k}+\frac{\delta(1+r)^2}{1+\delta+\delta^2}*M^2+\frac{(1+r)^2}{1+\delta}*M^3]}$ |

Note: $\mathrm{W}^1=\sum_{j=0}^{3}\frac{{Y_{1+j}}^1}{(1+r)^j}$, $\mathrm{k}=1+\delta+\delta^2+\delta^3$, $M^2=\frac{{Y_2}^2-{Y_2}^1}{1+r}+\frac{{Y_3}^2-{Y_3}^1}{(1+r)^2}+\frac{{Y_4}^2-{Y_4}^1}{(1+r)^3}$, $M^3=\frac{{Y_3}^3-{Y_3}^2}{(1+r)^2}+\frac{{Y_4}^3-{Y_4}^2}{(1+r)^3}$, $M^4=\frac{{Y_4}^4-{Y_4}^3}{(1+r)^3}$.

**Table C.2 Households' consumption changes under different situations (2)**

This table shows the third situation only under inconsistent time preference effect of using digital payment. The third situation is the households use cash payment in the first period and start to use digital payment from the second period. Also, we assume the households are only affected by inconsistent time preference effect of using digital payment. Then we calculate the actual consumption level and its growth rate in each period.

| | Third situation |
|---|---|
| Actual consumption level: | |
| First period | $\frac{W^1}{k}$ |
| Second period | $\left(\frac{1+\delta+\delta^2}{1+\beta_2\delta+\beta_2\delta^2}\right)\delta(1+r)\frac{W^1}{k}$ |
| Third period | $\left(\frac{1+\delta+\delta^2}{1+\beta_2\delta+\beta_2\delta^2}\right)\left(\frac{1+\delta}{1+\beta_3\delta}\right)\beta_2\delta^2(1+r)^2\frac{W^1}{k}$ |
| Last period | $\left(\frac{1+\delta+\delta^2}{1+\beta_2\delta+\beta_2\delta^2}\right)\left(\frac{1+\delta}{1+\beta_3\delta}\right)\beta_2\beta_3\delta^3(1+r)^3\frac{W^1}{k}$ |
| Actual consumption growth rate: | |
| Second period | $\left(\frac{1+\delta+\delta^2}{1+\beta_2\delta+\beta_2\delta^2}\right)\delta(1+r)-1$ |
| Third period | $\left(\frac{1+\delta}{1+\beta_3\delta}\right)\beta_2\delta(1+r)-1$ |
| Last period | $\beta_3\delta(1+r)-1$ |

**Table C.3 Households' consumption changes under different situations (3)**

This table shows the third situation under both inconsistent time preference effect and unexpected income changes effect of using digital payment. The fourth situation is the households use cash payment in the first period and start to use digital payment from the second period. Also, we assume the households are affected by both inconsistent

time preference effect and unexpected income changes effect of using digital payment. Then we calculate the actual consumption level and its growth rate in each period.

| | Fourth situation |
|---|---|
| Actual consumption level: | |
| First period | $\frac{W^1}{k}$ |
| Second period | $\left(\frac{1+\delta+\delta^2}{1+\beta_2\delta+\beta_2\delta^2}\right) * [\delta(1+r)\frac{W^1}{k} + \frac{1+r}{1+\delta+\delta^2} * M^2]$ |
| Third period | $\left(\frac{1+\delta+\delta^2}{1+\beta_2\delta+\beta_2\delta^2}\right)\left(\frac{1+\delta}{1+\beta_3\delta}\right)\beta_2 * \left[\delta^2(1+r)^2\frac{W^1}{k} + \frac{\delta(1+r)^2}{1+\delta+\delta^2} * M^2\right] + \frac{(1+r)^2}{1+\beta_3\delta} * M^3$ |
| Last period | $\left(\frac{1+\delta+\delta^2}{1+\beta_2\delta+\beta_2\delta^2}\right)\left(\frac{1+\delta}{1+\beta_3\delta}\right)\beta_2\beta_3 * \left[\delta^3(1+r)^3\frac{W^1}{k} + \frac{\delta^2(1+r)^3}{1+\delta+\delta^2} * M^2\right] + \frac{\beta_3\delta(1+r)^3}{1+\beta_3\delta} * M^3 + (1+r)^3 * M^4$ |
| Actual consumption growth rate: | |
| Second period | $\left(\frac{1+\delta+\delta^2}{1+\beta_2\delta+\beta_2\delta^2}\right)[\delta(1+r) + \frac{1+r}{1+\delta+\delta^2} * \frac{kM^2}{W^1}] - 1$ |
| Third period | $\left(\frac{1+\delta}{1+\beta_3\delta}\right)\beta_2\delta(1+r) - 1 + \frac{\frac{(1+r)^2}{1+\delta} * M^3}{[\delta(1+r)\frac{W^1}{k} + \frac{1+r}{1+\delta+\delta^2} * M^2]}$ |
| Last period | $\beta_3\delta(1+r) - 1 + \frac{(1+r)^3 * M^4}{[\delta^2(1+r)^2\frac{W^1}{k} + \frac{\delta(1+r)^2}{1+\delta+\delta^2} * M^2 + \frac{(1+r)^2}{1+\delta} * M^3]}$ |