

In victory or defeat: Consumption responses to wealth shocks

Alex Imas

Booth School of Business
University of Chicago

Tse-Chun Lin

HKU Business School
University of Hong Kong

Yan Luo

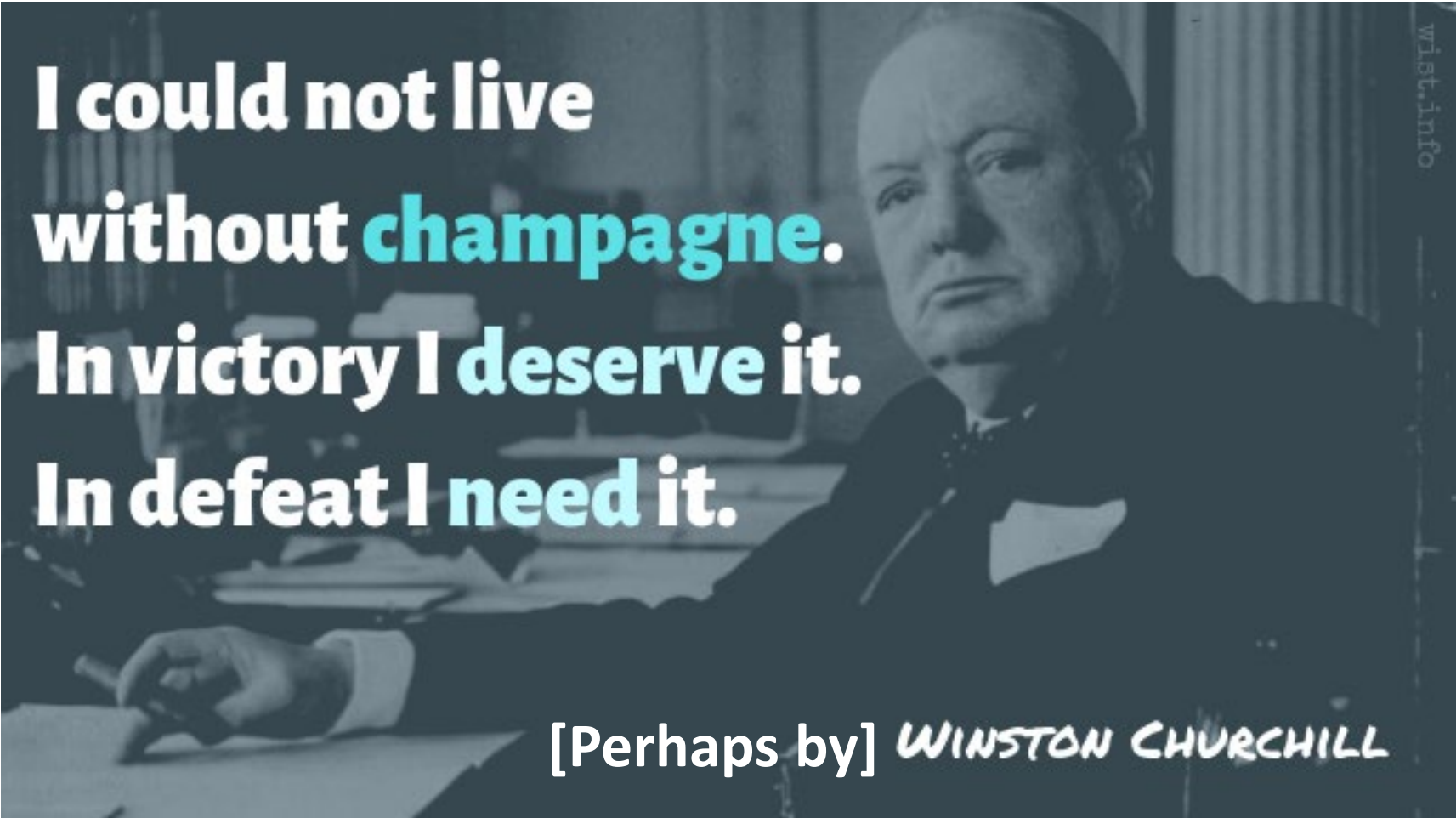
School of Management
Fudan University

Xiaohuan Wang

Shanghai National
Accounting Institute

ABFER 2024 Singapore

The title



**I could not live
without champagne.
In victory I deserve it.
In defeat I need it.**

[Perhaps by] *WINSTON CHURCHILL*

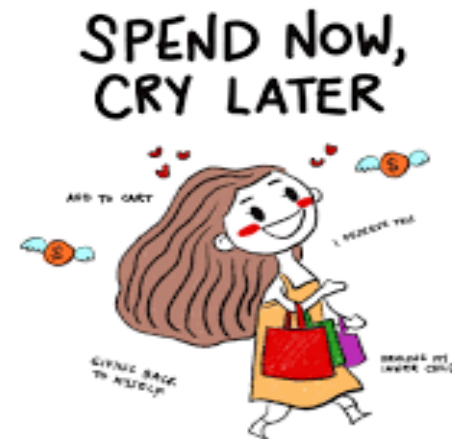
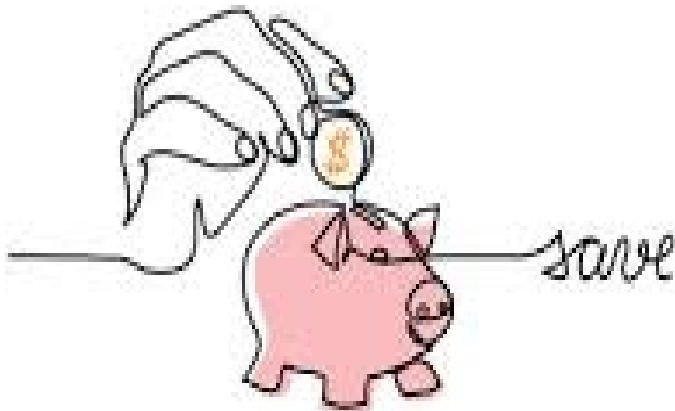
The question

- How do households adjust consumption shortly after experiencing large **negative** financial wealth shocks?

※ **cut** unnecessary consumption to make up for losses?



※ **increase** (hedonic) consumption to improve mood?



The challenge

- Existing studies have tried to estimate individuals' marginal propensity to consume (MPC) from wealth shocks.
- Challenge: lack of exact data on individuals' **consumption** linked with **wealth shocks**:
 - ※ **survey** (e.g., Dynan and Maki, 2001; Baker, Nagel, and Wurgler; 2007; Aaronson, Agarwal, and French, 2012; Paiella and Pistaferri, 2017)
 - ※ use administrative data to impute consumption as a residual of disposable income net of other transactions (e.g., Di Maggio, Kermani, and Majlesi, 2020; Koijen, Van Nieuwerburgh, and Vestman, 2015; Kolsrud, Landais, and Spinnewijn, 2019)

The challenge



Swedish Household Administrative data

- **annual** frequency
- reckon consumption from income and transactions

Maggio, Marco Di, Amir Kermani, and Kaveh Majlesi, (2020 JF)

- Estimate MPC separately for capital gains & dividend
- Wealth shocks from both sources affect consumption but to different degrees

The literature

- MPC literature: wealth shocks **positively** affect consumption in general

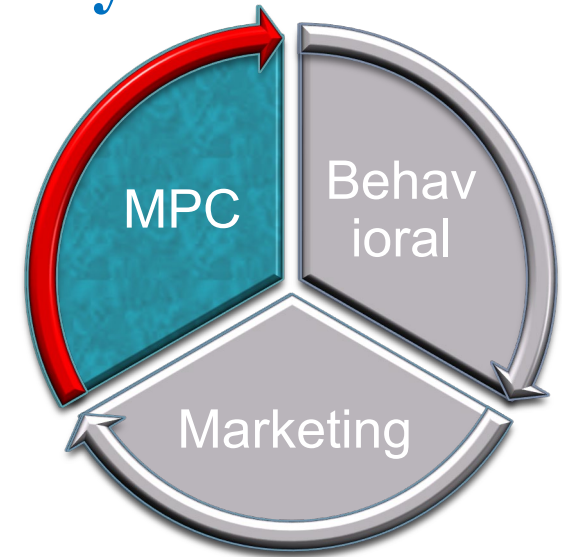
※ implicitly assuming a **linear** relation

* dividend income (Baker et al., 2007)

* stock market (Maggio et al., 2020)

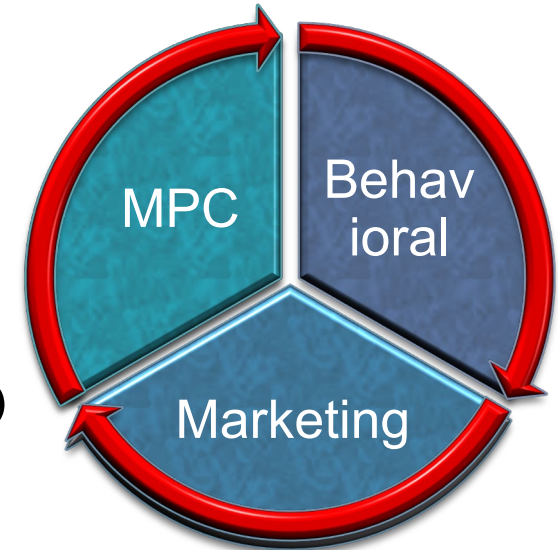
* housing market (Mian et al., 2013; Aladangady, 2017; Paiella and Pistaferri, 2017; Di Maggio et al., 2020)

* CARES Act (Baker et al., 2021)



The literature

- Behavioral literature: negative financial shocks induce **anxiety**, **sadness**, and **distress**
 - ※ hospitalization (Engelberg and Parsons, 2016)
 - ※ labor productivity (Bernstein et al., 2021)
 - ※ domestic violence (Lin and Pursiainen, 2023)
- Marketing literature: “hedonic” consumption allows individuals to psychologically recover from distress
 - ※ **retail therapy**: distress-motivated consumption to repair bad moods (Atalay and Meloy, 2011; Rick, Pereira, and Burson, 2014).



The hypotheses

- **Financial retail therapy:** increase hedonic consumption after experiencing negative financial wealth shocks to alleviate distress

H1: *in response to negative financial wealth shocks, individuals tend to temporarily increase their consumption as a retail therapy.*

H2: *in response to negative financial wealth shocks, the increase in consumption is more pronounced for that with a “hedonic” nature.*

The details

- A lab experiment:

- ✧ decisions on consumption of “leisure” after experiencing positive and negative wealth shocks



- Tests on observational data:

- ✧ weekly/monthly consumption via Alipay

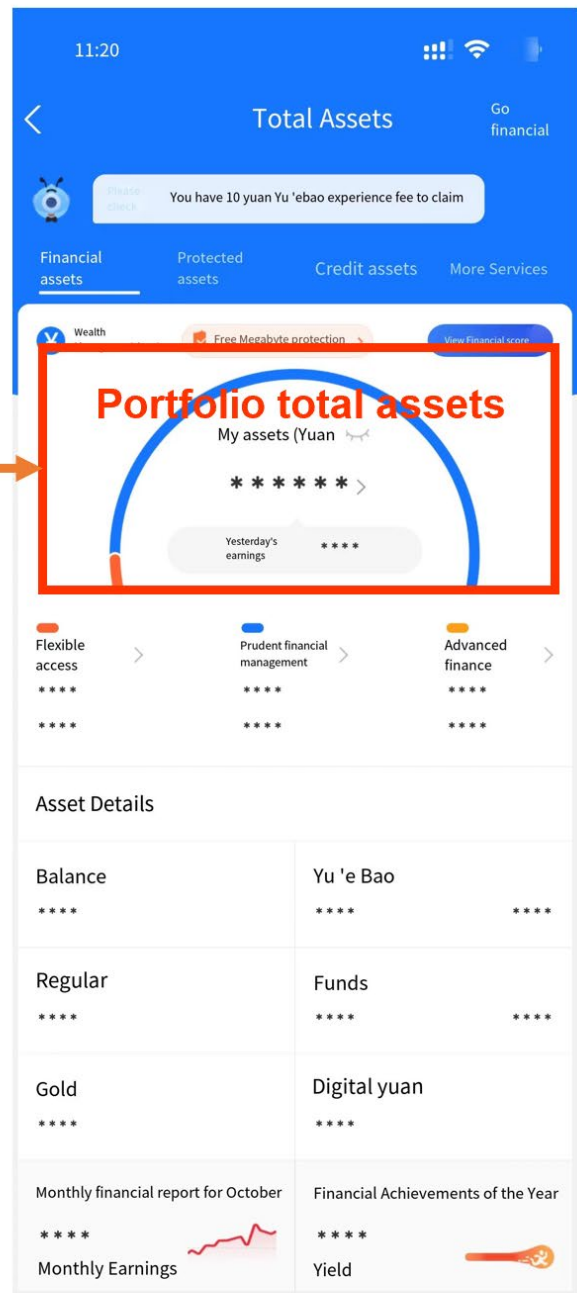
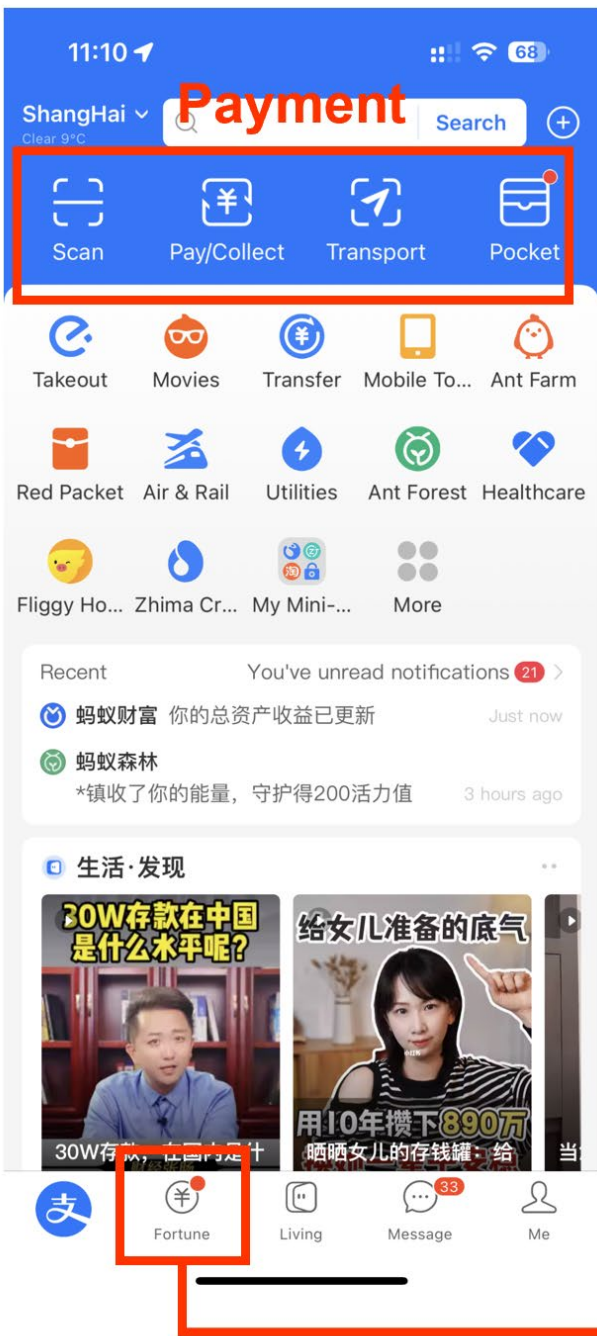
- ✧ investment returns on Ant Fortune via Alipay

consumption



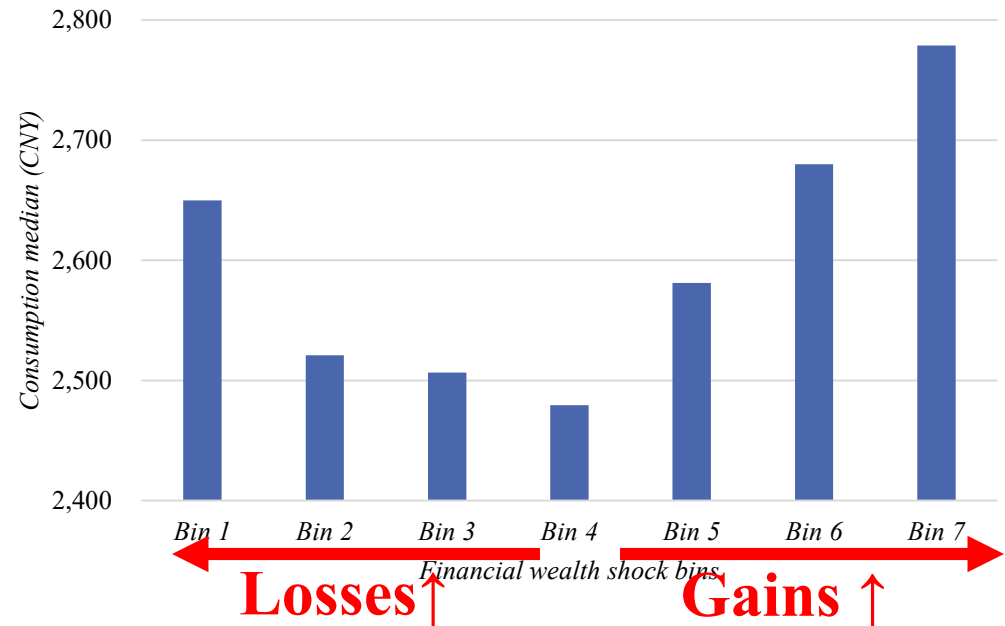
investment





The findings

- A **U-shaped** relation btw financial wealth shocks and total consumption



- More evident for **entertainment-related** consumption, relative to living- & development-related consumption
 - ※ strongest for **cosmetics, accessories, recreation**
- Robust to control of liquidity constraints, income effect

The contribution

- Add to the MPC literature
 - ※ individuals' **observed** data, focus on short-term relation
 - ※ document a novel **U-shaped** relationship
- Add to the psychological and behavioral literature on the consequences of distress triggered by negative wealth shocks
 - ※ existing studies: the consequences (hospitalization, productivity, domestic violence, ...)
 - ※ our study: how individuals **deal** with the distress

The experiment

- 283 participants from Prolific, an online crowdsourcing platform.
- \$1.00 base fee for completing the study



Neutral
\$1 endowment



Gain-or-Loss
\$1 to invest

- The neutral group is asked to solve a series of anagrams for two minutes.

The investment

- Gain-or-Loss group needs to make **four** successive rounds of investment decisions.
- In each round, participants could choose any amount between \$0 and \$0.25 to invest.
- “Succeed” with a chance of $1/6$ (17%) to make 6 times the amount invested.
- Participants’ prior payoff did not affect the amount they could invest in each round.

The consumption (of leisure)

- Afterward, participants could choose to rate pictures of various irksome images on their level of unpleasantness for up to 60 minutes.
- Participants decided how to allocate 60 minutes between **working on unpleasant tasks for money** or **more enjoyable activities**.
- If the allocation of work is larger than random number P , complete the task and receive \$12, otherwise complete no task and receive \$0.

The result

- Our hypothesis predicts fewer minutes of working (consuming more leisure) after experiencing both gains and losses:
 - ※ 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; $p=0.01$).
 - ※ Regressing the number of allocated minutes on the size of the **absolute return** indeed reveals a significant effect ($\beta=-8.91$; $p=0.018$)

The observational

- Four datasets from the Ant Group, all of which were randomly sampled
- Each dataset has its strengths and limitations in terms of data frequency, sample size, length of sample period, or variable availability

=> Use these four datasets in separate tests to utilize their strengths

The four datasets – strengths and limitations

Dataset	Features	
D1	Data frequency	Weekly
	Fund investment info.	Yes
	Total consumption info.	Yes
	Consumption category info.	No
	Consumption subcategory info.	No
	Income info.	No
	<ul style="list-style-type: none"> No. of unique individuals: 20,000. Sample period: 4 years 209 weeks, from August 2017 to July 2021. Observations: 3,614,861. 	

Dataset	Features	
D2	Data frequency	Monthly
	Fund investment info.	Yes
	Total consumption info.	Yes
	Consumption category info.	Yes
	Consumption subcategory info.	No
	Income info.	No
	<ul style="list-style-type: none"> No. of unique individuals: 100,000. Sample period: 4 years 48 months, from August 2017 to July 2021. Observations: 4,696,077. 	

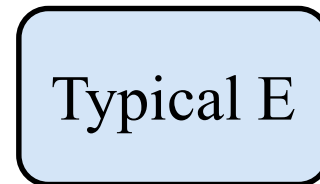
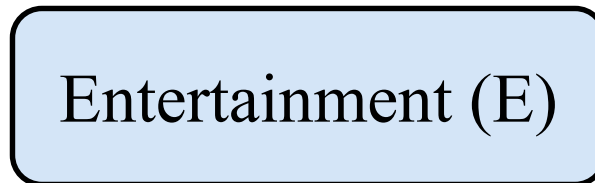
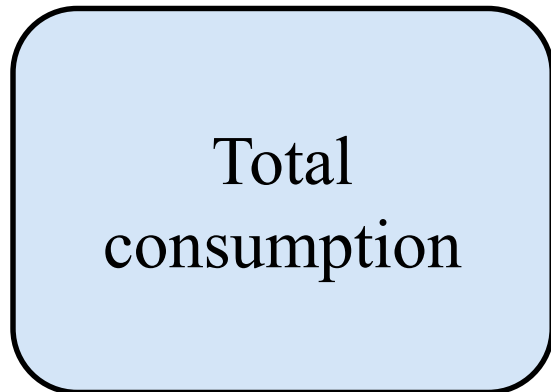
The four datasets – strengths and limitations

Dataset	Features	Dataset	Features		
D3	Data frequency	Monthly	D4	Data frequency	Monthly
	Fund investment info.	No		Fund investment info.	No
	Total consumption info.	Yes		Total consumption info.	Yes
	Consumption category info.	Yes		Consumption category info.	No
	Consumption subcategory info.	Yes		Consumption subcategory info.	No
	Income info.	No		Income info.	Yes
	<ul style="list-style-type: none"> No. of unique individuals: 40,000. Sample period: 2 years 24 months, from August 2017 to July 2019. Observations: 739,168. 	<ul style="list-style-type: none"> No. of unique individuals: 160,000. Sample period: 2 years 24 months, from August 2017 to July 2019. Observations: 2,931,714. 			

The regressions

$$\ln(csmp)_{i,t+1} = \alpha + \beta_1 \text{Positive invest ret}_{i,t} + \beta_2 \text{Negative invest ret}_{i,t} + \text{controls}_{t+1} + \varepsilon_{i,t+1}$$

D1 → **D2** → **D3**



Short-term influence of financial wealth shocks on consumption – testing H1

D1: weekly, investment return linked with total consumption

	(1)	(2)	(3)	(4)
	$\ln(\text{total_csmp})_{i,t+1}$	$\ln(\text{total_csmp})_{i,t+1}$	$\ln(\text{total_csmp})_{i,t+1}$	$\ln(\text{total_csmp})_{i,t+1}$
<i>Positive invest ret</i> _{<i>i,t</i>}	0.753*** (0.096)	0.617*** (0.085)	1.170*** (0.093)	1.015*** (0.083)
<i>Negative invest ret</i> _{<i>i,t</i>}	-0.497*** (0.101)	-0.424*** (0.094)	-0.645*** (0.098)	-0.711*** (0.092)
$\ln(\text{total_csmp})_{i,t}$		0.183*** (0.001)		1.174*** (0.001)
<i>Positive mkt ret</i> _{<i>t</i>}			1.883*** (0.065)	1.477*** (0.067)
<i>Negative mkt ret</i> _{<i>t</i>}			-0.645*** (0.098)	-0.505*** (0.070)
<i>Const</i>	5.854*** (0.001)	4.855*** (0.007)	5.826*** (0.001)	4.883*** (0.001)
Year-month FE	NO	NO	YES	YES
Year-week FE	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

Consumption breakdowns: Entertainment-, living-, and development-related consumption – testing H2

D2: monthly, investment return linked with E/L/D consumption

	(4)	(5)	(6)
	$\ln(csmp)_{i,t+1}$	$\ln(csmp)_{i,t+1}$	$\ln(csmp)_{i,t+1}$
	<i>Online</i>		
	<i>Entertainment</i>	<i>Living</i>	<i>Development</i>
<i>Positive invest ret_{i,t}</i>	0.100** (0.040)	0.141*** (0.033)	0.081 (0.051)
<i>Negative invest ret_{i,t}</i>	-0.197*** (0.057)	-0.111** (0.046)	-0.002 (0.075)
<i>Const</i>	4.943*** (0.001)	5.474*** (0.001)	4.508*** (0.001)
Year-month FE	YES	YES	YES
Individual FE	YES	YES	YES
Cluster by individual	YES	YES	YES
No. Observations:	2,852,495	3,326,181	1,818,935
Adj. R ²	0.000	0.000	0.000

Typical vs. other entertainment-related consumption – testing H2

D3: monthly, investment return linked with typical/other entertainment-related consumption

	(1)	(2)	(3)
	$\ln(csmp)_{i,t+1}$	$\ln(csmp)_{i,t+1}$	$\ln(csmp)_{i,t+1}$
	<i>Entertainment consumption</i>		
	<i>Entertainment</i>	<i>Accessories, cosmetics, and cultural recreation</i>	<i>All other entertainment-related consumption</i>
<i>Positive mkt ret_t</i>	1.203** (0.070)	1.730*** (0.095)	0.480*** (0.078)
<i>Negative mkt ret_t</i>	-1.482*** (0.072)	-1.933*** (0.096)	-0.721*** (0.082)
<i>Const</i>	4.919*** (0.002)	4.459*** (0.003)	4.674*** (0.003)
Month-of-the-year FE	YES	YES	YES
Year-month FE	N.A.	N.A.	N.A.
Individual FE	YES	YES	YES
Cluster by individual	YES	YES	YES
No. Observations:	739,168	287,150	631,532
Adj. R ²	0.001	0.003	0.001

The concerns

1. How could consumption \uparrow as financial constraints are tightened?
 - high household saving rate in China (45%-50%, CEIC)
 - the level of consumption is moderate: 200-300 USD p.m.
2. Changing liquidity conditions? (sell losing funds \Rightarrow liquidity \uparrow)
 - disposition effect: reluctant to sell losing positions
 \Rightarrow liquidity condition should not change much after losses
 - subsample test: exclude obs. that have sold position in $t-1$.
3. The income effect?
 - short-term effect, income is less likely to change frequently
 - control for income using dataset 4 with income data

Filter out the influence of changing liquidity constraints

D1: weekly, investment return linked with total consumption

	(1)	(2)	(3)
	$\ln(\text{total_csmpl})_{i,t+1}$	$\ln(\text{total_csmpl})_{i,t+1}$	$\ln(\text{total_csmpl})_{i,t+1}$
	Exclude investors who have sold losing funds in t	Exclude investors who have sold winning funds in t	Exclude investors who have sold any fund in t
<i>Positive invest ret_t</i>	0.754*** (0.096)	0.776*** (0.097)	0.757*** (0.097)
<i>Negative invest ret_t</i>	-0.493*** (0.102)	-0.496*** (0.102)	-0.491*** (0.102)
<i>Const</i>	5.854*** (0.001)	5.852*** (0.001)	5.853*** (0.001)
Year-week FE	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

Control for the income effect

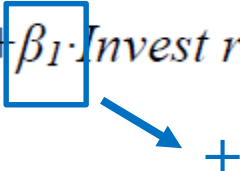
D4: monthly, income linked with total consumption

Financial wealth shocks captured by market returns

	(1)	(2)	(3)
	$\ln(\text{total_csmpt})_{i,t+1}$	$\ln(\text{total_csmpt})_{i,t+1}$	$\text{Total csmpt}_{i,t}$
<i>Positive mkt ret_t</i>	1.742*** (0.031)	1.407*** (0.029)	17.830*** (0.454)
<i>Negative mkt ret_t</i>	-1.341*** (0.029)	-1.112*** (0.029)	-15.207*** (0.416)
$\ln(\text{income})_{i,t}$	0.139*** (0.001)	0.124*** (0.001)	1.468*** (0.012)
$\ln(\text{total_csmpt})_{i,t}$		0.221*** (0.001)	
<i>Const</i>	7.052*** (0.006)	5.372*** (0.011)	-2.311*** (0.102)
Month-of-the-year FE	YES	YES	YES
Year-month FE	N.A.	N.A.	N.A.
Individual FE	YES	YES	YES
Cluster by individual	YES	YES	YES
No. Observations	2,931,714	2,771,714	2,931,714
Adj. R ²	0.042	0.090	0.024

The robustness

- The dependent variable in baseline tests: the natural logarithm of consumption, zero obs. are dropped
 - use the raw value of consumption as an alternative dependent variable
 - use the Poisson regression analysis recommended by Cohn et al., (2022) and Chen and Roth (2023).
- Use a quadratic model specification

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


Conclusion



Conclusion

- We show that individuals tend to increase hedonic consumption after experiencing both positive and negative investment shocks via:
 - ※ A stylized dynamic prospect theory model
 - ※ A experiment study based on the model with leisure as the hedonic consumption
 - ※ Proprietary Alipay consumption data
- The welfare implications of such a financial retail therapy can and should be further explored.

Thanks!

Table 2: Summary statistics

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

	N	Mean	Std	1%	25%	50%	75%	99%
$Ln(total_csm p)_{i,t}$	3,614,861	5.861	1.555	1.792	4.898	5.903	6.861	9.685
$Total\ csm p_{i,t}$	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%
$Total\ csm p_{i,t}$	4,696,077	5678.886	9467.878	71.808	1118.960	2555.640	5831.220	62672.580
$Offline\ csm p_{i,t}$	4,612,512	4196.952	8143.837	0.010	580.180	1553.730	3927.360	54910.770
$Online\ csm p_{i,t}$	4,118,602	1594.526	2786.338	0.010	195.640	590.705	1647.690	17147.150
$Entertainment\ csm p_{i,t}$	2,852,495	454.839	897.444	0.010	48.600	137.730	390.000	5080.519
$Living\ csm p_{i,t}$	3,326,181	617.411	1031.210	0.010	89.000	251.410	648.950	6024.886
$Development\ csm p_{i,t}$	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

Table 2: Summary statistics

Panel C: Dataset 3 (monthly data with individual-level consumption category and subcategory information)								
	N	Mean	Std	1%	25%	50%	75%	99%
<i>Entertainment csm_{p_{i,t}}</i>	739,168	404.098	819.590	6.000	55.000	141.000	358.000	5597.044
<i>Typical entertainment csm_{p_{i,t}}</i>	287,150	223.420	404.337	5.900	37.900	89.900	225.118	2803.092
<i>Other entertainment csm_{p_{i,t}}</i>	631,532	342.582	763.973	4.900	38.900	101.100	273.000	5260.490

Panel D: Dataset 4 (monthly data with individual-level total consumption and income information)								
	N	Mean	Std	1%	25%	50%	75%	99%
<i>Total csm_{p_{i,t}}</i>	2,931,714	10188.180	19240.800	46.803	1523.840	3781.290	9740.540	130587.800
<i>Income_{i,t}</i>	2,931,714	23698.060	63053.810	1.150	858.000	3916.000	15432.000	450020.000
<i>Positive mkt ret_{i,t}</i>	2,931,714	0.021	0.037	0.000	0.000	0.001	0.032	0.155
<i>Negative mkt ret_{i,t}</i>	2,931,714	-0.020	0.029	-0.087	-0.043	0.000	0.000	0.000

H2: Consumption breakdowns: Entertainment-, living-, and development-related consumption

Dataset 2: weekly linked inv. ret. and csmp breakdowns

	(1)	(2)	(3)
	$\ln(csmp)_{i,t+1}$	$\ln(csmp)_{i,t+1}$	$\ln(csmp)_{i,t+1}$
	<i>Total</i>	<i>Total</i>	
		<i>Offline</i>	<i>Online</i>
<i>Positive invest ret_{i,t}</i>	0.470*** (0.026)	0.588*** (0.032)	0.206*** (0.031)
<i>Negative invest ret_{i,t}</i>	-0.452*** (0.035)	-0.535*** (0.045)	-0.274*** (0.043)
<i>Const</i>	7.822*** (0.001)	7.253*** (0.001)	6.296*** (0.001)
Year-month FE	YES	YES	YES
Individual FE	YES	YES	YES
Cluster by individual	YES	YES	YES
No. Observations:	4,696,077	4,612,512	4,118,602
Adj. R ²	0.000	0.000	0.000

Table 8: Transformation of the dependent variable

Panel A: OLS regressions					
	(1)	(2)	(3)	(4)	(5)
	<i>Total consumption</i>	<i>Online consumption</i>	<i>Online consumption</i>		
			<i>Entertainment</i>	<i>Living</i>	<i>Development</i>
<i>Positive invest ret_t</i>	7.128*** (1.420)	3.354*** (0.604)	0.521* (0.274)	0.872*** (0.272)	0.758*** (0.357)
<i>Negative invest ret_t</i>	-2.725* (1.397)	-5.047*** (0.854)	-1.064*** (0.396)	-0.730* (0.386)	-0.640 (0.534)
<i>Const</i>	10.858*** (0.015)	16.007*** (0.012)	4.788*** (0.005)	6.329*** (0.006)	4.005*** (0.007)
Dataset used	Dataset 1	Dataset 2	Dataset 2	Dataset 2	Dataset 2
Data frequency	Weekly	Monthly	Monthly	Monthly	Monthly
Year-week FE	YES	N.A.	N.A.	N.A.	N.A.
Year-month FE	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

Table 8: Transformation of the dependent variable

Panel B: Poisson regressions					
	(1)	(2)	(3)	(4)	(5)
	<i>Total consumption</i>	<i>Online consumption</i>	<i>Online consumption</i>		
			<i>Entertainment</i>	<i>Living</i>	<i>Development</i>
<i>Positive invest ret_t</i>	2.820*** (0.001)	0.953*** (0.004)	0.870*** (0.010)	0.679*** (0.008)	-0.067*** (0.014)
<i>Negative invest ret_t</i>	-0.041*** (0.001)	-0.378*** (0.006)	-0.116*** (0.014)	-0.040*** (0.011)	0.136*** (0.202)
<i>Const</i>	6.972*** (0.000)	2.777*** (0.000)	1.456*** (0.001)	1.902*** (0.001)	1.235*** (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

	(1)	(2)	(3)	(4)	(5)
	$\ln(\text{csmp})_{i,t+1}$	$\ln(\text{csmp})_{i,t+1}$	$\ln(\text{csmp})_{i,t+1}$	$\ln(\text{csmp})_{i,t+1}$	$\ln(\text{csmp})_{i,t+1}$
	<i>Total consumption</i>	<i>Online consumption</i>	<i>Online consumption</i>		
			<i>Entertainment</i>	<i>Living</i>	<i>Development</i>
<i>Invest ret</i> ² _{<i>t</i>}	6.838*** (1.395)	1.267*** (0.266)	0.610* (0.356)	0.720** (0.284)	0.059 (0.455)
<i>Invest ret</i> _{<i>t</i>}	0.162*** (0.045)	-0.013 (0.022)	-0.029 (0.031)	0.024 (0.024)	0.050 (0.041)
<i>Const</i>	5.858** (0.001)	6.300*** (0.000)	4.945*** (0.000)	5.475*** (0.000)	4.508*** (0.001)
Dataset used	Dataset 1	Dataset 2	Dataset 2	Dataset 2	Dataset 2
Data frequency	Weekly	Monthly	Monthly	Monthly	Monthly
Year-week FE	YES	N.A.	N.A.	N.A.	N.A.
Year-month FE	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