In victory or defeat:

Consumption responses to wealth shocks*

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Abstract

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Keywords: Wealth shocks, Consumption responses, Behavioral finance, Individual investors, Financial retail therapy, Digital payment data

JEL: D10; D14; G12; G41; G51

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†† The authors acknowledge and appreciate the supports from the Digital Finance Open Research Platform (www.dfor.org.cn). All data is sampled, desensitized, and stored on the Ant Open Research Laboratory in an Ant Group Environment, which is only remotely accessible for empirical analysis.

"*I could not live without Champagne. In victory I deserve it. In defeat I need it...*"
Perhaps by Winston Churchill (1946)

1. Introduction

How do households adjust their consumption after experiencing large negative wealth shocks? Will they cut unnecessary consumption to make up for the losses or, on the contrary, increase certain consumption to deal with the adverse psychological shocks of wealth losses? Using a unique representative sample of detailed digital payment and mutual fund investment data at both weekly and monthly frequencies, we investigate how individuals change their consumption patterns shortly after experiencing large wealth shocks. Our results bring new insight into the short-term relation between consumption and wealth by providing novel evidence that individuals increase consumption—particularly that of a "hedonic" nature—following large positive *and* negative shocks.

The consumption-wealth relation has been highlighted as one of the main channels through which stock markets affect the economy. Understanding this relation and the mechanism behind it is of long-standing importance to policy makers (Cieslak and Vissing-Jørgensen, 2021). A large number of studies have studied and estimated people's marginal propensity to consume (MPC) from wealth. However, due to the lack of exact information on individuals' consumption and wealth shocks, these studies have primarily relied on survey data (e.g., Dynan and Maki, 2001; Baker, Nagel, and Wurgler; 2007; Paiella and Pistaferri, 2017) or indirect methods such as imputing consumption as a residual of other transactions (e.g., Di Maggio, Kermani, and Majlesi, 2020; Koijen, Van Nieuwerburgh, and Vestman, 2015; Kolsrud, Landais, and Spinnewijn, 2019).[1]

Although estimates in the aforementioned studies vary, the evidence generally suggests that wealth shocks positively affect individuals' consumption. However, none of the existing studies examine the influence of short-term positive and negative wealth shocks separately, implicitly assuming that the effect of the shocks on consumption is linear. Meanwhile, different streams of literature provide mixed guidance on how negative wealth shocks affect individuals' consumption. On the one hand, under conventional economic models, individuals experiencing large losses should reduce current consumption of inessential goods and services to smooth future consumption. On the other hand, large negative stock market shocks are events that induce anxiety, sadness, and stress (e.g., Engelberg and Parsons, 2016; Bernstein et al., 2021; Lin and Pursiainen, 2023).

The behavioral economics and psychology literatures suggest that such losses may increase consumption of "hedonic" goods and services that would allow the individuals to psychologically recover from distress. Prior work has shown that distress can indeed encourage unplanned purchases, which is termed "retail therapy" (e.g., Rick, Pereira, and Burson, 2014). Atalay and Meloy (2011) propose that such distress-motivated consumption can be strategically motivated to repair bad moods. In a series of lab

[1] Recent work by Baker, Farrokhinia, Meyer, Pagel, and Yannelis (2021) has used transaction data from a FinTech app to examine MPC from CARES Act stimulus payments. In contrast to theirs, our paper focuses on responses to negative wealth shocks.

experiments, the authors find that retail therapy has long-lasting positive impacts on mood such that the unplanned purchases do not lead to guilt or regret.

We show that consumption increases after a financial gain *or* loss are consistent with the dynamic predictions of Prospect Theory (Kahneman and Tversky, 1979; Barberis, 2012; Imas, 2016; Heimer, et al., 2020). The intuition, which is outlined formally in Appendix A.1, is as follows. After a negative shock, the positive upside of consumption is evaluated jointly with the loss and allows the person to recover from it. After a positive shock, the cost component of consumption is jointly evaluated with the gain, decreasing its weight in decision-making. The positive shock absorbs the price of consumption, allowing the investor to enjoy the experience without focusing on the cost. Importantly, in both cases, the "hedonic" consumption—in the sense that the individual derives utility in the same period as the purchase decision—is expected to change the most; other types of consumption, e.g., durables, are predicted to increase relatively smaller.

The framework predicts a *U*-shaped relation between wealth shocks and consumption, where consumption increases following both positive and negative fund holdings movements. Accordingly, we propose our first hypothesis that *in response to negative wealth shocks, individuals tend to temporarily increase their consumption as a retail therapy.* We also anticipate a stronger short-term surge in consumption specifically associated with "hedonic" attributes following negative wealth shocks. We thus propose the second hypothesis that *in response to negative wealth shocks, the increase in consumption is more pronounced for that with a "hedonic" nature.*

We begin our empirical investigation with an illustrative laboratory experiment that examines the predicted consumption *U*-shape in a controlled environment. Participants were recruited and randomly assigned to either a "neutral" or "gain-or-loss" condition. In the neutral condition, participants were endowed with a sum of money; in the gain-or-loss condition, they were endowed with the same amount of money and engaged in a financial investment task. The latter group experienced gains or losses as a result. All participants then faced a tradeoff between labor and leisure by deciding how much time to spend on an unpleasant task for additional compensation; time not allotted to the unpleasant task could be used for more pleasant activities such as browsing the internet, watching videos, etc. Consistent with the predictions outlined above, participants allocated substantially more time to pleasant activities—at a significant opportunity cost to themselves—in the gain-or-loss condition than in the neutral condition. Importantly, they were more willing to sacrifice compensation for a more pleasant experience after both financial gains *or* losses, and this relation increased with the magnitude of each outcome.

Given this motivating evidence, we proceed to test our predictions in real-world behavior utilizing four unique data sets from Ant Group, the Fintech giant in China.[2]

[2] The utilization of the four datasets is motivated by their unique strengths and limitations. The data set provided by Ant Financial has a limitation on the total number of observations. Hence, there are tradeoffs between number of accounts users (cross section), or number of periods (time series), or the frequency of observations (weekly vs. monthly). The detailed information of each data set is provided in Table 1.

Ant Group is the parent company of Alipay, China's dominating digital payment firm with about one billion users and more than 55% of the third-party digital payments market share. Alipay surpassed PayPal as the world's most popular mobile payment platform in 2013 and maintains the top spot afterward.[3] Additionally, Ant Group provides mutual fund distribution services through its Ant Fortune platform via Alipay. According to the Ant Group's IPO prospectus, as of June 2020, it has emerged as the largest online investment services platform in China, with assets under management matched and distributed through its platform totaling RMB 4.1 trillion. Given Alipay's status as the leading digital wallet in China and its connection to the Ant Fortune, we are able to establish a link between individuals' consumption data and their mutual fund investment data.

Our empirical results can be epitomized in Figure 1. The seven bins are constructed conditional on sample individuals' mutual fund investment returns experienced in month *t*. Across the seven bins, the median of sample individuals' consumption made through Alipay in month *t*+1 is plotted. In Bin 4, where wealth shocks are close to zero, the median monthly consumption stands at around 2,479 CNY, the lowest across the seven bins. More importantly, consumption increases from Bin 4 to 1, despite individuals encountering increasingly negative wealth shocks. In Bin 1, where individuals have just experienced the worst financial wealth shocks, median monthly consumption is 2,649 CNY, 6.9% higher than the benchmark group (Bin 4). This finding deviates from traditional models but aligns with our first hypothesis that

[3] https://merchantmachine.co.uk/the-countries-most-reliant-on-cash-in-2022/

individuals turn to retail therapy as a means of coping with the distress caused by financial setbacks.

[Insert Figure 1 about here]

We then perform formal regression analyses. Our baseline tests are conducted using weekly individual-level consumption and fund investment data for a sample of 20,000 unique individuals from August 2017 to July 2021.[4] We find a robust *U-shaped* relation between individuals' consumption and financial wealth shocks across all four datasets. In particular, the results hold irrespective of using the consumption and investment return data at weekly or monthly frequency. The results are also qualitatively similar when we use individuals' fund investment return or market index return to capture wealth shocks. The advantage of using individuals' fund investment return is that it better reflects the variation in wealth shocks across individuals. The advantage of using market index return is that it helps alleviate concerns about the representativeness of fund investment return as a proxy for wealth shocks. Throughout the tests, we account for both time and individual fixed effects. Adding time fixed effect helps mitigate concerns related to consumption seasonality, such as spending surges during events like the Chinese Double Eleven Shopping Festival or traditional holidays

[4] The other three datasets contain information on consumption breakdown or individuals' income records and encompass samples ranging in size from 40,000 to 160,000 unique individuals. As we are not able to obtain a single dataset with all the merits of the four, we use these alternative datasets to provide a more in-depth analysis of the short-term relation between consumption and wealth shocks from different angles.

such as the Spring Festival. Moreover, adding individual fixed effects controls potential influences from individual unobserved time-invariant factors.

Consistent with our second hypothesis, the increase in consumption is particularly prominent in the entertainment-related category compared to others, such as the living- or development-related category, after negative wealth shocks. Upon closer examination of consumption within the entertainment category, consumption subcategories with a stronger "hedonic" nature, such as accessories and cosmetics, exhibit a greater increase following individuals' financial losses. Notably, the absence of a decrease in living and development consumption suggests that the *U*-shaped pattern in entertainment-related consumption is not due to substitution. Total consumption also increases after a negative financial shock, primarily driven by, as the theoretical framework predicts, a response in entertainment-related consumption.

One may be concerned that the *U*-shaped result could be attributed to the relaxed liquidity constraints for our sample individuals after redeeming their losing funds. However, intuitively, the disposition effect would make these individuals more reluctant to sell their mutual funds with losses (e.g., Shefrin and Statman, 1985; Odean 1998; Barberis and Xiong, 2009; Frydman and Wang, 2020). To further address this concern, we conduct tests using subsamples that exclude observations with selling of losing funds in the previous period, selling of winning funds in the previous period, or selling of any funds in the previous periods. The result shows that the estimated coefficients of the variables in interest closely resemble those in the baseline tests.

Finally, we repeat baseline tests using the alternative data set that consists of 160,000 randomly selected Taobao entrepreneurs with data on both their Alipay consumption and business income from the Taobao platform.[5] With this alternative data set, we can control for income effects, which might change over time and thus not be captured by the individual fixed effect. We find qualitatively similar results.

Our study adds to several streams of the literature. First, we expand the studies on the relation between wealth shocks and consumption, which mainly focus on estimating the MPC following wealth shocks. For instance, Baker, Nagel, and Wurgler (2007) show that individuals' consumption is more likely to increase following wealth shocks from dividend income than from capital gains. Using the 2006 to 2009 housing collapse, Mian, Rao, and Sufi (2013) find that the average MPC of housing wealth is five to seven cents but varies considerably across ZIP codes. Paiella and Pistaferri (2017) show that the wealth effect is about three cents per (unexpected) euro increase in wealth and driven by house price changes. Aladangady (2017) finds that a one-dollar increase in home values results in a 4.7-cent increase in spending for homeowners. Di Maggio et al. (2020) estimate the MPC separately for capital gains and dividend income and show that wealth shocks from both sources affect individuals' consumption behavior but to different degrees. Baker et al. (2021) document a positive consumption response to

[5] Taobao is an online shopping platform for small businesses and individual entrepreneurs to open online stores that cater to individual consumers. According to Alexa rank, it is the eighth most-visited website in the world in 2021.

CARES Act stimulus payments but show that the size of the MPC depends on household liquidity as well as other sources of variation.[6]

Our study differs from prior work by documenting a striking *U*-shaped pattern in both experimental and high-frequency observational data. The results show that individuals tend to increase rather than decrease their short-term consumption, especially "hedonic" consumption after negative wealth shocks, a phenomenon we term *financial retail therapy*. We document this pattern by constructing a novel dataset that links large-scale and detailed individual-level weekly and monthly consumption with their fund investment data. Such a unique dataset allows us to examine: (1) individuals' *actual* consumption behavior rather than relying on reported consumption from surveys or imputed measures from other forms of transaction data and (2) individuals' short-term response to direct exposure to wealth shocks. The detailed individual-level consumption data facilitate a variety of robustness tests and help us further identify the proposed mechanism.

Second, our paper is related to recent studies on the psychological and behavioral consequences of wealth shocks. Engelberg and Parsons (2016) show that stock price movements affect the psychological conditions of investors, where large share price declines increase hospitalization rates. Bernstein, Maquade, and Townsend (2021) show that negative wealth shocks adversely affect the productivity of innovative

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[6] There is also another line of researches that examines the relation between individuals' financial wealth and consumption, but from an opposite perspective. For example, Ben-David and Bos (2021) shows that improving the convenience of impulsive consumption among individuals can worsen their financial well-being.

workers, which could result from their increased psychological distress and the reduction of resources that support productivity in wage employment.[7] Lin and Pursiainen (2023) find that stock market losses may trigger intimate partner violence due to escalated levels of stress. We contribute to this literature by investigating how individuals cope with negative wealth shocks. While the aforementioned studies highlight the negative psychological consequences of wealth shocks, we show that people may seek to alleviate this distress by increasing "hedonic" consumption. Finally, we add to the psychology literature on retail therapy by providing evidence from real-world field data.

2. Experimental evidence

We begin our investigation by providing initial evidence for the proposed *U*-shaped consumption relation in an experimental setting. This exercise allows us to directly test the predictions of how financial shocks impact consumption while accounting for potential unobservable factors that may be present in observational data. The experiment thus helps motivate the empirical investigation that follows by demonstrating the predicted effects in a controlled setting.

2.1 Methods

We recruited 283 participants from Prolific Academic Ltd (Prolific), an online crowdsourcing platform.[8] All were paid a $1.00 base fee for completing the study.

[7] In contrast, Li, Qian, Xiong, and Zou (2022) document a negative relation between monthly income from stock market investments and the investors' next-month work output.

[8] Gupta, Rigotti, and Wilsondoes (2021) summarizes the superiority of Prolific for conducting online experiments over Amazon Mechanical Turk and even the physical lab. In a nutshell, Prolific better curates the subject pool to make sure that participants are attentive and meet all of the qualification

The setup of the study largely follows the theoretical exercise outlined in Appendix A.1. Participants were randomly assigned to one of two conditions: the "neutral" condition and the "gain-or-loss" condition. In the neutral condition, participants were endowed with $1.00 and asked to solve a series of anagrams for two minutes; in the gains-or-loss condition, participants were given the same $1.00 to invest in four rounds of an investment task.

The investment task consisted of four successive rounds of investment decisions.[9] In each round, participants could choose how much of $0.25 they would like to invest in a lottery and how much to keep; they could invest any amount between $0 and $0.25 in one-cent increments. Participants were told that the lottery would "succeed" with a chance of 1/6 (17%) and they would make 6 times the amount invested; it would "fail" with a chance of 5/6 (83%) and they would lose the money invested. In each round, participants indicated the amount they would like to invest by moving a slider to a number between $0 and $0.25. Importantly, participants' prior gains and losses did not affect the amount they could invest in each round.

Whether the lottery succeeded or failed was determined as follows: in each round participants were assigned one "success number" between 1 and 6, which was displayed on the computer screen. After they indicated their investment amount, they were taken to a page where they could virtually roll a six-sided die. If the outcome equaled their

requirements (e.g., English speaking, gender, etc). As a result, there is much less noise in the data than other platforms.

[9] This task has been used to study myopic loss aversion and other financial anomalies (see Haigh and List, (2002), Gneezy and Potters (1997), and Imas (2016)).

success number (1/6 chance), then the lottery "succeded;" if the outcome was any other number (5/6 chance), then they lost the amount invested. A new success number was assigned after each round.

Both the lottery outcome and the investment earnings were reported in each round. At the end of the four rounds, participants' game payment was $1.00 (initial endowment) plus the earnings (gains and losses) from investments. The game payment was delivered in the form of a bonus.

After completing the tasks in the respective conditions, participants were told about a potential option to work on another task involving rating pictures of various irksome images on their level of unpleasantness for up to 60 minutes. This task was pre-tested to be generally disagreeable, such that the vast majority of people would be willing to pay money not to engage in it. Participants decided how to allocate 60 minutes between working on unpleasant tasks for money or a more enjoyable activity such as browsing the web and/or watching videos. This setup was meant to emulate the standard labor versus leisure tradeoff, where the person chooses "hedonic" consumption at the opportunity cost of financial remuneration. In our context, the "hedonic" consumption is the leisure (i.e., not rating irksome images). The allocation decision was incentivized using a version of the classic Becker-DeGroot-Marschak mechanism. Each participant was told that if the number of minutes they allocated to work on the task was larger than a random integer *P* between 0 and 60, they would complete the task for *P* minutes and receive $12.00; otherwise, they would not complete any tasks and receive $0.

We predicted that participants would allocate fewer minutes to working on the task, thus consuming more leisure, after experiencing both gains *and* losses ("gains-or-loss" condition) compared to the "neutral" condition. More importantly, since the size of gains and losses in the gain-or-loss condition are naturally confounded with risk preferences, among other endogenous factors, our analyses mostly focus on the Intention-to-Treat (ITT) method of comparing behavior across randomly-assigned treatments. This comparison allows us to identify a conservative causal effect of experiencing gains and losses compared to the neutral condition.[10]

2.2 Results

We find that participants in the gain-or-loss condition allocated nearly 20% less time to unpleasant activities than those in the neutral condition (29.8 vs. 36.2 minutes; $p = 0.01$). Looking at the binary distinction between a gain or a loss within the gain-or-loss condition, participants decreased their work minutes by 9.38 minutes after a gain and 12.04 minutes after a loss; this difference was not significant ($p > .8$). Finally, we can look at whether the *size* of the absolute return impacts the time allocated to unpleasant tasks. Regressing the number of allocated minutes on the size of the absolute return indeed reveals a significant effect ($\beta = -8.91$; $p = 0.018$).

[10] The estimated effect is conservative since some people in the gain-or-loss condition did not experience gains or losses.

These results provide initial evidence for a positive consumption response to financial gains *and* losses. We now proceed to investigate this relation in real-world behavior.

3. Institutional background and data

3.1 Institutional background: Alipay and Ant Fortune

Our data on individual-level consumption and fund investment is sourced from the Ant Group. Ant runs China's super app, Alipay, which is the dominating digital wallet in China and has emerged as the world's most popular mobile payment platform since 2013, followed by WeChat Pay, Google Pay, and PayPal with a wide margin. Alipay is integrated with all kinds of mini-programs and platforms, including the Ant Fortune, which is the largest online investment services platform in China measured by asset under management. We are thus able to link an individual's actual consumption data with his investment data. Data from Alipay was sampled and de-identified by the Ant Group Research Institute and stored in the Ant Open Research Laboratory in the Ant Group Environment.[11] The laboratory is a sandbox environment where the authors can remotely conduct empirical analysis and identifying information is not visible.

3.1.1 Alipay and its payment service

As disclosed by the IPO prospectus of the Ant Group, Alipay had 711 million monthly active users and over 1 billion annual active users in mainland China as of June 2020. At that point, the total volume of digital payment transactions on Alipay reached a

[11] https://www.dfor.org.cn/research/laboratory.

staggering 118 trillion yuan over the preceding 12 months, accounting for approximately 55% of the payment market share in China.

Through Alipay, we are able to analyze individuals' total consumption and its online and offline components. Alipay was established in 2004 to create trust between online sellers and buyers and facilitate trades and payments on Taobao, which is the e-commerce platform of Alibaba Group. Alipay is operated under Ant Group, while Taobao is run by Alibaba Group, which owns a roughly 33% stake in Ant Group.[12] In 2020, China's online retail sales were $1,414 billion, almost twice as large as those in the U.S., which is the 2nd largest e-commerce market. E-commerce in China accounts for 25% of its country-wide retail sales, compared to 14% in the U.S. While online retail sales in China make up 33% of total global e-commerce, three companies account for 89% of the total e-commerce market, and Taobao is on top of the list with 265.9 million visits per month. Taobao is now the world's largest e-commerce website and even surpasses popular online marketplaces such as Amazon. All transactions made on Taobao can only be settled through Alipay.

Although Alipay was invented to facilitate online trades and payments in the beginning, it is also widely used for offline consumption nowadays. Users could simply pay for offline consumption through scanning the QR-codes of Alipay, which is provided almost in all shops in China, even including street venders. In the datasets used in this study, we obtain information on sample individuals' total consumption

[12] In 2011, Alipay was transferred from Alibaba Group, a foreign-funded enterprise, to Zhejiang Alibaba to obtain its payment license in China. In June 2014, Zhejiang Alibaba was rebranded as Ant Financial, which was renamed again in July 2020 as Ant Group.

settled through Alipay, including both online and offline consumption. For some of the datasets we have obtained, the Ant further classifies online consumption into three categories (entertainment-related, living-related, and development-related consumption) and even subcategories. For offline consumption, however, consumption breakdown is not feasible as the Ant does not possesses such information.

3.1.2 Ant Fortune

Alipay is embedded with various platforms of the Ant Group, with Ant Fortune being one of them. Licensed Tech firms independent of fund families, brokers, and banks are allowed to distribute mutual funds on their platforms in China since 2012. Ant entered the platform business in 2015 after acquiring a mutual fund distribution license. The platform mutual fund distribution quickly becomes popular in China and Ant emerges as a leading player. According to Hong, Lu, and Pan (2023), platform distribution offers benefits for both investors and funds by “allowing both parties to access a broader market.” As more investors join a platform, the customer acquisition cost for funds is significantly reduced, enabling them to provide substantial discounts on subscription rates to investors on the platform. For example, while the subscription rate is typically 1.5% for investors subscribing to mutual funds through traditional channels like commercial banks, those subscribing through a mutual fund distribution platform like Ant Fortune can enjoy rates as low as 1.5‰. Additionally, investors can benefit from the convenience of managing their entire portfolio on a single platform, along with the reduced subscription fees.

According to the IPO prospectus of the Ant Group, Ant Fortune is China's largest online wealth management platform measured by asset under management (AUM), reported to be RMB 4,099 billion as of June 30, 2020. Ant Fortune partners with approximately 170 asset managers, including the vast majority of mutual fund companies and leading insurers, banks, and securities companies, offering over 6,000 mutual fund products to Alipay users. By the end of September 2021, the Ant Fortune has reached a distribution size of RMB 1.20 trillion, surpassing the second channel (the China Merchants Bank) by around 40%, and the third (Tiantian Fund Distribution) by over 100%.[13]

Given the wide popularity of wealth management platform in China and Ant Fortune's top position in this business over years, individuals' financial performance on this platform could reflect their financial wealth shocks in a representative way. Figure A1 displaces how Ant Fortune could be accessed through Alipay. The screenshot in the middle of Figure A1 depicts the interface of Ant Fortune, where an individual's mutual fund investment gains or losses are prominently displayed in the up right corner.

[Insert Figure A1 about here]

[13] https://www.amac.org.cn/researchstatistics/datastatistics/fundsalesindustrydata/

3.2. Data

3.2.1 Dataset features

We obtain four datasets from the Ant Group, all of which were randomly sampled at the individual account level. Each dataset has its strengths and limitations in terms of data frequency, sample size, length of sample period, or variable availability. As it is not feasible to compile a single dataset that encompasses the strengths of all four, we conducted our empirical investigation using these separate datasets. We test our main hypothesis, H1, using all four datasets to ensure the robustness of our results. Furthermore, we leverage the strengths of the different datasets to provide more in-depth evidence from various angles in support of our conjectures. Detailed information about the four datasets is summarized in Table 1.

[Insert Table 1 about here]

The initial dataset, Dataset 1, consists of 20,000 randomly selected Alipay users who have both consumption and Ant Fortune investment records. The data is available on a weekly basis over a 48-month period from August 2017 to July 2021. This dataset offers detailed information on individuals' investment records and total consumption at a high frequency, but does not have information on consumption breakdowns. Given its high frequency, this dataset is particularly suitable for testing short-term wealth effects on consumption decisions, and is therefore used for testing H1.

The second dataset, Dataset 2, comprises 100,000 randomly selected Alipay users with both consumption and Ant Fortune investment records. The data is available on a monthly basis over a 48-month period from August 2017 to July 2021. Dataset 2 has a lower frequency than Dataset 1, but includes information on individuals' Ant Fortune investment records, total consumption, and consumption breakdowns (living-, development-, and entertainment-related consumption). Therefore, Dataset 2 is particularly suitable for testing H2, which examines the variation in response to wealth shocks across different consumption categories.

The third dataset, Dataset 3, consists of 40,000 randomly selected Alipay users. This dataset is available on a monthly basis, covering a 24-month period from August 2017 to July 2019. It does not include information on individuals' Ant Fortune investment records, thus we can only use monthly market index return to proxy for concurrent individuals' financial wealth shocks. However, this dataset further divides entertainment-related consumption into nine subcategories (accessories, cosmetics, sports, household appliances, car-related, recreation services, travel, dining, and living services.), enabling us to identify those with typical "hedonic" characteristics, such as accessories and cosmetics. This dataset is thus utilized to advance the testing of H2 by examining individuals' consumption response to wealth shocks based on subcategories within entertainment-related consumption.

The last dataset, Dataset 4, contains 160,000 randomly selected Taobao entrepreneurs with data on both their Alipay consumption and business income from the Taobao platform.[14] This sample enables us to connect individuals' consumption with their business income data. The data is accessible on a monthly basis for a 24-month period from August 2017 to July 2019. Again, this dataset does not have individuals' Ant Fortune investment records, therefore monthly market index return is used as a proxy for their financial wealth shocks. Nevertheless, the availability of business income data in this dataset allows us to investigate the impact of wealth on consumption decisions while controlling for the income effect.

3.2.1 Summary statistics

Table A1 in the Appendix demonstrates the process of deriving the final sample for each of the four datasets. Table 2 presents summary statistics of the main variables used in each sample, with their definitions described in Table A2. Panel A of Table 2 shows that in Dataset 1, the average weekly consumption for sample individuals is CNY 1,091.[15] Panel B shows that the average monthly consumption of sample individuals in Dataset 2 is CNY 5,679, with a median of CNY 2,556. Within this sample, online consumption accounts for approximately 28.1% of total consumption. Within online consumption, around 28.5% is allocated to entertainment-related purchases, which

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[14] Taobao is an online shopping platform for small businesses and individual entrepreneurs to operate online stores. According to Alexa rank, it is the eighth most-visited website in the world in 2021.

[15] According to China's National Bureau of Statistics, the average annual consumption for urban residents in China is 30,307 CNY, which could be translated into an average weekly consumption of 583 CNY. The data could be found here: www.stats.gov.cn/sj/zxfb/202302/t20230203_1901342.html.

The higher average weekly consumption data in our sample, relative to that reported by China's National Bureau of Statistics, may be attributed to the fact that typical Alipay users fall within the age range of 30-40, who are likely to have higher income and consumption than the national average. The requirement that sample individuals must have investment data with the Ant Fortune might further skew our sample towards a population with a better financial position than the average.

represents roughly 8.0% of the total consumption. Panels C shows that in Dataset 3, sample individuals' average monthly entertainment-related consumption is CNY 404, which is close to that in Dataset 2 (CNY 455). It confirms that sample individuals are comparable across datasets. Summary statistics of Dataset 3 further shows that around 55.2% of sample individuals' entertainment-related consumption is allocated to typical entertainment-related consumption, namely for purchases of accessories and cosmetic. In Dataset 4, as shown in Panel D, the average monthly consumption (CNY 10,188) is much higher than that in Dataset 2, which is not surprising as individuals in this dataset run their own business on Taobao. The average monthly income of this sample is CNY 23,698, about two times of average monthly consumption.

[Insert Table 2 about here]

As mentioned in Section 3.2.1, Datasets 1 and 2 have information on individuals' Ant Fortune investment records, while Datasets 3 and 4 do not. Therefore, for samples derived from Datasets 1 and 2, we can utilize both individual- and market-level measures to capture financial wealth shocks that sample individuals have encountered. For samples from Datasets 3 and 4, only market-level measures can be used to proxy for wealth shocks. Since our focus is on the distinct impact of positive and negative wealth shocks on consumption decisions, we present separate summary statistics of these shocks in Table 2. The individual-level wealth shock variable $Positive\ invest\ ret_{i,t}$ ($Negative\ invest\ ret_{i,t}$) equals i's investment return on Ant Fortune in period t if it is positive (negative) and zero otherwise. The market-level wealth shock variable *Positive* *mkt* ret_t (*Negative mkt* ret_t) equals the value-weighted stock market returns of Chinese A-share market in period *t* if it is positive (negative) and zero otherwise.

4. Empirical investigation utilizing individual-level data from the Ant

4.1 Affirming the U-shaped relation: Baseline regressions

We initiate the regression estimations by utilizing Dataset 1, which consists of weekly individual-level consumption and investment data. We test H1 using Eq. (1):

$$Ln(total\_csmp)_{i,t+1} = \alpha+\beta_1 \cdot Positive\ invest\ ret_{i,t} + \beta_2 \cdot Negative\ invest\ ret_{i,t} + controls_{t+1} + \varepsilon_{i,t+1}, \quad (1)$$

where the dependent variable is the natural logarithm of individual *i*'s total consumption in week *t+1*. If individuals increase their consumption after experiencing positive (negative) financial wealth shocks, β_1 (β_2) should be significantly positive (negative), and vice versa. Week and individual fixed effects are both controlled and the standard errors are clustered at the individual level. Results are reported in Table 3.

[Insert Table 3 about here]

Column (1) shows that β_1 and β_2 equal to 0.753 and −0.497, respectively, both of which are significant at the 1% level. It confirms the *U*-shaped relation, as illustrated in Figure 1, between individuals' short-term consumption and the financial wealth shocks they have just encountered. The results are robust to the control of past consumption in column (2). In columns (3) and (4), *Positive mkt* ret_t and *Negative mkt* ret_t are included in the regression as additional proxies for market-wide wealth shocks.[16] The coefficients on both positive individual- and market-level financial wealth shock measures are significant positive, while the coefficients on both negative individual- and market-level financial wealth shock measures are significant negative.

Collectively, results in Table 3 show strong and robust evidence that the short-term relation between individuals' financial wealth shocks and their consumption is *U*-shaped: individuals consume more when they experience larger positive *or* negative financial wealth shocks in the previous week. The positive consumption response to a negative wealth shock points to a psychological mechanism where the individuals attempt to recover from financial distress through consumption. The results render support to H1.

4.2. Variation conditional on the "hedonic" nature of consumption

If the heightened spending triggered by adverse wealth shocks is indeed a form of retail therapy, as we have posited, this impact is likely to be most pronounced in the consumption of goods and services that provide greater "hedonic" satisfaction, as outlined in H2. In this section, we conduct further tests using Datasets 2 and 3, which have a lower frequency (monthly) than Dataset 1 but provide more detailed information on consumption breakdowns.

[16] When including the weekly market index return in regressions, controlling for week fixed effects is not feasible. Therefore, in columns (3) and (4) of Table 3, we control for individual and year-month fixed effects.

4.2.1 Consumption breakdown: Living-, development-, and entertainment-related consumption

As stated in Section 3.1.1, Alipay is commonly used for both online and offline transactions. Ant Group further classifies online consumption into three groups: entertainment, living, and development. Entertainment consumption involves non-essential purchases such as accessories, cosmetics, and travel. Living consumption encompasses essential purchases like groceries, while development consumption pertains to education, training, and books. Among these categories, entertainment-related consumption undoubtedly has the greatest potential to provide "hedonic" satisfaction.

We leverage Dataset 2, which contains monthly individual-level investment and consumption breakdown information, to explore the variability in consumption response to wealth shocks across the three consumption categories. The results are reported in Table 4.

[Insert Table 4 about here]

Columns (1) to (3) replicate the baseline tests from Eq. (1) using Dataset 2 with monthly frequency. The findings are consistent with those presented in Table 3, which utilizes Dataset 1 with weekly frequency: the coefficients on *Positive invest* $ret_{i,t}$ and *Negative invest* $ret_{i,t}$ are significantly positive and negative, respectively, at the 1% level. The results suggest that the *U*-shaped pattern identified in Section 4.1 is not unique to the sample used, and that the pattern remains robust when examining online and offline consumption separately.

Further, we repeat the tests for entertainment-, living-, and development-related consumption separately in columns (4) to (6). The Ant Group only categories consumption for online consumption, thus offline consumption is excluded for this consumption category-based analysis.[17] As long as sample individuals' payment habits (online vs. offline) do not change dramatically during the sample period, focusing on online consumption information only should not systematically bias our results.

The results are supportive of our conjecture: the coefficient on *Negative invest ret*$_{i,t}$ is of the greatest magnitude in column (4) where entertainment-related consumption is examined, is almost halved in column (5) where living-related consumption is considered, and turns to be indistinguishable from zero in column (6) where development-related consumption is analyzed.

It is also worth noting that when total consumption is examined using Dataset 1 in Table 3 or using Dataset 2 in column (1) of Table 4, the magnitude of the coefficient on *Negative invest ret*$_{i,t}$ is smaller than that of the coefficient on *Positive invest ret*$_{i,t}$. When entertainment consumption is examined separately in column (4) of Table 4, however, the magnitude of the coefficient on *Negative invest ret*$_{i,t}$ is approximately twice that of the coefficient on *Positive invest ret*$_{i,t}$. This suggests that the increase in

[17] The Ant performs consumption calcification based on information provided by Taobao, where online consumption is made. For offline consumption, however, such classification is not feasible as no additional information about the purchase is transferred back to the Ant.

entertainment consumption following negative wealth shocks is much greater than that following positive wealth shocks.

Taken together, the results suggest that although individuals generally increase their total consumption after experiencing financial losses, the increase is the most pronounced in entertainment-related consumption. The evidence is compatible with our conjecture that individuals use consumption, especially "hedonic" consumption, to alleviate financial distress and renders support to H2.

4.2.2 Subcategories within entertainment-related consumption

We advance the investigation by delving into subcategories of entertainment-related consumption. Dataset 3 is utilized for this test as it is the only dataset containing the required information. The entertainment-related consumption is divided into nine subcategories: accessories, cosmetics, sports, household appliances, car-related, recreation services, travel, dining, and living services. Among these nine subcategories, we hypothesize that the *U*-shaped pattern should be especially noticeable in the accessories and cosmetics categories, which are with small to moderate costs that still allow for "hedonic" consumption to take place.[18] This is in contrast to "travel," which typically comes at a higher cost, or "car-related" and "household appliances," which are closer to durable goods and likely not associated with "hedonic" consumption. As

[18] As outlined in Appendix A.1, Prediction 2 of the theoretical framework holds when the consumption prospect comes at a small to moderate cost.

individual level investment data is not available in Dataset 3, we use concurrent market return to proxy for individuals' wealth shocks. The results are reported in Table 5.

[Insert Table 5 about here]

Column (1) demonstrates the persistence of the *U*-shaped pattern when Dataset 3 is utilized and when consumption related to entertainment is examined independently. Moreover, the coefficient on negative wealth shock, represented by market return in month *t*, exhibits a greater magnitude than that of the coefficient on positive wealth shock. These results align with those in column (4) of Table 4, where Dataset 2 is employed. Once again, the findings indicate that our results are not specific to the samples or wealth shock measures utilized.

In columns (2) and (3), we perform tests where we separately examine the dynamics in individuals' consumption for typical entertainment-related consumption, "accessories & cosmetics", and other entertainment-related consumption after experiencing financial wealth shocks. Again, in both columns, the coefficient on $Negative\ mkt\ ret_t$ is significantly negative and has a magnitude greater than that on $Positive\ mkt\ ret_t$. More importantly, the magnitude of the coefficient on $Negative\ mkt\ ret_t$ is much greater for "accessories & cosmetics" than for other entertainment-related consumption, rendering further support to H2.

4.3 Addressing the confounding influence

4.3.1 Changing liquidity constraints

The *U*-shaped relationship between consumption and wealth shocks in the previous week, as shown in Section 4.1, aligns with the laboratory experimental evidence in Section 2 and bolsters our proposition regarding the role of consumption as “financial retail therapy”. However, consumption decision could also be affected by individuals’ liquidity constrains: when such constrains are relaxed, individuals are likely to consume more in the following period (e.g., Baugh, Ben-David, Park and Parker, 2021; Agarwal, Hadzic, Song and Yildirim, 2023). If individuals tend to sell their positions after experiencing either large positive or negative wealth shocks, their reduced liquidity constraints might also lead to increased consumption.

We conjecture that changing liquidity constraints resulting from position liquidation is not likely to be the main driver of our results, especially for the increased consumption after negative wealth shocks. The pervasive disposition effect maintains that individuals are likely to sell wining rather than losing financial assets (e.g., Shefrin and Statman, 1985; Odean 1998; Barberis and Xiong, 2009; Frydman and Wang, 2020). An et al. (2023) further show that the disposition effect for a stock significantly weakens if the portfolio is at a gain, but is large when it is at a loss. Thus, after experiencing financial losses, individuals are less rather than more likely to sell their financial positions.

To further filter out the influence of changing liquidity constraints caused by selling financial assets, we divided Dataset 1 into three subsamples where individual-week observations are excluded if individual *i* sells (1) any losing position in week *t*-1, (2) any winning position in week *t*-1, or (3) any position in week *t*-1. The first (second) subsample is specifically used to test whether increased consumption following negative (positive) wealth shocks results from individuals' increased liquidity from selling losing (winning) position. We re-perform the baseline tests using each of the three subsamples and report the results in Table 6.

[Insert Table 6 about here]

Across all the three columns in Table 6, the coefficient on positive and negative individual level wealth shocks remain significantly positive and negative, respectively. The magnitude of the coefficients is quite close to that in Table 3 with the full sample. This evidence confirms that our results could not be explained individuals' increased liquidity from selling positions after experiencing positive or negative wealth shocks.

4.3.2 Income effect

To ease the concern that the influence of stock market fluctuations on consumption operates through an income effect, we re-run the analyses using Dataset 4 consists of randomly selected Taobao entrepreneurs with monthly data on both their Alipay consumption and business income. We are thus able to control for the income effect when using this dataset. However, as individual level investment data is not available for this sample, we use monthly market return to proxy for wealth shocks for sample individuals. The results are reported in Table 7.

[Insert Table 7 about here]

Columns (1) to (3) show that the control of sample individuals' income does not affect our main findings: coefficients on positive and negative wealth shock proxies are significantly positive and negative, respectively, at the 1% level. In column (4), a quadratic equation is tested: *market return* is stock market performance in month *t*, and *market return*^{2} is designed to capture the *U*-shaped relationship. The significant positive coefficient on *market return*^{2} further confirms a *U*-shaped relation between stock market shocks and individuals' consumption, even with the control of the income effect.

4.4. Sensitivity checks

4.4.1 Retain observations with zero-valued outcomes

In the baseline tests, we utilize the natural logarithm of individuals' consumption as the dependent variable. This approach leads to the exclusion of observations with zero weekly or monthly consumption. We do not employ the traditional log (1+Y) approach to include observations with zero-valued outcomes, as recent studies by Cohn, Liu, and Wardlaw (2022) and Chen and Roth (2023) have shown that OLS regressions using log(1+Y) may yield inconsistent estimators in such instances. The Log(Y) regression we have used, however, may result in a loss of valuable information. Therefore, we conduct robustness tests using the raw value of consumption, in hundreds of yuan, as the dependent variable, ensuring that observations with weekly or monthly zero consumption are retained in the sample.

We replicate the primary test for H1 as shown in column (1) of Table 3 and the primary tests for H2 as shown in columns (3) to (6) of Table 4 using the alternative dependent variable. The results are presented in Panel A of Table 8. Furthermore, in Panel B of the Table 8, we utilize Poisson regression analysis, as recommended by both Cohn, Liu, and Wardlaw (2022) and Chen and Roth (2023). It should be noted the Ant Open Research Laboratory currently does not support running Poisson regression with high-dimensional fixed effects and standard error clustering, hence they are only implemented in Panel A when OLS regressions are conducted. In Poisson regressions, however, we controlled for month-of-the-year fixed effects to address variations in consumption driven by shopping events such as China's Double Eleven Shopping Festival or traditional holidays such as the Spring Festival.

[Insert Table 8 about here]

The findings in both panels of Table 8 validate the *U*-shaped short-term relationship between individuals' financial wealth shocks and their consumption. Furthermore, individuals are more inclined to elevate their entertainment-related consumption, a category of consumption that is more "hedonic" in nature compared to others, following negative financial wealth shocks.

4.4.2 Quadratic specification

In previous tests, we categorize investment returns of individuals into positive and negative components to capture the *U*-shaped relationship. While this approach offers a clear economic interpretation, it may not ensure the best fit. Thus, in robustness checks, we use a quadratic equation to capture the *U-shaped* relation as follows:

$$Ln(total\_csmp)_{i,t+1} = \alpha + \beta_1 \cdot Invest\ ret^2_{i,t} + \beta_2 \cdot Invest\ ret_{i,t} + controls_{i,t+1} + \varepsilon_{i,t+1}, \qquad (2)$$

where the dependent variable is the natural logarithm of individual *i*'s weekly total consumption in week *t*+1, $Invest\ ret_{i,t}$ is individual *i*'s investment return on Ant Fortune platform in week *t*, and $Invest\ ret^2_{i,t}$ is designed to capture the *U-shaped* relation. The results are reported in Table 9. The significantly positive β_1 confirms that there is a *U*-shaped relation between individuals' consumption and the financial wealth shocks have recently experienced.

[Insert Table 9 about here]

5. Conclusion

Our paper investigates how individual investors change their consumption patterns after experiencing financial wealth shocks. We find that people increase their total consumption after experiencing large financial gains *and* losses. The primary driver of this relation is the increase in consumption with a "hedonic" nature. A controlled lab experiment provides further corroborative evidence: compared to a neutral benchmark, people increase positive experiences after both gains and losses—even at a cost to themselves. This *U*-shaped relation between financial wealth shocks and consumption is consistent with a model where people engage in retail therapy to alleviate distress stemming from negative outcomes.

The convergent evidence from both the lab and the field, combined with auxiliary analyses using additional data sources, provide support for the robustness of the *U*-shaped relation between individual investors' consumption and financial wealth shocks. Given that individuals derive direct utility from purchasing entertainment-related goods and services following investment losses in the personal fund portfolio, our results suggest that negative financial wealth shocks may lead to a double whammy for people's wealth in short-run. The spending from retail therapy could potentially aggravate their wobbling financial health, which can lead to further stress and the need for more retail therapy. Although a full welfare analysis is outside the scope of the current paper, this suggests scope for potential policy to mitigate downstream consequences from financial losses.

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Figure 1: U-shaped relation between financial wealth shocks and consumption. This figure plots sample individuals' monthly consumption made through Alipay conditional on the financial wealth shocks they have just experienced, during the period from August 2017 to July 2021. To capture the degree of financial wealth shocks, we classify individual-month observation into seven bins conditional on sample individuals' investment return on the Ant Fortune platform in the previous month, and the cutoffs are as follows: *Bin 1* $\in$*(min, –0.05), Bin 2* $\in$*[–0.05, –0.02), Bin 3* $\in$*[–0.02, –0.001), Bin 4* $\in$*[–0.001, 0.001), Bin 5* $\in$*[0.001, 0.02), Bin 6* $\in$*[0.02, 0.05), Bin 7* $\in$ *[0.05, max)*. The vertical axis represents the median of consumption (CNY) of individuals in each financial wealth shock bin. This sample includes 4,696,077 individual-month observations.

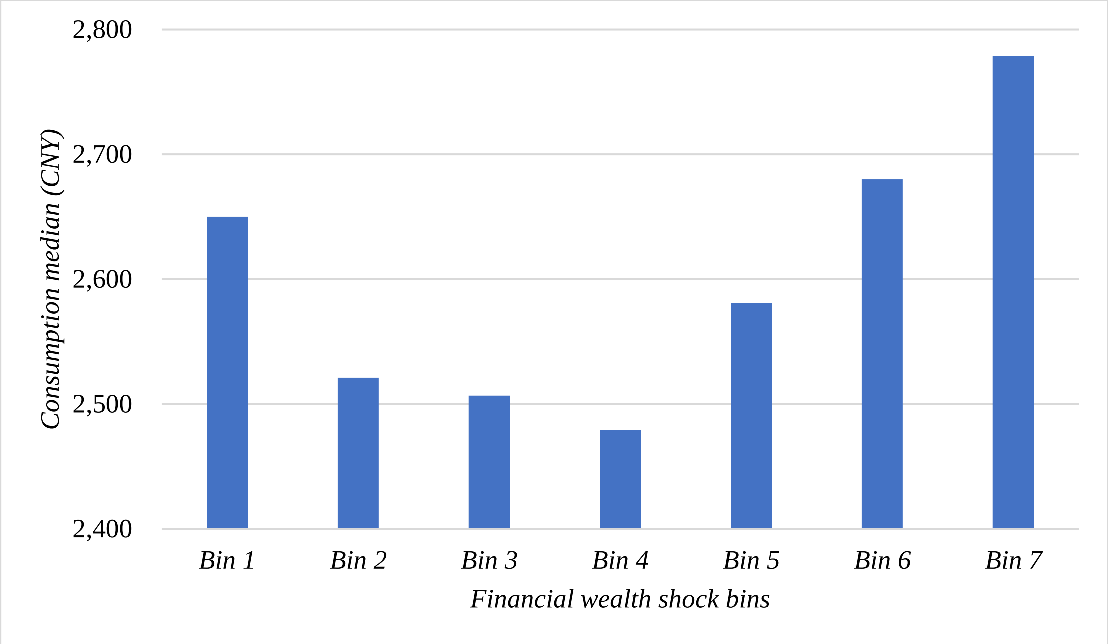

Table 1: Dataset description.

This table summitries key information about the four datasets used in this study.

Dataset	Features	Advantages	Limitations	Used for testing	Used in
1	Data frequency: Weekly Fund investment info.: Yes Total consumption info.: Yes Consumption category info.: No Consumption subcategory info.: No Income info.: No • No. of unique individuals: 20,000. • Sample period: 4 years 209 weeks, from August 2017 to July 2021. • Observations: 3,614,861.	• High frequency. • Linked consumption and investment data at the individual level. • Longer period (4 years)	• No breakdown information for total consumption • Consumption data is not linked to income data at the individual level.	***H1***	Table 3 Table 6 Table 8
2	Data frequency: Monthly Fund investment info.: Yes Total consumption info.: Yes Consumption category info.: Yes Consumption subcategory info.: No Income info.: No • No. of unique individuals: 100,000. • Sample period: 4 years 48months, from August 2017 to July 2021. • Observations: 4,696,077.	• Has consumption category information. • Linked consumption and investment data at the individual level. • Longer period (4 years)	• Lower frequency. • Consumption data is not linked to income data at the individual level.	***H1, H2***	Table 4 Table 9
3	Data frequency: Monthly Fund investment info.: No	• Has consumption category and subcategory information.	• Lower frequency • Shorter sample period (2 years)	***H1*** & further exploration of	Table 5

	Total consumption info.: Yes Consumption category info.: Yes Consumption subcategory info.: Yes Income info.: No • No. of unique individuals: 40,000. • Sample period: 2 years 24months, from August 2017 to July 2019. • Observations: 739,168.		• Consumption data is not linked to investment data at the individual level. • Consumption data is not linked to income data at the individual level.	***H2***: typical vs. other entertainment-related consumption	
4	Data frequency: Monthly Fund investment info.: No Total consumption info.: Yes Consumption category info.: No Consumption subcategory info.: No Income info.: Yes • No. of unique individuals: 160,000. • Sample period: 2 years 24months, from August 2017 to July 2019. • Observations: 2,931,714.	• Linked consumption and income data at the individual level.	• Lower frequency. • Shorter sample period (2 years). • No breakdown information for total consumption. • Consumption data is not linked to investment data at the individual level.	Further validate ***H1***: Control for the income effect	Table 7

Table 2: Summary statistics.

Panels A to D report summary statistics of the main variables in Dataset 1, 2, 3, and 4, respectively. Variables are at the weekly frequency in Panel A, and at the monthly frequency in Panels B to D. *Total csmp*$_{i,t}$ is the total consumption (in yuan) made by individual *i* in period *t* through Alipay. It is divided into offline (*Offline csmp*$_{i,t}$) and online consumption (*Online csmp*$_{i,t}$) in Panel B where Dataset 2 is examined. The Ant further classifies online consumption into three categories: entertainment-related (*Entertainment csmp*$_{i,t}$), living-related (*Living csmp*$_{i,t}$), and development-related (*Development csmp*$_{i,t}$) consumption for Dataset 2. In Panel C where Dataset 3 with subcategory information of entertainment-related consumption is examined, we identify the accessories and cosmetic subcategories as typical entertainment-related consumption, and the rest subcategories (sports, household appliances, car-related, recreation services, travel, dining, and living services) as other entertainment-related consumption. *Invest ret*$_{i,t}$ is individual *i*'s investment return on the Ant Fortune platform in period *t*. *Positive invest ret*$_{i,t}$ (*Negative invest ret*$_{i,t}$) equals *Invest ret*$_{i,t}$ when it is positive (negative) and zero otherwise. *Positive mkt ret*$_t$ (*Negative mkt ret*$_t$) equals value-weighted return of the A-share market in period *t* when it is positive (negative), and zero otherwise. *Income*$_{i,t}$ is the business income of individual *i* in period *t*, which is available in Dataset 4 comprised of entrepreneurs running their business on the Taobao platform.

Panel A: Dataset 1 (weekly data with individual-level investment and consumption information)

	N	Mean	Std	1%	25%	50%	75%	99%
Ln(total_csmp)$_{i,t}$	3,614,861	5.861	1.555	1.792	4.898	5.903	6.861	9.685
Total csmp$_{i,t}$	3,614,861	1091.359	2292.652	6.000	134.000	366.000	954.000	106069.000
Invest ret$_{i,t}$	3,614,861	0.002	0.019	−0.065	0.000	10.000	0.004	0.062
Positive invest ret$_{i,t}$	3,614,861	0.006	0.013	0.000	0.000	0.000	0.004	0.062
Negative invest ret$_{i,t}$	3,614,861	−0.005	0.012	−0.065	0.000	0.000	0.000	0.000
Positive mkt ret$_{i,t}$	3,614,861	0.011	0.015	0.000	0.000	0.002	0.019	0.063
Negative mkt ret$_{i,t}$	3,614,861	−0.009	0.015	−0.059	−0.011	0.000	0.000	0.000

Panel B: Dataset 2 (monthly data with individual-level investment, total consumption, and consumption category information)

	N	Mean	Std	1%	25%	50%	75%	99%
Total csmp$_{i,t}$	4,696,077	5678.886	9467.878	71.808	1118.960	2555.640	5831.220	62672.580
Offline csmp$_{i,t}$	4,612,512	4196.952	8143.837	0.010	580.180	1553.730	3927.360	54910.770

Online csmp$_{i,t}$	4,118,602	1594.526	2786.338	0.010	195.640	590.705	1647.690	17147.150
Entertainment csmp$_{i,t}$	2,852,495	454.839	897.444	0.010	48.600	137.730	390.000	5080.519
Living csmp$_{i,t}$	3,326,181	617.411	1031.210	0.010	89.000	251.410	648.950	6024.886
Development csmp$_{i,t}$	1,818,935	350.396	806.185	0.010	29.940	81.410	215.800	4091.476
Invest ret$_{i,t}$	4,696,077	0.006	0.037	−0.097	0.000	0.000	0.011	0.142
Positive invest ret$_{i,t}$	4,696,077	0.013	0.028	0.000	0.000	0.000	0.011	0.142
Negative invest ret$_{i,t}$	4,696,077	−0.008	0.019	−0.097	0.000	0.000	0.000	0.000

Panel C: Dataset 3 (monthly data with individual-level consumption category and subcategory information)

	N	Mean	Std	1%	25%	50%	75%	99%
Entertainment csmp$_{i,t}$	739,168	404.098	819.590	6.000	55.000	141.000	358.000	5597.044
Typical entertainment csmp$_{i,t}$	347,462	223.511	404.887	5.866	38.000	89.900	225.000	2805.604
Other entertainment csmp$_{i,t}$	630,329	341.913	763.444	4.900	38.800	100.600	272.000	5257.382

Panel D: Dataset 4 (monthly data with individual-level total consumption and income information)

	N	Mean	Std	1%	25%	50%	75%	99%
Total csmp$_{i,t}$	2,931,714	10188.180	19240.800	46.803	1523.840	3781.290	9740.540	130587.800
Income$_{i,t}$	2,931,714	23698.060	63053.810	1.150	858.000	3916.000	15432.000	450020.000
Positive mkt ret$_{i,t}$	2,931,714	0.021	0.037	0.000	0.000	0.001	0.032	0.155
Negative mkt ret$_{i,t}$	2,931,714	−0.020	0.029	−0.087	−0.043	0.000	0.000	0.000

Table 3: Short-term influence of financial wealth shocks on consumption.

This table examines the short-term influence of financial wealth shocks on consumption, utilizing Dataset 1 with weekly individual-level consumption and investment information over the period from August 2017 to July 2021. The dependent variable is the natural logarithm of individual *i*'s total consumption made through Alipay in week *t+1*. *Positive invest ret*$_{i,t}$ (*Negative invest ret*$_{i,t}$) equals individual *i*'s investment return on the Ant Fortune platform in week *t* when it is positive (negative) and zero otherwise. *Positive mkt ret*$_t$ (*Negative mkt ret*$_t$) equals value-weighted return of the A-share market in week *t* when it is positive (negative), and zero otherwise. All continuous variables are winsorized at 1% and 99%. The standard errors are clustered at the individual level and reported in parentheses. N.A. indicates that the fixed effect is not applicable to the model. *, **, and *** indicate significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Ln(total_csmp)$_{i,t+1}$	*Ln(total_csmp)*$_{i,t+1}$	*Ln(total_csmp)*$_{i,t+1}$	*Ln(total_csmp)*$_{i,t+1}$
Positive invest ret$_{i,t}$	0.753***	0.617***	1.170***	1.015***
	(0.096)	(0.085)	(0.093)	(0.083)
Negative invest ret$_{i,t}$	−0.497***	−0.424***	−0.645***	−0.711***
	(0.101)	(0.094)	(0.098)	(0.092)
Ln(total_csmp)$_{i,t}$		0.183***		1.174***
		(0.001)		(0.001)
Positive mkt ret$_t$			1.883***	1.477***
			(0.065)	(0.067)
Negative mkt ret$_t$			−0.645***	−0.505***
			(0.098)	(0.070)
Const	5.854***	4.855***	5.826***	4.883***
	(0.001)	(0.007)	(0.001)	(0.001)
Time FE (month)	NO	NO	YES	YES
Time FE (week)	YES	YES	N.A.	N.A.
Individual FE	YES	YES	YES	YES
Cluster by individual	YES	YES	YES	YES
No. Observations	3,614,861	3,293,284	3,614,861	3,293,284
Adj. R^2	0.000	0.034	0.001	0.031

Table 4: Consumption breakdowns: Entertainment-, living-, and development-related consumption.

This table examines the short-term influence of financial wealth shocks on different categories of consumption, utilizing Dataset 2 with monthly individual-level information on consumption, consumption breakdowns, and investment over the period from August 2017 to July 2021. In columns (1) to (3), the dependent variable is the natural logarithm of individual *i*'s total consumption, offline consumption, online consumption, respectively, in month *t+1*. In columns (4) to (6), the dependent variable is the natural logarithm of individual *i*' entertainment-, living-, and development-related consumption, respectively, in month *t+1*. Only online consumption is considered in columns (4) to (6) as the consumption breakdown information provided by the Ant is not available for offline consumption. *Positive invest ret*$_{i,t}$ (*Negative invest ret*$_{i,t}$) equals individual *i*'s investment return on the Ant Fortune platform in month *t* when it is positive (negative) and zero otherwise. All continuous variables are winsorized at 1% and 99%. The standard errors are clustered at the individual level and reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(csmp)$_{i,t+1}$	*Ln(csmp)*$_{i,t+1}$	*Ln(csmp)*$_{i,t+1}$	*Ln(csmp)*$_{i,t+1}$	*Ln(csmp)*$_{i,t+1}$	*Ln(csmp)*$_{i,t+1}$
	Total	*Total*		*Online*		
		Offline	*Online*	*Entertainment*	*Living*	*Development*
Positive invest ret$_{i,t}$	0.470***	0.588***	0.206***	0.100**	0.141***	0.081
	(0.026)	(0.032)	(0.031)	(0.040)	(0.033)	(0.051)
Negative invest ret$_{i,t}$	−0.452***	−0.535***	−0.274***	−0.197***	−0.111**	−0.002
	(0.035)	(0.045)	(0.043)	(0.057)	(0.046)	(0.075)
Const	7.822***	7.253***	6.296***	4.943***	5.474***	4.508***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time FE (month)	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Cluster by individual	YES	YES	YES	YES	YES	YES
No. Observations:	4,696,077	4,612,512	4,118,602	2,852,495	3,326,181	1,818,935
Adj. R^2	0.000	0.000	0.000	0.000	0.000	0.000

Table 5: Typical vs. other entertainment-related consumption

This table examines the short-term influence of financial wealth shocks on subcategories of entertainment-related consumption, utilizing Dataset 3 with monthly individual-level information on consumption subcategories and investment over the period from August 2017 to July 2019. In Dataset 3, the Ant categorizes individuals' entertainment-related consumption into nine subcategories: accessories, cosmetics, sports, household appliances, car-related, recreation services, travel, dining, and living services. We identify the accessories and cosmetics subcategories as typical entertainment-related consumption as they are of small to moderate costs that allow for "hedonic" experiences. The other seven subcategories are grouped as other entertainment-related consumption. The dependent variable is the natural logarithm of individual *i*'s total entertainment-related consumption, typical entertainment-related consumption, and other entertainment-related consumption in month $t+1$, respectively, in columns (1), (2), and (3). *Positive mkt ret$_t$* (*Negative mkt ret$_t$*) equals value-weighted return of the A-share market in week *t* when it is positive (negative), and zero otherwise. All continuous variables are winsorized at 1% and 99%. The standard errors are clustered at the individual level and reported in parentheses. N.A. indicates that the fixed effect is not applicable to the model. *, **, and *** indicate significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
	$Ln(csmp)_{i,t+1}$	$Ln(csmp)_{i,t+1}$	$Ln(csmp)_{i,t+1}$
		Entertainment consumption	
	Entertainment	*Accessories & Cosmetics*	*All other entertainment-related consumption*
Positive mkt ret$_t$	1.203**	1.744***	0.457***
	(0.070)	(0.094)	(0.079)
Negative mkt ret$_t$	−1.482***	−1.945***	−0.701***
	(0.072)	(0.096)	(0.082)
Const	4.919***	4.462***	4.671***
	(0.002)	(0.003)	(0.003)
Month-of-the-year FE	YES	YES	YES
Time FE (month)	N.A.	N.A.	N.A.
Individual FE	YES	YES	YES
Cluster by individual	YES	YES	YES
No. Observations:	739,168	347,462	630,329
Adj. R^2	0.001	0.002	0.000

Table 6: Filter out the influence of changing liquidity constraints.

This table examines the short-term influence of financial wealth shocks on consumption, utilizing subsamples formed using Dataset 1 with weekly individual-level consumption and investment information to filter out the effect of changing liquidity constraints. Columns (1), (2), and (3) report results of subsample tests that exclude individuals how have redeemed funds with negative return in month *t*, funds with positive return in month *t*, or any funds in month *t*, respectively. The dependent variable is the natural logarithm of individual *i*'s total consumption made through Alipay in week *t+1*. *Positive invest ret*$_{i,t}$ (*Negative invest ret*$_{i,t}$) equals individual *i*'s investment return on the Ant Fortune platform in week *t* when it is positive (negative) and zero otherwise. The standard errors are clustered at the individual level and reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
	Ln(total_csmp)$_{i,t+1}$	*Ln(total_csmp)*$_{i,t+1}$	*Ln(total_csmp)*$_{i,t+1}$
	Exclude observations redeeming losing funds	Exclude observations redeeming wining funds	Exclude observations redeeming any funds
Positive invest ret$_t$	0.754***	0.776***	0.757***
	(0.096)	(0.097)	(0.097)
Negative invest ret$_t$	−0.493***	−0.496***	−0.491***
	(0.102)	(0.102)	(0.102)
Const	5.854***	5.852***	5.853***
	(0.001)	(0.001)	(0.001)
Time FE (week)	YES	YES	YES
Individual FE	YES	YES	YES
Cluster by individual	YES	YES	YES
No. Observations	3,585,540	3,548,826	3,530,725
Adj. R^2	0.000	0.000	0.000

Table 7: Control for the income effect.

This table examines the short-term influence of financial wealth shocks on consumption with the control of the income effect, utilizing Dataset 4 with monthly individual-level consumption and income information during the sample period from August 2017 to July 2019. Dataset 4 is comprised of 16,000 randomly selected entrepreneurs running their business on the Taobao platform. The dependent variable is the natural logarithm of individual *i*'s total consumption made through Alipay in month *t+1*. *Mkt ret*$_t$ is value-weighted return of the A-share market in month *t*, which is used to proxy for concurrent financial wealth shocks for sample individuals, as individual-level investment data are not available for this dataset. *Positive mkt ret*$_t$ (*Negative mkt ret*$_t$) equals *Mkt ret*$_t$ when it is positive (negative), and zero otherwise. *Ln(income)*$_{i,t}$ is the natural logarithm of individual *i*'s business income obtained on the Taobao platform in month *t*. Columns (1) to (3) report results of linear regressions, while column (4) reports results of quadratic specification. All continuous variables are winsorized at 1% and 99%. The standard errors are clustered at the individual level and reported in parentheses. N.A. indicates that the fixed effect is not applicable to the model. *, **, and *** indicate significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Ln(total_csmp)$_{i,t+1}$	*Ln(total_csmp)*$_{i,t+1}$	*Total csmp*$_{i,t}$	*Ln(total_csmp)*$_{i,t+1}$
Positive mkt ret$_t$	1.742***	1.407***	17.830***	
	(0.031)	(0.029)	(0.454)	
Negative mkt ret$_t$	−1.341***	-1.112***	−15.207***	
	(0.029)	(0.029)	(0.416)	
Mkt ret^2_t				9.604***
				(0.194)
Mkt ret$_t$				−0.046***
				(0.014)
Ln(income)$_{i,t}$	0.139***	0.124***	1.468***	0.140***
	(0.001)	(0.001)	(0.012)	(0.001)
Ln(total_csmp)$_{i,t}$		0.221***		
		(0.001)		
Const	7.052***	5.372***	−2.311***	7.083***
	(0.006)	(0.011)	(0.102)	(0.006)
Month-of-the-year FE	YES	YES	YES	YES
Time FE (month)	N.A.	N.A.	N.A.	N.A.
Individual FE	YES	YES	YES	YES
Cluster by individual	YES	YES	YES	YES
No. Observations	2,931,714	2,771,714	2,931,714	2,931,714
Adj. R^2	0.042	0.090	0.024	0.042

Table 8: Transformation of the dependent variable.

This table examines the short-term influence of financial wealth shocks on consumption and its categories utilizing Dataset 1 or 2, depending on the variables needed for the tests. Panels A and B report the results of OLS and Poisson regressions, respectively. In both panels, the dependent variable is individual *i*'s total and online consumption in columns (1) and (2), and entertainment-related, living-relate, and development-related consumption in columns (3) to (5). All the consumption refers to that made through Alipay in period *t+1*, and is measured in hundreds of yuan. *Positive invest ret*$_{i,t}$ (*Negative invest ret*$_{i,t}$) equals individual *i*'s investment return on the Ant Fortune platform in period *t* when it is positive (negative) and zero otherwise. All continuous variables are winsorized at 1% and 99%. The standard errors are clustered at the individual level and reported in parentheses. N.A. indicates that the fixed effect is not applicable to the model. *, **, and *** indicate significance at 10%, 5%, and 1% level, respectively.

Panel A: OLS regressions					
	(1)	(2)	(3)	(4)	(5)
	Total consumption	*Online consumption*	*Online consumption*		
			Entertainment	*Living*	*Development*
Positive invest ret$_t$	7.128***	3.354***	0.521*	0.872***	0.758***
	(1.420)	(0.604)	(0.274)	(0.272)	(0.357)
Negative invest ret$_t$	−2.725*	−5.047***	−1.064***	−0.730*	−0.640
	(1.397)	(0.854)	(0.396)	(0.386)	(0.534)
Const	10.858***	16.007***	4.788***	6.329***	4.005***
	(0.015)	(0.012)	(0.005)	(0.006)	(0.007)
Dataset used	Dataset 1	Dataset 2	Dataset 2	Dataset 2	Dataset 2
Data frequency	Weekly	Monthly	Monthly	Monthly	Monthly
Time FE (week)	YES	N.A.	N.A.	N.A.	N.A.
Time FE (month)	N.A.	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
Cluster by individual	YES	YES	YES	YES	YES
No. Observations:	4,159,158	4,118,602	2,852,495	3,326,181	1,818,935
Adj. R^2	0.000	0.000	0.000	0.000	0.000

Panel B: Poisson regressions					
	(1)	(2)	(3)	(4)	(5)
	Total consumption	*Online consumption*	*Online consumption*		
			Entertainment	*Living*	*Development*
Positive invest ret$_t$	2.820***	0.953***	0.870***	0.679***	−0.067***
	(0.001)	(0.004)	(0.010)	(0.008)	(0.014)
Negative invest ret$_t$	−0.041***	−0.378***	−0.116***	− 0.040***	0.136***
	(0.001)	(0.006)	(0.014)	(0.011)	(0.202)
Const	6.972***	2.777***	1.456***	1.902***	1.235***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Dataset used	Dataset 1	Dataset 2	Dataset 2	Dataset 2	Dataset 2
Data frequency	Weekly	Monthly	Monthly	Monthly	Monthly
Month-of-the-year FE	YES	YES	YES	YES	YES
No. Observations:	3,614,861	4,118,602	2,852,495	3,326,181	1,818,935
Pseudo. R^2	0.999	0.518	0.161	0.252	0.072

Table 9: Quadratic specification.

This table examines the short-term influence of financial wealth shocks on consumption and its categories utilizing Dataset 1 or 2, depending on the variables needed for the tests. The dependent variable is the natural logarithm of individual *i*'s total, online, entertainment-related, living-relate, and development-related consumption in columns (1) to (5), respectively. All the consumption refers to that made through Alipay in period *t+1*. *Invest* $ret_{i,t}$ is individual *i*'s investment return on the Ant Fortune platform in period *t*. All continuous variables are winsorized at 1% and 99%. The standard errors are clustered at the individual level and reported in parentheses. N.A. indicates that the fixed effect is not applicable to the model. *, **, and *** indicate significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	$Ln(csmp)_{i,t+1}$	$Ln(csmp)_{i,t+1}$	$Ln(csmp)_{i,t+1}$	$Ln(csmp)_{i,t+1}$	$Ln(csmp)_{i,t+1}$
	Total consumption	*Online consumption*	*Online consumption*		
			Entertainment	*Living*	*Development*
Invest ret^2_t	6.838***	1.267***	0.610*	0.720**	0.059
	(1.395)	(0.266)	(0.356)	(0.284)	(0.455)
Invest ret_t	0.162***	−0.013	−0.029	0.024	0.050
	(0.045)	(0.022)	(0.031)	(0.024)	(0.041)
Const	5.858**	6.300***	4.945***	5.475***	4.508***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Dataset used	Dataset 1	Dataset 2	Dataset 2	Dataset 2	Dataset 2
Data frequency	Weekly	Monthly	Monthly	Monthly	Monthly
Time FE (week)	YES	N.A.	N.A.	N.A.	N.A.
Time FE (month)	N.A.	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
Cluster by individual	YES	YES	YES	YES	YES
No. Observations:	3,614,861	4,118,602	2,852,495	3,326,181	1,818,935
Adj. R^2	0.000	0.000	0.000	0.000	0.000

Appendix

A.1 An Illustrative Model

In this section, we develop a simple model of dynamic prospect theory (Barberis, 2012; Imas, 2016) to help illustrate why investors may engage in retail therapy after experiencing both gains and losses in the stock market. To do so, we model prospective consumption as a simple lottery $L = (x^g, p;\ x^l, 1 - p)$, where $x^g > 0 > x^l$ and $x^g > |x^l|$. We believe that this modeling choice makes sense particularly in the case of entertainment or infrequently-purchased luxury goods as consumption may either be worth the cost if the experience is a good one (e.g. the movie is excellent and more than the ticket price), or not (e.g. the movie is terrible). A person does not know the realization ahead of time and acts based on her beliefs about the chance that the experience will be a good or bad one.

The investor evaluates the consumption prospect using a Prospect Theory value function $V(x|r) \in \mathbb{R}$. Let V satisfy all the properties of the Prospect Theory value function, which is differentiable everywhere except at a kink at r:

$$v(x|r) = \begin{cases} v(x-r) & if\ x - r \geq 0 \\ -\lambda \cdot v(|x-r|) & if\ x - r < 0 \end{cases}$$

where $V(r|r) = 0$, v is concave, and the parameter $\lambda > 1$ represents the degree of loss aversion.

The value function differs from the assumptions of standard Expected Utility Theory in several noteworthy ways. First, outcomes are evaluated relative to a reference point r. Second, the value function is "*S*" shaped, such that V is concave over gains and convex over losses. This assumption, also known as diminishing sensitivity, implies that individuals are risk-averse over gains and risk-seeking over losses. Third, the function displays a kink at the referent—steeper in the loss domain than in the gain domain.

In setting up the decision problem, consider an investor who makes a choice in one of three scenarios. The scenarios differ depending on the value of the investor's recent stock market performance z. In the "neutral" scenario, the investor has not experienced a recent loss or gain in the stock market ($z^n = 0$). In the "gain" scenario, $z^g > 0$; in the "loss" scenario, $z^l < 0$. For simplicity, let $x^g > z^g = |z^l| > |x^l|$. In all three scenarios, we follow Imas (2016) in assuming that recent prior losses are evaluated jointly with the prospect being evaluated. Finally, for simplicity, assume that the reference point is equal to the status quo, $r = 0$. It is now straightforward to derive the predictions.

The investor faces a choice between consuming the prospect L or not. In the "neutral" scenario, she will choose the prospect if $pv(x^g) - (1-p)\lambda v(|x^l|) > 0$. In the "loss" scenario, the investor chooses the prospect if $pv(x^g + z^l) - (1-p)\lambda v(|x^l + z^l|) > -\lambda v(|z^l|)$.

Prediction 1: *An investor will be more willing to consume the prospect in the "loss" scenario than in the "neutral" scenario.*

For Prediction 1 to hold, it is necessary to show that if the investor accepts L in the "neutral" scenario, even when indifferent, she would always be willing to accept L in the "loss" scenario. Particularly, the investor's valuation of the prospect is greater in the "loss" scenario than in the "neutral" scenario. For this to hold, the following condition needs to be met:

$$\lambda > \frac{p[v(x^g) - v(x^g + z^l)]}{(1-p)[v(|x^l|) - v((x^l + z^l|)] + v(|x^l|)}$$

We now show that this condition holds for any level of loss aversion $\lambda > 1$.

Proof: Replacing z^l in the denominator with x^l and $v(|2x^l|)$ with $2v(|z^l|)$ and rearranging terms, by subadditivity of concave function of v (since $v(0) = 0$), if

$$\lambda > \frac{v(x^g) - v(x^g + x^l)}{v(|x^l|)}$$

holds, then the preceding expression does as well. Given that $x^g > 0 > x^l$ and $x^g > |x^l|$, $v(x^g) - v(x^g + x^l) \leq v(|x^l|)$ by the subadditivity of the concave function v, such that $\frac{v(x^g) - v(x^g + x^l)}{v(|x^l|)} \leq 1$. Since the right-hand side of the preceding expression is (weakly) less than 1, it follows that the first prediction holds for all $\lambda > 1$. ■

In the “gain” scenario, the investor chooses the prospect if $pv(x^g + z^g) + (1-p)v(x^l + z^g) > v(z^g)$.

Prediction 2: *An investor will be more willing to consume the prospect in the “gain” scenario than in the “neutral” scenario if she is sufficiently loss averse.*

Similar to the logic above, Prediction 2 will hold if the following expression holds:

$$\lambda > \frac{pv(x^g + z^g) + (1-p)v(x^l + z^g) - v(x^g)}{(1-p)v(|x^l|)}$$

Unlike in the case of negative performance, however, the condition for Prediction 2 to hold is parameter-dependent. The investor needs to be sufficiently loss averse to be more likely to consume the prospect after the positive performance than in the “neutral” scenario.

At the same time, it is straightforward to show that the degree of loss aversion required is sufficiently low for the expression above to hold in practice.

The logic follows the analysis from Barberis and Xiong (2009). If the positive performance z^g is larger than the potential loss from consuming the prospect x^l, the investor's decision is not affected by loss aversion; her decision to consume the prospect is driven by the size of the prior gain and the concavity of the value function v. Since the decision is not subject to loss aversion, the investor will behave more or less as if she was risk-neutral—particularly over small to moderate stakes (this assumption is made explicit in Koszegi and Rabin (2006, 2007)). On the other hand, the investor's decision in the "neutral" case is subject to loss aversion. As famously demonstrated in the calibration theorem of Rabin (2000), loss aversion induces substantially more risk aversion than the standard concavity assumption. Thus one would expect the investor to be more likely to consume the product after the positive performance—when her decision is not subject to loss aversion—than in the "neutral" case for most parameter values. For example, Prediction 2 will hold for the parameter estimates from Tversky and Kahneman (1992) as long as the consumption prospect is small to moderate in magnitude.

A.2 Figures and Tables

Figure A1: The interface of Alipay and its Ant Fortune platform.

The figure illustrates the interface of Alipay and its Ant Fortune platform. The screenshot on the left depicts the Alipay interface, where users can access the Ant Fortune platform through the "Fortune" tab at the bottom. Upon clicking the "Fortune" tab, users will be directed to the Ant Fortune interface, where their portfolio assets and recent mutual fund investment gains/losses are displayed, as shown in the middle screenshot. Further clicking on the "New Gains" tab will lead to another interface displaying more detailed information about the user's asset composition.

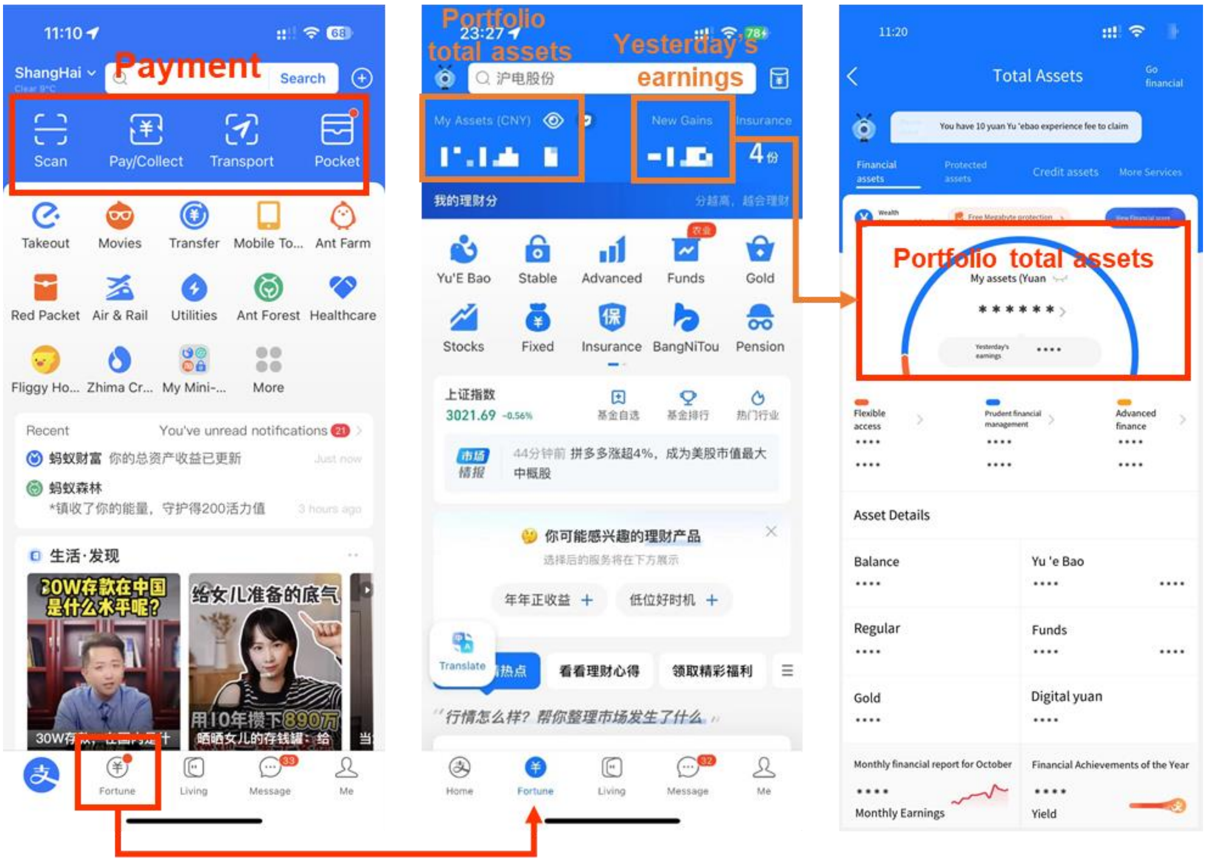

Table A1: Sample selection.

This table illustrates how the final samples are derived and the number of observations.

Panel A: Dataset 1 (individual-week observations)		
	Obs. No.	**Final sample**
Weekly dataset: Original sample	4,180,000	
Obs. with account matching error	−842	
Obs. in the first week (without investment data in the previous week)	−20,000	**4,159,158 (T8)**
Obs. with zero total consumption in week *t* (logarithm is not applicable in baseline tests)	−544,297	**3,614,861 (T3, 6, 9)**
Panel B: Dataset 2 (individual-month observations)		
	Obs. No.	**Final sample**
Monthly dataset: Original sample	4,800,000	
Obs. with account matching error	−3923	
Obs. in the first month (without investment data the previous month)	−100,000	
Obs. with zero total consumption in month *t*	−0	**4,696,077 (T4, 8, 9)**
Obs. with zero consumption in the category of:		
offline consumption	−83,565	**4,612,512 (T4, 8, 9)**
online consumption	−577,475	**4,118,602 (T4, 8, 9)**
entertainment-related consumption	−1,843,582	**2,852,495 (T4, 8, 9)**
living-related consumption	−1,369,896	**3,326,181 (T4, 8, 9)**
development-related consumption	−2,877,142	**1,818,935 (T4, 8, 9)**
Panel C: Dataset 3 (individual-month observations)		
	Obs. No.	**Final sample**
Monthly dataset: Original sample	960,000	
Obs. with zero entertainment-related consumption in month *t* (logarithm is not applicable)	−220,830	**739,168 (T5)**
Obs. with zero consumption in the subcategory of:		
accessories & cosmetics	−612,538	**347,462 (T5)**
other entertainment-related consumption	−329,671	**630,329 (T5)**
Panel D: Dataset 4 (individual-month observations)		
	Obs. No.	**Final sample**
Monthly dataset: Original sample	3,840,000	
Obs. with zero income in month *t* (logarithm is not applicable)	−908,286	**2,931,714 (T7)**

Table A2: Sample individuals' average consumption and its breakdowns (in RMB).

This table reports the conditional mean and median of the monthly consumption amount in yuan for the sample individuals. The data utilized in this table aligns with the data presented in Table 4. The total consumption represents the combined value of both online and offline consumption. Online consumption is further divided into three categories by the Ant: entertainment-, living-, and development-related consumption. The remaining categories are unclassified.

Month-of-the-year	Total consumption		Total consumption				Online consumption							
			Offline consumption		Online consumption		Entertainment consumption		Living consumption		Development consumption		Un-Classified	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1	6,091	2,984	4,557	1,872	1,640	664	436	134	679	299	343	85	742	263
2	4,258	1,819	3,359	1,201	1,085	385	366	126	409	163	310	76	544	173
3	5,546	2,470	4,081	1,461	1,571	600	440	135	587	247	344	88	701	235
4	5,585	2,463	4,223	1,539	1,467	550	416	126	550	229	342	80	657	217
5	5,066	2,093	3,845	1,284	1,371	505	413	127	532	219	309	75	627	206
6	5,993	2,682	4,239	1,526	1,841	664	554	157	662	270	416	89	764	257
7	5,610	2,434	4,363	1,591	1,346	486	410	125	498	195	306	73	615	193
8	5,816	2,631	4,501	1,724	1,423	514	428	136	523	200	331	78	651	201
9	5,484	2,476	4,144	1,570	1,481	551	404	122	577	234	329	79	683	223
10	5,536	2,544	4,205	1,625	1,439	553	375	119	578	238	303	72	638	209
11	6,749	3,261	4,241	1,549	2,528	1,097	702	217	951	458	482	100	934	342
12	6,447	3,053	4,670	1,824	1,818	732	455	145	746	324	351	83	778	267

Table A3: Variables definitions.

This table provides definitions of key variables used in the study.

Variables	Definition
Invest ret$_{i,t}$	individual *i*'s investment return on the Ant Fortune platform in period *t*
Positive invest ret$_{i,t}$	equals *Invest ret*$_{i,t}$ when it is positive and zero otherwise
Negative invest ret$_{i,t}$	equals *Invest ret*$_{i,t}$ when it is negative and zero otherwise
Total csmp$_{i,t}$	total consumption (in yuan) made by individual *i* in period *t* through Alipay, which is comprised of both offline and online consumption
Offline csmp$_{i,t}$	the offline consumption component of *Total csmp*$_{i,t}$
Online csmp$_{i,t}$	the online consumption component of *Total csmp*$_{i,t}$
Entertainment csmp$_{i,t}$	entertainment-related consumption, which is one of the three consumption categories identified by the Ant, with the other two being living- and development-related consumption. It is important to note that these consumption categories are specific to online consumption, as the necessary classification is not available for offline consumption.
Living csmp$_{i,t}$	living-related consumption, which is one of the three consumption categories identified by the Ant, with the other two being entertainment- and development-related consumption. It is important to note that these consumption categories are specific to online consumption, as the necessary classification is not available for offline consumption.
Development csmp$_{i,t}$	development-related consumption, which is one of the three consumption categories identified by the Ant, with the other two being entertainment- and living-related consumption. It is important to note that these consumption categories are specific to online consumption, as the necessary classification is not available for offline consumption.
Mkt ret$_{t}$	value-weighted return of the A-share market in period *t* [Source: CSMAR]
Positive mkt ret$_{t}$	equals *Mkt ret*$_{t}$ when it is positive, and zero otherwise [Source: CSMAR]
Negative mkt ret$_{t}$	equals *Mkt ret*$_{t}$ when it is negative, and zero otherwise [Source: CSMAR]