In victory or defeat:

Consumption responses to wealth shocks[*]

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Abstract

Using a novel representative sample of digital payment data, we observe a robust *U*-shaped relationship between individual investors' monthly entertainment-related consumption and stock market returns in the previous month. Contrary to the prediction of the wealth effect, individuals increase their entertainment-related consumption after experiencing large positive *and* negative stock market shocks. We show that the latter effect, termed "financial retail therapy," is consistent with a dynamic model of Prospect Theory, and provide further evidence for it in a controlled laboratory experiment. Finally, we show that our results are not driven by income effects or wealth shock measurement errors.

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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"*I could not live without Champagne. In victory I deserve it. In defeat I need it...*"
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 data, we investigate how individuals change their consumption patterns after experiencing large stock market movements. Our results bring new insight into the relationship between consumption and wealth by providing novel evidence that individuals increase consumption—specifically entertainment-related purchases—following large positive *and* negative shocks.

The consumption-wealth relationship has been highlighted as one of the main channels through which stock markets affect the economy. Understanding this relationship 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 stock market wealth shocks positively affect individuals' consumption. However, none of the existing studies examine the influence of positive and negative stock market shocks separately, implicitly assuming that the effect of stock market 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 consumption—particularly of inessential goods and services—in order to smooth future consumption patterns. 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, 2022).

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—a phenomenon 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

[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 the current work, this research looks at responses to positive wealth shocks.

of lab 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, only "hedonic" consumption—in the sense that the individual derives utility in the same period as the purchase decision—is expected to change; other types of consumption, e.g., durables, are not predicted to increase. The framework thus predicts a *U*-shaped relationship between stock market wealth shocks and hedonic consumption, where consumption increases following both positive and negative stock market movements.

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 relationship increased with the magnitude of each outcome.

Given this motivating evidence, we then proceed to test our predictions in real-world behavior utilizing a unique dataset from Ant Group—the fintech giant in China—which contains monthly individual-level consumption data. 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. The individual-level data allow us to trace the actual monthly consumption in various categories by 40,000 individuals from August 2017 to July 2019. Our analyses focus on entertainment-related online consumption as a proxy for the type of hedonic consumption that is predicted to respond to wealth shocks.

Based on the 693,310 individual-month observations, we find a robust *U-shaped* relationship between individuals' monthly entertainment-related consumption and stock market index returns in the previous month. We control for city-month-of-the-year joint fixed effects (i.e., 100 cities X 12 months of the year from January to

December) and individual account fixed effects in all the empirical tests, and the standard errors are clustered at the individual account level. Adding city-month-of-the-year joint fixed effects mitigates the concern that our findings are driven by seasonality within a year or shopping surges during holidays/festivals such as Alibaba's Singles Day on November 11. Including account fixed effects mitigates potential influences of individual unobserved time-invariant factors on consumption decisions.

Our results show that individuals tend to increase their consumption for entertainment following large positive stock market shocks. This finding is perhaps not surprising and in line with the conventional wealth effect. However, as in the experiment, individuals increase their entertainment consumption even more following large negative stock market shocks. Such a pattern is not consistent with standard models that predict lower consumption after negative wealth or future cash flow shocks and brings into question the implicit assumption in the prior work that consumption responses are a linear function of wealth. These results support the predictions of a framework where people attempt to repair and recover from prior financial losses by increasing their hedonic consumption. As further evidence for the model, we show that the *U*-shaped consumption pattern is substantially less pronounced for non-entertainment-related consumption, which highlights the role of retail therapy in alleviating financial distress. Notably, the lack of decrease in non-entertainment implies that the *U*-shaped pattern in entertainment-related consumption is not due to substitution; overall consumption also increases after a negative financial shock, and this increase is primarily driven by—as the theoretical framework predicts—a response in entertainment-related consumption.

There are two potential concerns with the main tests above. First, monthly stock market movements are correlated with macroeconomic conditions, which could affect individuals' current or expected income. Thus, the *U*-shaped consumption-wealth relationship may be driven by income effects. Second, we use stock market index returns to proxy for peoples' stock market wealth shocks, assuming that market returns are a good proxy for wealth shocks at the individual level. Such a market-level measure does not consider cross-sectional heterogeneity and may not accurately capture stock market wealth shocks at the investor level.

To address these two potential concerns, we perform robustness tests using two alternative samples from Ant Group. The first alternative sample consists of 160,000 randomly selected Taobao entrepreneurs with data on both their Alipay consumption and business income from the Taobao platform.[2] With this alternative sample, we can control for income effects in our estimation. Our second alternative sample contains 210,000 randomly selected individuals who not only use Alipay for consumption payments but also make mutual fund investments through the mutual fund distribution platform of Ant Group. We are, therefore, able to match individuals' consumption data with their monthly mutual fund investment returns, which helps us detect stock market wealth shocks at the individual level more directly. We find qualitatively similar results

[2] 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.

using these two alternative samples: individuals tend to increase their entertainment-related consumption after experiencing negative stock market wealth shocks even when the income effects are controlled for and when stock market shocks are measured at the individual level.

Our study adds to several streams of the literature. First, we expand the studies on the relationship 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 CARES Act stimulus payments but show that the size of the MPC depends on household liquidity as well as other sources of variation.

Our study differs from this prior work by documenting a striking *U*-shaped pattern in both experimental and real-world data. The results show that individuals tend to increase rather than decrease their 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 monthly consumption data with stock market wealth shocks measured at both market and individual levels. Such a unique dataset allows us to examine individuals' *observed* consumption behavior rather than relying on reported consumption from surveys or imputed measures from other forms of transaction data. As outlined in Sections 3 and 4, the detailed individual-level consumption data facilitate a variety of robustness tests and help us further identify the proposed mechanism.

Second, our paper is also 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 workers, which could result from their increased psychological distress and the reduction of resources that support productivity in wage employment.[3] Lin and Pursiainen (2022) 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,

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

we add to the psychology literature on retail therapy by providing evidence from real-world field data.

The rest of the paper proceeds as follows. Section 2 presents initial experimental evidence for the impact of positive and negative financial shocks on people's behavior. Section 3 outlines the dataset and documents the *U*-shaped relationship between entertainment-related consumption and financial shocks. Section 4 provides evidence of robustness. Section 5 discusses our findings and concludes.

2. Experimental evidence

We begin our investigation by providing initial evidence for the proposed *U*-shaped consumption relationship 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.[4] All were paid a $1.00 base fee for completing the study.

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

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.[5] 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 success number (1/6 chance), then the lottery “succeded;” if the outcome was any other

[5] 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)).

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.[6]

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 ($\beta = -8.91$; $p = 0.018$).

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

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

3. Empirical investigation utilizing individual-level data

3.1 Data and sample description

Our individual digital payment account data are provided by the Ant Group—the fintech giant in China—from its mobile and online payments application Alipay. Alipay was initially launched in 2003 as a payment escrow solution to resolve the trust issues between buyers and sellers 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.[7]

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.[8] Taobao is now the world's largest e-commerce website and even surpasses popular online marketplaces such as Amazon. Because all transactions made on Taobao can only be settled through Alipay, the consumption data obtained from Alipay for the purchases made on Taobao are expected to depict individuals' online consumption behavior in a representative way.

[7] 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.

[8] According to the Webretailer report, which can be viewed at: https://www.webretailer.com/b/online-marketplaces-china/# The_largest_online_marketplaces_in_China

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.[9] The laboratory is a sandbox environment where the authors can remotely conduct empirical analysis and identifying information is not visible.

We obtain detailed data on monthly consumption made in Taobao shops via Alipay for 40,000 randomly selected individuals from August 2017 to July 2019. Ant Group categorizes online Taobao consumption into three groups: consumption for entertainment, consumption for living, and consumption for development. Consumption for entertainment includes purchases for non-necessities such as accessories, cosmetics, and travel. Consumption for living includes purchases for necessities such as grocery shopping. Consumption for development refers to purchases related to education, training, books, etc. We combine consumption for living and consumption for development into one group and label it as non-entertainment-related consumption.

We require our sample individuals to have made at least one entertainment-related purchase during the sample period, which results in 39,997 unique individuals and 948,605 individual-month observations in our final sample. Appendix A.2 describes how the final sample is selected. Statistics of the sample individuals' average monthly consumption made on Taobao, the breakdowns of Taobao consumption, and their average monthly total consumption made through Alipay (consumption through

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

Taobao's online platform and Alipay's offline QR codes) are reported in Appendix A.2.[10] The average monthly total consumption has grown from around 2,927 CNY (approximately 439 USD) in August 2017 to 4,357 CNY (approximately 654 USD) in July 2019.[11] Consumption made through Taobao accounts for around 40% to 65% of an individual's total consumption made through Alipay. Panel A of Table 1 reports summary statistics of sample individuals' entertainment-related consumption.

[Insert Table 1 about here]

We collect value-weighted stock market returns in the A-share market from China Stock Market & Accounting Research (CSMAR) to quantify stock market shocks. During the sample period from August 2017 to July 2019, the average monthly stock market return is –0.1% with a standard deviation of 5.1%, as reported in Panel B of Table 1. We further classify the monthly market returns into eight bins: $BIN1_t \in (-\infty, -0.08)$; $BIN2_t \in [-0.08, -0.04)$; $BIN3_t \in [-0.04, -0.02)$; $BIN4_t \in [-0.02, 0)$; $BIN5_t \in [0, 0.02)$; $BIN6_t \in [0.02, 0.04)$; $BIN7_t \in [0.04, 0.08)$; $BIN8_t \in [0.08, \infty)$. The average monthly market return of the eight bins ranges from –8.74% to 15.52%. The wide variation in monthly market returns during the sample period enables us to examine the impact of stock market shocks on individuals' consumption behavior. For the 24 sample months, 14 are in the gain domain, while 10 are in the loss domain. In the loss domain

[10] As Taobao took off with Chinese consumers embracing e-commerce, Alipay also caught on the rising momentum of mobile commerce and became the dominant payment method within Alibaba's marketplaces and even beyond. Nowadays, individuals can use Alipay to pay for their purchases in online Taobao shops as well as in offline ecosystems through its QR codes. The total consumption includes both online Taobao consumption and offline purchases made through the QR codes of Alipay. We focus on online consumption in our investigation as the nature of the consumption could only be identified for such purchases. The nature of offline purchases made through Alipay could not be identified.

[11] The USD values are calculated based on exchange rates at the end of respective months.

where negative wealth shocks occur, BIN 1 with the lowest market return contains one sample month, BIN 2 with the 2nd lowest market return contains five sample months, and both BINs 3 and 4 contain two sample months.

3.2 Stock market shocks and entertainment-related consumption: Baseline tests

We examine the non-linear relation between individuals' entertainment consumption and stock market returns using three sets of tests. First, we estimate the following quadratic equation:

$$Log(ent\_csmp)_{i,t+1} = \alpha+\beta_1\ market\ return^2_t + \beta_2\ market\ return_t + controls_{t+1} + \varepsilon_{i,t+1} \quad (1)$$

where the dependent variable is the natural logarithm of individual *i*'s entertainment-related consumption in month *t*+1, *market return* is stock market performance in month *t*, and *market return*^{2} is designed to capture the *U*-shaped relationship. We are mainly interested in the coefficient β_1 that captures the quadratic relationship between entertainment-related consumption and stock returns. We control for city-month-of-the-year joint fixed effects and individual account fixed effects in all the empirical tests, and the standard errors are clustered at the individual account level. The result reported in the first column of Table 2 is consistent with our hypotheses. The significantly positive β_1 indicates that there is a *U*-shaped relation between stock market shocks and individuals' entertainment-related consumption.

[Insert Table 2 about here]

In the second column of Table 2, we separately test whether positive and negative stock market shocks affect entertainment-related consumption in different ways. We estimate the following regression:

$$Log(ent\_csmp)_{i,t+1} = \alpha + \beta_1\ market\ return^{+}_{t} + \beta_2\ market\ return^{-}_{t} + controls_{t+1} + \varepsilon_{i,t+1} \quad (2)$$

where the dependent variable is the natural logarithm of individual *i*'s entertainment-related consumption in month *t*+1, *market return*$^{+}$ equals to stock market return in month *t* if it is positive and zero otherwise, and *market return*$^{-}$ equals to stock market return in month *t* if it is negative and zero otherwise. If individuals increase their entertainment-related consumption even after experiencing large stock market downturns, β_2 should be significantly negative.

The result shows that the coefficients on *market return*$^{+}$ and *market return*$^{-}$ are both significant at the 1% level. The positive sign on *market return*$^{+}$ suggests that positive stock market shocks increase subsequent entertainment-related consumption, which is consistent with standard theory. The negative sign on *market return*$^{-}$, however, indicates that negative stock market shocks *also* increase entertainment-related consumption, supporting the financial retail therapy hypothesis.

In the third test, we perform bin analysis to analyze individuals' consumption patterns following different levels of stock market returns in a non-parametric way. Specifically, we assign market return into eight bins and estimate the following regression:

$$Log(ent\_csmp)_{i,t+1} = \beta_1\, BIN1_t + \beta_2\, BIN2_t + \beta_3\, BIN3_t + \beta_4\, BIN4_t + \beta_5\, BIN5_t + \beta_6\, BIN6_t + \beta_7\, BIN7_t + \beta_8\, BIN8_t + controls_{t+1} + \varepsilon_{i,t+1} \quad (3)$$

where $BIN1_t$ to $BIN8_t$ are indicators of eight market return bins: $BIN1_t \in (-\infty, -0.08)$; $BIN2_t \in [-0.08, -0.04)$; $BIN3_t \in [-0.04, -0.02)$; $BIN4_t \in [-0.02, 0)$; $BIN5_t \in [0, 0.02)$; $BIN6_t \in [0.02, 0.04)$; $BIN7_t \in [0.04, 0.08)$; $BIN8_t \in [0.08, \infty)$.

The third column of Table 2 shows that the logarithm of entertainment-related consumption is the highest in BIN 1 following the largest negative stock market shock. The second-highest level of entertainment-related consumption occurs in BIN 8 following the largest positive stock market shocks. Figure 1 plots average individuals' entertainment-related consumption following the eight market return bins graphically, where a *U*-shaped relation is evident. The pattern is consistent with the findings in the previous two columns.

[Insert Figure 1 about here]

Collectively, the results in Table 2 and Figure 1 show strong and robust evidence that the relationship between stock market shocks and individuals' hedonic consumption is *U*-shaped. Compared with periods of relative financial stability, individuals consume more entertainment-related goods and services when they experience larger positive *or* negative stock market shocks in the previous period. While the response to positive shocks is consistent with standard theory, a similar response after a negative shock points to a psychological mechanism where the individuals attempt to recover from financial distress through hedonic consumption.

3.3 Reverse causality analysis

In previous tests, we have shown how individuals' entertainment-related consumption in month t+1 is affected by stock market shocks in month t. To address potential endogeneity concerns, we follow Engelberg and Parsons (2016) and Lin and Pursiainen (2022) to perform a reverse-causality analysis, in which we regress individuals' entertainment-related consumption in month t+1 on stock market shocks measured in t+2. The results are reported in Table 3 and illustrated graphically in Figure 2.

[Insert Table 3 and Figure 2 about here]

We find no *U*-shaped pattern when the relationship between individuals' entertainment-related consumption and stock market shocks is examined in a reversed way. This finding lends support to our argument that stock market shocks have a causal *U*-shaped relationship with hedonic consumption.

3.4 Subcategory analysis of entertainment-related consumption

In the previous tests, we focus on individuals' consumption of entertainment, as we predicted that this type of consumption was a good proxy for the type of hedonic consumption that our theoretical framework predicts would be affected by financial shocks. In this section, we unpack the entertainment-related consumption category further.

Ant Group breaks down the entertainment-related consumption into nine categories: accessories, cosmetics, sports, household appliances, car-related, recreation services, travel, dining, and living services. Among these nine subcategories, we conjecture that the *U*-shaped pattern will be particularly prominent in the categories of accessories and cosmetics, which are items with small to moderate costs that still allow for hedonic consumption to take place.[12] 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.

In Table 4, we separately estimate influences of stock market shocks on sample individuals' consumption of "accessories & cosmetics" and for other entertainment-related consumption.[13] Panel A shows that the coefficient on *market return*^{2} is significantly positive in both subgroups, but its magnitude in the "accessories & cosmetics consumption" subgroup is about three times greater than that in the "other entertainment-related consumption" subgroup.

[Insert Table 4 about here]

Panel B shows that individuals increase both "accessories & cosmetics" consumption and other entertainment-related consumption after experiencing large positive and negative stock market shocks. Consistently, the magnitudes of the coefficients on both $mkt\ ret+_t$ and $mkt\ ret-_t$, are much greater for "accessories & cosmetics" than for other entertainment-related consumption. The result of the bin analysis in Panel C is plotted in Figure 3, which shows the same pattern as the results in Panels A and B.

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

[13] We find similar results if we include "dining" in the entertainment-related consumption category. However, given that the data is from individuals' online Taobao consumption records, "dining" here is most likely the food vouchers or processed food for delivery, which does not fit the definition of hedonic consumption.

3.5 Non-entertainment-related consumption

In all previous results, we focus on individuals' entertainment-related consumption, as such consumption is a closer proxy to the type of hedonic consumption predicted by our financial retail therapy hypothesis. However, it may be the case that the *U*-shaped relationship between financial shocks and entertainment-related consumption is due to substitution, such that overall consumption following negative shocks decreases in a way that is consistent with standard models. In this subsection, we examine how stock market fluctuations affect individuals' non-entertainment-related consumption. As mentioned above, Ant Group categorizes online Taobao consumption into three categories: entertainment, living, and development. We combine consumption for living and development into one group as non-entertainment-related consumption. We repeat the baseline tests but replace entertainment-related consumption with non-entertainment-related consumption and report the results in Table 5.

[Insert Table 5 about here]

We find that the relationship between non-entertainment-related consumption and stock market shocks is also *U*-shaped but to a much lesser extent, compared with the entertainment-related counterpart. These results imply that the *U*-shaped relationship in entertainment-related consumption is not due to substitution; in contrast to the predictions of standard models, consumption increases after negative financial shocks, and this is driven primarily by a response in entertainment-related consumption.

4. Robustness tests with alternative samples

In Section 3, we showed that individuals' entertainment-related consumption increases significantly following both positive and negative stock market shocks. The substantial increase in entertainment-related consumption after negative stock market shocks is of particular interest. Such a consumption pattern is not consistent with the prediction of standard theory but is consistent with the implications of the proposed framework and the experimental results.

There are two potential concerns with our previous analyses. First, stock market fluctuations may vary with macroeconomic conditions, which in turn affect individuals' current or future income. Therefore, the influence of stock market wealth shocks on individuals' consumption behavior may operate through an income effect. Second, in our previous tests, we use stock market returns to proxy for individuals' personal financial wealth shocks, with the presumption that individuals' stock market investment returns are highly correlated with market movements. Although the prior studies have used aggregate stock return measures as proxies for individuals' wealth shocks (e.g., Engelberg and Parsons, 2016 and Lin and Pursiainen, 2022), the market-level measure can be noisy and does not consider cross-sectional differences in individuals' financial wealth shocks.

In this section, we perform robustness tests using two alternative samples obtained from Ant Group to address these two potential concerns. In the first alternative sample, we randomly select a group of 160,000 Taobao entrepreneurs, i.e., people who run their businesses on the Taobao platform. Given that all transactions generated on the Taobao platform need to be settled through Alipay, we are able to obtain the business income data for these randomly-selected Taobao entrepreneurs. We then match these individuals' business income data with their Alipay consumption data. By doing so, we can control for the income effect when examining consumption responses to stock market wealth shocks.

In the second alternative sample, we randomly select a group of 210,000 individuals who make mutual fund investments on the mutual fund distribution platform of Ant Group. The IPO prospectus of Ant Group disclosed that it has the largest online investment services platform in China measured by asset under management (AUM), reported to be RMB4,099 billion on June 30, 2020. Ant Group partners with approximately 170 asset managers, including the vast majority of mutual fund companies and leading insurers, banks, and securities companies, which enables Ant Group to offer more than 6,000 products to Alipay users. This second alternative sample contains individuals' monthly mutual fund investment return data, which are merged with their monthly Alipay consumption data. Accordingly, we can capture stock market wealth shocks at the individual level rather than using market return data.

4.1 Addressing the income effect

To ease the concerns that the influence of stock market fluctuations on entertainment-related consumption operates through an income effect, we re-run the analyses using the first alternative sample with business income data of Taobao entrepreneurs. This alternative sample contains 2,753,680 individual-month observations.

We perform the same three sets of baseline tests with the additional control of individuals' business income and report the results in Table 6. The coefficient on the business income variable is significantly positive, consistent with the expected positive relationship between income and consumption. However, Column (1) shows that the coefficient on squared stock market return remains significantly positive at the 1% level, implying a *U*-shaped relationship between stock market shocks and entertainment-related consumption even after controlling for a potential income effect.

Column (2) shows that the coefficient on positive stock market shocks is nonsignificant after factoring in the income effect. This is consistent with our theoretical framework as the prediction after gains is driven by an increase in the individual's wealth, which facilitates hedonic consumption by cushioning against its costs. Importantly, however, the coefficient on negative stock market shocks remains significantly negative, suggesting that financial distress prompts hedonic consumption even after controlling for income. Consistently, Column (3) shows that after controlling for income, the entertainment-related consumption of individuals in this alternative sample is still the highest in BIN 1 following the largest negative market shocks. Together, the results in Table 6 suggest that the observed increase in entertainment-related consumption is indeed driven by financial shocks rather than variations in individuals' business income.

[Insert Table 6 about here]

4.2 Measuring stock market wealth shocks at the individual level

The second alternative sample contains randomly selected individuals who not only use Alipay for their consumption payments but also make mutual fund investments through Ant Group's investment platform. The data enable us to capture individuals' stock market wealth shocks more precisely based on their monthly mutual fund investment returns.

This sample includes 4,830,000 (210,000 individuals spanning 23 months) individual-month observations.[14] We then repeat the three sets of baseline tests with the individuals' fund returns, instead of the market returns, in the previous month as the independent variable. The results are reported in Table 7.

[Insert Table 7 about here]

In Column (1), the significantly positive coefficient on $Fund\ ret^{2}_{i,t}$ suggests that the relationship between individuals' entertainment-related consumption and their returns from mutual fund investments is *U*-shaped. Column (2) shows that the coefficients on $Fund\ ret+_{i,t}$ and $Fund\ ret-_{i,t}$ are significantly positive and negative, respectively, in line with individuals increasing their entertainment-related consumption after experiencing both positive and negative mutual fund investment returns. Column (3) displays the logarithm of individuals' entertainment-related consumption across different levels of

[14] To reduce the influences of outliers at the individual-month return level, we winsorize invididuals' monthly fund returns at the 5% level at both tails. We find qualitatively similar results if we use invididuals' mutual fund investment gains and losses as the independent variable and control for their investment size (non-tabulated).

mutual fund investment returns earned in the previous month. Again, when the loss domain is examined, i.e., BINs 1 to 4, individuals' entertainment-related consumption increases monotonically with the magnitude of the negative fund returns. All these results are consistent with our main findings.

Lastly, with this second alternative sample, we further examine the *U*-shaped relationship conditional on individuals' risk tolerance level. In China, mutual fund distribution platforms are required to assess individuals' risk tolerance levels, usually through surveys, before allowing them to make mutual fund investments on the platform. Based on the risk tolerance data provided by the Ant Group, we classify sample individuals into two subgroups: risk-averse and risk-seeking. In Table 8, we examine the relationship between individuals' entertainment-related consumption and mutual fund investment returns conditional on individuals' risk tolerance levels. For subsamples with risk-averse and risk-seeking individuals, the results persistently show that individuals tend to increase their entertainment-related consumption following negative returns, suggesting that the financial retail therapy effect is not driven by individuals' risk attitudes.

[Insert Table 8 about here]

5. Conclusion

Our paper investigates how individual investors change their consumption patterns after experiencing financial shocks. We find that people increase their entertainment-related consumption after experiencing large stock market gains *and* losses. A controlled lab experiment provides further corroborative evidence: compared to a neutral benchmark, people increase positive experiences after both financial gains and losses—even at a cost to themselves. This *U*-shaped relationship between financial outcomes 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 relationship between individual investors' monthly entertainment-related consumption and financial wealth shocks. Given that individuals derive direct utility from purchasing entertainment-related goods and services following investment losses in the stock market, our results suggest that negative financial shocks may lead to a double whammy for people's wealth. 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. Stock market shocks and entertainment-related consumption: Bin analysis

This figure plots the relationship between individuals' entertainment-related consumption made through Taobao and stock market shocks during the sample period from August 2017 to July 2019 based on the market return bin analysis reported in Column 3 of Table 2. An order three polynomial trend line is used to fit the data. The vertical axis shows the natural logarithm of individuals' online entertainment-related consumption paid through Alipay in month *t+1* conditional on bins defined based on market return in month *t*. The sample period is divided into eight bins according to monthly market returns and $BIN1_t$ to $BIN8_t$ are dummy variables indicating these bins: $BIN1_t$ (–∞, –0.08), $BIN2_t$ [–0.08, –0.04), $BIN3_t$ [–0.04, –0.02), $BIN4_t$ [–0.02, 0), $BIN5_t$ [0, 0.02), $BIN6_t$ [0.02, 0.04), $BIN7_t$ [0.04, 0.08), and $BIN8_t$ [0.08, ∞). This sample includes 948,605 individual-month observations.

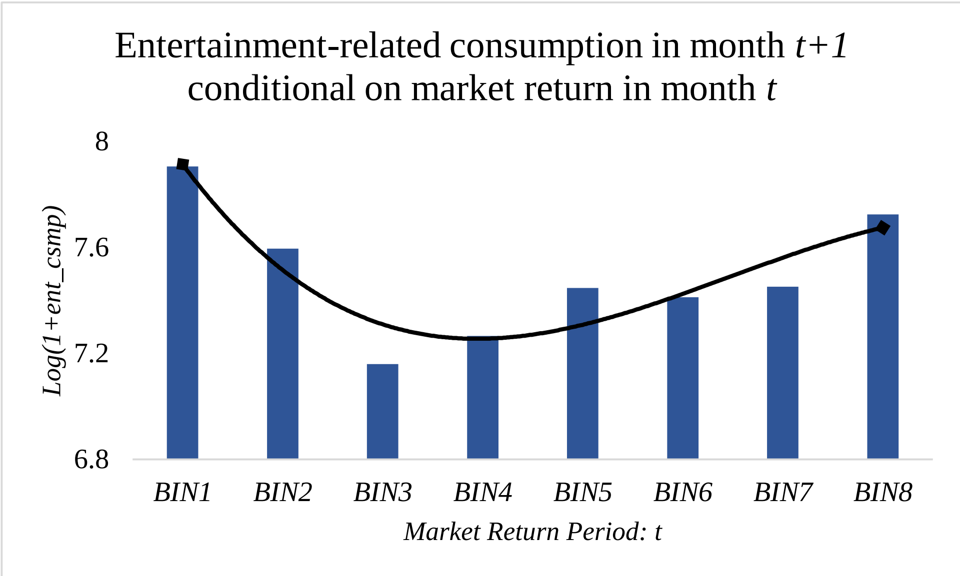

Figure 2. Reverse-causality analysis

This figure plots how individuals' entertainment-related consumption made through Taobao is associated with leading stock market shocks during the sample period from August 2017 to July 2019 based on market return bin analysis reported in Table 4. The vertical axis shows the natural logarithm of individuals' online entertainment-related consumption paid through Alipay in month *t+1* conditional on bins defined based on market return in month *t+2*. Sample months are divided into eight bins according to market returns in month *t+2* and $BIN1_{t+2}$ to $BIN8_{t+2}$ are dummies indicating these bins: $BIN1_{t+2}$ (–∞, –0.08), $BIN2_{t+2}$ [–0.08, –0.04), $BIN3_{t+2}$ [–0.04, –0.02), $BIN4_{t+2}$ [–0.02, 0), $BIN5_{t+2}$ [0, 0.02), $BIN6_{t+2}$ [0.02, 0.04), $BIN7_{t+2}$ [0.04, 0.08), and $BIN8_{t+2}$ [0.08, ∞). This sample includes 948,605 individual-month observations.

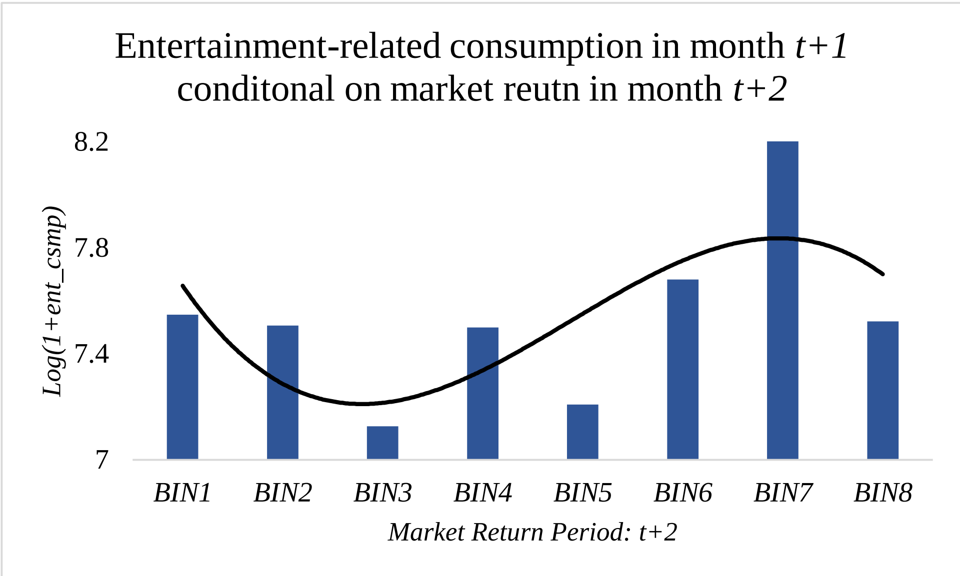

Figure 3. Typical vs. other entertainment-related consumption

This figure plots the relationship between individuals' Taobao consumption within entertainment subcategories and stock market shocks during the sample period from August 2017 to July 2019 based on the market return bin analysis reported in panel C of Table 5. Order 3 polynomial trend lines are used to fit the data. We partition sample individuals' entertainment-related consumption into two subcategories: typical and other entertainment-related consumption. Consumption of accessories & cosmetics is considered typical entertainment-related consumption, and other consumption for entertainment is classified as other entertainment-related consumption. The vertical axis shows the natural logarithm of each consumption subcategory paid through Alipay in month *t+1* conditional on bins defined based on market return in month *t*. The sample period is divided into eight bins according to monthly market returns and $BIN1_t$ to $BIN8_t$ are dummy variables indicating these bins: $BIN1_t$ (–∞, –0.08), $BIN2_t$ [–0.08, –0.04), $BIN3_t$ [–0.04, –0.02), $BIN4_t$ [–0.02, 0), $BIN5_t$ [0, 0.02), $BIN6_t$ [0.02, 0.04), $BIN7_t$ [0.04, 0.08), and $BIN8_t$ [0.08, ∞). This sample includes 948,605 individual-month observations.

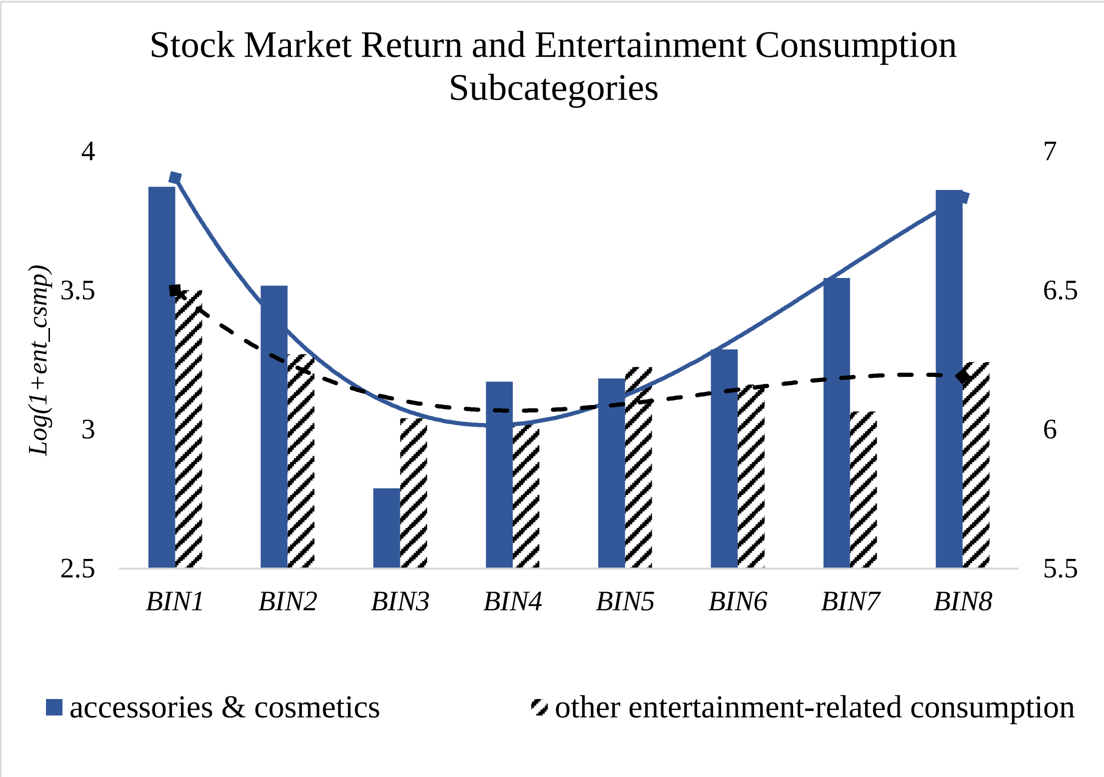

Table 1. Summary Statistics

Panel A reports the summary statistics of the main variables used in the empirical investigation. *Log(1+ent_csmp)* is the natural logarithm of the sample individual's monthly online entertainment-related consumption (in cents) made through Alipay. The variable $mkt\ ret_t$ is stock market return in month t, $mkt\ ret+_t$ equals to market return in month t if it is positive and zero otherwise, and $mkt\ ret-_t$ equals to market return in month t if it is negative and zero otherwise. The sample period is divided into eight bins according to monthly market returns and $BIN1_t$ to $BIN8_t$ are dummy variables indicating these bins: $BIN1_t$ (–∞, –0.08), $BIN2_t$ [–0.08, –0.04), $BIN3_t$ [–0.04, –0.02), $BIN4_t$ [–0.02, 0), $BIN5_t$ [0, 0.02), $BIN6_t$ [0.02, 0.04), $BIN7_t$ [0.04, 0.08), and $BIN8_t$ [0.08, ∞). Panel B reports the distribution of sample months within each market return bin. Panel B reports the distribution of personal characteristics.

Panel A: Summary statistics								
	N	Mean	Std	Min	25%	Median	75%	Max
Log(1+ent_csmp)	948,605	7.461	4.173	0	7.074	9.051	10.198	17.852
Log(1+typical_ent_csmp)	948,605	3.317	4.469	0	0	0	8.477	17.634

Panel B: Distribution of market returns			
	Mean	Median	Std
mkt ret	–0.001	0.005	0.052
mkt ret+	0.019	0.005	0.034
mkt ret–	–0.019	0	0.029
Market Return	BIN	Conditional Mean	Count
(–∞, –0.08]	1	–8.74%	1
(–0.08 , –0.04]	2	–5.90%	5
(–0.04 , –0.02]	3	–2.95%	2
(–0.02 , 0]	4	–1.16%	2
(0 , 0.02]	5	0.73%	6
(0.02 , 0.04]	6	3.13%	6
(0.04 , 0.08]	7	6.48%	1
(0.08 , +∞)	8	15.52%	1

Table 2. Stock market shocks and individuals' entertainment-related consumption

This table examines the relationship between stock market shocks and individuals' entertainment-related consumption made through Taobao during the sample period from August 2017 to July 2019. The dependent variable is the natural logarithm of individual *i*'s entertainment-related consumption paid through Alipay in month *t+1*. The variable $mkt\ ret_t$ is stock market return in month *t*, $mkt\ ret+_t$ equals to market return in month *t* if it is positive and zero otherwise, and $mkt\ ret-_t$ equals to market return in month *t* if it is negative and zero otherwise. The sample period is divided into eight bins according to monthly market returns and $BIN1_t$ to $BIN8_t$ are dummy variables indicating these bins: $BIN1_t$ (–∞, –0.08), $BIN2_t$ [–0.08, –0.04), $BIN3_t$ [–0.04, –0.02), $BIN4_t$ [–0.02, 0), $BIN5_t$ [0, 0.02), $BIN6_t$ [0.02, 0.04), $BIN7_t$ [0.04, 0.08), and $BIN8_t$ [0.08, ∞). Column 1 reports the results of quadratic estimations. Column 2 reports the results of positive and negative market return analysis. Column 3 reports the market return bin analysis. This sample includes 948,605 individual-month observations. 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)
	$Log(1+ent\_csmp)_{i,t+1}$	$Log(1+ent\_csmp)_{i,t+1}$	$Log(1+ent\_csmp)_{i,t+1}$
$mkt\ ret^2_t$	19.844***		
	(1.239)		
$mkt\ ret_t$	–1.121***		
	(0.098)		
$mkt\ ret+_t$		2.044***	
		(0.179)	
$mkt\ ret-_t$		–3.237***	
		(0.192)	
const	7.409***	7.340***	
	(0.005)	(0.008)	
$BIN1_t$			7.905
$BIN2_t$			7.595
$BIN3_t$			7.159
$BIN4_t$			7.266
$BIN5_t$			7.447
$BIN6_t$			7.412
$BIN7_t$			7.452
$BIN8_t$			7.724
City * Month fixed effect	YES	YES	YES
Individual fixed effect	YES	YES	YES
No. Observations:	948,605	948,605	948,605
Adj. R^2:	0.0003	0.0003	0.0007

Table 3. Reverse-causality analysis

This table examines how individuals' entertainment-related consumption made through Taobao is associated with leading stock market shocks. The dependent variable is the natural logarithm of individual *i*'s entertainment-related consumption paid through Alipay in month *t+1*, and the independent variables are indicators for market return bins measured in month *t+2*. The variables $BIN1_{t+2}$ to $BIN8_{t+2}$ are dummies indicating these bins: $BIN1_{t+2}$ (–∞, –0.08), $BIN2_{t+2}$ [–0.08, –0.04), $BIN3_{t+2}$ [–0.04, –0.02), $BIN4_{t+2}$ [–0.02, 0), $BIN5_{t+2}$ [0, 0.02), $BIN6_{t+2}$ [0.02, 0.04), $BIN7_{t+2}$ [0.04, 0.08), and $BIN8_{t+2}$ [0.08, ∞). This sample includes 948,605 individual-month observations. The standard errors are clustered at the individual level and reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% level, respectively.

	(1) $Log(1+ent\_csmp)_{i,t+1}$
Bin Period	Market return measured in *t+2*
$BIN1_{t+2}$	7.548
$BIN2_{t+2}$	7.507
$BIN3_{t+2}$	7.127
$BIN4_{t+2}$	7.500
$BIN5_{t+2}$	7.209
$BIN6_{t+2}$	7.680
$BIN7_{t+2}$	8.242
$BIN8_{t+2}$	7.523
City * Month fixed effect	YES
Individual fixed effect	YES
No. Observations:	948,605
Adj. R^2:	0.0020

Table 4. Typical vs. other entertainment-related consumption

This table examines the relationship between stock market shocks and individuals' consumption made through Taobao within entertainment subcategories. We partition sample individuals' entertainment-related consumption into two subcategories: typical and other entertainment-related consumption. Consumption of accessories & cosmetics is considered typical entertainment-related consumption, and other consumption for entertainment is classified as other entertainment-related consumption. Column 1 reports results for the accessories & cosmetics subcategory, and Column 2 reports results for all other entertainment-related consumption. The dependent variable is the natural logarithm of individual *i*'s consumption paid through Alipay in month $t+1$. The variable $mkt\ ret_t$ is stock market return in month t, $mkt\ ret+_t$ equals to market return in month t if it is positive and zero otherwise, and $mkt\ ret–_t$ equals to market return in month t if it is negative and zero otherwise. The sample period is divided into eight bins according to monthly market returns and $BIN1_t$ to $BIN8_t$ are dummy variables indicating these bins: $BIN1_t$ (–∞, –0.08), $BIN2_t$ [–0.08, –0.04), $BIN3_t$ [–0.04, –0.02), $BIN4_t$ [–0.02, 0), $BIN5_t$ [0, 0.02), $BIN6_t$ [0.02, 0.04), $BIN7_t$ [0.04, 0.08), and $BIN8_t$ [0.08, ∞). In each panel, Column 1 reports the results for typical entertainment-related consumption (accessories, jewelry, and cosmetics), and Column 2 reports the results for remaining entertainment-related consumption. The standard errors are clustered at the individual level and reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% level, respectively.

Panel A: Quadratic Equation		
	(1)	(2)
	$Log(1+typical\_ent\_csmp)_{i,t+1}$	$Log(1+other\_ent\_csmp)_{i,t+1}$
	Consumption for accessories & cosmetics	Consumption for all other entertainment-related consumption
$mkt\ ret^2_t$	33.435***	8.911***
	(1.256)	(1.349)
$mkt\ ret_t$	–1.194***	–0.918***
	(0.099)	(0.107)
const	3.229***	6.168***
	(0.005)	(0.006)
City * Month fixed effect	YES	YES
Individual fixed effect	YES	YES
No. Observations:	948,605	948,605
Adj. R^2:	0.0008	0.0000

Panel B: Up vs. Down Markets		
	(1)	(2)
	Log(1+typical_ent_csmp)$_{i,t+1}$	*Log(1+other_ent_csmp)$_{i,t+1}$*
	Consumption for accessories & cosmetics	Consumption for all other entertainment-related consumption
mkt ret+$_t$	4.538***	0.389***
	(0.182)	(0.195)
mkt ret–$_t$	–5.195***	–1.743***
	(0.194)	(0.209)
const	3.131***	6.150***
	(0.007)	(0.008)
City * Month fixed effect	YES	YES
Individual fixed effect	YES	YES
No. Observations:	948,605	948,605
Adj. R^2:	0.0010	0.0000

Panel C: Bin Analysis		
	(1)	(2)
	Log(1+typical_ent_csmp)$_{i,t+1}$	*Log(1+other_ent_csmp)$_{i,t+1}$*
	Consumption for accessories & cosmetics	Consumption for all other entertainment-related consumption
BIN1$_t$	3.873	6.501
BIN2$_t$	3.517	6.271
BIN3$_t$	2.788	6.041
BIN4$_t$	3.172	6.017
BIN5$_t$	3.183	6.225
BIN6$_t$	3.288	6.161
BIN7$_t$	3.545	6.065
BIN8$_t$	3.861	6.242
City * Month fixed effect	YES	YES
Individual fixed effect	YES	YES
No. Observations:	948,605	948,605
Adj. R^2:	0.0021	0.0002

Table 5. Stock market shocks and individuals' non-entertainment-related consumption

This table examines the relationship between stock market shocks and individuals' non-entertainment-related consumption made through Taobao. The dependent variable is the natural logarithm of individual *i*'s non-entertainment-related consumption paid through Alipay in month $t+1$. The variable $mkt\ ret_t$ is stock market return in month *t*, $mkt\ ret+_t$ equals to market return in month *t* if it is positive and zero otherwise, and $mkt\ ret–_t$ equals to market return in month *t* if it is negative and zero otherwise. The sample period is divided into eight bins according to monthly market returns and $BIN1_t$ to $BIN8_t$ are dummy variables indicating these bins: $BIN1_t$ (–∞, –0.08), $BIN2_t$ [–0.08, –0.04), $BIN3_t$ [–0.04, –0.02), $BIN4_t$ [–0.02, 0), $BIN5_t$ [0, 0.02), $BIN6_t$ [0.02, 0.04), $BIN7_t$ [0.04, 0.08), and $BIN8_t$ [0.08, ∞). Column 1 reports the results of quadratic estimations, Column 2 reports the results of positive and negative market return analysis, and Column 3 reports the market return bin analysis. 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)
	$Log(1+nonent\_csmp)_{i,t+1}$	$Log(1+nonent\_csmp)_{i,t+1}$	$Log(1+nonent\_csmp)_{i,t+1}$
$mkt\ ret^2_t$	5.808***		
	(0.694)		
$mkt\ ret_t$	–0.279***		
	(0.055)		
$mkt\ ret+_t$		0.764***	
		(0.100)	
$mkt\ ret–_t$		–1.025***	
		(0.107)	
const	10.134***	10.115***	
	(0.003)	(0.004)	
$BIN1_t$			10.257
$BIN2_t$			10.240
$BIN3_t$			9.938
$BIN4_t$			9.976
$BIN5_t$			10.152
$BIN6_t$			10.168
$BIN7_t$			10.098
$BIN8_t$			10.276
City * Month fixed effect	YES	YES	YES
Individual fixed effect	YES	YES	YES
No. Observations:	948,605	948,605	948,605
Adj. R^2:	0.0000	0.0001	0.0005

Table 6. Robustness test: Disentangle the income effect

This table examines the relationship between stock market shocks and individuals' entertainment-related consumption made through Taobao using an alternative sample with 160,000 randomly selected Taobao entrepreneurs from August 2017 to July 2019. The dependent variable is the natural logarithm of individual *i*'s consumption for entertainment paid through Alipay in month $t+1$. The variable $mkt\ ret_t$ is stock market return in month t, $mkt\ ret+_t$ equals to market return in month t if it is positive and zero otherwise, and $mkt\ ret–_t$ equals to market return in month t if it is negative and zero otherwise. The sample period is divided into eight bins according to monthly market returns and $BIN1_t$ to $BIN8_t$ are dummy variables indicating these bins: $BIN1_t$ (–∞, –0.08), $BIN2_t$ [–0.08, –0.04), $BIN3_t$ [–0.04, –0.02), $BIN4_t$ [–0.02, 0), $BIN5_t$ [0, 0.02), $BIN6_t$ [0.02, 0.04), $BIN7_t$ [0.04, 0.08), and $BIN8_t$ [0.08, ∞). $Log(business\ income)_{i,t}$ is the natural logarithm of sample individuals' business income from running their Taobao enterprises. Column 1 reports the results of quadratic estimations, Column 2 reports the results of positive and negative market return analysis, and Column 3 reports the market return bin analysis. 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)
	$Log(1+ent\_csmp)_{i,t+1}$	$Log(1+ent\_csmp)_{i,t+1}$	$Log(1+ent\_csmp)_{i,t+1}$
$mkt\ ret^2_t$	5.364***		
	(0.710)		
$mkt\ ret_t$	–0.794***		
	(0.056)		
$mkt\ ret+_t$		–0.029	
		(0.115)	
$mkt\ ret–_t$		–1.349***	
		(0.110)	
const	7.496***	7.484***	
	(0.020)	(0.020)	
$BIN1_t$			7.704
$BIN2_t$			7.484
$BIN3_t$			7.403
$BIN4_t$			7.207
$BIN5_t$			7.489
$BIN6_t$			7.408
$BIN7_t$			7.144
$BIN8_t$			7.424
$Log(business\ income)_{i,t}$	0.030***	0.030***	0.037***
	(0.002)	(0.002)	(0.002)
City * Month fixed effect	YES	YES	YES
Individual fixed effect	YES	YES	YES
No. Observations:	2,753,680	2,753,680	2,753,680
Adj. R^2:	0.0003	0.0003	0.0004

Table 7. Robustness tests using alternative sample 2: Measure stock market wealth shocks using mutual fund investment returns at the individual level

This table examines the relationship between stock market shocks and individuals' entertainment-related consumption made through Taobao using alternative sample 2, which contains 210,000 randomly selected individuals who not only use Alipay for consumption payments but also make mutual fund investments through the mutual fund distribution platform of Ant, from August 2017 to July 2019. The dependent variable is the natural logarithm of individual *i*'s entertainment-related consumption paid through Alipay in month *t+1*. The variable $Fund\ ret_{i,t}$ is individual *i*'s mutual fund investment return in month *t*, $Fund\ ret+_t$ equals to mutual fund investment return in month *t* if it is positive and zero otherwise, and $Fund\ ret-_t$ equals to mutual fund investment return in month *t* if it is negative and zero otherwise. We divide sample individuals' monthly mutual fund investment performance into eight bins according to their return in month *t*, and $BIN1_t$ to $BIN8_t$ are dummy variables indicating these bins: $BIN1_t$ (–∞, –0.08), $BIN2_t$ [–0.08, –0.04), $BIN3_t$ [–0.04, –0.02), $BIN4_t$ [–0.02, 0), $BIN5_t$ [0, 0.02), $BIN6_t$ [0.02, 0.04), $BIN7_t$ [0.04, 0.08), and $BIN8_t$ [0.08, ∞). Column 1 reports the results of quadratic estimations. Column 2 reports the results of positive and negative return analysis. Column 3 reports the results of the bin analysis. 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)
	$Log(1+ent\_csmp)_{i,t+1}$	$Log(1+ent\_csmp)_{i,t+1}$	$Log(1+ent\_csmp)_{i,t+1}$
$Fund\ ret^2_{i,t}$	15.471***		
	(0.985)		
$Fund\ ret_{i,t}$	0.357***		
	(0.060)		
$Fund\ ret+_{i,t}$		2.230***	
		(0.112)	
$Fund\ ret-_{i,t}$		–1.496***	
		(0.106)	
const	5.707***	5.691***	
	(0.001)	(0.002)	
$BIN1_t$			5.816
$BIN2_t$			5.796
$BIN3_t$			5.780
$BIN4_t$			5.661
$BIN5_t$			5.837
$BIN6_t$			5.833
$BIN7_t$			5.839
$BIN8_t$			5.842
City * Month fixed effect	YES	YES	YES
Individual fixed effect	YES	YES	YES
No. Observations:	4,830,000	4,830,000	4,830,000
Adj. R^2:	0.0000	0.0001	0.0003

Table 8. Robustness tests using alternative sample 2: Cross-sectional variation conditional on individuals' risk attitudes

This table examines the relationship between stock market shocks and individuals' entertainment-related consumption made through Taobao using alternative sample 2, which contains 210,000 randomly selected individuals who not only use Alipay for consumption payments but also make mutual fund investments through the mutual fund distribution platform of Ant, conditional on individuals' risk attitudes from August 2017 to July 2019. The dependent variable is the natural logarithm of individual *i*'s entertainment-related consumption paid through Alipay in month $t+1$. The variable $Fund\ ret_t$ is individual *i*'s mutual fund investment return in month *t*, $Fund\ ret+_t$ equals to mutual fund investment return in month *t* if it is positive and zero otherwise, and $Fund\ ret–_t$ equals to mutual fund investment return in month *t* if it is negative and zero otherwise. We divide sample individuals' monthly mutual fund investment performance into eight bins according to their return in month *t*, and $BIN1_t$ to $BIN8_t$ are dummy variables indicating these bins: $BIN1_t$ (–∞, –0.08), $BIN2_t$ [–0.08, –0.04), $BIN3_t$ [–0.04, –0.02), $BIN4_t$ [–0.02, 0), $BIN5_t$ [0, 0.02), $BIN6_t$ [0.02, 0.04), $BIN7_t$ [0.04, 0.08), and $BIN8_t$ [0.08, ∞). Panel A reports the results of quadratic estimations, Panel B reports the results of positive and negative return analysis, and Panel C reports the results of the bin analysis. Columns (1) and (2) report the results for subgroups of risk-averse and risk-seeking individuals. The standard errors are clustered at the individual level and reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% level, respectively.

Panel A: Quadratic Equation		
	(1)	(2)
	$Log(1+ent\_csmp)_{i,t+1}$	$Log(1+ent\_csmp)_{i,t+1}$
Risk attitude	Risk-averse	Risk-seeking
$Fund\ ret^2_{i,t}$	15.373***	15.032***
	(1.494)	(1.344)
$Fund\ ret_{i,t}$	0.230**	0.360***
	(0.094)	(0.081)
const	5.427***	5.919***
	(0.002)	(0.002)
City * Month fixed effect	YES	YES
Individual fixed effect	YES	YES
No. Observations:	2,101,286	2,475,214
Adj. R^2:	0.0000	0.0000
Panel B: Up vs. Down Markets		
	(1)	(2)
	$Log(1+ent\_csmp)_{i,t+1}$	$Log(1+ent\_csmp)_{i,t+1}$
Risk attitude	Risk-averse	Risk-seeking
$Fund\ ret+_{i,t}$	2.142***	2.218***
	(0.173)	(0.152)
$Fund\ ret–_{i,t}$	–1.658***	–1.433***
	(0.162)	(0.144)
const	5.412***	5.903***
	(0.002)	(0.002)
City * Month fixed effect	YES	YES

Individual fixed effect	YES	YES
No. Observations:	2,101,286	2,475,214
Adj. R^2:	0.0001	0.0001

Panel C: Bin Analysis		
	(1)	(2)
	$Log(1+ent\_csmp)_{i,t+1}$	$Log(1+ent\_csmp)_{i,t+1}$
Risk attitude	Risk-averse	Risk-seeking
$BIN1_t$	5.548	6.022
$BIN2_t$	5.526	6.003
$BIN3_t$	5.519	5.986
$BIN4_t$	5.387	5.873
$BIN5_t$	5.552	6.038
$BIN6_t$	5.561	6.030
$BIN7_t$	5.564	6.049
$BIN8_t$	5.551	6.054
City * Month fixed effect	YES	YES
Individual fixed effect	YES	YES
No. Observations:	2,101,286	2,475,214
Adj. R^2:	0.0002	0.0002

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. Sample individuals' average monthly consumption made through Alipay

This figure plots the sample average of monthly total Taobao consumption and Taobao entertainment-related consumption (in RMB) over the sample period from August 2017 to July 2019. The sample includes 948,605 individual-month observations.

Unit: RMB

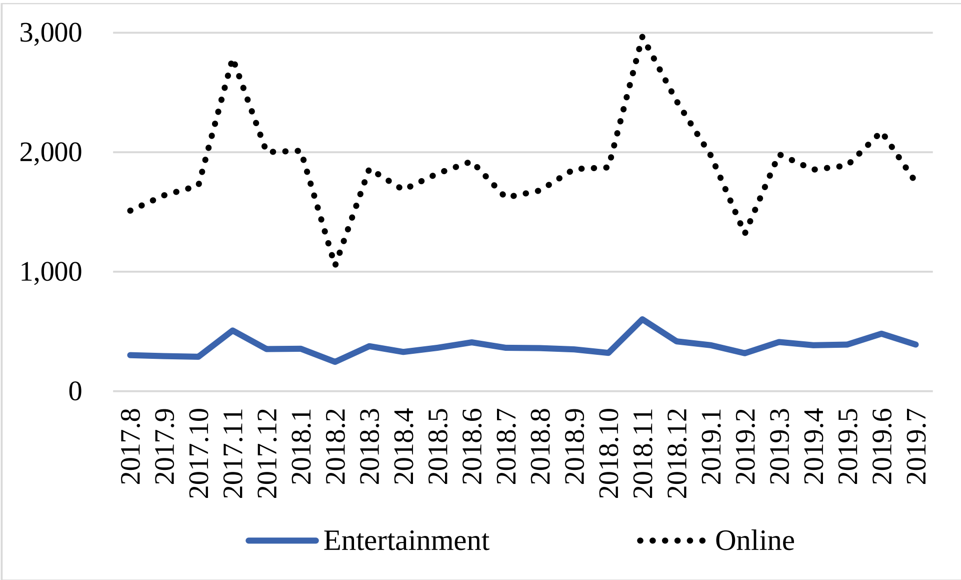

Table A1. Sample selection.

This table illustrates how the final sample is derived and the number of observations and unique individuals.

	Obs. No.	Unique individuals
Original sample	960,000	40,000
Observations that have made at least one entertainment-related purchase during the whole sample period	948,605	39,997
Final sample	948,605	39,997

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

This table shows sample individuals' average total consumption made through Alipay, total Taobao consumption, and the breakdown of Taobao consumption in each month over the sample period.

Month	The breakdown of Taobao consumption					Total Taobao consumption	Total Alipay consumption (through Taobao and offline QR codes)
	Entertainment	Entertainment (Conditional Mean)	Entertainment (Conditional Median)	Non-Entertainment	Un-Classified		
2017.8	302.94	400.90	115.10	697.75	510.48	1511.17	2927.73
2017.9	295.54	394.82	113.64	801.07	542.83	1639.44	3157.46
2017.10	289.11	384.52	112.46	860.58	570.56	1720.25	3189.98
2017.11	507.47	630.94	172.00	1334.27	945.96	2787.70	4316.99
2017.12	352.09	453.82	129.00	1007.37	642.08	2001.54	3743.39
2018.1	355.92	464.29	132.00	1031.41	625.03	2012.36	3839.43
2018.2	246.48	361.14	116.00	463.97	338.37	1048.82	2646.44
2018.3	376.69	474.30	144.57	858.19	627.35	1862.23	3628.55
2018.4	328.64	426.96	128.00	779.39	576.19	1684.22	3447.96
2018.5	364.77	464.15	139.00	827.31	629.54	1821.62	3549.30
2018.6	409.66	518.56	148.64	866.55	647.89	1924.10	3713.40

2018.7	364.92	457.18	138.80	722.68	532.89	1620.49	3487.46
2018.8	361.61	453.55	142.24	747.70	571.38	1680.69	3688.15
2018.9	350.63	453.02	131.00	881.59	627.04	1859.26	4068.22
2018.10	321.36	415.37	125.80	901.93	649.22	1872.51	3887.64
2018.11	601.93	721.23	214.78	1441.27	923.04	2966.24	5073.68
2018.12	416.79	525.19	152.90	1169.91	839.65	2426.35	4880.39
2019.1	384.34	504.59	144.00	956.36	631.83	1972.53	4442.53
2019.2	317.26	424.70	140.90	572.41	427.17	1316.84	3183.46
2019.3	412.18	514.73	158.79	907.19	664.54	1983.91	4348.73
2019.4	384.20	492.63	144.19	845.08	623.73	1853.01	4140.92
2019.5	391.43	493.63	148.70	850.84	646.50	1888.77	4342.19
2019.6	481.54	587.79	181.08	965.94	725.64	2173.12	4668.94
2019.7	391.87	487.13	148.90	779.72	578.85	1750.44	4356.81